COGNITIVE NEUROPROSTHETICS:

BODY OWNERSHIP AND AGENCY FOR
BRAIN-MACHINE ACTIONS

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Abstract

Humankind is in a state of rapidly accelerating technological advance, where once-distant future technologies have consistently become today's reality. Paralleling these developments in machines and technology is an accelerated accumulation of knowledge driven by a boom in societal interest to understand the human brain, also motivated by scientific advances. Yet, as we progressively move toward technology-assisted tool use, tele-presence systems, medical robotics, and brain-machine interfaces aimed at the repair and augmentation of human cognitive and motor capacities, there is an increasing need to understand what happens when brain "merges" with machine. What are the subjective, perceptual, motor, and neural consequences of such a partnership? Can we use this knowledge to perhaps better understand enhancement, rehabilitation, and repair of neurological disability via neuroprosthetic devices? Here, I investigate these issues by providing converging evidence from a set of experiments designed to draw links between two previously independent research domains: the cognitive neuroscience of bodily self-consciousness and brain-machine interfaces. Through common motor imagery paradigms and with the aid of virtual reality, neuroimaging, and probabilistic modeling, in this thesis I explore the intersection of these two paths of contemporary fascination.

Keywords: sense of agency; limb ownership; sensorimotor system; multisensory integration; motor imagery; Bayesian inference; psychophysics; brain-machine interface; virtual reality; electroencephalography

Résumé

L'humanité est poussée par l'acceleration rapide des avancées technologiques où les technologies à venir, jadis éloignées, sont systématiquement devenues réalité. Parallèlement à ces développements technologiques se produit une accumulation accélérée des connaissances, poussée par une augmentation de intérêt sociétal pour la compréhension du cerveau humain—elle aussi stimulée par des progrès scientifiques. Pourtant, alors que nous nous orientons progressivement vers une expansion des systèmes de télé-présence, de la robotique médicale, et des interfaces cerveau-machine destinées à la réparation et à l'augmentation des capacités cognitives et motrices de l'homme, le besoin de comprendre ce qui se passe quand le cerveau "fusionne" avec la machine se fait de plus en plus pressant. Quels sont les conséquences subjectives, perceptives, neurologiques, et motrices d'un tel mariage? Peut-on utiliser cette connaissance pour mieux comprendre l'amélioration, la réhabilitation et la réparation des maladies neurologiques par neuroprothèse? J'examine ici ces questions en fournissant les preuves convergentes d'une série d'expériences destinées à lier deux domaines de recherche indépendants: les neurosciences cognitives de la conscience de soi et les interfaces cerveau-machine. Avec des paradigmes communs d'imagerie motrice et avec l'aide de la réalité virtuelle, neuroimagerie, et modélisation probabiliste, dans cette thèse, j'explore l'intersection de ces deux voies de fascination contemporaine.

Mot-clés: sens de l'agentivité; incorporation de membres; système sensorimoteur; intégration multisensorielle; imagination motrice; inférence Bayesienne; psychophysique; interfaces cerveau-machine; réalité virtuelle; électroencéphalographie.

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1. Introduction

The feeling that our body and its parts belong to us (sense of ownership) and the sensation of being the cause of our own actions (sense of agency) have been defined as two key components of bodily self-consciousness and experience. However, little is currently known about how body ownership and agency can be exploited in neuroprosthetics and whether principles from the cognitive neuroscience of body ownership and agency for bodily limbs and movements extend to those of machine-controlled “bodies” and “movements”. Here, I ask two main research questions: (1) *Can we contribute to the future design of ecological neuroprosthetic devices by embedding additional multisensory information giving rise to bodily ownership for these devices?* and (2) *Does our sense of agency for bodily movements extend to machine-controlled movements generated exclusively by thought?*

To address these questions, this thesis establishes a bi-directional link between the fields of **cognitive neuroscience** and **brain-machine interfaces** (BMIs). In particular, two concepts inspired by work from the cognitive neuroscience of bodily self-consciousness, the **sense of ownership** *(Section 1.1.1)* and the **sense of agency** *(Section 1.1.4)*, are investigated in the context of brain-machine interface paradigms *(Section 1.3)*. I present empirical data gathered and analyzed with novel paradigms that combine techniques and methods from **cognitive psychology, neuroimaging**, **computational neuroscience**, **psychophysics**, **haptics**, **virtual reality** and **non-invasive BMIs**. I will propose that technology-driven engineering approaches can be applied to basic research in cognitive neuroscience in order to gain new insights about the human brain and its functions, and that such evidence would be much more limited or impossible to obtain without such technology. Furthermore, I suggest a new approach to engineering BMIs that exploits the structure and function of the brain based on basic research from the cognitive neurosciences to better inform design of BMIs.

This introduction sets the stage for the conceptual, methodological and theoretical concepts later discussed in the constituent scientific articles. First, an overview is provided of work from the cognitive neurosciences on **body and limb representations in the brain**, concentrating on the concepts of body parts ownership and agency. Next, I provide a brief background on the **human motor system** and the associated behavioral and neural mechanisms behind covert and overt movement. Finally, I introduce the basics and **state-of-the-art** in **brain-machine interfaces**, highlighting their theoretical and practical potential.

1.1 The scientific investigation of bodily self-consciousness

The study of human self-consciousness is a multidisciplinary effort that has become a subject of great scientific interest in recent years (Gallagher, 2000; Christoff et al. 2011; Blanke & Metzinger, 2008). Until recently, approaches to the theoretical and empirical study of self-consciousness have focused on “higher-level” concepts of the self, such as autobiographical memory, language, self-recognition, and personality (Gillihan and Farah, 2005; Northoff et al., 2006, Legrand and Ruby, 2009). More recently, a complementary approach to investigate self-consciousness has emerged, concentrated rather on the study of “lower-level”, **bodily mechanisms of the self**, such as the integration and representation of multisensory information coming from somatosensory, proprioceptive, motor, visual and vestibular signals (Berlucchi and Aglioti, 1997, 2009; Botvinick, 2004; Damasio, 2000; Jeannerod, 2006, 2007; Vogeley and Fink, 2003). This approach focuses on the mechanisms behind representational encoding of the body’s various multisensory and sensorimotor states, including sensory information from external sensors (exteroceptive; *e.g.* visual, tactile and auditory) as well as internal sensory input (interoceptive; *e.g.* visceral signals from internal organs; Damasio et al., 2000; Craig, 2002; Critchley et al., 2004; Tsakiris et al., 2011).

Systematic manipulation of such multisensory bodily mechanisms has recently been suggested as a potential complement to research efforts in neuroprosthetics and neurorehabilitation (Ehrsson et al., 2008; Marasco et al., 2011). In this thesis I explore this possibility, concentrating upon the **multisensory experience of human upper-limbs** and its relationship to neuroprosthetic feeling and control. Specifically, I explore the below-defined notions of ownership and agency in the context of brain-machine interface actions.

1.1.1 Body and limb ownership

The experience that our body and its parts belong to us and not to others, so-called body **ownership**, has been identified as a key aspect of bodily self-consciousness (de Vignemont, 2010; Gallagher, 2000; Tsakiris 2010; Makin et al. 2008). Empirical studies of the multisensory mechanisms underpinning ownership of the body and its parts have emphasized the importance of integrating visual, tactile and proprioceptive signals (Botvinick, 2004; Botvinick and Cohen, 1998; Tsakiris and Haggard, 2005; Ehrsson et al., 2005). The most often-used paradigm to experimentally study ownership for upper limbs is the so-called **rubber hand illusion** (RHI**;** Figure 1). In this perceptual illusion, participants fixate on an artificial hand (visual cue) being stroked by a paintbrush in synchrony with stroking on their own corresponding and occluded hand (tactile cue) (Botvinick and Cohen, 1998). These visuo-tactile cues provided to the fake and real hands lead to an alteration in bodily experience, resulting in the feeling that the artificial hand is one's own hand (as measured by subjective questionnaires). This feeling of illusory ownership is generally associated with a recalibration of the perceived position

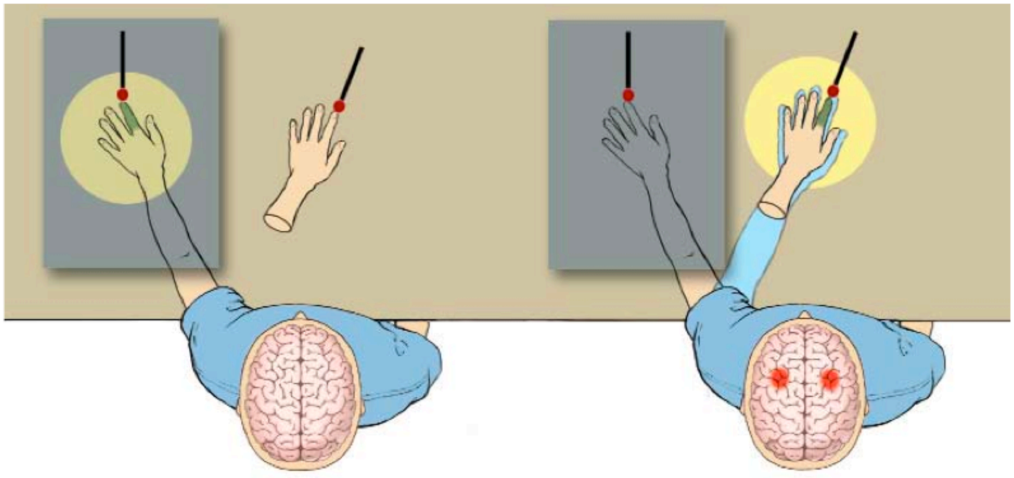

Figure 1: Manipulating upper-limb ownership: the Rubber Hand Illusion. *Left:* Applying visuo-tactile stimulation to one's real, occluded hand (grey box) at the same time and same location as on an artificial, visible limb (in front of the participant) leads to an emergence of illusory ownership for the artificial hand. *Right:* This illusory ownership is associated with the experience that the touch sensation originates at the artificial hand, that the artificial hand is one's own hand, and is accompanied with a recalibration of perceived hand position toward the artificial hand as well as modulation of neural activity in bilateral fronto-parietal cortex. Illustration from (Botvinick, 2004).

of the participant's real hand, mislocalized toward the artificial hand. The illusion is disrupted if the visuo-tactile cues provided to the artificial and real hands are spatially or temporally incongruent, or when non-body control objects are used in place of an artificial hand (Botvinick & Cohen, 1998; Tsakiris & Haggard, 2005; for reviews see Makin et al., 2008; Blanke, 2012).

1.1.2 Understanding ownership: Conceptual and computational models of multisensory integration

Limb ownership is influenced by factors such as visuo-tactile stroke duration (Tsakiris & Haggard, 2005; Rohde et al., 2011), distance between proprioceptive and visual hand position (Lloyd, 2007), visual hand form (Tsakiris et al., 2009; Armel & Ramachandran, 2003), laterality of stroking (Ocklenburg et al, 2010), visual hand posture (Costantini & Haggard, 2007) response modality (motor vs. verbal; Kammers et al., 2009), and even skin tone (Farmer et al., 2012). To explain these diverse findings in terms of the computational architecture underlying the emergence of illusory ownership and touch referral in the RHI paradigm, several conceptual models have been proposed (Makin et al., 2008; Tsakiris, 2010). Common to these models is the emphasis placed on the

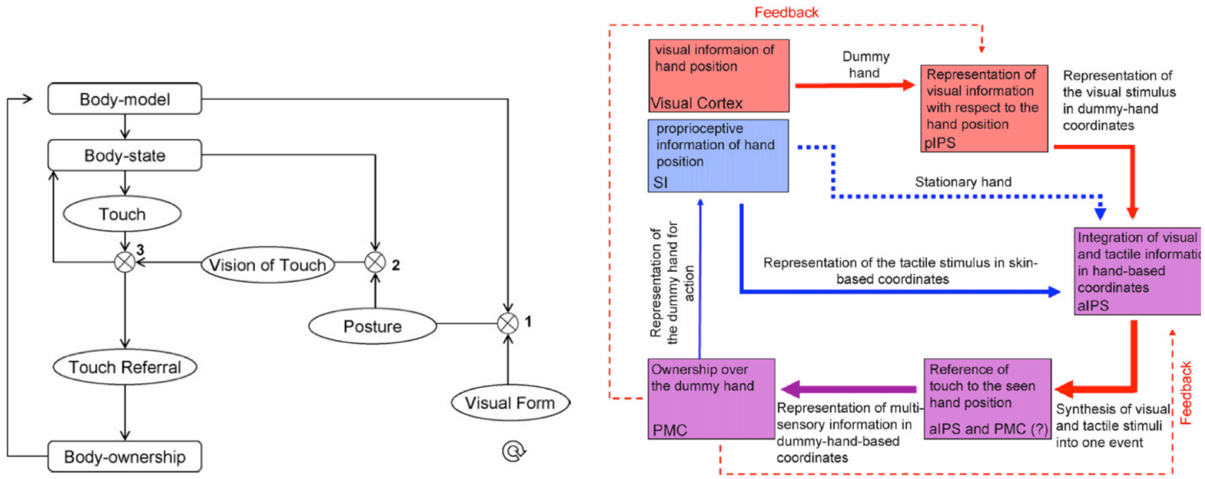

Figure 2: Conceptual models of limb ownership. These two models account for the illusory effects of the rubber hand illusion by describing functional comparisons between visual, proprioceptive, and tactile cues that are further mediated by internal models of the body and its posture. *Left:* From (Tsakiris, 2010). *Right:* From (Makin et al., 2008).

proper integration of **visual**, **proprioceptive**, and **tactile** cues as well as the requirement of an **internal representation of body state** (Figure 2). However, current conceptual models lack rigorous mathematical description and, to date, no empirical validation of the framework is provided.

On the other hand, **computational probabilistic inference models** (employing Bayesian theory; review in Ernst and Bülthoff, 2004) have been successfully used to model a wide range of neural learning (Rezende et al., 2011; Steimer et al., 2009), sensorimotor (Körding and Wolpert, 2006), and perceptual phenomena (Yuille and Kersten, 2006; Stocker and Simoncelli, 2006; Deneve and Pouget, 2004). The starting premise behind these computational models is that the brain has a learned representation of some causal structure of the environment. Perceptual states are then generated by inference: given incoming multisensory information, the brain integrates these signals and infers their source in a probabilistic manner. The response of each sensory apparatus is generally assumed to be Gaussian, that is, it can be characterized by a mean response and a precision (variance).

To better understand these models, consider the case where one is charged with the task of localizing another person in space. To begin with, assume that the brain has learned a simple causal model that seeing someone's lips move (visual cue) is coupled with sound (auditory cue) stemming from the same location. This single source (the person) thus provides two sensory cues to the observer (Figure 3). Under a **Bayesian multisensory integration model**, the process of localizing the person is described as an inference made from the integration of the visual and auditory cues, where optimal localization is made by combining the sensory cues with preference toward the more precise sensory modality (Figure 3 left).

These models therefore seem appropriate to apply to the trimodal sensory integration present during the RHI, yet in contrast to the above example, the RHI has the additional feature that **the source of visual information may or may not arise from the subject's own hand**. Thus, any computational account of the RHI must allow

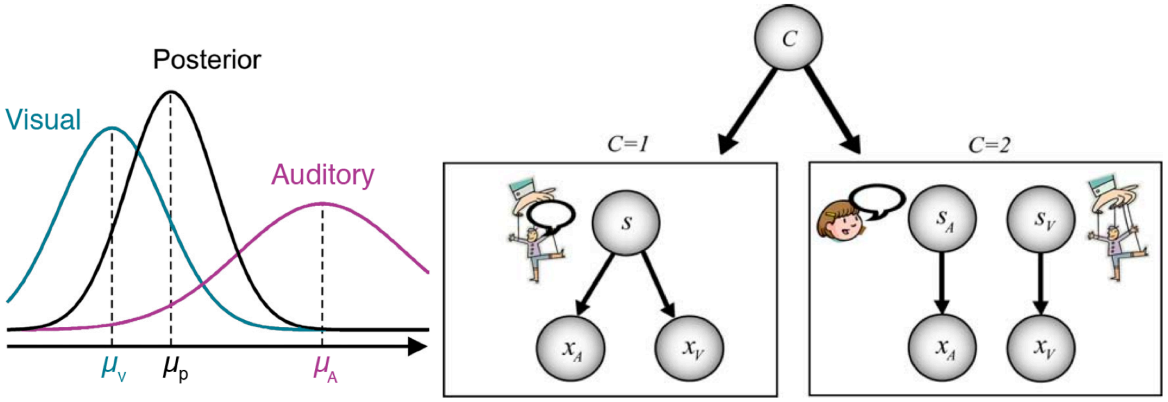

Figure 3: Bayesian causal inference models. A Bayesian inference framework to describe object location in space. *Left:* Assuming perceived sensory cues (here visual and auditory) come from the same source and are each characterized by a mean (μ_V,μ_A) and some variance, optimal localization involves merging these sensory cues (posterior, μ_P), favoring the more precise modality (here visual). Illustration adapted from (Prsa et al., 2012). *Right:* Now visuo-auditory sensory cues may come from two sources (*e.g.* during ventriloquist performances). As in the single source case, object localization is still described using Bayesian multisensory integration of perceived sensory signals X_V and X_A, but now requires one to additionally make statistical inferences on whether there is a single (S) or plural (S_A, S_V) cause. Illustration from (Körding et al., 2007).

for sensory cues to originate from more than one source. **Causal inference models** are a more general class of statistical inference models that precisely allow for this case (Beierholm et al., 2008; Körding et al., 2007). To draw analogy to the previous example in sound localization, this may be that the persons lips are moving without accompanied sound but that a third party is producing the auditory signal (Figure 3). Ventriloquists often exploit this situation, inducing the perceptual illusion that visual and auditory cues stem from a single source (the dummy) when in fact they come from two independent sources (the ventriloquist and the dummy).

Applying causal inference models in conjunction with Bayesian multisensory integration models to explain the illusory effects of the RHI thus represents a conceptual framework that allows for probabilistic multisensory integration to be tempered by the feeling of ownership over the body part. However, in contrast to current, purely conceptual models, this framework further permits one to understand illusory ownership in well-described mathematical terms whose theoretical predictions can be rigorously tested against empirical data. Furthermore, it allows for a precise definition of the set of trimodal sensory configurations necessary to induce or abolish the feeling of limb ownership.

1.1.3 Ownership: Neural mechanisms

Over the past decade, several neuroimaging studies have begun to characterize the brain mechanisms of illusory hand ownership. By inducing illusory ownership of an artificial limb while measuring BOLD activity via fMRI, bilateral premotor and intraparietal cortices as well as the cerebellum (Ehrsson et al., 2004, 2005) were found to be associated with illusory hand ownership. Correlational evidence between the subjective experience of ownership (as measured by questionnaire scores) and BOLD activity modulation suggests further involvement by premotor cortex, cerebellum, bilateral anterior insular, and anterior cingulate cortices (Ehrsson et al., 2004, 2007). Employing a paradigm in which the artificial hand was approached by a threatening stimulus, additional fMRI studies have implicated the posterior parietal cortex (Lloyd et al., 2006), and supplementary motor area (Ehrsson et al., 2007). Further regions, including the right posterior insula, sensorimotor cortices (precentral and postcentral gyri), as well as primary somatosensory cortex, were reported to modulate as a function of illusory hand ownership in a PET study (Tsakiris et al., 2007). Moreover, clinical studies in stroke patients showed that an inability to experience illusory hand ownership was related to lesion location and damaged connections between premotor, frontal operculum, basal ganglia, parietal, and prefrontal cortices (Zeller et al., 2011).

Complementing these findings about the functional and anatomical networks reflecting the experience of illusory ownership, several EEG studies have investigated the **electrophysiology of illusory ownership**. Using an evoked-potential design with somatosensory stimulation (SEPs via hand tapping) following induction of the RHI, it was shown that both the late and N140 components of the SEP are modulated by illusory hand ownership (Press et al., 2008). These electrophysiological modulations were observed over fronto-parietal regions, and likely reflected activation in sensorimotor regions. Relatedly, SEPs recorded over primary somatosensory cortex under a different illusory hand ownership paradigm (numbness illusion) were shown to be modulated by the strength of illusory ownership (Dieguez et al., 2009). Finally, in a RHI-like paradigm, an increase in inter-electrode synchrony in the lower gamma-band (30–50 Hz) over parietal scalp regions was reported during the integration of tactile and visual cues in peripersonal space (Kanayama et al. 2007, 2009).

In summary, this wide-ranging network of brain regions associated with illusory hand ownership during the RHI include the **intraparietal cortex, primary somatosensory cortex** (**precentral** and **postcentral gyri**), the **ventral premotor cortex,** the **right insular lobe,** the **anterior cingulate cortex,** and the **cerebellum** (Ehrsson et al., 2004, 2005, 2007; Tsakiris et al., 2007; Lloyd et al., 2006; Zeller et al., 2011). Several regions, including **premotor** and **parietal cortices** were additionally shown to be associated with electrophysiological modulation of SEPs and gamma-band oscillations.

1.1.4 The sense of agency

Alongside body ownership, the **sense of agency** (SOA), or the experience of being the causal author of one's own actions, has been targeted as one of the core aspects to phenomenal experience of bodily self-consciousness (David et al., 2008, Newen and Vogeley, 2003; Gallagher, 2000). Pioneering work in the study of self-awareness, self-identification, and the sense of agency dates back to the 1960s (*e.g.* Nielson, 1963), but with implications for dysfunctional action attribution in neuropsychiatric disorders such as schizophrenia (Frith et al., 2000; Blakemore et al., 2002), the perceptual and temporal coupling of actions to their effects (Haggard et al., 2002) and volitional and intentional causation systems (Jeannerod, 2006; Haggard, 2008; Wegner, 2002; Marcel, 2003), the study of SOA has recently witnessed a renaissance of scientific and philosophical interest (Pacherie, 2008; Gallagher, 2000; Metzinger, 2003).

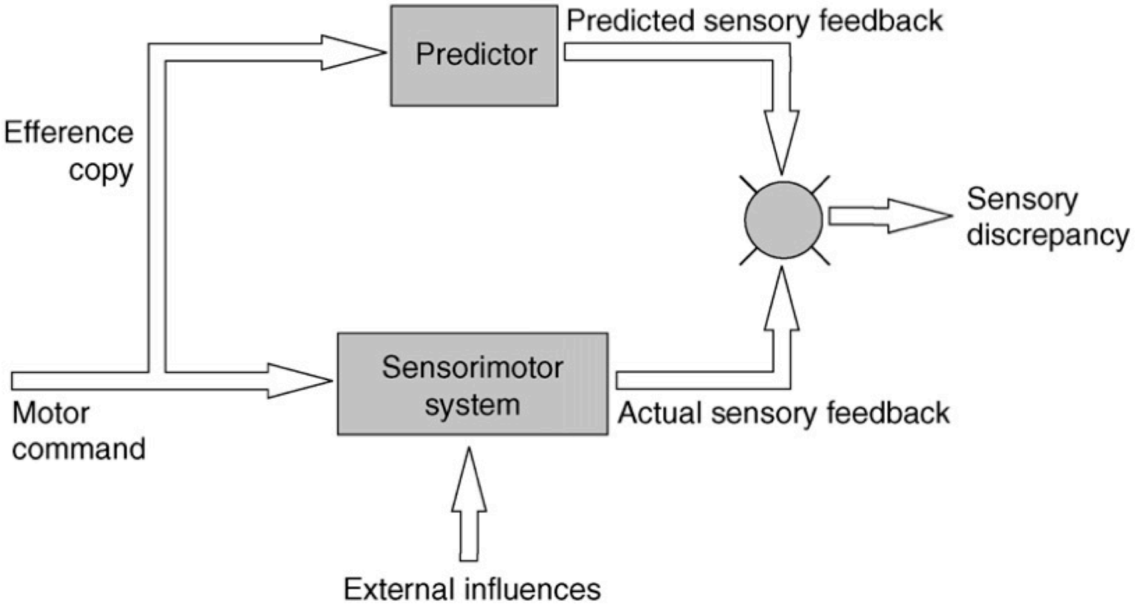

Figure 4: Predictive models of the motor system. The most prominent conceptual model to explain the disturbances in the sense of agency to bodily actions is inspired by models of motor control. These predictive accounts hold that discrepancies between predicted and actual sensory feedback lead to disturbed sense of agency (from Schubotz, 2007).

Several theoretical accounts have been put forth to explain a diverse set of empirical findings on SOA for bodily actions. Extending earlier proposals based on oculomotor control (von Holst and Mittelstaed, 1950; Sperry, 1950), Wolpert and colleagues proposed more recently the distinction of self-produced versus externally produced actions might be related to systems underlying sensorimotor comparison in motor control (Wolpert et al., 1995; Frith, 1987; Blakemore and Frith, 2003; Frith et al., 2000; Figure 4). This prominent **sensorimotor comparator model** (or **central monitoring hypothesis**) thus holds that perturbations of SOA are due to sensorimotor discrepancies in the predicted (**efferent**) and actual (**re-afferent**) sensory consequences of our movements (Blakemore et al, 2002; David et al., 2008). This model is supported by a number of empirical studies that experimentally inject temporal and spatial conflicts between movements and their sensory consequences, demonstrating that our experience of being the agent of our actions is malleable and dependent upon spatial and temporal coherence of actions and their effects (Daprati et al., 1997; Fourneret and Jeannerod, 1998; Farrer et al., 2003; Sato and Yasuda, 2005; Sato, 2009; Figure 5).

Despite its compelling and parsimonious account on the origin of SOA disturbance, the sensorimotor comparator model lacks explanatory power for the important and everyday case where SOA is attributed to action representations that are formed but no movement is executed and no re-afferent sensory feedback is present (*e.g.* thoughts, action observation, or motor imagery; Jeannerod, 2007; Georgieff and Jeannerod, 1998; Jeannerod, 2006; Campbell, 1999). Furthermore, SOA over joint actions in human dyads cannot be accounted for by such an account, as efferent motor signals could have originated from either person in the pair (van der Wel, 2012). Given these deficits, recent multifactorial predictive internal models have been proposed to allow for comparisons between action predictions and consequences to occur at both sensorimotor and perceptual levels (Pacherie, 2008; Knoblich and Repp, 2009; Moore et al., 2009). This **hierarchical comparator model** posits that a conglomeration of

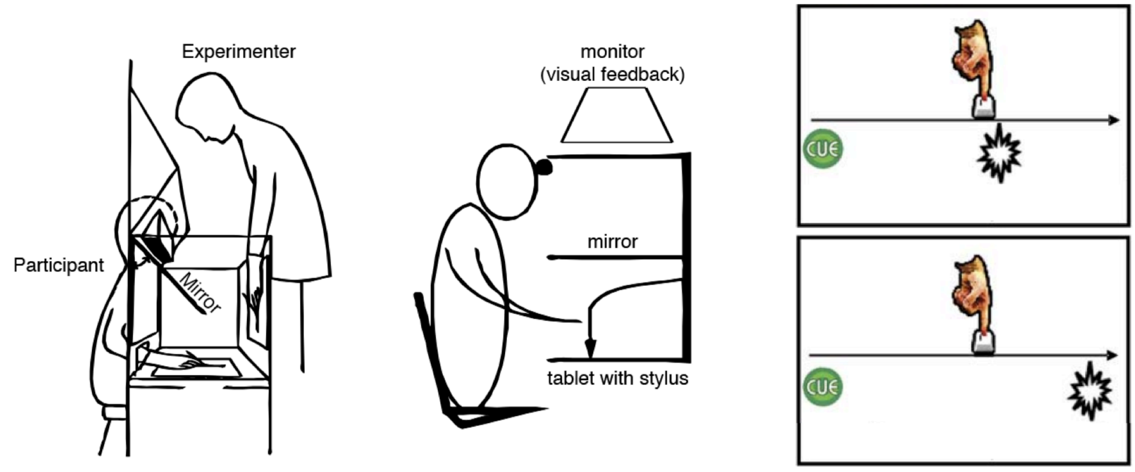

Figure 5: Classical experimental paradigms to introduce sensorimotor conflicts and manipulate the sense of agency over bodily movements. By inserting deviations between bodily actions and their sensory consequences, various experimental setups have been used to show our sense of agency to be dependent on spatial and temporal coherence between action and effect. To introduce spatial conflicts, participants were asked to draw a straight line to an end point while their hand was occluded from vision. *Left:* The experimenter manually perturbed the line participants saw using a fold away mirror (from Nielson, 1963). *Middle:* Using a tablet and stylus, the line was digitally perturbed (from Fourneret and Jeannerod, 1998). *Right:* An example of visuo-motor temporal delay. Participants press a key and see a flash on a screen that is either temporally coherent with (top) or perturbed with a temporal delay (bottom) (adapted from Stetson et al., 2006).

motor, perceptual, and distal cognitive factors all influence SOA.

By contrast, the **theory of apparent mental causation** (Wegner, 2002) considers SOA to be dependent on three factors: first, the environmental settings must be such that action consequences can be interpreted without a potential alternative cause (exclusivity); second, the action must be consistent with prior intentions (consistency); and third, that one's thought or intention must temporally precede the action (priority). According to this theory, if these three criteria are met, a postdictive attribution of (illusory) will is assigned to the action. Support for this theory comes from a series of experiments that manipulate these three principles and measure one's illusory will (Wegner et al., 2004; Wegner and Wheatley, 1999; Wegner, Fuller, & Sparrow, 2003). It is worth noting that the hierarchical multifactorial comparator model also attempts to assimilate these findings, allowing for predictions to be made at the perceptual or cognitive levels.

1.2 Mental imagery

Mental imagery is a process in which internal representations of perceptual information are accessed through "the mind's eye". As with thoughts, these internal and subjective processes are not necessarily coupled with direct overt behavior and have thus been difficult to investigate scientifically. Initial experiments that asked participants to compare a rotated object to the same object in its canonical orientation (unrotated) found that response times to whether the two objects were the same depended on the angle of rotation between the two objects (Shepard and Metzler, 1971). Using such implicit measurements of imagery from experimental psychology in combination with modern techniques in neuroimaging, researchers have begun to characterize the neural mechanisms behind mental imagery (Kosslyn et al., 2001; Zacks, 2008; Decety et al., 1989).

Research on mental imagery has been further categorized into work on visual (Farah, 1984; Kosslyn et al., 1997), auditory (Halpern and Zatorre, 1999), and motor imagery (Jeannerod, 1995; Jeannerod and Frak, 1999; Decety et al., 1994) (for other forms of mental imagery and for review see Kosslyn et al., 2001; Pylyshyn, 2003). Throughout this thesis, I employ **mental imagery paradigms in the motor context**. As our motor system is responsible for nearly all of our ability to communicate and interact with the world, the cortex has a vast and consistent neural architecture dedicated to motor planning and motor output. These prevalent motor representations have been extensively studied in the context of **motor imagery**, where the behavioral and neural consequences have been progressively revealed *(Section 1.2.1)*. In addition, motor system engagement through motor imagery is of **clinical relevance** as it has been shown to improve actual motor performance (Driskell et al. 1994; Gentili et al. 2006) and is utilized as a neurorehabilitation technique for motor disorders (de Vries and Mulder, 2007; Stevens et al., 2003). Finally, as we explore in *Section 1.3.2*, the reliability of electrophysiological responses to motor imagery has led to decoding of these signals for brain-machine interfaces (Pfurtscheller et al., 1997).

1.2.1 Motor imagery: Behavioral and neural mechanisms

Inspired by the visual object rotation task of Shepard and Metzler described above, a similar task was designed to probe imagery in the motor context. In this task, participants were shown rotated left or right hands and asked to report whether the image was of a left or right hand (Parsons, 1987). Again, response times were found to depend on the orientation angle of the target hand. However, in contrast to the neutral object rotation visual imagery task, response times were influenced by the biomechanical constraints of the arm trajectory that one would have had to follow in order to match the reference hand posture (Parsons, 1994). These experiments were further extended with evidence that response times for judging the feasibility of grasping a rotated object correspond to the time it takes to physically grasp such an object (Frak et al., 2001). Taken together, these findings suggest that the **subjects internally simulate actions** to match their own body parts to the external, reference stimuli and thus represent implicit behavioral measures of the internal process of motor imagery (for a review see Jeannerod and Frak, 1999).

Converging evidence from multiple lines of research has demonstrated distinct, yet partially overlapping brain networks involved during **motor observation**, **execution**, and **imagery** (Slachevsky et al., 2001; Grezes and Decety, 2001; Rizzolatti et al.; 1996; Caldara et al., 2004; for reviews, see Fadiga and Craighero, 2004; Decety, 1996). The most frequently reported neural structures associated with these shared motor representations include **premotor**, **supplementary motor**, **primary motor**, **cingulate** and **posterior parietal** regions using fMRI (Porro et al. 1996, 2002; Lotze et al. 1999, 2003; Gerardin et al. 2000; Naito et al. 2002; Kuhtz-Buschbeck et al. 2003; Dechent et al. 2004; Meister et al. 2004; Roth et al. 1996; Ross et al. 2003; meta-analysis in McNorgan, 2012) and PET (Krams et al. 1998; Jackson et al. 2003). However, it is still debated whether a common system of **motor representation** underlies motor observation, execution and imagery, and several recent studies characterized the shared and dissociable neural signatures using fMRI (Macuga & Frey, 2011) and human intercranial electrophysiology (Miller et al., 2010).

Concerning the **electrophysiology of motor imagery**, earlier work measuring local field potentials in the primary motor cortex of monkeys reported spiking activity to encode yet-to-be-made movement trajectories, presumably reflecting an imagery process related to planned motor movements (Georgopoulos et al., 1988). In human premotor, motor, and somatosensory cortices, motor inhibition, execution and observation, as well as other sensorimotor tasks have been to modulation of the neural oscillations in the **mu rhythm** (8 – 13 Hz oscillations) (Pineda, 2005; Niedermeyer, 1993; Gastaut, 1952; Howe and Sterman, 1972). Both intracranial electrophysiology (Gastaut & Bert, 1954; Mukamel et al., 2010; Tremblay et al., 2004) and surface EEG (Cochin et al., 1998, 1999) consistently show comparable mu rhythm suppression during both the execution and the observation of different movements. Moreover, the mu rhythm is also modulated by touch (Pfurtscheller, 1981) and the observation of touch of another person (Cheyne et al., 2003). Recent evidence from fMRI-EEG studies have shown the mu-rhythm to covary with the BOLD signal in dorsal premotor, inferior parietal, and primary somatosensory cortices during both action execution and observation (Arnstein et al., 2011), and with the **beta-rhythm** (14 – 30 Hz) as well as the BOLD signal in sensorimotor regions during motor imagery. Mu- and beta-oscillations have also been investigated with respect to **imagined unilateral upper limb movements** (Neuper et al., 2006) and have been linked to **mu-** and **beta-suppression** in **parietal cortex** (Pfurtscheller et al., 1997a) and **premotor** and **primary sensorimotor** areas (Pfurtscheller & Neuper, 1997b; Pfurtscheller et al., 1997c). Finally, **gamma-band** activity (above 30 Hz) has also been linked to lateralized effects of motor imagery (Pfurtscheller and Neuper, 2002; Miller et al., 2010; for a review see Hari and Salmelin, 1997).

1.3 Brain-machine interfaces

Brain-machine interfaces (BMIs) use advanced signal processing and machine learning techniques combined with a contemporary neuroanatomical and neurophysiological understanding of brain processing in order to **extract and decode user intent in real-time** from ongoing brain activity (Nicolelis, 2003; Lebedev and Nicolelis, 2006). BMIs form a **bi-directional communication channel between brain and machine** in which users relay commands in the form of brain activity patterns to software that recognizes and translates brain signals into a corresponding action. In turn, the brain-machine loop is closed as the outcome of one's translated brain signal is fed back to the user as sensory input (*e.g.* visual, tactile, or auditory), permitting one to adjust the coupling between brain and machine (Figure 6). BMIs have demonstrated potential towards the restoration of upper limb functions in non-human primates (Velliste et al., 2008; Carmena et al., 2003; Chapin et al., 1999; Moritz et al., 2008; Serruya et al., 2002) and humans (Hochberg et al., 2006, 2012) and have been used as a new communication channel for those with severe motor disabilities including paralysis (Birbaumer et al., 1999).

1.3.1 The fundamental elements of a BMI

All brain-machine interfaces can be decomposed into a shared chain of processing steps. Below, I provide a brief overview of each of the steps involved in this framework

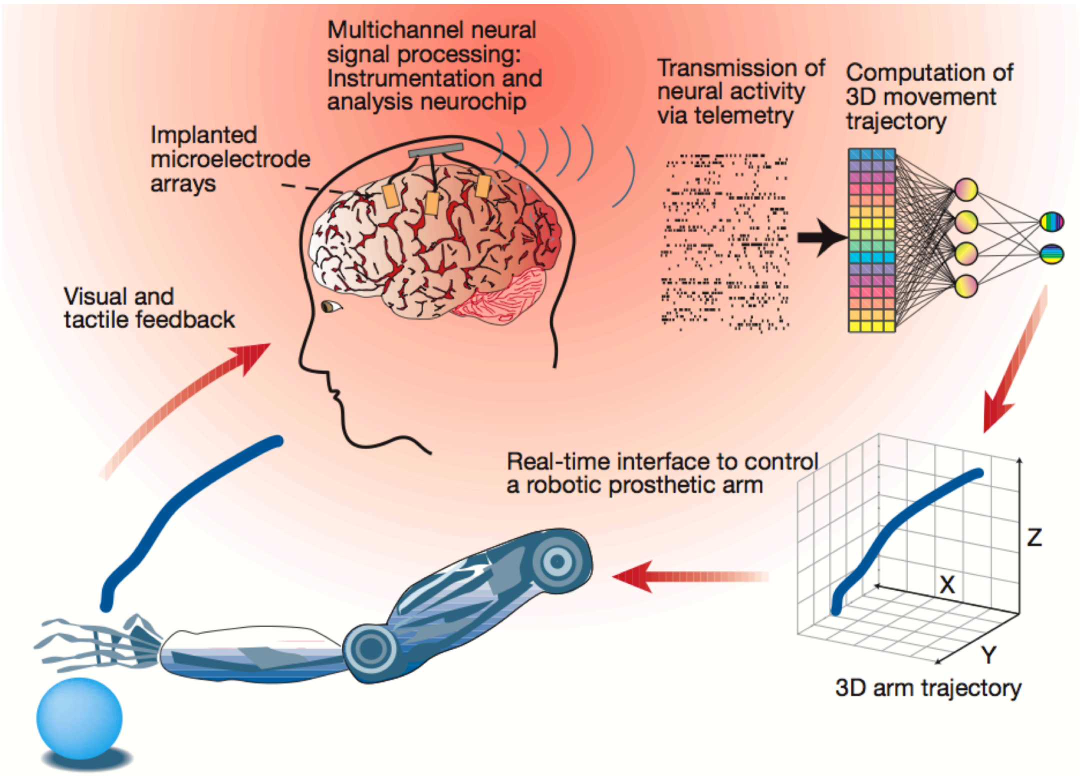

Figure 6: A closed loop brain-machine interface. This schematic represents a brain-machine interface in the context of a motor neuroprosthetic device. Motor signals are decoded in real-time from the cortex using advanced signal processing techniques. Thus, motor intent is converted into a 3D arm trajectory that updates a robotic actuator to move accordingly. Importantly, to close the control loop, sensory cues (*e.g.* visual, tactile, proprioceptive) must be fed back to the user either via external or direct brain stimulation. This thesis makes the claim that as we advance toward everyday use of such technologies, brain-machine actions will become progressively more important in clinical, societal, and legal contexts, but will also inform basic research in the neurosciences (see *Section 4.5*). Illustration from (Nicolelis, 2001).

as further detail can be obtained from other in-depth reviews (Nicolelis, 2003; Lebedev and Nicolelis, 2006; Schwartz et al., 2006; Kübler et al., 2001; Wolpaw et al., 2002; Millan et al., 2010; Birbaumer, 2006).

To begin, brain signals are acquired using non-invasive (*e.g.* fMRI, scalp EEG, NIRS, PET, MEG) or invasive (intracranial, subdural ECoG or intracellular EEG) neuroimaging **acquisition** techniques. The choice of acquisition source determines the experimental design, the types of control signals that can be extracted, and who the end users of the system are (healthy subjects or a targeted clinical group). Next, acquired signals are **preprocessed** to remove any non-neural artifacts and to shape the data into compact representations called features. **Feature extraction** represents a critical step in any BMI system, as eventual decoding performance depends on robust and reliable features that accurately account for mental intent. After creating feature representations of the neural signals, mathematical models (**classifiers**) are trained to categorize future features into learned classes of feature patterns. Next, predictions from the classifier output are transferred into controlling software (*e.g.* a spelling application) or hardware (*e.g.* a robotic prosthesis) **applications**. The output from this application is provided as **sensory feedback** to the BMI user so that future modulation of brain signals can be adjusted to optimize the brain-machine coupling.

1.3.2 BMI control signals and motor imagery-based BMIs

Various control signals have been used in BMIs (for reviews see Wolpaw et al, 2002; Andersen et al., 2004), including synaptic and extracellular field potentials (Georgopoulos et al., 1988; Carmena et al. 2003; Nicolelis 2001), local field potentials at the surface of the cortex (Miller et al., 2010), hemodynamic modulation of the BOLD response (Hinterberger et al., 2004; Weiskopf et al; 2003), NIRS (Sitarem et al., 2009; Coyle et al., 2004), surface EEG-based sensorimotor rhythms (Pfurtscheller et al. 2006; Wolpaw et al. 2002), and event-related potentials such as steady-state visual evoked potentials (Wang et al., 2008), P300 responses (Guger et al., 2009), and error potentials (Buttfield et al., 2006; Ferrez and Millan, 2008).

Since voluntary modulation of **sensorimotor rhythms** (*e.g.* **central mu- and beta- rhythms**; Niedermeyer, 2005) can be measured in a **non-invasive** manner, they have been used and studied extensively as control signals for non-invasive BMIs (Pfurtscheller et al., 1997a; Pfurtscheller et al., 2006; Neuper et al., 2009; Pfurtscheller and Neuper, 2001). Patients with motor disabilities such as paralysis due to stroke or spinal cord injury are able to modulate sensorimotor rhythms via motor imagery (Buch et al., 2008; for a review see Birbaumer et al., 2008). Moreover, motor imagery has also been used to detect willful modulation of brain activity for those with disorders of consciousness (Owen et al., 2006).

In summary, motor imagery leads to reliable neural modulations (S*ection 1.2.1*) that reflect internal motor representations while circumventing the descending pathways regulating the musculoskeletal system. For these reasons, **motor imagery paradigms** are used throughout the work in this thesis as a **liaison** between **cognitive neuroscience** and **brain-machine interfaces**.

1.3.3 *Multimodal sensory feedback in BMIs*

Human cognition and perception is largely shaped by multisensory experience (Ghazanfar and Schroeder, 2006) and as discussed in *Section 1.1.1*, the confluence of proprioceptive, visual, and tactile sensory information is crucial to the feeling of ownership over limbs. Moreover, normal motor control depends on multimodal body state estimates (van Beers et al., 1999; Sober and Sabes, 2005) and motor control guided purely by vision is slow and demands more attention than in multimodal situations (Ghez et al., 1995). Important limitations in current BMI systems, such as severely diminished quality and accuracy of motor control as compared to healthy controls (Hochberg et al., 2006), has been linked to a current lack of multisensory feedback in these devices (Birbaumer et al., 1999; Abbott, 2006; Hatsopoulos and Donoghue, 2009). Thus, one potential avenue for improvement of control and sensation over neuroprosthetic and BMI-controlled devices could be to augment these devices with mechanisms to provide coherent multisensory feedback (Nicolelis, 2003).

Several recent studies have demonstrated successful integration of multimodal sensory feedback into invasive BMIs as tested in monkeys. After being trained to control a virtual arm with voluntary modulation of activity in primary motor cortex, monkeys were provided direct electrical stimulation to primary somatosensory cortex to simulate artificial touch sensation for objects that the virtual arm encountered (O’Doherty et al., 2011). Importantly, when performing an active exploration task with a virtual arm combined with artificial touch sensation, monkeys behaved similarly to how they would with their actual limbs. This was taken as evidence that the multisensory nature of the BMI led to embodiment of the virtual limb. In a similar paradigm, monkeys were trained to control a visual cursor with motor cortex activity while their arm was passively displaced to follow the cursor trajectory (Suminski et al., 2010). Contrasting BMI control while receiving pure-visual feedback against a condition where visuo-proprioceptive feedback was provided, the authors demonstrated that BMI performance was enhanced by multimodal feedback. They further showed that the spatial congruence between the sensory modalities was important to the performance improvements. Collectively, these studies show the potential of providing additional, complementary sensory information in BMIs.

Though most non-invasive BMIs exclusively provide unimodal visual feedback, some research has addressed sensory feedback substitution, replacing the visual modality with auditory (Furdea et al., 2009; Hinterberger et al., 2004; Nijboer et al., 2008), vibrotactile (Chatterjee et al, 2007; Brouwer and van Erp, 2010; Cincotti et al., 2007) or proprioceptive (Gomez-Rodriguez et al., 2010) sensory feedback. On the other hand, multimodal, non-invasive BMI systems remain relatively unexplored (Wagner et al., 2012). Several studies have investigated combined visuo-auditory feedback, reporting a multimodal enhancement of BMI performance in P300 paradigms (Belitski et al, 2011; Klobassa et al, 2009), but a decrease in performance for multimodal versus unimodal regulation of slow cortical potentials (Hinterberger et al., 2004). Finally, recent work has shown that providing visuo-proprioceptive feedback to the hand via a robotic exoskeleton can improve BMI performance (Ramos-Murguialday et al., 2012). Importantly, this multimodal feedback led to motor learning effects, suggesting that multimodal feedback can additionally help in BMI skill acquisition. In this thesis, I expand upon these first investigations, exploring the effects of decoding motor imagery in non-invasive BMIs while inducing illusory ownership over artificial hands with multimodal visuo-tactile feedback.

2. Overview and Results

The aim of this chapter is to provide a brief overview of the main motivations, methods and findings for the scientific articles collected in *Section 3*. In addition to these articles, this thesis contains results for ongoing work on the sense of agency that will be presented in the discussion (Evans et al., *in preparation;* Section *4.2*).

2.1 Personal Contributions

I was involved in all stages of the experimental studies presented in this thesis. To be more specific, below I outline my individual contribution to each of the included scientific articles.

1. Evans, N., Blanke, O. Shared electrophysiology mechanisms of body ownership and motor imagery. (2013) *NeuroImage*. vol. 64 pp. 1-13

Personal contribution: design, implementation, recording, analysis, writing

2. Evans, N., Blanke, O. Illusory hand ownership alters decoding performance in a motor imagery based brain-machine interface. (*in preparation)*

Personal contribution: design, implementation, recording, analysis, writing

3. Rezende, DJ., **Evans, N.**, Gerstner, W., Blanke, O. Computational embodiment of a virtual limb. (*submitted)*.

Personal contribution: design, implementation, recording, analysis (experiment 2), writing

4. Evans, N., Gale, S., Blanke, O. The psychology of machine-controlled actions. *(submitted)*.

Personal contribution: design, implementation, recording, analysis, writing

2.2 Studies on body ownership and brain-machine interfaces

2.2.1 Study 1: The electrophysiology of hand ownership and its relation to motor imagery of hands

Though several neuroimaging studies on body parts ownership have begun to reveal the multisensory brain networks underlying illusory ownership, the electrophysiology of illusory ownership remains relatively unstudied. Moreover, the networks associated with hand ownership displayed spatial similarities with the regions activated during motor imagery of hands. Thus, we designed a virtual reality environment with automatized, machine-controlled visuo-tactile stimulation to induce changes in illusory hand ownership while recording 64-channel EEG. Using this setup, we first analyzed cortical oscillations and their neural generators reflecting changes in illusory body ownership. Next, we investigated - in the same subjects - brain oscillations and their neural generators during a unilateral hand motor imagery paradigm and directly compared ownership-related brain activations to oscillations present during motor imagery.

Methods

Participants were seated at a table with their arms resting (palms up) on their legs while a head-mounted display projected two virtual arms (or non-body objects) extending from the participants' body above their real arms (Figure 7). For the illusory ownership experiment, participants passively received machine-programmed visuo-tactile stimulation (haptic vibratory motors and virtual visual stimuli), in one of four experimental conditions (synchronous or asynchronous visuo-tactile stimulation on bodily or non-body control objects). We measured illusory ownership with subjective questionnaires and looked for selective changes in electrical brain activity that reflected such ownership. Our spectral and statistical EEG analyses involved looking for modulations in frequency power across experimental conditions at the single electrode, cluster, and source generator levels.

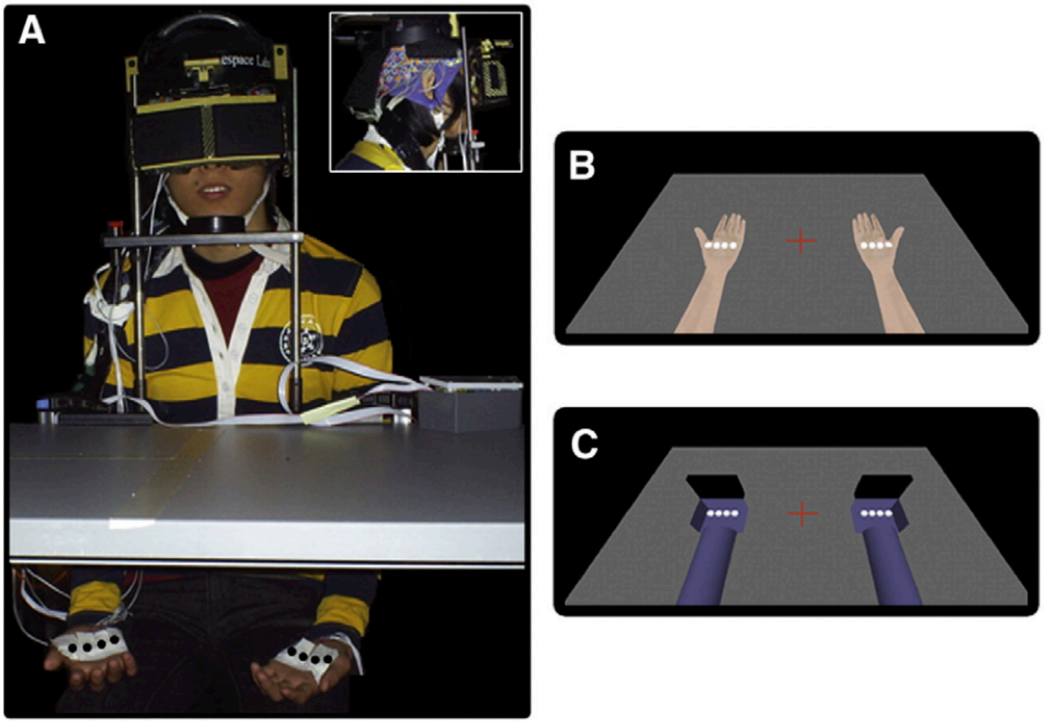

Figure 7: A fully automated setup to induce illusory ownership over virtual arms. ***A)*** Participants were stimulated on their hands via eight, programmed haptic motors while they saw a immersive virtual scene of two ***B)*** virtual arms or ***C)*** virtual non-body control objects projected in stereo. Visuo-tactile stimuli could be applied to the real and virtual hands with millisecond precision and was used to induce illusory ownership over the virtual hands.

In a second experiment with the same subject sample, participants saw the same visual virtual scene while performing a lateralized motor imagery task (imagined left or right hand clasping). We performed the same EEG analysis as in the first experiment in order to directly contrast results between the two studies. Finally, we performed an overlap analysis at the scalp and voxel (inverse solution) levels, comparing the spectral features and anatomical regions associated with illusory ownership and motor imagery.

Main Results

We first showed that illusory ownership could be induced using our novel, automated setup combining haptic stimulation and stereoscopic virtual visual stimuli. Statistical analysis on subjective reports indicated that only the synchronous, body stroking condition (henceforth referred to as illusion condition) significantly differed from all other conditions on the questionnaire item concerning illusory ownership.

EEG analysis at the single electrode level (electrodes C3 and C4 located over left and right sensorimotor hand regions, respectively) showed a body-selective, stroking-dependent modulation in mu-band power. Specifically, at electrode C4 a significant difference in mu-band power was found between the illusion condition and asynchronous stroking on the bodily visual objects. No such difference was found for the control objects. Electrode cluster analysis revealed two clusters of electrodes that differed from the baseline condition across the experimental conditions. These clusters were located over bilateral fronto-parietal regions, primarily centered over hand regions and again showed selective mu-band modulations in the illusion condition (predominantly in the right cluster; Figure 8 left). Finally, we computed an inverse solution for the illusion condition and found the observed mu-band suppression associated with illusory ownership to be localized to left and right fronto-parietal, sensorimotor regions (Brodmann areas 4/6; Figure 8 right).

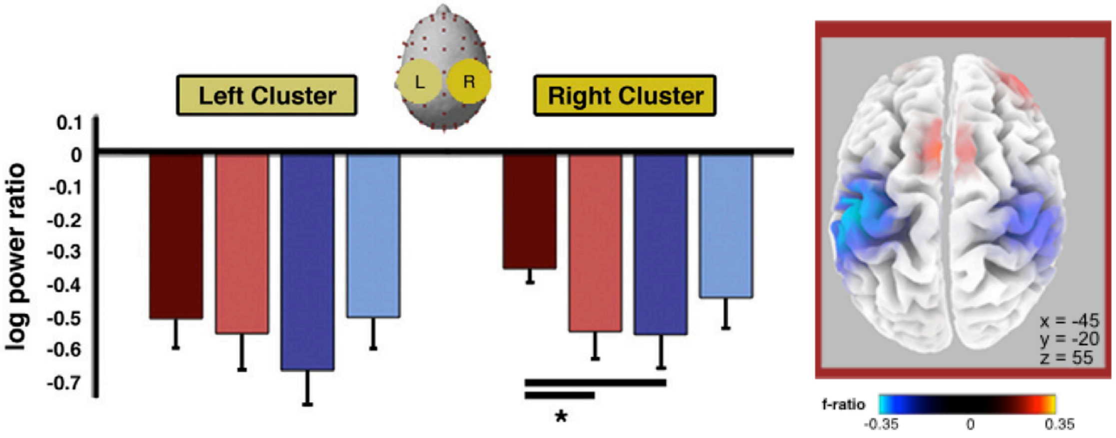

Figure 8: Illusory ownership is associated with selective modulation of mu-band power over fronto-parietal regions. *Left:* Mu-band log power ratios for the four experimental conditions in two sensorimotor electrode clusters. Only the illusion condition (dark red) led to differential modulation, and reflected subjective illusory ownership scores (not shown). *Right:* Inverse solution of the illusion condition showed mu-band suppression to be localized to bilateral sensorimotor cortex.

Analysis on the EEG data collected during lateralized motor imagery showed classical electrophysiological changes over sensorimotor cortex. In particular, mu- and beta-band activity was found to be contralaterally suppressed and ipsilaterally enhanced with respect to the imagined hand movement. This pattern of activity was confirmed with the same chain of analysis as used in the illusory ownership experiment (single electrode, cluster, and inverse solution).

Finally, we contrasted mu-band peak activity, scalp electrode, and voxel overlap across the two studies and demonstrated strong anatomical and spectral overlap between the electrophysiological mechanisms underlying illusory ownership and motor imagery (Figure 9).

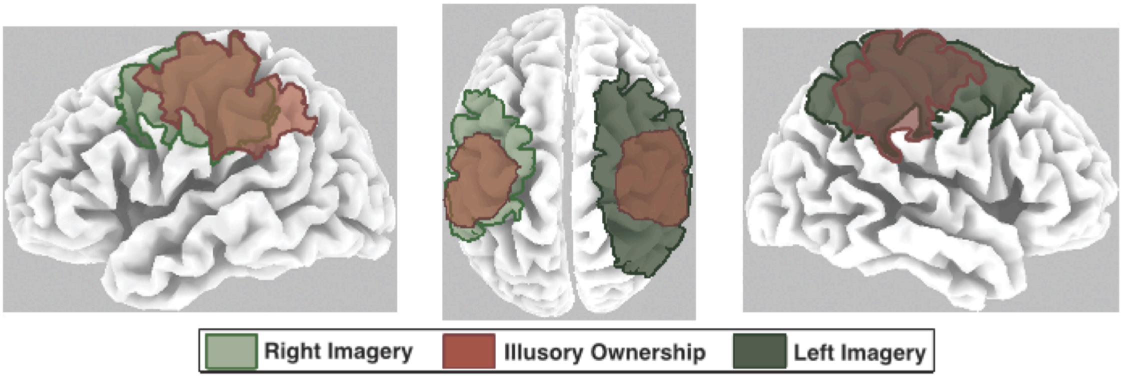

Figure 9: Illusory ownership and motor imagery show strong spectral and spatial overlap in fronto-parietal regions. Two electrophysiological studies showed that motor imagery for hands and illusory ownership over hands lead to similar spectral modulation in the mu-band over bilateral (though right-predominant) fronto-parietal regions.

2.2.2 Study 2: Inducing ownership over hands to alter single-trial decoding of motor imagery

Despite recent encouraging advances in providing multimodal feedback to monkeys for motor control of invasive BMIs (O'Doherty et al., 2011; Suminski et al., 2010), multimodal, non-invasive BMI systems remain relatively unexplored (Wagner et al., 2012). Our results from Study 1 hinted at the potential for improvement of non-invasive BMIs by manipulation of body ownership. Thus, to extend our work from Study 1 and test if we could directly exploit our neuroscientific findings on the link between illusory ownership and motor imagery, we applied our illusory ownership paradigm to a BMI motor imagery task.

Methods

We induced illusory ownership over two virtual hands by providing coherent visuo-tactile stimulation to the real and virtual hands while recording 64-channel electroencephalography (Figure 7) in the same participants as in Study 1 (in a different session). While receiving this constant and bilateral stimulation on both hands, participants performed a unilateral motor imagery task, imagining to clasp their left or right hand. Participants also performed the motor imagery task in experimental conditions where visuo-tactile stimulation was applied asynchronously and on non-body objects. Two additional baseline conditions were measured where participants performed motor imagery in the absence of visuo-tactile stimulation or with only tactile stimulation (no corresponding visual stroke). To assess the influence of illusory ownership on BMI classification performance, we first performed an offline, single-trial decoding analysis of the imagined hand (left vs. right) in each of the experimental conditions from Study 1. Next, we measured the electrophysiological effects of performing unilateral motor imagery while experiencing illusory ownership for two virtual hands. To do so, we contrasted mu-band power from data during passive visuo-tactile stimulation (Study 1) against spectral power in the same conditions during motor imagery.

Main Results

Our decoding analysis showed that illusory ownership led the highest classification performance of all visuo-tactile experimental conditions (asynchronous stroking on body objects, stroking on control objects; Figure 10). Of note, classification performance was found to significantly increase in the illusion condition versus asynchronous stroking on non-body objects. Importantly, statistical feature selection methods used in the decoding analysis independently verified that electrodes over the same bilateral sensorimotor hand regions implicated in Study 1 were most important in distinguishing between left and right imagery trials during motor imagery. However, classification performance was found to be highest when participants performed motor imagery in the absence of visuo-tactile stimulation and the addition of tactile stimulation significantly reduced performance. Frequency analysis revealed that the addition of motor imagery to each of the four visuo-tactile stimulation conditions (from Study 1) led to substantial changes in mu-band oscillations in all conditions except for the illusion condition. Namely, mu-band log power ratios were found to move toward the baseline condition in all experimental conditions except in the illusion condition.

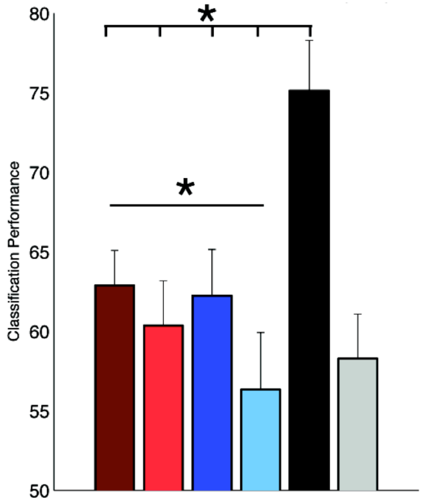

Figure 10: Illusory ownership alters single-trial decoding performance in a non-invasive BMI. Decoding performance (average over 10-fold cross validation) for a binary classification of left vs. right hand motor imagery. While performing motor imagery, participants receive task-irrelevant visuo-tactile stimulation on their real hands (and their virtual counterparts). The visuo-tactile stimulation during the illusion condition (dark red) led to a boost in decoding performance over asynchronous stroking on non-body objects (light blue), yet best performance was found for trials where no visuo-tactile stimulation was applied (black).

Though these results support the hypothesis that the mu-band power may be an invariant measure of illusory ownership useful to alter non-invasive BMI performance, we are in the process of finishing a more in-depth analysis. In this ongoing work we discuss our results in the context of the search for reliable, online neural measures that reflect illusory ownership.

2.2.3 Study 3: Computationally modeling body ownership

In a diverse set of experiments employing different experimental paradigms, hand ownership as studied in the RHI has been reported to be sensitive to a wide variety of parameters including visuo-tactile stroke duration (Tsakiris & Haggard, 2005; Rohde et al., 2011), distance between proprioceptive and visual hand position (Lloyd, 2007), visual hand form (Tsakiris et al., 2009; Armel and Ramachandran, 2003), laterality of stroking (Ocklenburg et al, 2010), visual hand posture (Constantini & Haggard, 2007) response modality (motor vs. verbal; Kammers et al., 2009), and even skin tone (Farmer et al., 2012). Despite this wealth of literature describing a wide variety of behavioral effects and conditions under which the RHI is enhanced or breaks down, only a few conceptual frameworks have been put forth to comprehensively explain the computational mechanisms behind the emergence of illusory ownership (Makin et al., 2008; Tsakiris, 2010). Given the success of inducing illusory ownership with our automated setup *(2.2.1)*, we sought to exploit the primary advantage of our programmable setup: systematic control of sensory input during the RHI. In an empirical study, we manipulated visual, tactile, and proprioceptive cues over a large range of values and in a large number of experimental trials in order to explore the input-output relationship between multisensory cues and the recalibration of perceived hand position (proprioceptive drift) associated with the RHI. We then designed a computational, causal inference model to describe the illusory effects of the RHI in terms of Bayesian multisensory integration. Our model, which considers hand ownership as a probabilistic regulator upon how incoming multisensory cues are integrated, closely accounts for our empirical data and thus demonstrates the potential of inducing illusory hand ownership in terms of systematic and probabilistic “lower-level” multisensory manipulations.

Methods

We used an automated haptics and virtual reality setup similar to that employed in *Section 2.2.1* in order to induce the RHI. In a first study, we verified our setup to induce the RHI by providing unilateral, synchronous vibrotactile stimulation on the participant's right hand while they saw a virtual right hand being stroked. We manipulated the posture of the virtual hand (congruent to the body posture or rotated by 90 degrees) as well as the synchrony of stroking (synchronous or asynchronous) and measured illusory ownership via subjective reports. In a second study, participants received visuo-tactile stimulation on the artificial and real hands for a variable amount of stroking time after which they were asked to estimate the position of their real hand (perceived hand position). On a trial-by-trial basis, we manipulated the separation between the visual and proprioceptive hand positions (visuo-proprioceptive separation), the synchrony of visuo-tactile stroking on the virtual and real hands (visuo-tactile delay), and the duration of stroking (trial length). For each configuration of these parameters, we measured the distance between the participant's actual and perceived hand positions (proprioceptive drift). We then describe a probabilistic, hierarchical Bayesian multisensory integration model to account for the perceived hand position as a function of these manipulated parameters.

Main Results

The results from the first study showed our virtual reality setup to again induce comparable changes in illusory ownership to our previous work *(2.2.1)* as well as RHI setups with manual stimulation on rubber hands (Botvinick and Cohen, 1998; Tsakiris and Haggard, 2005). By analyzing hundreds of trials of hand localizations for variable degrees of visuo-tactile stroking synchrony (0 to 800 ms) on a wide range of visuo-proprioceptive hand separations (0 to 35 cm), we observed that proprioceptive drift depends differently on incoming sensory cues as a function of our manipulated experimental parameters (Figure 11). In particular, for small visuo-proprioceptive separations (< 10 cm), participants systematically mislocalized their hand toward the visual hand regardless of the amount of visuo-tactile delay, indicating that visual capture

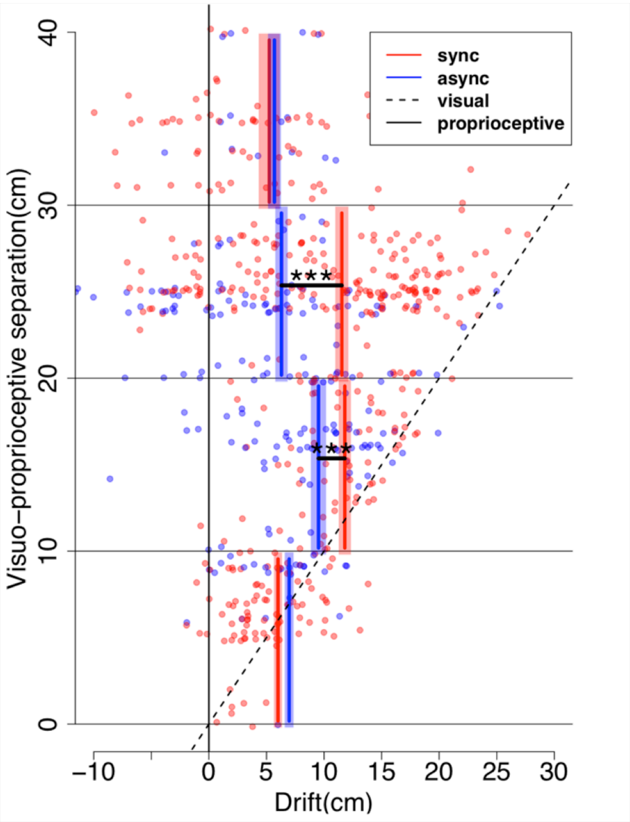

Figure 11: Recalibration of perceived hand position depends on visuo-proprioceptive separation and visuo-tactile delay. Perceived hand localizations for a wide range of visuo-proprioceptive hand separations. Drift is taken as the difference between perceived and actual hand positions. Responses following the solid black line indicate accurate hand localizations (*i.e.* actual proprioceptive hand position) whereas the dotted line indicates responses that follow where participants saw the virtual hand. Participants perceived their hand near the virtual hand for small visuo-proprioceptive separations and near their actual hand for large separations, independent to visuo-tactile delay. In intermediate separations (10-30 cm), synchronous visuo-tactile delay leads to perceived drifts toward the virtual hand whereas asynchronous stroking pushes perceived hand localizations toward the real hand.

dominates the perceived hand position. By contrast, proprioceptive drift was altered as a function of visuo-tactile delay for visuo-proprioceptive separations between 10 and 30 cm, where synchronous stroking led to larger drifts than asynchronous stroking. Interestingly, maximum proprioceptive drift was found for synchronous stroking at visuo-proprioceptive separations between 15 and 20 cm, in line with previous reports (Tsakiris and Haggard, 2010; Botvinick and Cohen, 1998; see corresponding article *Section 3.2*, Table S2). For large visuo-proprioceptive separations (> 30 cm), proprioceptive drift was diminished (*i.e.* participants perceived their hand to be localized close to their actual hand position) and visuo-tactile delay again did not influence perceived hand position. Concerning stroke duration (trial length), we found that longer stroking durations for asynchronous trials resulted in significantly smaller drifts than for short stroking durations. Taken together, this distribution of proprioceptive drift suggests that participants fuse visual, proprioceptive, and tactile cues differentially depending on a complex interaction of our manipulated parameters.

To better understand these empirical data, we constructed a computational model that accounted for visual, proprioceptive, and tactile cues as well as a "higher-level" notion of ownership for the hand. Our model accurately accounted for both the mean and variance of the observed empirical measurements, suggesting that proprioceptive drift can be explained as a behavioral consequence of statistical fusion of incoming sensory cues. Importantly, the model assigns a probability of ownership over the virtual hand for the full range of visuo-proprioceptive separations, rendering it a useful computational tool to select per-subject parameters that will lead to maximum illusory effects.

2.3 Studies on sense of agency and brain-machine interfaces

2.3.1 Study 4: The sense of agency for brain-machine actions

Though an extensive and growing literature has investigated the sense of agency (SOA) over movements of the fingers (Repp, 2005, 2006; Repp and Knoblich, 2007; Knoblich and Repp, 2009), hands (Daprati et al., 1997; Daprati and Sirigu, 2002; van den Bos and Jeannerod, 2002), arms (Nielsen, 1963; Fourneret and Jeannerod; 1998, Franck et al., 2001; Synofzik et al., 2006) and recently, the full body (Kanape et al., 2010), all of these studies probe our sense of causal authorship over actions mediated by the musculoskeletal system of the body. One novel avenue to explore actions that circumvent the standard motor outputs of the body could be to investigate SOA in the context of actions driven by direct cortical decoding (BMI-actions). Here, we asked whether SOA also extends to BMI-actions and whether SOA for BMI-actions is influenced by insertion of delay between real-time decoded neural activity and its visual sensory consequences.

Methods

Participants were trained to modulate electrical brain activity over sensorimotor cortices with a cued motor imagery task. They were instructed to imagine left or right hand clasping to move a visual cursor to the left or right of a screen, respectively. In a first experiment, we injected a delay (six delays ranging from 0 to 3750 ms at 750 ms intervals) between the decoded cortical activity and its visual consequences on a trial-by-trial basis (henceforth referred to as “visuo-neural delay”; Figure 12). We additionally tested insertion of spatial conflicts by manipulating the direction of the cursor to be either congruent or opposite (incongruent) to the trained directional association (*e.g.* for incongruent trials, left imagery moved the cursor to the right).

In a second study we sought to confirm the effects of the first study and to additionally test shorter visuo-neural delays (6 delays: 0 to 1s in 250ms intervals, and 3.75s). Only spatially congruent trials were tested in Study 2 and we additionally recorded electromyography (EMG) signals from the forearms to assess the role of any limb muscle contractions on SOA judgments.

For each trial, we measured real-time classification performance as the percentage of time frames that classifier output corresponded to the cued side and SOA as a two alternative forced-choice answer to whether or not participants felt they were controlling the cursor during that trial.

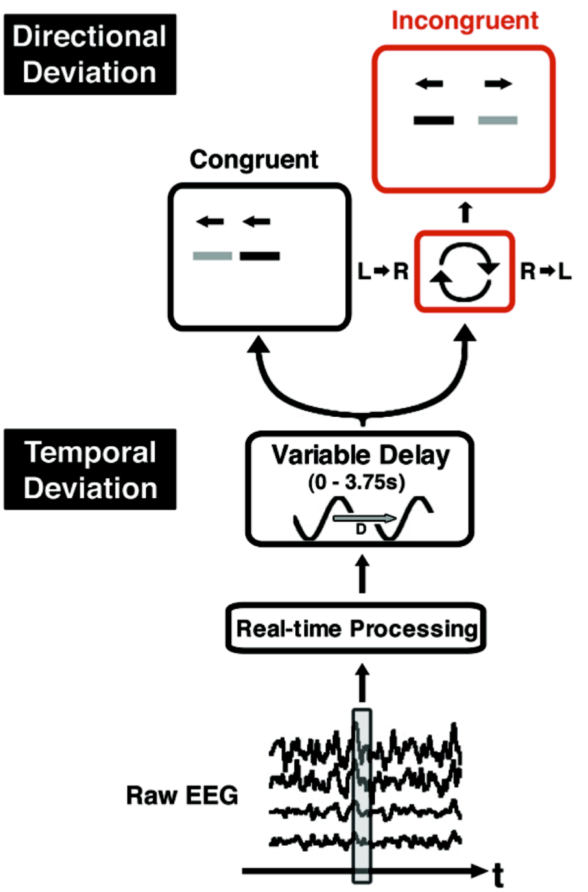

Figure 12: Experimental design to test the sense of agency for BMI-actions. Raw, real-time EEG data was sampled at 128Hz, processed and classified to correspond to left or right motor imagery. Real-time classifier output was then subjected to a temporal deviation (0 to 3.75s in 750ms intervals) and a spatial manipulation. Congruent trials followed the associated learning (*e.g.* left motor imagery leads to left cursor displacements), whereas incongruent trials inverted this relationship. The final signal was then translated to a visual cursor position update (8ms latency).

Main Results

We found SOA for BMI-actions to be low for incongruent and high for congruent feedback and that SOA depends differently on delay for congruent and incongruent trials ($F_{(5,7)}$ = 5.76; P = 0.001; Figure 13). In particular, SOA significantly decreased from 84 to 58% with increasing delay in congruent trials (P = 0.001), but was not modulated in incongruent trials (20-34%; P = 0.13). Our data from Study 2 confirmed the effect of visuo-neural delay on SOA ($F_{(5,6)}$ = 7.82; P = 0.0001), but showed that only the largest visuo-neural delay modulated SOA judgments.

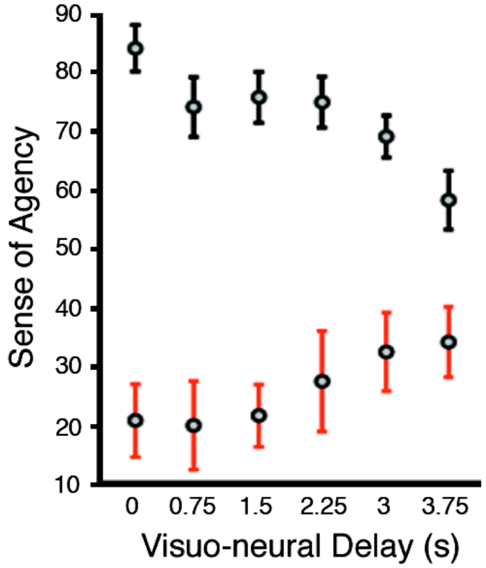

Figure 13: Sense of agency for BMI-actions. Sense of agency for BMI-actions is high for congruent and low for incongruent trials. Additionally, SOA was found to decrease as a function of visuo-neural delay for congruent BMI-actions (in black). By contrast, incongruent spatial deviations (in red) were strong enough to dampen the effect of visuo-neural delay.

Average EEG classification performance remained high and showed no differences across experimental conditions. Moreover, EEG analysis on the statistically-derived classification features and frequency power changes showed that participants used the expected mu-/ beta-band oscillations over bilateral sensorimotor cortex to control the cursor movements in all experimental conditions. Furthermore, EMG results showed no distinguishing relationship to motor imagery side. Taken together, we argue that SOA modulation therefore cannot be accounted for by differences across conditions in the decoder performance or by minor limb movements or covert muscle contractions.

Finally, our psychometric analysis on individual trials (fitting psychometric SOA curves to classification performance for low and high delays) showed low classification performance to be associated with low SOA and high classification performance with high SOA. The inverse relationship was found for incongruent trials (low classification performance: high SOA; high classification performance: low SOA). Insertion of delay led to systematic changes in the psychometric slope (sensitivity) as well as the point of subjective equality (PSE) for both congruent and incongruent trials. These analyses collectively show the influence of visuo-neural delay on subtle and highly systematic trial-by-trial fluctuations in classification performance and the result on perceived BMI-action authorship.

3. Scientific Articles

3.1

Shared electrophysiology mechanisms of illusory ownership and motor imagery

NeuroImage 64 (2013) 216–228

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Shared electrophysiology mechanisms of body ownership and motor imagery

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ABSTRACT

Although we feel, see, and experience our hands as our own (body or hand ownership), recent research has shown that illusory hand ownership can be induced for fake or virtual hands and may be useful for neuroprosthetics and brain–computer interfaces. Despite the vast amount of behavioral data on illusory hand ownership, neuroimaging studies are rare, in particular electrophysiological studies. Thus, while the neural systems underlying hand ownership are relatively well described, the spectral signatures of body ownership as measured by electroencephalography (EEG) remain elusive. Here we induced illusory hand ownership in an automated, computer-controlled manner using virtual reality while recording 64-channel EEG and found that illusory hand ownership is reflected by a body-specific modulation in the mu-band over fronto-parietal cortex. In a second experiment in the same subjects, we then show that mu as well as beta-band activity in highly similar fronto-parietal regions was also modulated during a motor imagery task often used in paradigms employing non-invasive brain–computer interface technology. These data provide insights into the electrophysiological brain mechanisms of illusory hand ownership and their strongly overlapping mechanisms with motor imagery in fronto-parietal cortex. They also highlight the potential of combining high-resolution EEG with virtual reality setups and automatized stimulation protocols for systematic, reproducible stimulus presentation in cognitive neuroscience, and may inform the design of non-invasive brain–computer interfaces.

Introduction

Human self-consciousness has become an increasingly prominent issue in the cognitive neurosciences in recent years (Blanke and Metzinger, 2008; Christoff et al., 2011; Gallagher, 2000). Whereas earlier research focused mainly on higher-level aspects such as memory, personality, or language and how these functions relate to the self and self-consciousness (Gillihan and Farah, 2005; Legrand and Ruby, 2009; Northoff et al., 2006), recent studies have started to investigate more basic aspects of self-consciousness, especially how we experience and perceive our body. Such mechanisms of bodily self-consciousness consist of brain mechanisms encoding the different multisensory and sensorimotor states of the body (Berlucchi and Aglioti, 1997, 2009; Botvinick, 2004; Damasio, 2000; Jeannerod, 2006, 2007; Vogeley and Fink, 2003).

One aspect that has been investigated intensively over the last decade is the experience that our body and its parts belong to us and are not those of other people, so-called body ownership. Ownership for one's hand has been proposed to constitute a crucial aspect of bodily self-consciousness (De Vignemont, 2011; Gallagher, 2000; Makin et al., 2008; Tsakiris, 2010) and an increasing number of empirical data on the neural underpinnings of body ownership have pointed to the importance of multisensory integration of visual, tactile and proprioceptive signals (Botvinick, 2004; Botvinick and Cohen, 1998; Ehrsson et al., 2005; Tsakiris and Haggard, 2005). A widely used paradigm to study the multisensory perception of upper limbs is the rubber hand illusion (RHI; Botvinick and Cohen, 1998) where participants watch an artificial hand (visual cue) being stroked by a paintbrush in synchrony with stroking on their own corresponding and occluded hand (tactile cue). This visuo-tactile manipulation alters bodily experience, inducing the illusion that the artificial hand being touched is one's own hand (measured by questionnaire ratings) and is generally associated with a measurable mislocalization of the participant's hand towards the fake hand. The illusion does not occur when the stroking provided to the real hand and the artificial hand is not synchronous, when the fake hand does not match the posture of the real hand, or when control objects are stroked (Botvinick and Cohen, 1998; Ehrsson et al., 2004; Tsakiris and Haggard, 2005).

To investigate the brain mechanisms of illusory hand ownership, most neuroimaging studies have manipulated the synchrony of experimenter-applied visuo-tactile stroking and the congruence of posture or handedness of the fake and real hands. Using fMRI, illusory ownership as induced by synchronous visuo-tactile stroking on congruent fake hand postures was found to be reflected by BOLD activity in bilateral premotor cortices (Ehrsson et al., 2004), cerebellum (Ehrsson et al., 2005), and intraparietal cortices (Ehrsson et al.,

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2004, 2005). If the fake hand is threatened by bringing a needle near to it, other studies found that activity in the supplementary motor area (Ehrsson et al., 2007) and posterior parietal regions (Lloyd et al., 2006) reflects illusory ownership. In addition, activity in bilateral anterior insular and anterior cingulate cortices (Ehrsson et al., 2007) or activity in premotor cortex and cerebellum (Ehrsson et al., 2004) was found to correlate with the strength of ownership illusion (as measured by questionnaire ratings). In a PET study, Tsakiris et al. (2007) reported that activity in the right posterior insula, sensorimotor cortices (precentral and postcentral gyri), as well as primary somatosensory cortex was associated with illusory hand ownership. Moreover, activity in the right insula and left somatosensory cortex correlated with the magnitude of proprioceptive drift (Tsakiris et al., 2007), a phenomenon classically associated with illusory hand ownership (Botvinick and Cohen, 1998; but see also Rohde et al., 2011). Finally, clinical studies in stroke patients showed a relationship between lesion location and damaged connections between premotor, frontal operculum, basal ganglia, parietal, and prefrontal cortices with the inability to experience illusory ownership for a fake hand (Zeller et al., 2011). To summarize, neuroimaging studies across a variety of RHI setups and imaging techniques (e.g. fMRI, PET, lesion mapping) have revealed a wide network of brain regions associated with illusory body ownership during the RHI. These regions include the intraparietal cortex, primary somatosensory cortex (precentral and postcentral gyri), the ventral premotor cortex, the right insular lobe, the anterior cingulate cortex, and the cerebellum (Ehrsson et al., 2004, 2005, 2007; Lloyd et al., 2006; Tsakiris et al., 2007; Zeller et al., 2011).

Concerning electrophysiological correlates of illusory hand ownership, several EEG studies using somatosensory evoked potentials (SEPs) or frequency analysis have also been carried out. For example, Kanayama et al. (2007, 2009) reported that gamma-band oscillations over parietal scalp regions varied according to the strength of illusory hand ownership in a RHI-like paradigm. These authors observed an increase in inter-electrode synchrony in the lower gamma-band (30–50 Hz) over parietal scalp regions during the integration of tactile and visual cues in peripersonal space. In an ERP study, Press et al. (2008) showed enhancement of the N140 and late somatosensory SEP components (evoked by hand tapping) after a period of synchronous stroking of a rubber hand, likely reflecting activation in somatosensory regions of the parietal cortex and/or premotor cortex. Related work using a different illusory hand ownership paradigm (numbness illusion) measured SEPs and implicated primary somatosensory cortex (Dieguez et al., 2009) based on the observation that the earliest cortical SEP component after median nerve stimulation (N20 component) was enhanced and correlated in strength with illusory ownership. Across these electrophysiological studies employing diverse experimental procedures, these data reveal that premotor and parietal cortex activity as well as gamma-band oscillations have most consistently been linked to illusory hand ownership.

Yet, in a number of related sensorimotor tasks, neural oscillations over central areas including premotor, motor, and somatosensory cortices have been linked rather to the mu rhythm (8–13 Hz oscillations). Sensorimotor tasks (Pineda, 2005), motor action execution, inhibition, and observation (Gastaut, 1952; Howe and Sterman, 1972; Niedermeyer and Lopes da Silva, 1993) are reflected in such mu oscillations. Additionally, both intracranial electrophysiology (Gastaut and Bert, 1954; Mukamel et al., 2010; Tremblay et al., 2004) and surface EEG (Cochin et al., 1999, 1998) consistently show comparable mu rhythm suppression during both the execution and the observation of different movements. Mu oscillations have also been investigated with respect to motor imagery (review in Neuper et al., 2006) and have been linked to mu suppression in parietal cortex, premotor, and primary sensorimotor areas (Pfurtscheller and Neuper, 1997; Pfurtscheller et al., 1997a). These oscillations during hand motor imagery have also been decoded online in non-invasive brain–computer interfaces (Pfurtscheller et al., 1997b). The mu rhythm is also modulated by touch (Pfurtscheller, 1981), the observation of touch of another person (Cheyne et al., 2003), and covaries with the BOLD signal in dorsal premotor, inferior parietal, and primary somatosensory cortices during both action execution and observation (Arnstein et al., 2011). More recently, it has also been shown that changes in body ownership for a full body as seen in a virtual reality environment are reflected in mu-activity in premotor, sensorimotor, and medial prefrontal cortices (Lenggenhager et al., 2011).

To summarize, despite this frequential and anatomical convergence of illusory hand ownership and hand motor imagery, the spatial and spectral relationship between motor imagery and illusory hand ownership has not been studied directly in the same individuals. Moreover, hand motor imagery is often used in non-invasive brain–computer interfaces (e.g. Pfurtscheller and Neuper, 2001) and it has recently been speculated that illusory ownership over virtual and prosthetic limbs may benefit neuroprosthetics and neuro-rehabilitation (Ehrsson et al., 2008; Marasco et al., 2011). Here, we designed a virtual reality environment with automatized, machine-controlled visuo-tactile stimulation to induce changes in illusory hand ownership while recording 64-channel EEG. Using this setup, we first analyzed cortical oscillations and their neural generators reflecting changes in illusory body ownership. Next, we investigated – in the same subjects – brain oscillations and their neural generators during a hand motor imagery paradigm (e.g. Pfurtscheller et al., 1997b) and directly compared ownership-related brain activations with oscillations present during motor imagery.

Materials and methods

Participants

12 healthy, right-handed participants were recruited (ages 22.7 ± 4.1 *mean* ± *SD*; 3 females). All participants had normal or corrected-to-normal vision and gave informed consent prior to participation. The study was undertaken in accordance with the ethical standards as defined in the Declaration of Helsinki and was approved by the local ethics research committee at the University of Lausanne.

Tactile stimulation

Tactile stimulation was provided with a total of eight button-style vibration motors (Precision Microdrives, London, UK) affixed in a line to the palms of the participants' hands (Fig. 1A). On each hand, a custom-made set of four vibration motors (12 mm diameter; 1.7 g; maximum rotation frequency 150 Hz) was placed with an inter-vibrator distance of 2 cm. The motors were programmed to vibrate in sequence to simulate a continuous, stroke-like movement lasting 450 ms (75 ms per motor; 50 ms inter-motor vibration pause). This type of sequence was chosen to automatize the stroking patterns that are generally used to manually stroke participants' hands to induce the RHI (i.e. Botvinick and Cohen, 1998; Ehrsson et al., 2004). The direction of the stroking sequence was either inward, toward a central fixation cross (6 subjects), or outward, away from the fixation cross (6 subjects). An inter-stroke interval of 400 ms was inserted between strokes to aid in perceiving the sequence of vibrations as a single motion.

Stimuli and virtual reality

Visual stimuli were rendered in stereo (XVR; VRMedia, Pisa, Italy) on a Fakespace Wide5 head-mounted display (HMD; Fakespace Labs, Mountain View, CA, USA). The HMD displayed a virtual scene with either two virtual arms or two virtual non-body control objects visually projected as extending from the body and resting on a tabletop (Figs. 1B, C). Four virtual spheres on each palm of the two virtual arms (or two virtual control objects) visually represented the four vibration motors on the real hands. Visual "vibrations" were represented by changing the virtual motor's color from white to red and animating it to visually jitter between

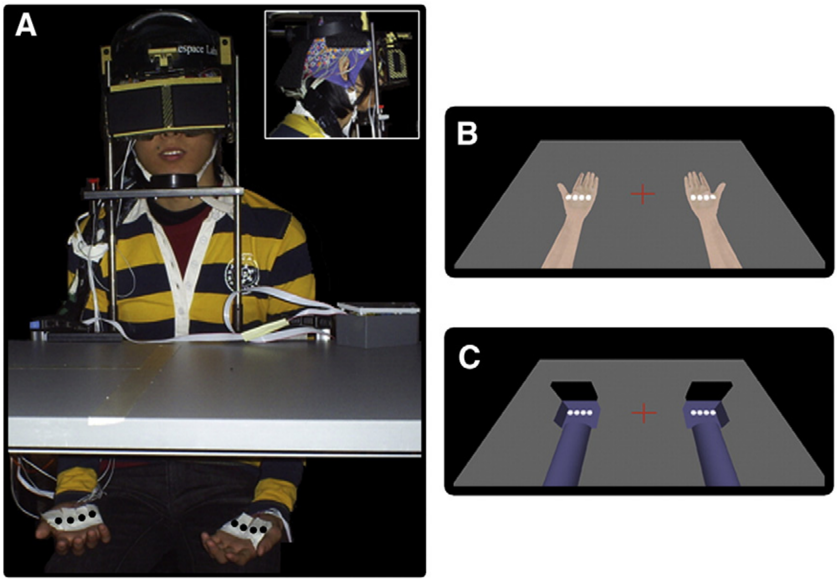

Fig. 1. Experimental setup and visuo-tactile stimulation. A, 64-channel EEG (small inset) was recorded while visual stimuli were presented on a head-mounted display. Tactile stimulation was provided by vibration motors affixed to the palm of the left and right hands. B, Participants saw either stereoscopic virtual arms or C, virtual non-body objects projecting from their body onto a virtual table (~20 cm above where they felt their hands to be on their laps).

±1 cm from its original position for the entire duration of the physical vibration.

Procedure

Participants were seated at a table with their arms resting (palms up) on their legs (Fig. 1A). Head movements were restrained with a chin rest and the experiment took place in a darkened room. The HMD fully blocked the subject's vision of the table, the physical arms and vibrators, and the rest of the room. In order to approximately calibrate the perspective of the virtual scene to that of the physical scene, the HMD was individually fitted to each participant such that the virtual and physical tables aligned. The two virtual arms (or two virtual control objects) were projected above the participant's physical arms (elevated by approx. 20 cm).

Synchronous visuo-tactile stimulation was defined such that visual and tactile vibrations occurred with no temporal delay and with spatial congruency between visual and tactile stimuli. To achieve asynchronous visuo-tactile stimulation for a given stroke (i.e. pattern of four vibrations), we inserted a random delay of 50 to 150 ms of the onset of the visual stimulation with respect to the onset of the tactile stimulation and randomly varied the direction of visual stroking (inward or outward; see Costantini and Haggard, 2007) while maintaining the same physical vibration sequence.

Pilot study

In a pilot study, using the same automated experimental setup as used in the main experiment, we induced changes in subjective (self-reports) and behavioral measures (proprioceptive drift) that are compatible with previous RHI experiments using unilateral visuo-tactile stimulation (see Supplementary material). In particular, our pilot results indicate that illusory hand ownership and perceived hand position were shifted toward the virtual hand for synchronous as compared to asynchronous visuo-tactile stroking (i.e. significant change in proprioceptive drift; Botvinick and Cohen, 1998; Tsakiris and Haggard, 2005). In contrast to the bilateral induction of the RHI (illusory ownership experiment) and bilateral presentation of visual hands (both illusory ownership and motor imagery experiments), the pilot study involved unilateral induction of the RHI. In the main experiments, we only measured subjective responses (illusory body ownership) as we were mostly interested in illusory hand ownership and its relation to motor imagery, and because we wished to avoid augmenting the already long experimental protocol.

Hand ownership

Following the behavioral pilot study confirming that our automatized and virtual reality setup induces comparable changes in hand ownership to those described in previous RHI studies using manually applied stroking, we carried out an EEG study to investigate the neural mechanisms of illusory hand ownership. We manipulated the strength of illusory hand ownership using a 2×2 factorial design with the factors Stroking and Object. The Stroking factor consisted of two levels of visuo-tactile stimulation (synchronous and asynchronous; as defined above). The Object factor was composed of two levels: virtual arms or virtual non-body control objects. An additional baseline condition was recorded, resulting in a total of five conditions. Each experimental condition was repeated three times and their presentation order was randomized and balanced within and across subjects.

Participants were asked to fixate on a cross that was placed centrally between the hands/objects located at a visual angle of 37° to the left and right. For 10 s, participants received visuo-tactile stimulation according to one of the experimental conditions. For the baseline condition, no tactile stimulation was provided to the hands and EEG was recorded at rest as participants fixated between the hands/objects as in the experimental conditions. To quantify hand ownership (Botvinick and Cohen, 1998; Slater et al., 2008) participants were asked to verbally respond to four questions (on a 1–7 Likert scale) immediately following visuo-tactile stimulation. The four questions were projected on the virtual table: 1) *It seemed as if I were feeling the vibrations in the location where I saw the virtual hands being vibrated*, 2) *It seemed as though the vibrations I felt were caused by the vibrations I saw on the virtual hands*, 3) *I felt as if the virtual hands were my own hands*, and 4) *I felt as if my (real) hands were moving or drifting towards the virtual hands' position.*

Motor imagery

We wished to additionally investigate how the neural mechanisms behind motor imagery of hand movements overlap with the neural systems activated during the experience of hand ownership.

Participants were asked to fixate on a green fixation cross that was shown for 500 ms and was located centrally between the hands or the control objects. The fixation cross was briefly replaced by a centrally presented left or right arrow cue for 500 ms and finally replaced by another central fixation cross in red that was shown for 4.5 s. While fixating on the red fixation cross, participants were asked to imagine clasping and unclasping the cued hand (right or left hand; Pfurtscheller et al., 1997b). It is important to note that while performing motor imagery, participants received the same visual scene as during the RHI procedure (bilateral visual hand stimuli; e.g. Neuper et al., 2009). Each experimental block consisted of 30 randomized trials (15 left hand imagery, 15 right hand imagery trials) and was repeated three times, resulting in 90 trials.

EEG: Preprocessing

64-channel EEG was sampled at 2048 Hz (Biosemi Inc, Amsterdam, Netherlands), downsampled to 512 Hz, and subjected to visual inspection in the time and frequency domains (e.g. Tadi et al., 2009). Electrodes with >50 μV DC-offset were rejected. The mean percentage of electrodes included was 92% (59 ± 1 electrodes; *mean* ± *SD*). Timeframes with eye blinks and transient conductance shifts were marked as artifacted in a semi-automated manner (see Lenggenhager et al., 2011).

To analyze the RHI data, thirty total seconds of recorded EEG per condition were broken into 2 s epochs (14 ± 1 s; *mean* ± *SD* per subject, per condition). For motor imagery, 2 min of total EEG data was collected for the period immediately following the imagery cue and was further broken into 2.25 s epochs (60 ± 19 epochs; *mean* ± *SD* per subject, per condition). Note that the motor imagery EEG data were part of a larger study (Evans & Blanke; *unpublished results*), leading to the difference in number of data epochs analyzed for RHI and motor imagery periods. To maximize usage of non-artifacted data, epochs were fit with 25% overlap between timeframes marked as artifacted (see above). Prior to computing power spectral densities (PSD), scalp potentials were re-referenced with respect to the average reference, the linear trend was removed, and a Hann window was applied to each epoch (Blackman and Tukey, 1959). PSDs were then computed at a 0.5 Hz resolution for each epoch with a Fast Fourier Transform (Matlab, Mathworks, Natick, Massachusetts, USA) in the following three frequency bands alpha/mu (8–13 Hz), beta (14–25 Hz) and gamma (25–55 Hz). Finally, PSD values for each subject s, experimental condition c, frequency band f, and electrode e, $P_e(s,c,f)$, were averaged across epochs and a log power ratio (LPR) was computed by taking the logarithm of the result of dividing each PSD by the subject's mean baseline PSD, $M_e(s,f)$, (i.e. Oberman et al., 2005). The LPRs, $L_e(s,c,f)$, thus took the form:

$$L_e(s,c,f) = ln(P_e(s,c,f)) – ln(M_e(s,f))$$

EEG: Statistical analysis

Hand ownership during visuo-tactile stimulation

Single electrode analysis. We analyzed EEG signals recorded at electrodes C3 and C4, located over left and right hand sensorimotor cortex (Oberman et al., 2005; Pfurtscheller and Neuper, 1994). These electrodes were selected on the basis of the hypothesized location of the overlap between brain activity associated with illusory hand ownership and hand motor imagery (e.g. Kanayama et al., 2009; Munzert et al., 2009) and because somatosensory evoked potentials at electrodes C3 and C4 have been shown to be modulated by illusory ownership (Peled et al., 2003; Press et al., 2008). We note, however, that EEG changes at scalp electrodes C3/C4 may result from neural generators at close and distant locations in the brain (Michel and Murray, 2012). LPRs were contrasted across the four experimental conditions using a 2 × 2 repeated-measures ANOVA and were further analyzed with post-hoc t-tests corrected for multiple comparisons (Bonferroni correction).

Cluster analysis. Next, we searched for scalp electrodes where LPRs reflected changes in illusory ownership. For this, we first determined for each electrode, each experimental condition, and each frequency band whether the LPRs significantly differed from the baseline condition (i.e. LPR of 0) using two-tailed, paired t-tests (see Oberman et al., 2005). This resulted in one scalp distribution of p-values for each experimental condition (Bonferroni corrected for multiple comparisons; Maris and Oostenveld, 2007). In the case when electrodes had been rejected during preprocessing for one or more subjects (see EEG: Preprocessing section), the statistical tests were performed with fewer measurements (i.e. a smaller sample size). Neighboring significant electrodes were then formed into spatial clusters by taking the union of the sets of all significant electrodes across the four experimental conditions and requiring that each member electrode have at least two neighbors (for a similar method, see Lenggenhager et al., 2011; Mitsis et al., 2008). This clustering technique resulted in the formation of clusters of electrodes that significantly differ from the baseline condition in at least one, but not necessarily all of the experimental conditions. Potential neighbors were defined as electrodes falling within a radius of 3 cm and, under this definition, the mean number of neighbors per electrode was 4. Electrode labels for all significant electrodes and the resulting clusters in the mu band (8–13 Hz) are presented in Table 1. Finally, for each experimental condition, a per-subject LPR was computed within each cluster by taking the mean LPR of the cluster's member electrodes. Statistical differences between experimental conditions were gaged using a 2 × 2 repeated-measures ANOVA on the distribution of LPRs across subjects. We additionally analyzed whether subjective questionnaire ratings for the ownership question (item 3) correlated (Pearson correlation) with the per-subject, mean LPRs in the electrode clusters for mu-, beta-, and gamma-bands.

Motor imagery

Motor imagery has been shown to exhibit lateralized effects over sensorimotor cortex, particularly in the mu- and beta-bands (Pfurtscheller and Neuper, 1997), and also in the gamma band (Miller et al., 2010; Pfurtscheller and Neuper, 2001). To verify whether our paradigm and experimental setup using automated stroking and virtual reality was also associated with these EEG changes, we analyzed LPRs in mu, beta, and gamma bands over left and right sensorimotor scalp regions (at the

Table 1
Significant electrodes used in whole-scalp cluster analyses. Electrode labels (10–20 system) for scalp electrodes surviving statistical correction in the mu-band (8–13 Hz) for the illusory hand ownership and motor imagery of hands studies. Contiguous, significant, individual electrodes were then grouped, resulting in two sensorimotor clusters (see Materials and methods section).

	Individual electrodes	Clustered
Illusory ownership		
Body sync	C6, CP6, T8	Left cluster: C1, C3, CP1, CP3
Body async	C3, C4, T8, CP6	
Object sync	C1, C3, CP1, CP3, FT8, FC6, C4, CP4, CP6	Right cluster: C4, C6, CP4, CP6
Object async	C4, C6	
Motor imagery		
Left imagery	C1, C3, C5, CP1, P9, PO7, C4, C6, CP6, CP2, P2, P4, P6, PO4	Left cluster: C1, C3, CP1, C5
Right imagery	C1, C3, C5, CP1, P9, PO7, C4, C6, CP6, CP2, P2, P4, P6, PO4	Right cluster: C4, C6, CP6, CP2, P2, P4, P6, PO4

level of single electrodes, C3 and C4, and at the cluster level) during left and right motor imagery. We used these classical neurophysiological responses to motor imagery as a biomarker that participants performed the motor imagery task. No further questionnaire or behavioral measures related motor imagery process was performed, because the experiment was already long. As a baseline condition, we calculated the average of left and right motor imagery on a per-electrode (scalp) or per-voxel (inverse solution) basis. Statistical differences were assessed using a 2×2 repeated-measures ANOVA with the factors Imagery (left or right hand) and Electrode side (left or right scalp hemisphere). Finally, post-hoc, two-tailed t-tests were used to further analyze any main effects or interactions (Bonferroni corrected).

Source localization

Cortical neural generators for scalp potentials were computed with a pseudo-inverse of the electrical lead field (sLORETA; Pascual-Marqui, 2002) using a head model extracted from a “standard” brain template (MNI152; Fuchs et al., 2002). Raw EEG data were preprocessed as in the scalp-level analysis. Electrodes previously rejected from scalp level analysis were replaced with a linear interpolation. Cross-spectra were computed in mu-, beta- and gamma-bands, were averaged per-subject and per-condition, and an inverse transformation matrix was applied to the cross spectra. Finally, an F-ratio was computed at the voxel level to statistically contrast each experimental condition to the baseline condition, as performed in an earlier work on body ownership (e.g. Lenggenhager et al., 2011) and related work (Oberman et al., 2005; Pineda, 2005). This contrast was also used for our analysis at the level of the scalp electrodes. Statistical maps were log transformed, participant-wise normalized, and corrected for Type I errors (SnPM; Nichols and Holmes, 2002). All reported coordinates are in MNI (Montreal Neurological Institute) space.

We additionally wished to verify that differences between the body synchronous and body asynchronous conditions observed at the single trace and cluster levels remained consistent at the voxel level. For this, we first determined two spherical ROIs based on the contrasts obtained separately from the inverse solution for the body synchronous and the body asynchronous conditions versus the baseline condition. The center of each ROI was defined as the left and right hemispheric centroids of the union of all supra-threshold voxels (F-ratio < -0.175) and the volume of the ROI defined by a 10 mm radius. The mean log power across voxels in these two ROIs was then determined for both body conditions.

Overlap analysis

To assess spectral and spatial commonalities between hand ownership and hand motor imagery at the scalp level, a meta-set of electrodes was composed for both study 1 and for study 2. To build these two electrode meta-sets, the union of the clustered electrodes from each study was taken (c.f. Table 1, rightmost column). These clustered electrodes originated from the set of electrodes differing from the baseline condition in at least one, but not necessarily all experimental conditions from each respective study.

We analyzed similarities in the spectral profiles by taking the per-subject peak power frequency from the mean power spectra in the two meta-sets. Differences in peak power frequency were separately assessed for the left and right hemispheres using paired, two-tailed t-tests. Next, we computed spatial overlap at the scalp level by counting overlapping electrodes from the two meta-sets separately in the left and right hemispheres.

A similar method was used to compute spatial overlap at the voxel level. Supra-threshold voxels were taken from the respective inverse solutions using the same mask (F-ratio < -0.175) for each experimental condition. In order to then compare the significant voxels associated with motor imagery with those associated with illusory hand ownership in each of the four experimental conditions, we collapsed left and right motor imagery data sets into a single data set of significant voxels. To do so, we applied the supra-threshold mask to the inverse solutions for both left and right imagery and then took the union of the significant voxels from these two sets. Left hemispheric (MNI X coordinate <0) and right hemispheric (MNI X coordinate >0) overlaps were quantified separately by counting the number of overlapping and non-overlapping voxels. To assess the overall overlap in each experimental condition from the illusory hand ownership study, the mean of the left and right hemispheric overlap was taken, resulting in one percentage overlap value per condition.

Results

Self-reported illusory hand ownership

A Friedman non-parametric ANOVA revealed a significant effect of the experimental condition on subjective ratings for each item of the questionnaire (Q1: $\chi^2_{(12,3)}=18.82$; Q2: $\chi^2_{(12,3)}=16.78$; Q3: $\chi^2_{(12,3)}=20.01$; Q4: $\chi^2_{(12,3)}=20.87$; all $p<0.001$). Fig. 2 shows that illusory hand ownership (Q3) was largest in the synchronous, body stroking condition (henceforth referred to as illusion condition). Post-hoc, non-parametric Wilcoxon matched pair tests (all comparisons were Bonferroni corrected) revealed, as predicted, that only the illusion condition significantly differed from all other conditions (all $p<0.01$). Importantly, only the illusion condition resulted in positive illusory hand ownership and no significant difference was found between the non-body control objects ($p>0.05$).

For items 1 and 2, post-hoc Wilcoxon matched pair tests revealed a significant difference between synchronous and asynchronous stroking for both body and non-body objects (both $p<0.01$). No significant difference in subjective ratings between body and non-body objects was observed for synchronous (both $p>0.10$) or for asynchronous stroking (both $p>0.10$). For item 4, the post-hoc tests showed a significant difference between synchronous and asynchronous stroking for bodily objects ($p<0.02$), but no such difference for non-body objects ($p>0.10$). The full questionnaire results are plotted in Supplemental Fig. S1.

Electrophysiology of illusory hand ownership

Single electrode analysis (electrodes C3/C4)

For mu-band activity at electrode C4, a repeated-measures ANOVA revealed a significant two-way interaction between Synchrony and Object ($F_{1,11}=6.43$, $p<0.05$) but no main effects of Synchrony or Object (both $p>0.20$). The mu-band power in the illusion condition was found to be less strongly suppressed than in the remaining conditions and thus differed significantly from the asynchronous body condition ($p<0.01$) as

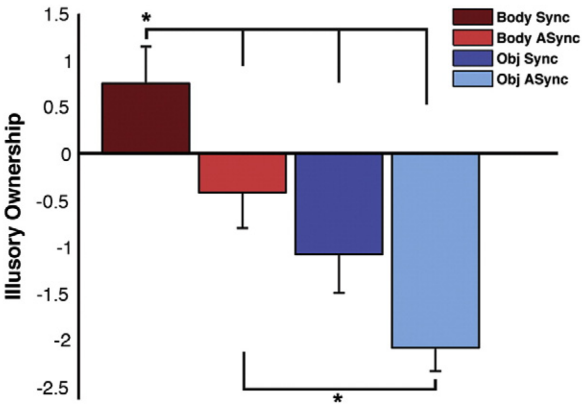

Fig. 2. Illusory hand ownership. Mean questionnaire scores probing the subjective experience of illusory ownership during visuo-tactile stimulation (Question 3; error bars SEM). Two types of stimulation (synchronous, asynchronous) were performed on two different visual objects (hands or control objects). * indicates a significant difference between experimental conditions ($p<0.05$; *Wilcoxon matched pairs test; corrected*).

well as the synchronous object condition ($p<0.05$; Fig. 3B). No such difference was found between synchronous and asynchronous stroking for the non-body control objects ($p>0.05$). At electrode C3, mu-band power did not show any significant interaction or main effects (all $p>0.10$).

In beta- and gamma-bands at electrode C4, no significant main effects or interactions were found (all $p>0.05$). Beta and gamma-band analysis at electrode C3 revealed no interaction or main effect of Object (all $p>0.05$), but a main effect of Synchrony in the beta-band ($F_{1,11}=8.58$; $p<0.01$) and the gamma-band ($F_{1,11}=4.73$, $p<0.05$). A full summary of the mean LPRs is presented in Table 2.

Cluster analysis

For each experimental condition, at least one electrode (mean: 5) was found to significantly differ from the baseline condition in the mu-band (Table 1; left column). Using our clustering technique, we found the electrode clusters (assembled across the experimental conditions; see Materials and methods section) to be localized to scalp regions over right and left sensorimotor cortex (Fig. 3A; left cluster: 4 electrodes, right cluster: 4 electrodes; Table 1, right column). Statistical analysis for the right mu-band cluster revealed a two-way interaction between Synchrony and Object ($F_{1,11}=6.59$, $p<0.05$) but no main effects (both $p>0.2$). Mu-band power in the illusion condition was found to be less strongly suppressed than the remaining conditions and to be significantly different than the asynchronous body condition ($p<0.05$; Fig. 3C) as well as the synchronous object condition ($p<0.05$). No such difference was found between synchronous and asynchronous stroking for the non-body control objects ($p>0.05$). For the left cluster, a trend towards significance was found for the interaction term ($p=0.09$) without any main effects (all $p>0.35$). Beta and gamma-band analysis in both left and right mu-defined clusters did not reveal any significant interactions or main effects (all $p>0.05$). The mean mu-band LPRs in the left and

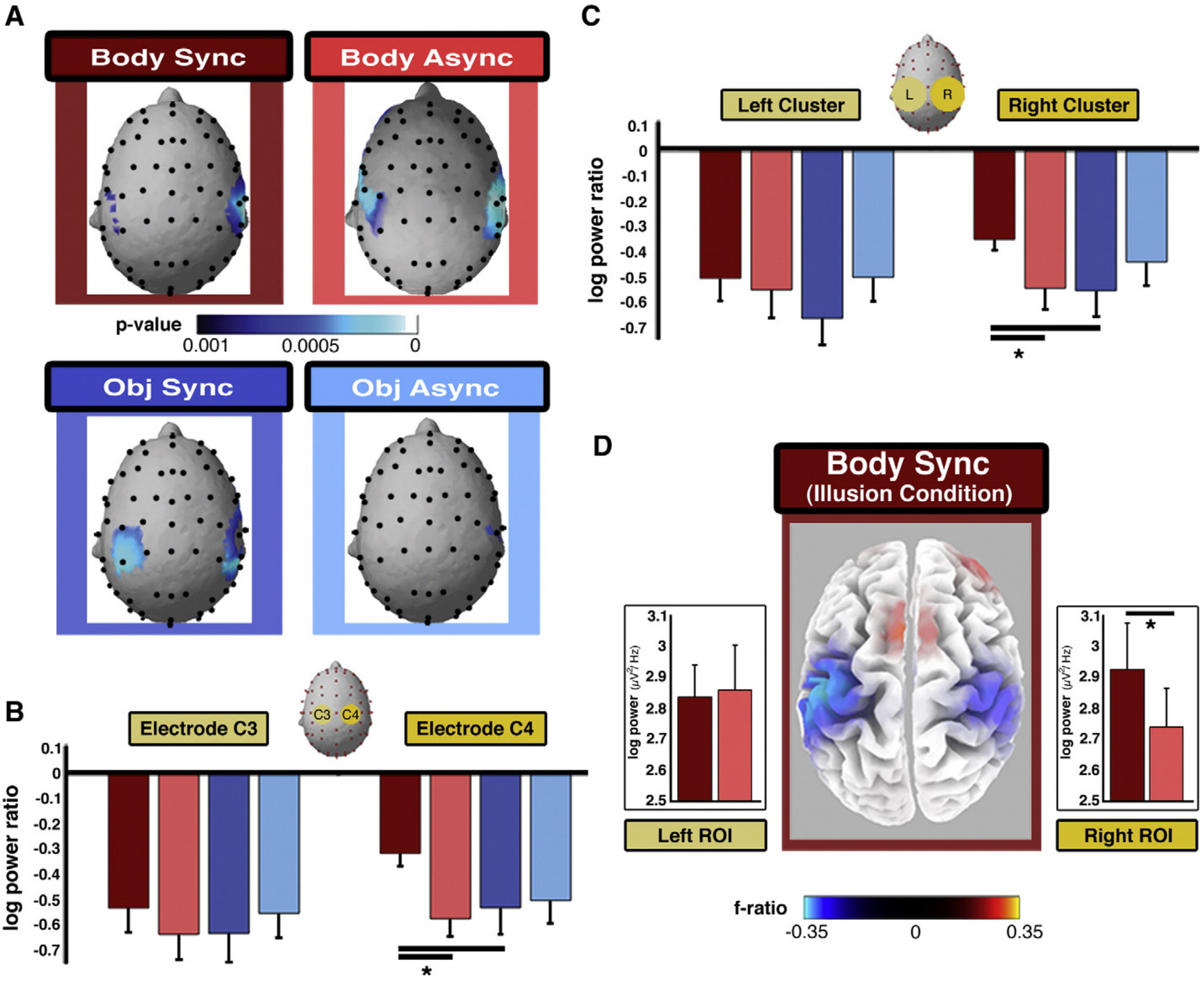

Fig. 3. Electrophysiological results for illusory ownership. A, Statistical scalp maps in top-view for each visuo-tactile condition showing the location of electrodes that significantly differ from the baseline condition in the mu-band (8–13 Hz). Blue indicates power suppression with respect to baseline and gray indicates non-significance. B, Mean log power ratios in the mu-band (mean ± SEM) for the four visuo-tactile conditions at single electrodes over sensorimotor cortex. In electrode C4, we observed a body-selective, synchrony-dependent mu-band suppression whereas C3 showed a similar but non-significant pattern. C, left and right electrode clusters (4 electrodes left; 4 right) show a body selective, synchrony-dependent mu-band modulation in the right cluster and a similar but non-significant trend in the left cluster. D, Source localization for the contrast of the illusion condition against the baseline condition shows mu-band suppression to be localized to bilateral sensorimotor cortex (centered at the left and right postcentral gyrus). To the left and right, log power is plotted in voxel-level ROIs (as defined in Materials and methods section) for body synchronous and body asynchronous conditions.

right clusters for the illusion condition were not found to correlate with the questionnaire responses for question 3 (all $p>0.05$). In the beta and gamma bands, no electrodes were found to significantly differ from the baseline condition. Thus, no electrode clusters were defined for beta- or gamma-bands.

Source localization

The mu-band suppression found at the single electrode and cluster levels in the illusion condition was localized to the sensorimotor cortex and extended from premotor to posterior parietal cortex. Its maximal focus was found at the right and left postcentral gyrus (right: $F=-0.35$; Brodmann areas 3/4; peak MNI coordinates: $X=40$, $Y=-25$, $Z=55$; left: $F=-0.30$; Brodmann areas 3/4; peak MNI coordinates: $X=-45$, $Y=-20$, $Z=55$).

To confirm the log power difference observed at the single trace and cluster levels at the voxel level, we defined two ROIs (see Materials and methods section). The left hemispheric ROI had its centroid at $X=-41$, $Y=-26$, $Z=49$ and the right ROI at $X=40$, $Y=-28$, $Z=45$. In agreement with single trace and cluster analyses, log power was found to differ between the body synchronous and body asynchronous conditions in the right hemispheric ROI ($p<0.05$) but not in the left hemispheric ROI ($p>0.05$). In Fig. 3D, log power for the synchronous body condition and asynchronous body conditions is plotted for both ROIs and is plotted alongside the inverse solution for the illusion condition.

In summary, illusory hand ownership was reflected in the suppression of mu-band power at the postcentral gyrus extending into premotor cortex and posterior parietal cortex. These localized oscillatory modulations were absent for control conditions under otherwise identical visuo-tactile conditions. Beta and gamma-band activity did not reflect illusory ownership, visuo-tactile synchrony, or the sight of a virtual arm at the cluster level. Rather, these frequency bands were modulated by visuo-tactile synchrony at scalp electrode C3, and were not found to be body-specific.

Motor imagery of hands

Using single trace (electrodes C3, C4), cluster, and source localization analyses, we next studied whether mu, beta and gamma-band power yields contralateral suppression (event-related desynchronization) and ipsilateral enhancement (event-related synchronization) during lateralized motor imagery tasks (Pfurtscheller and Neuper, 1997; Pfurtscheller et al., 1997b) and how this compares to the observed changes in illusory hand ownership. For this, we applied a 2×2 repeated-measures ANOVA with the factors Imagery (left or right imagery) and Electrode side (left or right hemisphere). Table 2 summarizes the mean log powers in the left and right motor imagery conditions.

Table 2

Log power ratios for each experimental condition in single trace and cluster analyses. Mean and standard error of log power ratios (illusory ownership) and log power (motor imagery). Values are provided for single trace analyses (electrodes C3 and C4) as well as cluster analyses (left and right clusters; see Materials and methods section, Figs. 3 and 4).

	Electrode C3	Electrode C4	Left cluster	Right cluster
Illusory ownership (mu)				
Body sync	−0.53 ± 0.10	−0.31 ± 0.05	−0.51 ± 0.09	−0.35 ± 0.05
Body async	−0.64 ± 0.10	−0.57 ± 0.07	−0.55 ± 0.11	−0.54 ± 0.08
Object sync	−0.63 ± 0.11	−0.53 ± 0.10	−0.66 ± 0.10	−0.55 ± 0.10
Object async	−0.55 ± 0.10	−0.50 ± 0.09	−0.50 ± 0.10	−0.44 ± 0.09
Motor imagery (mu)				
Left imagery	0.14 ± 0.04	−0.20 ± 0.05	0.10 ± 0.04	−0.18 ± 0.05
Right imagery	−0.22 ± 0.05	0.13 ± 0.04	−0.17 ± 0.06	0.13 ± 0.04
Motor imagery (beta)				
Left imagery	0.06 ± 0.02	−0.13 ± 0.04	0.04 ± 0.01	−0.12 ± 0.03
Right imagery	−0.11 ± 0.03	0.09 ± 0.03	−0.06 ± 0.02	0.08 ± 0.03

Single electrode analysis (electrodes C3/C4)

A repeated-measures ANOVA on the mu-band LPRs showed a significant two-way interaction between Imagery and Electrode side ($F_{1,11}=25.89$, $p<0.01$) without significant main effects (both $p>0.5$). Further testing revealed that this was caused by a significant difference in mu-band power between contralateral and ipsilateral motor imagery at C3 ($p<0.01$) and at C4 ($p<0.01$; Fig. 4C) and, in particular, a stronger suppression in mu-band power at C3 for right imagery (compared to right imagery at C4; $p<0.01$) and at C4 for left imagery (compared to left imagery at C3; $p<0.01$).

In the beta-band, the same pattern was observed as in the mu-band, namely a significant two-way interaction ($F_{1,11}=15.77$, $p<0.01$) and a significant difference between contralateral and ipsilateral motor imagery at electrodes C3 ($p<0.01$) and C4 ($p<0.01$). As for mu-band power, beta-band power was also significantly suppressed for right motor imagery in electrode C3 (as compared to C4; $p<0.01$) and suppressed for left motor imagery in electrode C4 (as compared to C3; $p<0.01$).

In the gamma-band, statistical analysis also revealed a two-way interaction ($F_{1,11}=10.43$, $p<0.01$). Only a significant difference between ipsilateral and contralateral band power in electrode C3 ($p<0.01$) was observed, whereas no such difference was present in electrode C4 ($p>0.1$). Following the pattern of mu- and beta-bands, gamma-band power was significantly suppressed for right motor imagery in electrode C3 (as compared to C4; $p<0.01$) and suppressed for left motor imagery in electrode C4 (as compared to C3; $p<0.05$).

Cluster analysis

For left and right motor imagery, 14 electrodes were found to significantly differ from the baseline condition in the mu-band. These electrodes were clustered at scalp regions over left and right sensorimotor cortex (compare Fig. 3A with Fig. 4A; left cluster: 4 electrodes and right cluster: 8 electrodes; see Table 1). For the beta-band, we found the same clusters (14 electrodes, yielding two clusters: 4 left and 8 right). No electrodes were found to significantly differ from the baseline condition for left or right motor imagery in the gamma-band.

A repeated-measures ANOVA on the cluster LPRs showed a two-way interaction in the mu-band (Imagery × Electrode side; $F_{1,11}=14.31$, $p<0.01$). Post-hoc analysis showed that in both clusters, contralateral mu-band power significantly differed from ipsilateral mu-band power (left cluster: $p<0.01$; right cluster: $p<0.01$; Fig. 4D). As expected, this difference was due to a stronger suppression of mu-band power in the left cluster for right imagery (compared to right imagery in the right cluster; $p<0.01$) and a stronger suppression in the right cluster for left imagery (compared to left imagery in the left cluster; $p<0.01$). The same pattern was found in the beta-band (Imagery × Electrode side interaction; $F_{1,11}=13.71$, $p<0.01$), where contralateral band power significantly differed from ipsilateral band power (left cluster: $p<0.01$; right cluster: $p<0.01$). As observed in the mu-band, beta-band power was suppressed contralaterally: in the left cluster for right imagery (as compared to right imagery in the right cluster; $p<0.01$) and in the right cluster for left imagery (as compared to left imagery in the left cluster; $p<0.01$).

Source localization

During left motor imagery, mu-band power suppression was localized to right premotor and primary motor cortices ($F=-0.31$; Brodmann areas 4/6; peak MNI coordinates: $X=35$, $Y=-15$, $Z=70$) and mu-band power enhancement to left premotor and primary motor cortices ($F=0.20$; Brodmann areas 4/6; peak MNI coordinates: $X=-45$, $Y=-15$, $Z=50$; see Fig. 4B, left). The opposite was found for right motor imagery: suppression in left premotor and primary motor cortices ($F=-0.27$; Brodmann areas 4/6; peak MNI coordinates: $X=-45$, $Y=-15$, $Z=50$) and mu-band power enhancement in right

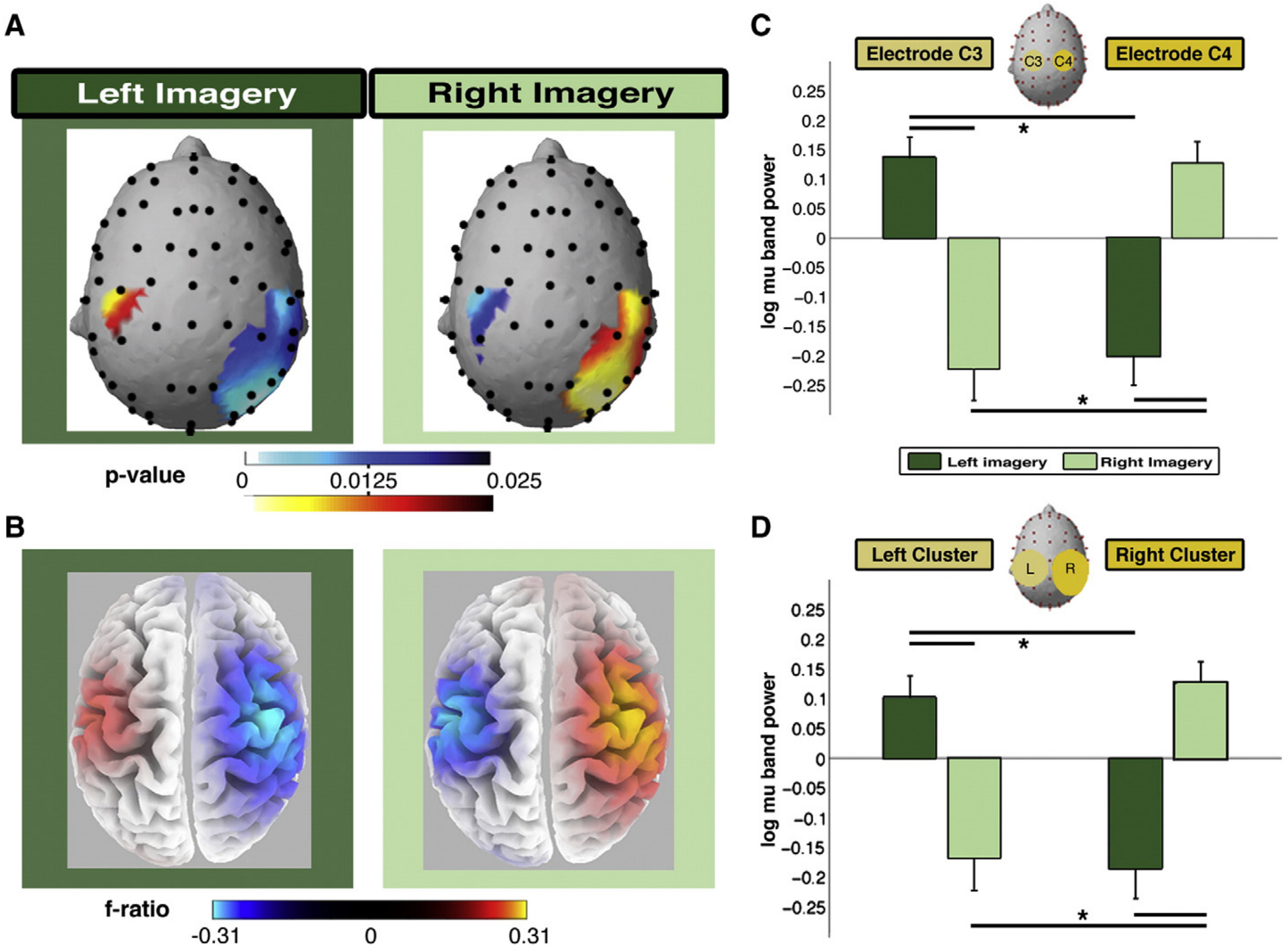

Fig. 4. Electrophysiological results for left/right hand motor imagery. A, Statistical scalp maps for left and right motor imagery showing the location of electrodes that significantly differ from the baseline condition in the mu-band (8–13 Hz). Blue indicates power suppression with respect to baseline, red indicates activation with respect to baseline. B, Inverse solutions of lateralized motor imagery periods reveal sensorimotor mu-band modulation in the form of contralateral suppression and ipsilateral activation. C, Log mu-band power (mean ± SEM) for left and right motor imagery at electrode C3 and electrode C4 and D, log mu-band power (mean ± SEM) in the left and right electrode clusters (4 electrodes left; 8 right) showed significant differences across imagery side (left/right) and hemisphere (left/right).

premotor and primary motor cortices (F = 0.25; Brodmann areas 4/6; peak MNI coordinates: X = 40, Y = −10, Z = 65; see Fig. 4B, right).

Contralateral beta-band suppression was found for both left and right motor imagery and was centered in precentral gyrus, extending from premotor to parietal areas (left imagery: F = −0.08; Brodmann area 6; peak MNI coordinates: X = 30, Y = −15, Z = 50; right imagery: F = −0.07; Brodmann area 6; peak MNI coordinates: X = −35, Y = −5, Z = 45); ipsilateral enhancement was also found for both left and right imagery and was focused at the middle frontal gyrus extending from premotor to parietal regions (left imagery: F = −0.06; Brodmann area 6; peak MNI coordinates: X = −35, Y = −5, Z = 60; right imagery: F = −0.08; Brodmann area 6; peak MNI coordinates: X = 35, Y = 0, Z = 65).

Spatial and spectral overlap between ownership and motor imagery

These results suggest that lateralized motor imagery as well as illusory hand ownership is reflected by mu-band oscillations in sensorimotor cortex, including premotor and posterior parietal cortices. To further investigate this finding, we looked at the spectral profile across subjects for ownership and motor imagery, contrasting peak power responses in the frequency domain and further investigated the anatomical overlap between the two sets of activations at the scalp and inverse solution levels.

This analysis revealed that the spectral profile of mu-suppression was the same for motor imagery and illusory ownership as tested here; by contrasting the per-subject peak spectral power in the left hemisphere, we found no significant difference between peak power frequency during illusory ownership (10.0 ± 0.42 Hz; mean ± SEM) and motor imagery (9.6 ± 0.36 Hz; $p > 0.05$). Moreover, no peak power response difference was observed in the right hemisphere between these two processes (ownership: 9.7 ± 0.3 Hz; motor imagery: 10.1 ± 0.3 Hz; $p > 0.05$).

Concerning spatial overlap at the scalp level, 6 of 8 (mean: 75%) of the significant electrodes found in the cluster analysis for illusory ownership overlapped with significant electrodes found during motor imagery (full summary in Table 3). In Fig. 5, the inverse solutions for illusory hand ownership, right hand imagery, and left hand imagery are overlaid, showing strong spatial overlap in voxel space (mean: 86.9%; percentage overlap for illusory ownership and motor imagery). Computing overlap for each experimental condition showed that the illusion condition led to the strongest overlap with motor imagery (mean across hemispheres: 89%) as compared to the body asynchronous and object synchronous conditions (mean across hemispheres: 78% and 72%, respectively). The weakest overlap was found for the object-asynchronous condition (49%).

Discussion

Here we induced and manipulated systematic changes in illusory hand ownership for two virtual hands using a fully automated setup combining tactile stimulation, virtual reality and electrical neuroimaging. Mu-band activity, but not beta or gamma-band activity, reflected illusory hand ownership and these changes were localized to fronto-parietal cortex. These data provide novel insights into the brain mechanisms of body ownership and related aspects of bodily self-consciousness, and highlight the potential of combining high-resolution EEG with virtual reality setups and automatized stimulation protocols for systematic, reproducible stimulus presentation in neuroscience (i.e. Bohil et al., 2011; Lenggenhager et al., 2011; Slater et al., 2008). Mu-band activity in highly similar regions was also modulated during hand motor imagery. Although premotor and posterior parietal cortices have been involved in illusory hand ownership and motor imagery respectively, the present study is the first to show common mechanisms of these two processes in these regions and in the mu band, within the same subjects.

Hand ownership as studied in the RHI has been shown to be sensitive to various parameters including visuo-tactile stroke duration (Rohde et al., 2011; Tsakiris and Haggard, 2005), distance between proprioceptive and visual hand position (Lloyd, 2007), and visual hand posture (Costantini and Haggard, 2007). In the large majority of these studies, the experimenter applied the visuo-tactile stroking manually (but see also Schütz-Bosbach et al., 2009) and to one hand. Here we describe an automatized and programmed RHI setup that makes the different stimulation-related parameters explicit and reproducible across the different visuo-vibratory conditions. These well-defined spatio-temporal parameters should facilitate the comparison and development of future behavioral and neuroimaging studies related to illusory hand ownership, for instance to those that have already been applied in the field of neuro-prosthetics (Marasco et al., 2011). Moreover, an automated RHI setup overcomes previous experimental constraints as it allowed us, for instance, to simultaneously apply visuo-tactile stimulation to both hands. Using this novel set-up, we have shown that comparable effects can be achieved when using automatized visuo-tactile stimulation in an immersive virtual reality scenario with virtual hands projecting from one's shoulders in stereo vision.

Concerning illusory referral of touch (questions 1 and 2), our setup was effective and induced strong illusions of touch that were dependent on the synchrony of stroking. Yet, this was not found to be body-specific (as in Armel and Ramachandran, 2003; Lenggenhager et al., 2007) and could in the present study be due to the fact that the non-body objects were similar in size and form to the hands (for discussion see Tsakiris, et al., 2009). We also note that many of the aforementioned RHI studies (e.g. Botvinick and Cohen, 1998; Ehrsson et al., 2004; Tsakiris and Haggard, 2005) did not collect self-reports for non-body control objects. Concerning illusory hand ownership (item 3), the present self-reports provide evidence that such changes can be induced in a body-specific and synchrony-dependent fashion with our automated setup (see also Slater et al., 2008). We observed similar effects also for illusory drift in hand position (question 4). Accordingly, the present questionnaire data extend and complement earlier work that has studied illusory ownership over virtual hands presented on a distanced projection screen (Slater et al., 2008), on a monitor (Hägni et al., 2008), or via video-projector (Ijsselsteijn et al., 2006) as well as more traditional RHI studies (Botvinick and Cohen, 1998; Tsakiris and Haggard, 2005).

Table 3

Anatomical overlap between illusory ownership and motor imagery. Illusory ownership data (illusion condition) is spatially compared to motor imagery (see Materials and methods section). Percentage overlap is quantified separately in the left and right hemisphere for significant, mu-band modulated scalp electrodes and voxels. *Top half*: The number of overlapping scalp electrodes (from left and right sensorimotor electrode clusters as defined in Table 1) between illusory hand ownership and motor imagery of hands. *Bottom half*: The number of overlapping voxels (from inverse solution contrasts; see Results section for voxel coordinates).

	Imagery with ownership	Ownership with imagery
Scalp clusters (electrodes)		
Left hemisphere	3 of 4 (75%)	3 of 4 (75%)
Right hemisphere	3 of 4 (75%)	3 of 8 (38%)
Source generators (voxels)		
Left hemisphere	198 of 201 (98.5%)	198 of 367 (54%)
Right hemisphere	258 of 324 (79.6%)	258 of 336 (76.8%)

Fronto-parietal regions reflect ownership

Previous neuroimaging work not only revealed the prominent involvement of premotor and intraparietal cortices in illusory hand ownership, but also implicated other brain regions such as primary somatosensory cortex, insular cortex, anterior cingulate cortex, and the cerebellum (Ehrsson et al., 2004, 2005, 2007; Lloyd et al., 2006; Tsakiris et al., 2007; Zeller et al., 2011). The present inverse solution data link illusory hand ownership to bilateral premotor and posterior parietal cortices (Ehrsson et al., 2004, 2005, 2007) as well as the postcentral gyrus (Ehrsson et al., 2005; Lloyd et al., 2006; Schaefer et al., 2006a, 2006b; Tsakiris et al., 2007; see also Schaefer et al., 2007).

Concerning the lateralization of brain activation, our data suggest a predominant involvement of the right fronto-parietal cortex. This is difficult to compare with prior neuroimaging studies on the RHI as these have adopted a wide range of tactile stimulation protocols. Most authors manually applied visuo-tactile stroking either unilaterally to the right (Costantini and Haggard, 2007; Ehrsson et al., 2004, 2005, 2007; Lloyd, 2007; Lloyd et al., 2006; Tsakiris et al., 2007), or unilaterally to the left dorsum and fingers of the hand (Botvinick and Cohen, 1998; Kanayama et al., 2007, 2009; Schaefer et al., 2006a, 2006b; Tsakiris and Haggard, 2005). We extended the diversity of the employed RHI protocols and stimulated the palm bilaterally in an automatized fashion, confirming and extending previous findings on illusory hand ownership. Furthermore, these different stimulation protocols resulted in distributed, but partially overlapping patterns of brain activity associated with illusory hand ownership. In previous reports, unilateral visuo-tactile stroking led to brain activity contralateral (Lloyd et al., 2006; Schaefer et al., 2006a, 2006b; Tsakiris et al., 2007), bilateral (Ehrsson et al., 2004, 2005, 2007; Lloyd et al., 2006; Press et al., 2008), or ipsilateral with respect to the stimulated hand (Lloyd et al., 2006; Tsakiris et al., 2007). Using EEG source analysis and bilateral visuo-tactile stimulation, we observed activity in bilateral fronto-parietal regions. Despite the bilateral pattern of activation at the level of the inverse solution, however, statistical analyses at the single electrode and cluster levels only revealed significant effects over right fronto-parietal regions (whereas the same analysis was not significant at C3 or the left cluster). The present findings are therefore in favor of a selective or predominant right hemispheric involvement in illusory hand ownership and are consistent with a behavioral study reporting stronger illusory ownership in the left hand as opposed to the right hand (Ocklenburg et al., 2010). This right lateralization of hand ownership is further supported by the prevalence of right-hemispheric lesions leading to the neuropsychological condition of somatoparaphrenia, during which patients report abnormal ownership for their left contralesional limb (for a review see Vallar and Ronchi, 2009; Karnath and Baier, 2010). Future research should investigate differences between unilateral and bilateral visuo-tactile stimulations as well as differences between

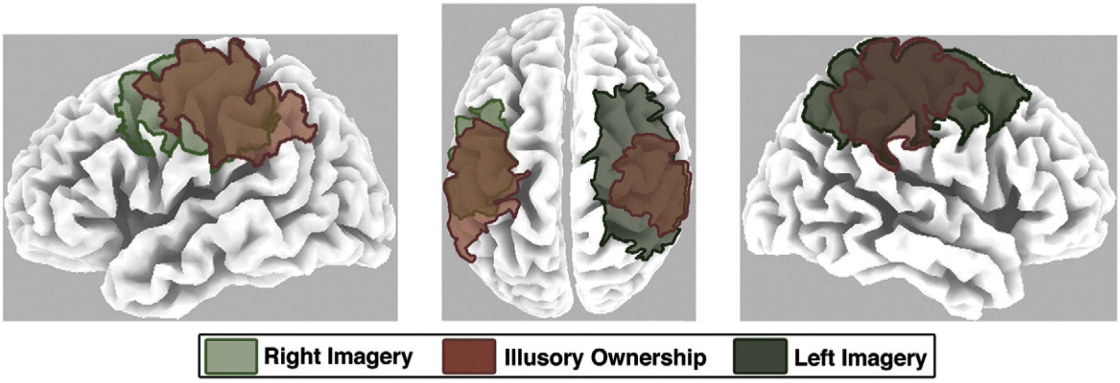

Fig. 5. Overlap between illusory hand ownership and motor imagery. Anatomical overlap for mu-band suppression was based on the inverse solution analysis. Side and top views of inverse solutions (compare Figs. 3D and 4B), showing strong anatomical overlap of supra-threshold voxels (F-ratio$<$1.75) corresponding to mu-band suppression during the illusion condition and left and right motor imagery.

manually versus automated visuo-tactile stimulation and how these influence the recruitment of right versus left fronto-parietal cortex.

Previous clinical studies using overlap analysis in stroke patients also suggested that fronto-parietal damage in insular cortex could be responsible for variable dysfunctions in limb ownership including somatoparaphrenia (e.g. Karnath and Baier, 2010). Such an implication of the insula has also been found for illusory hand ownership by experimentally manipulating visuo-tactile information in healthy subjects (Tsakiris et al., 2007), although the insular activity in this study correlated only with implicit measures of the RHI (proprioceptive drift) and not with subjective changes in illusory hand ownership as tested in the present study. Although we cannot exclude that insular cortex was also activated in the present study and may have influenced the observed fronto-parietal EEG patterns, this is rather unlikely given our inverse solution results and that activity in the insula can be detected with EEG methods (Mulert et al., 2003).

Electrophysiology of ownership

The present frequency analysis revealed that illusory hand ownership was reflected in mu-band suppression in fronto-parietal regions, but not beta or gamma-band oscillations in this or other regions. By simultaneously measuring EEG and PET/fMRI, sensorimotor alpha and mu-band suppression has been associated with increased cerebral activity (Goldman et al., 2002; Oakes et al., 2004). Furthermore, mu-band suppression has been linked to sensorimotor processing (Pineda, 2005), such as action execution and observation (Gastaut, 1952), tactile stimulation (Pfurtscheller, 1981), and observed tactile stimulation of others (Cheyne et al., 2003). Here, we found mu-band activity to distinguish between the illusion condition and the three control conditions. Namely, the illusion condition led to less mu-band suppression than the control conditions. We thus found greater activation of fronto-parietal cortex during both non-body and the asynchronous body conditions, concordant with previous EEG and PET data on illusory hand ownership (Lenggenhager et al., 2011; Tsakiris et al., 2007). This brain activation pattern also excludes that mere visuo-tactile matching or the sight of a virtual hand accounts for the observed mu-band changes. Increased activation, as reflected by greater suppression with respect to the baseline condition, has been proposed to be due to greater multisensory visuo-tactile conflict (Fink et al., 1999; Lenggenhager et al., 2011). In further agreement with the observed mu-band modulation in the present study, illusory hand ownership has been associated with decreased cortical excitability and cortical inhibition of the motor cortex (Schütz-Bosbach et al., 2006, 2009). Accordingly, we argue that fronto-parietal cortex is less activated and/or inhibited during synchronous visuo-tactile stimulation (illusion condition) as compared to the baseline condition, where no visuo-tactile stimulation was applied.

In a series of EEG experiments, illusion strength during the RHI was linked to an increase in inter-electrode, phase-locking synchrony in the gamma-band over parietal cortex (Kanayama et al., 2007, 2009). Though the present data mainly point to a close association of illusory hand ownership with changes in mu oscillations, our data are also in partial agreement with the data by Kanayama and colleagues. We found a main effect of visuo-tactile synchrony over central scalp regions (electrode C3, left cluster) that was reflected by beta-band suppression and an increase in gamma-band activity. Kanayama et al. (2007) reported gamma changes to be maximal over the central-parietal region (i.e. electrode Pz). However, since these authors were mainly interested in crossmodal synchrony effects during the RHI, they restricted their analysis to high-beta and low-gamma bands (20–100 Hz); frequency bands known to be associated with bimodal integration (for a review, see Calvert and Thesen, 2004). As such, no direct comparison can be made with our results that show illusory hand ownership to be selectively associated with mu-band power suppression. We note, however, that in contrast to these authors, our data do not suggest that beta or gamma-band activity is related to illusory hand ownership, because activity changes in these bands did not reflect illusory hand ownership depending on our experimental factors of stroking synchrony and the sight of virtual hands or objects. Importantly, visuo-tactile stimulation in these previous studies by Kanayama et al. (2007, 2009) was always performed on body-like objects, i.e. no object control conditions were carried out to test for body specificity of synchrony-related changes in hand ownership. We also note that the collected subjective reports in the two studies by Kanayama and colleagues suggest that most participants did not experience illusory ownership within their experimental setting, whereas in the present experimental setup, illusory ownership was significantly modulated. We thus suggest that these earlier EEG results represent a low-level effect of receiving bimodal (visuo-tactile) stimulation in a synchronous or asynchronous manner, rather than illusory hand ownership. Such comparisons, however, ought to be made cautiously, as the experimental setup and paradigm differ substantially from the current study.

Shared spectral and anatomical mechanisms between motor imagery and ownership

Our motor imagery results follow classical electrophysiological responses over sensorimotor cortex (Pfurtscheller and Neuper, 1997; Neuper et al., 2006). These are characterized by contralateral mu- and beta-band desynchronization (suppression) and ipsilateral mu- and beta-band synchronization (enhancement) and were found here at both the level of single electrode and cluster analyses. The application of a linear, distributed inverse solution localized these changes to contralateral and ipsilateral fronto-parietal cortex including premotor and posterior parietal cortices as well as the postcentral gyrus. These regions have been involved in a number of studies in motor imagery (see reviews from Grèzes and Decety, 2001; Munzert et al., 2009). Several studies using neuroimaging (Kosslyn et al., 2001), transcranial magnetic stimulation (Ganis et al., 2000), or clinical investigations (Sirigu et al., 1996) showed that motor imagery shares neural mechanisms with movement planning (Decety et al., 1989) and movement execution (Gerardin et al., 2000; Parsons et al., 1995), in particular in premotor cortex (e.g. Ionta et al., 2010) and parietal cortex (e.g. Overney and Blanke, 2009). Activity in both the inferior parietal cortex (Wolbers et al., 2003) and the premotor cortex (de Lange et al., 2006; Malouin et al., 2003) increases as a function of imagery demand. Of relevance for the present study, premotor cortex and posterior parietal cortex are activated in the RHI (Ehrsson et al., 2004, 2005) and activation in premotor cortex has been found to correlate with illusion strength. Moreover, RHI and motor imagery have been shown to depend on multisensory mechanisms, including vision and proprioceptive signals (Botvinick and Cohen, 1998; Ionta and Blanke, 2009; Ionta et al., 2012; Lloyd, 2007) and changes in illusory hand ownership alter the speed of motor imagery (Ionta et al., 2012). To our knowledge, our results show for the first time at the neural level a strong anatomical overlap between illusory hand ownership and hand motor imagery in the same subjects showing that common structures are recruited for both processes. That is, the activation changes due to motor imagery activated to a large extent the same regions that were modulated by illusory hand ownership with the former being somewhat more widespread than the latter. This overlap was maximal during the illusion condition and minimal during asynchronous visuo-tactile stimulation during the non-body object condition.

Common brain mechanisms between hand ownership and hand motor imagery were further confirmed using frequency analysis. Thus, concerning the involved frequency bands, both motor imagery and illusory hand ownership were associated with mu-band modulation. However, motor imagery was characterized by contralateral mu- and beta-band desynchronization in fronto-parietal cortex (suppression; i.e. Pfurtscheller and Neuper, 1997; Pfurtscheller et al., 1997b), whereas our illusory hand ownership manipulation was characterized by mu-band desynchronization, especially in the right fronto-parietal cortex, that was body-specific and depended on visuo-tactile stimulation. These frequency data suggest that hand motor imagery and illusory hand ownership rely on similar electrophysiological mechanisms in fronto-parietal cortex, while partly differing in their spectral signatures.

There are several limitations to the present study. We note that the present experiment was designed as a precursor to future work investigating the impact of illusory ownership on BCI performance involving bilateral presentation of the visual hands during unilateral motor imagery. This was one of the reasons why we decided to induce ownership bilaterally in the present study, measuring the spatial and spectral overlap of illusory ownership and motor imagery by comparing bilateral RHI data against a combination of two unilateral motor imagery data sets. This constraint may have been a limitation concerning the present overlap analysis, as recruited brain structures and overlap may be different from those described here if unilateral RHI data are compared with unilateral motor imagery (or if bilateral RHI data are compared with bilateral hand motor imagery).

Also, in the present study participants saw static virtual hands while performing motor imagery and this may have interfered with motor imagery mechanisms due to incongruency between the imagined movement and the static virtual hands. Recent neuroimaging evidence has also suggested that providing visual postural consequences congruent with the motor imagery strategy may enhance corticospinal activity in M1 (Mercier et al., 2008). Given this, future studies may additionally manipulate the visual feedback during motor imagery to investigate the effects of non-stationary visual feedback on brain mechanisms of motor imagery as well as the shared mechanisms of the RHI and motor imagery. Furthermore, collection of additional behavioral measures of motor imagery performance could allow for comparisons between the strength of illusory ownership and imagery ability. Further work is needed to investigate and compare the brain mechanisms of unilateral and bilateral hand ownership and motor imagery.

Collectively, these anatomical and spectral data reveal that motor imagery in fronto-parietal cortex shares neural mechanisms not only with several different motor-related aspects such as movement execution and movement planning, but also with multisensory mechanisms related to illusory hand ownership. It has been speculated that illusory ownership over virtual and prosthetic limbs may benefit neuroprosthetics and neuro-rehabilitation (Ehrsson et al., 2008; Marasco et al., 2011). The present data show that the computer-controlled induction of hand ownership alters – at least partly – the same fronto-parietal oscillations that can be used in non-invasive brain computer interfaces. These approaches have utilized motor imagery for motor control via online exploitation of spectral features from the mu- and beta-bands (8–26 Hz) over sensorimotor cortex (Lebedev and Nicolelis, 2006; Millán et al., 2010; Pfurtscheller and Neuper, 2001; Pfurtscheller et al., 1997b; Wolpaw and McFarland, 2004). Based on the present findings, we argue that automatized illusory hand ownership may be used to guide or improve control of external devices including robotic arms using non-invasive brain computer interface technology as well as to control prosthetic arms that are interfaced with the peripheral nervous system (Marasco et al., 2011; Navarro et al., 2005).

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.neuroimage.2012.09.027.

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Supplemental Material:

Shared electrophysiology mechanisms of body ownership and motor imagery

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We performed an informal pilot study to verify that our automated induction of the RHI generates comparable illusory effects to previous RHI setups (*e.g.* Botvinick & Cohen, 1998; Tsakiris & Haggard, 2005; Slater et al., 2008).

Pilot Methods

Participants

15 healthy, right-handed subjects (8 females; ages: 19-29 years, mean±SD: 24.7 ± 3.2 years) were recruited and paid for their voluntary participation. All participants had normal or corrected-to-normal vision and gave informed consent before being included in the study. The study was undertaken in accordance with the ethical standards as defined in the Declaration of Helsinki and was approved by the local ethics research committee at UNIL.

Visual and Tactile Stimuli

Visual and tactile stimuli were applied as in the main experiments (see *Materials and Methods*). In contrast to the main experiments, only the left hand was shown in the virtual scene and the vibration motors were affixed in a line to the participants' left index finger.

Experimental Apparatus

Participants were seated in an Ascension Reactor2 motion capture area (Inition, London, UK) in a fixed chair ~10cm in front of a two-tiered table. Participants were instructed to rest their left arm on a foam cushion located on the lower tier of the table. A distance of ~15 cm separated the two tiers of the table, providing sufficient space for the left arm to remain untouched by the upper tier. The upper tier of the table was covered with a black cloth. To ensure head stability and a stable virtual scene, the head was restrained with a chin rest. The HMD was individually fitted to each subject and fully blocked their vision of the table in front of them. To prevent any external auditory cues, participants listened to white noise through a set of headphones.

Procedure

The participant's real left arm was placed to the left of the visual (virtual) arm (15 cm separation). The location of the left index finger in this calibrated position was marked and recorded using a motion capture marker. The top tier of the table was then placed over the real left arm and a second motion capture marker was positioned on the upper tier to the right of the participant such that the participant could guide it with his or her right hand. The subjects were instructed to relax their left arm and to refrain from any type of movement.

The motion capture area was used to measure the position of the perceived hand position in a semi-automated fashion. Two active, infrared motion capture markers were used to track the difference between the perceived finger position and real position of the tip of the left index finger (proprioceptive drift).

Experimental Design

The experiment was divided into two experimental conditions: synchronous and asynchronous visuo-tactile stimulation, as defined in the main text (see *Methods and Materials*). Each experimental condition was given in a block of eight trials (20s each) followed by a hand localization resulting in eight localizations of perceived hand position per condition.

Each trial proceeded as follows: participants were asked to focus on the virtual hand in the virtual scene. For 20s, the participant received visuo-tactile stroking according to the experimental condition. After this 20s period, the screen turned black and an auditory cue was provided to signal the localization phase. With their right hand, participants were instructed to slide a motion capture marker along the surface of the upper tier of the table until the center of the marker was directly above the perceived location of the tip of left index finger. After verbally confirming the hand localization, subjects were instructed to displace the motion capture marker back to an arbitrary position on the right side of the table.

Proprioceptive Drift and Subjective Reports

Proprioceptive drift was measured by taking the distance in the x-plane between two motion capture markers: one at the perceived hand position, as placed by the participant, and the second at the tip of the left index finger. At the end of each eight-trial condition block, the strength of the subjective experience of the RHI was gauged with a questionnaire referring to the entire condition block of eight trials. The questionnaire was composed of the nine questions from the original RHI questionnaire adopted to the virtual environment (Botnivick & Cohen, 1998; Slater et al., 2008).

Pilot Results

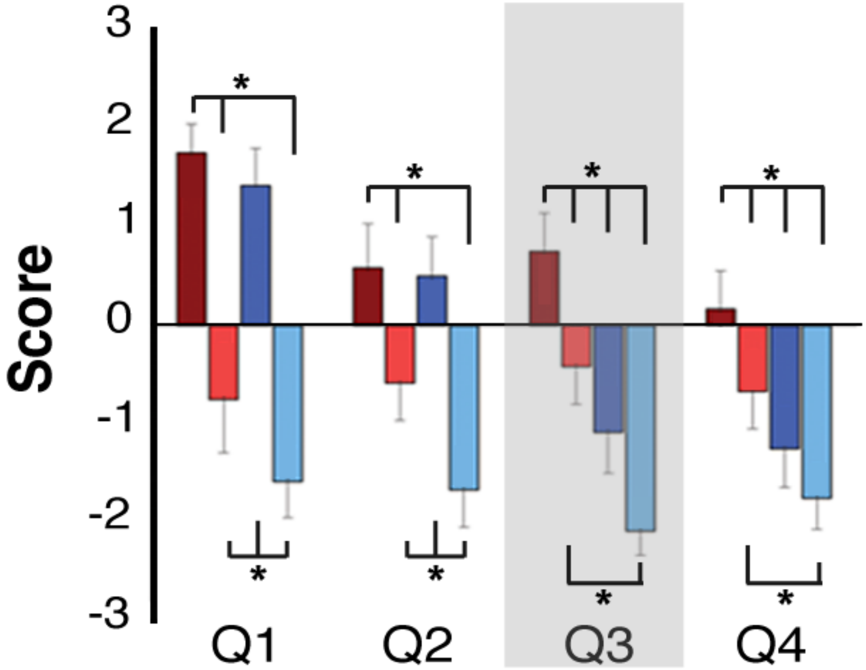
Questionnaire

Since only two experimental conditions were tested in this pilot experiment, we tested for differences in questionnaire ratings between synchronous and asynchronous stimulation using non-parametric, Wilcoxon matched pair tests for each question (Bonferonni corrected for multiple comparisons). These analyses revealed a significant increase in reported scores for synchronous as compared to asynchronous visuo-tactile stimulation for Q1 (synch: 6.33±0.32; asynch: 2.40±0.34; *mean±SEM*), Q2 (synch: 4.0±0.57; asynch: 2.07±0.44) and Q3 (synch: 4.13±0.50; asynch: 2.20±0.41; all $p < 0.005$). No difference was found between the synchronous and asynchronous conditions for questions 4-9 (all $p > 0.05$). These results are consistent with reported illusory experiences in standard RHI setups (Botvinick & Cohen, 1998; Tsakiris & Haggard, 2005), in which synchronous visuo-tactile stimulation leads to perceptual changes in perceived location of touch (questions 1-2) and illusory ownership of the fake hand (question 3). Questions 4-9 are often regarded as control questions as they generally remain unaffected by the experimental manipulation of visuo-tactile synchrony (*e.g.* Slater et al., 2008).

Proprioceptive Drift

To measure the distance between the perceived and actual hand position (proprioceptive drift), we took the average perceived location of the left index finger across the eight proprioceptive judgments in both the synchronous and asynchronous conditions. For the synchronous visuo-tactile stroking condition, the drift in perceived hand location toward the position of the virtual hand (2.2 ± 1.8 cm; *mean±SEM*) was significantly larger as compared to asynchronous condition (0.1 ± 1.6 cm; *mean±SEM*) ($p < 0.05$, *one-tailed paired t-test*), consistent with previous RHI setups (Botvinick & Cohen, 1998; Tsakiris & Haggard, 2005; Slater et al., 2008).

Supplemental Figures



Supplemental Figure S1.

Self-report scores for all items of the questionnaire. Mean questionnaire scores (error bars SEM) probing illusory experiences during visuo-tactile stimulation (see *Methods and Materials*). In Figure 2, Question 3 (illusory ownership) is highlighted. * indicates a significant difference between experimental conditions ($p < 0.05$; *Wilcoxon matched pairs test*; *corrected*).

Supplemental References

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3.2

Illusory ownership alters decoding performance in a motor imagery based brain-machine interface

Illusory hand ownership alters decoding performance in a motor imagery based brain-machine interface

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Abstract

Recent work in cognitive neuroscience has demonstrated that providing coherent multisensory stimulation to real and fake limbs can induce the illusory sensation that the artificial limb is one’s own (ownership). We recently showed that illusory hand ownership leads to similar electrophysiological changes over fronto-parietal cortex as those associated with unilateral motor imagery of the hand, a commonly used paradigm in brain-machine interfaces (BMI; Evans & Blanke, 2012). These findings suggest that non-invasive BMI performance might be influenced by the application of multimodal feedback leading to illusory ownership. To test this, here we performed offline single-trial decoding of left versus right hand imagery while manipulating hand ownership with visuo-tactile stimulation on participants’ real (felt) and virtual (seen) hands. Our results show illusory ownership to lead to an increase decoding performance with respect to incoherent visuo-tactile stimulation conditions. However, compared with a motor imagery condition without visuo-tactile stimulation and ownership modulation, we observed a general reduction in decoding performance during tactile stimulation. We discuss these results in their contribution to the ongoing quest towards the design of multisensory neuroprosthetic devices that ‘feel’ like real limbs.

Introduction

Brain-machine interfaces (BMIs) use advanced signal processing and machine learning techniques in combination with a contemporary neuroanatomical and neurophysiological understanding of brain processing in order to extract, decode, and translate intent in real-time from ongoing brain activity (Nicolelis, 2003; Wolpaw, 2007). Recent advances in neurophysiology and signal processing have led to BMIs demonstrating potential for the restoration of upper limb function in non-human primates (Velliste et al., 2008; Carmena et al., 2003; Moritz et al., 2008; Serruya et al., 2002) and humans (Hochberg et al., 2006, 2012). Despite these promising results, there remain important limitations in current BMI systems, in particular, the diminished quality of motor control for these devices as compared to healthy limbs (Hochberg et al., 2006). As it is well known that human cognition and perception is largely shaped by multisensory experience (Ghazanfar and Schroeder, 2006), and that reliable motor control requires multimodal sensory information (van Beers et al., 1999; Sober and Sabes, 2005), it is hypothesized that the present deficiencies in BMI control may be due to a lack of multisensory feedback in these devices (Birbaumer et al., 1999; Abbott, 2006; Hatsopoulos and Donoghue, 2009).

Research addressing this issue has recently embedded multimodal sensory feedback into invasive BMIs for monkeys. After learning to control a virtual arm with voluntary modulation of activity in primary motor cortex, monkeys were provided direct electrical stimulation to primary somatosensory cortex to simulate artificial touch sensation for objects that the virtual arm encountered (O'Doherty et al., 2011). Importantly, when performing an active exploration task with a virtual arm combined with artificial touch sensation, monkeys behaved similarly to how they would with their actual limbs. This was taken as evidence that the multisensory nature of the BMI led to embodiment of the virtual limb. In a similar paradigm, monkeys were trained to control a visual cursor with motor cortex activity while their arm was passively displaced to follow the cursor trajectory (Suminski et al., 2010). Contrasting BMI control during pure-visual feedback against a condition where visuo-proprioceptive feedback was provided, the authors demonstrated that BMI performance was enhanced by multimodal feedback. They further showed that performance was selectively modulated in that it depended on the spatial congruence across the sensory modalities. Collectively, these first studies show the potential to improved BMI control via application of coherent multimodal sensory feedback.

Progress in research using invasive BMIs in monkeys faces several practical issues including long-term stability, limited sample sizes, and restrictive, clinical experimental settings (Lebedev and Nicolelis, 2006). To circumvent these concerns, an alternative line of research has investigated the potential of decoding intent with non-invasive neuroimaging techniques (Pfurtscheller et al., 1997; Pfurtscheller et al., 2006; Millan et al., 2010; Wolpaw et al., 2002). Though most non-invasive BMIs exclusively provide unimodal visual feedback, some research has also addressed sensory feedback substitution, replacing the visual modality with auditory (Furdea et al., 2009; Hinterberger et al., 2004; Nijboer et al., 2008), vibrotactile (Chatterjee et al, 2007; Brouwer and van Erp, 2010; Cincotti et al., 2007) or proprioceptive (Gomez-Rodriguez et al., 2010) sensory feedback. Multimodal, non-invasive BMI systems remain relatively unexplored and have led to mixed results (Wagner et al., 2012). Several studies have investigated combined visuo-auditory feedback, reporting a multimodal enhancement of BMI performance in P300 paradigms (Belitski et al, 2011; Klobassa et al, 2009), but a decrease in performance for multimodal versus unimodal regulation of slow cortical potentials (Hinterberger et al., 2004). Finally, mirroring the above-described results in monkeys, recent work has shown that providing visuo-proprioceptive feedback to the hand via a robotic exoskeleton can improve BMI performance (Ramos-Murguialday et al., 2012).

One potential avenue for further improvement of control and sensation over BMIs and neuroprosthetic devices may come from paradigms developed in the context of the cognitive neuroscience of bodily self-consciousness. Empirical studies of the multisensory mechanisms underpinning the sense that the body and its parts belong to us and not another (ownership) have emphasized the importance of proper integration of visual, tactile and proprioceptive signals (Botvinick, 2004; Botvinick and Cohen, 1998; Tsakiris and Haggard, 2005; Ehrsson et al., 2004). The most often-used paradigm to experimentally study ownership for upper limbs is the so-called rubber hand illusion (RHI). In this perceptual illusion, participants fixate on an artificial hand (visual cue) being stroked by a paintbrush in synchrony with stroking on their own corresponding and occluded hand (tactile cue) (Botvinick and Cohen, 1998). The visuo-tactile cues provided to the artificial and real hands lead to an alteration in bodily experience and result in the feeling that touch sensation is transferred to the artificial hand and that the artificial hand is one's own hand (as measured by subjective questionnaires). This feeling of illusory ownership is generally associated with a recalibration of the perceived position of the real hand, mislocalized toward the artificial hand. The illusion is abolished if the visuo-tactile cues are spatially or temporally incongruent, or if non-body control objects are used in place of an artificial hand (Botvinick & Cohen, 1998; Tsakiris & Haggard, 2005; review in Makin et al., 2008; Blanke, 2012).

Recent work has indicated that the RHI can be used on amputees to induce illusory ownership over peripheral prosthetic devices (Marasco et al., 2011; Ehrsson et al., 2008). Linking these paradigms to research in non-invasive BMIs, we recently showed that illusory hand ownership leads to similar electrophysiological changes over bilateral fronto-parietal cortex as those associated with unilateral motor imagery of the hand, a commonly used paradigm in non-invasive BMIs (Evans & Blanke, 2012). In particular, we demonstrated strong anatomical and spectral overlap between these processes, primarily in the mu-band (8 to 13 Hz sensorimotor oscillations) and speculated that this selective modulation may be of importance to BMIs, as mu- and beta-band (14 – 30 Hz) oscillations have been investigated with respect to imagined unilateral upper limb movements in non-invasive BMIs (Pfurtscheller et al., 1997; Pfurtscheller and Neuper. 2002; Wolpaw et al. 2002; review in Neuper et al., 2006).

Despite the hypothesized potential for ownership modulation to influence BMI performance, no study to date has attempted to test BMI decoder performance while manipulating ownership. Here, we induced illusory ownership over two virtual hands by providing task-irrelevant visuo-tactile stimulation to the real and virtual hands while recording 64-channel electroencephalography (EEG). While receiving this stimulation constantly and simultaneously on both hands, participants performed a unilateral motor imagery task, imagining to clasp their left or right hand. Participants also performed the motor imagery task in experimental conditions where visuo-tactile stimulation was applied asynchronously, on non-body objects, or not at all. Using this experimental design, we first assess whether illusory hand ownership influences decoding performance in a standard BMI paradigm. Then, to better understand any difference in decoding performance, we explore the spectral effects on mu-band power of illusory ownership manipulation during motor imagery.

Materials and Methods

The present study took place as a separate experimental session with the same participants and experimental setup as in a previous report (Evans & Blanke, 2012), where further details regarding our automated setup can be found.

Participants

12 healthy, right-handed participants were recruited (ages 22.7 ± 4.1 *mean±SD*; 3 females). All participants had normal or corrected-to-normal vision and were naïve motor imagery BMI users. The study was undertaken in accordance with the ethical standards as defined in the Declaration of Helsinki and were approved by the local ethics research committee at the University of Lausanne.

Procedure

Participants were seated at a table with their arms resting (palms up) on their legs. Head movements were restrained with a chin rest and the experiment took place in a darkened room. Visual stimuli were rendered in stereo on a head-mounted display showing a virtual scene with either two virtual arms or two virtual non-body control objects visually projected as extending from the body and resting on a tabletop (projected above the participant's physical arms by approx. 20 cm).

Four virtual spheres on each palm of the two virtual arms (or non-body control objects) visually represented the four vibration motors on the real hands. Visual "vibrations" were represented by changing the virtual motor's color from white to red and animating it to visually jitter and corresponded to physical tactile stimulation via four haptic vibration motors affixed in a line to each of the palms of the participants' hands. The motors were programmed to vibrate in sequence to simulate a continuous, stroke-like movement in order to automate the stroking patterns that are generally manually applied to induce the RHI (i.e. Botvinick & Cohen, 1998; Ehrsson et al. 2004). In half of the participants the direction of the stroking sequence was either inward, toward a centralized fixation cross and in half it was outward.

Synchronous visuo-tactile stimulation was defined such that visual and tactile vibrations occurred with no temporal delay and with spatial congruency between visual and tactile stimuli. Asynchronous visuo-tactile stimulation was achieved by inserting a random delay of 50 to 150 ms of the onset of the visual stimulation with respect to the onset of the tactile stimulation and randomly varied the direction of visual stroking while maintaining the same physical vibration sequence.

Experimental design

We previously reported that our automatized and virtual reality setup induced both the subjective and behavioral effects generally associated with the RHI (as measured by questionnaires and proprioceptive drift, respectively; Evans and Blanke, 2012). As in this previous study, here we manipulated the strength of illusory hand ownership using a 2x2 factorial design with the factors Stroking and Object. The Stroking factor consisted of two levels of visuo-tactile stimulation (synchronous and asynchronous; as defined above). The Object factor was composed of two levels: virtual arms or virtual non-body control objects. Two additional baseline conditions were recorded while participants saw virtual arms: one without visuo-tactile stimulation and one with just tactile stimulation (no visual counterpart).

Motor imagery during visuo-tactile stimulation

Participants focused on a central fixation cross placed between the hands/objects (visual angle of 37° to the left and right) while receiving visuo-tactile stimulation according to one of the experimental conditions. At the beginning of each trial, the fixation cross remained green for 500 ms, followed by a left or right arrow cue for 500 ms. Finally, the directional cue was replaced with a red fixation cross that remained for 4.5 s. Participants were asked to imagine clasping and unclasping the cued hand (right or left hand; Pfurtscheller et al. 1997) as soon as they saw the directional cue. It is important to note that visuo-tactile stimulation was cue independent, that is, it was applied to both hands simultaneously and continuously. Each experimental block consisted of 30 randomized trials (15 left hand imagery, 15 right hand imagery trials) and was repeated three times, resulting in 90 trials.

EEG: Preprocessing

64-channel EEG was sampled at 2048 Hz (Biosemi Inc, Amsterdam, Netherlands), downsampled to 512Hz, and subjected to visual inspection in the time and frequency domain. Electrodes with $> 50\ \mu$V DC-offset were rejected. The mean percentage of electrodes included was 92% (59±1 electrodes; *mean±SD*). Timeframes with eye blinks and transient conductance shifts were marked as artifacted in a semi-automated manner (see Lenggenhager et al., 2011; Evans & Blanke, 2012) and artifacted trials were discarded.

EEG: Offline decoding of motor imagery

Using a 10-fold cross-validation scheme, trials were shuffled and split into training and test sets for each subject and each experimental condition. Data from the training set was used to compute per-subject common spatial patterns (CSPs; Blankertz et al., 2008). Next, feature vectors were constructed by bandpass filtering the raw EEG (mu-band: 8 to 13 Hz and mu/beta-bands: 8 to 30 Hz). These filtered signals were re-projected through the first three and last three CSPs, and log variance was computed across timeframes. Using these feature vectors, coefficients for a binary classifier were computed (linear fisher discriminant) and used on test set with the same procedure. Note that per-subject CSPs and classifier coefficients were computed independently to the test set.

Decoding performance was then computed per subject as the mean performance across cross validation folds.

As low performance from naïve (untrained) non-invasive BMI users is common (Guger et al., 2003), most studies investigate performance in trained participants. To closer follow this tradition, we excluded any participants from our analyses that were unable to perform the task above chance (50%) in the baseline condition (no visuo-tactile stimulation). For the remaining participants, paired, two-tailed t-tests (adjusted for multiple comparisons using the Holm-Bonferroni correction) were used to test for differences in classification performance across experimental conditions.

Visualizing Common Spatial Patterns

We collected the first and last CSP weights (*i.e.* the most important weights for left and right imagery) for each cross validation fold, participant, and experimental condition and projected these per-electrode spatial weights onto the scalp in order to generate scalp topographies (Blankertz et al., 2008). Since CSP weights are of arbitrary and relative value (*i.e.* absolute magnitude is important), before averaging the CSP weights within and across participants, the weights were normalized for each fold, participant, and condition using a min-max normalization.

EEG: Spectral analyses of motor imagery and ownership

4.5 s of EEG data (per trial) was collected for the period immediately following the directional cue (total accepted epochs: 60±19 s; *mean±SD* per subject, per condition). Prior to computing power spectral densities (PSD), scalp potentials were re-referenced with respect to the average reference, the linear trend was removed, and a Hann window was applied to each epoch. PSDs were then computed at a 0.5 Hz resolution for each epoch with a Fast Fourier Transform

(Matlab, Mathworks, Natick, Massachusetts, USA) in the alpha/mu frequency band (8-13 Hz). Finally, we computed mean log power ratios (LPR) across all epochs and participants at each electrode (*e.g.* Oberman et al. 2005; Evans & Blanke, 2012).

Differences in LPRs

We previously showed illusory ownership and lateralized motor imagery to selectively modulate mu-band power in the same participants under this paradigm (Evans & Blanke, 2012). To investigate the electrophysiological effects of providing selective forms of visuo-tactile stimulation during motor imagery, we compared mu-band log power ratios obtained in the previous study against those in the present study during motor imagery. Mu-band LPRs were computed at electrodes C3 and C4 over central hand regions (Oberman et al., 2005; Pfurtscheller & Neuper, 1994).

Next, we computed the difference between LPRs with and without motor imagery (*i.e.* during each condition in the present study versus each condition from our previous study). This procedure resulted in a difference of LPR at both electrodes C3 and C4 for both left and right motor imagery. We then collapsed the data further by only considering contralateral motor imagery (i.e. differences were computed between experimental conditions during right motor imagery for electrode C3, and left motor imagery for electrode C4). Finally, we collapsed these data into one data set corresponding differences between each experimental condition in the absence of, and during contralateral motor imagery. For each condition, the distribution of LPR differences was individually contrasted against 0 (*i.e.* no difference) using paired, two-tailed t-tests (Holm-Bonferroni corrected).

Results

Single-trial decoding

To test our hypothesis that ownership manipulation might selectively modulate decoding performance in the BMI motor imagery task, we first performed single-trial decoding of left vs. right motor imagery using mu-band features (see *Methods and Materials*). This analysis revealed the highest classification performance to be in the synchronous body stroking condition (henceforth referred to as illusion condition; Figure 1A). In particular, average classification performance was found to significantly increase in the illusion condition with respect to asynchronous stroking on non-body objects (from 56% to 63%; $P = 0.02$), and importantly, no such difference was found between the non-body control objects ($P = 0.15$). This boosting effect of the illusion condition over asynchronous stroking on non-body control objects was also found at the single-subject level (7 of 9 subjects; Figure 1B). However, on average, we did not find the illusion condition to lead to significant performance differences when compared to asynchronous stroking on bodily objects or synchronous stroking on non-body objects (both $P > 0.05$), though the majority (6 of 9) of the participants showed an increase in decoding performance in the illusion condition versus asynchronous stroking on bodily objects (Figure 1C).

Despite the observed decoding performance changes due to ownership manipulation, performance was found to be highest when participants performed motor imagery in the absence of visuo-tactile stimulation (Figure 1D). By comparing the two baseline conditions, we found the addition of tactile stimulation to significantly reduce performance (from 75% to 58%; $P < 0.001$). This reduction in decoding performance with respect to the baseline condition without tactile stimulation was also found for all other experimental conditions (all $P < 0.003$).

Finally, we tested decoding performance using features computed from both mu- and beta-bands (8 to 30 Hz) and found general, increased performance as compared to features computed solely in the mu-band (mean performance across conditions from 58% to 66%; $P = 0.02$). This was driven by significant performance increases in three conditions (asynchronous, body stroking: 56% to 65%, $P = 0.01$; no visuo-tactile baseline: 75% to 80%, $P = 0.03$; tactile-only baseline: 58% to 67%, $P = 0.03$). However, the performance boost observed in the illusion condition using solely mu-band features was abolished using these wider spectral features (illusion condition vs. asynchronous stroking on non-body objects; $P > 0.05$).

Mu-band oscillations during motor imagery and visuo-tactile stimulation

By comparing mu-band LPRs for each experimental condition during motor imagery to the same conditions in the same participants during passive stimulation (see *Methods*), we found motor imagery to substantially alter mu-band oscillations in all conditions except for the illusion condition. In particular, by computing a difference in LPR ratio for each condition and testing this distribution of differences against 0, we found significant changes mu-band LPRs for all conditions except the illusion condition (Figure 2A).

Relevant spatial features for decoding motor imagery during illusory ownership

Finally, to evaluate the relative contribution of electrodes to mu-band discrimination of left versus right motor imagery during the illusion condition, we projected the group CSP weights as scalp topographies. This analysis revealed sensorimotor regions contralateral to the imagery side to be of most importance for decoding (Figure 2B), providing further independent evidence that mu-band oscillations over fronto-parietal regions are of import during both motor imagery and illusory ownership (Evans & Blanke, 2012).

Discussion

Using an automated setup to induce illusory ownership over two virtual hands while participants imagined to move their left or right hand, we found illusory ownership to significantly alter offline, single-trial decoding performance. In particular, decoding performance for left versus right hand was increased during synchronous stroking on bodily objects as compared to asynchronous stroking on virtual non-body objects. Several recent studies have also shown that providing multimodal, visuo-proprioceptive feedback can boost BMI performance over unimodal visual feedback in invasive BMIs for monkeys (Suminski et al., 2010) and for non-invasive BMIs in humans (Ramos-Murguialday et al., 2012). Importantly, these studies stress that performance is only increased if visual and proprioceptive cues are spatially and temporally coherent, and are thus compatible with the present findings that show selective increases depending on visuo-tactile spatial and temporal coherence.

However, unlike in previous RHI studies (Botvinick & Cohen, 1998; Tsakiris & Haggard, 2005; Tsakiris et al., 2009), we did not find performance to be independently influenced by visual form and synchrony of stroking. Though our previous studies hinted that selective modulations in the mu-band might influence the decoded features for a standard motor imagery task (Evans & Blanke, 2012), the spatial origin of these mu-band alterations and whether they can be distinguished on a single-trial level remains unclear. Further work is needed to directly link ownership-induced changes in the mu-band to anatomical substrates, for instance by using combined EEG-fMRI paradigms. Such insight might help design signal processing techniques that can better distinguish between these subtle multisensory conflicts at the single-trial level and given the course spatial resolution of scalp EEG.

By directly comparing motor imagery without tactile stimulation and with tactile stimulation, we found a significant decrease in decoding performance due to the addition of tactile stimulation. This result stands in contrast to previous reports demonstrating similar decoding performance for vibrotactile feedback and visual-only feedback in motor imagery based, non-invasive BMIs (Cincotti et al., 2007; Chatterjee et al., 2007). However, these studies both employed unimodal vibrotactile feedback whereas we employed bimodal, visuo-tactile feedback. Closer to the present work, previous studies testing unimodal visual and auditory as well as bimodal visuo-auditory feedback in non-invasive BMIs did not find bimodal feedback to boost performance as compared to unimodal feedback (Hinterberger et al., 2004). These results suggest that it may be that multimodal feedback is detrimental to non-invasive BMI control (but see Ramos-Murguialday et al., 2012).

In previous studies providing vibrotactile feedback, stimulation was provided either on the biceps (Chatterjee et al., 2007) or on the upper chest (Cincotti et al., 2007) in contrast to the present study, where we vibrated the hands. Thus, the observed decline in performance may be that participants were unable to reliably perform motor imagery of the hands due to distraction from visuo-tactile stimulation on the same body part. Several studies have explored the interplay between attentional mechanisms and the neural systems supporting imagery and action (Johansen-Berg, 2003; Passingham, 1996; Sacco et al., 2006), but further research is needed to directly test the effect of sensory stimulation distraction on mental and motor imagery ability and attention.

Concerning the electrophysiological effects of performing somatosensory stimulation during motor imagery, it has been shown that mu- and beta-band power is modulated by touch (Pfurtscheller, 1981; Salenius et al., 1997), the anticipation of touch (van Ede et al., 2010), the observation of touch on others (Cheyne et al., 2003), as well as by motor imagery (Pfurtscheller et al., 1997). Thus, the influence of somatosensory stimulation on mu- and beta-band features may impact decoding performance using spectral features from these bands. To step around this technical issue, future research may rather employ interleaved paradigms, where tactile stimulation and decoding are not performed simultaneously. Such an approach may introduce additional latency, as decoding periods are more infrequent, so novel paradigms may need to be used such as rapid alternation between stimulation and decoding periods (*e.g.* O'Doherty et al., 2011) or by applying stimulation during a 'priming' period and later decoding (Salamin et al., 2010).

Finally, our analysis on mu-band LPRs showed that motor imagery influences mu-band activity during visuo-tactile stimulation in a body-selective, synchrony-dependent manner. Namely, mu-band power was found to be invariant to the addition of motor imagery. We interpret this finding as further evidence that the mu-band selectively encodes illusory ownership and believe this finding to be of importance for future work investigating real-time neural measures of ownership to guide neuroprosthetic control.

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Figures

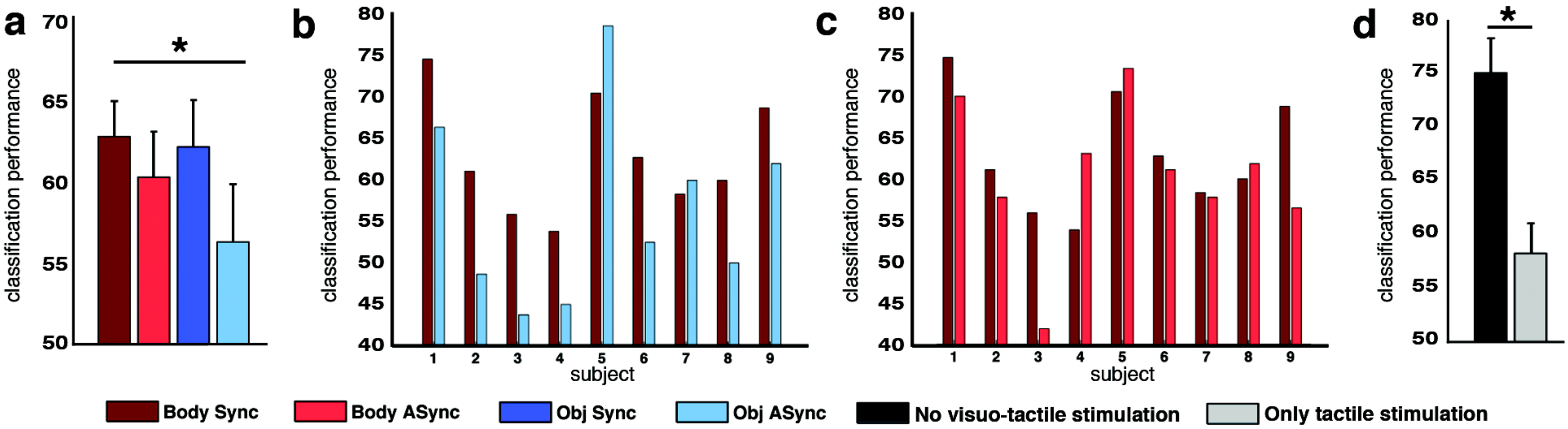

Figure 1. Decoding performance. ***A)*** Mean classification performance across subjects (N=9) and cross validation folds (X=10) in the four visuo-tactile stroking conditions. Synchronous stroking on bodily visual objects led to an increase in performance with respect to asynchronous stroking on non-body control objects. No such difference was found between synchronous and asynchronous stroking on the control objects. ***B)*** The two significantly different conditions from (A) plotted at the single-subject level. 7 of 9 participants witnessed an increase in decoding performance. ***C)*** Single subject plots for synchronous and asynchronous bodily stroking. 6 of 9 participants witnessed an increase in decoding performance, but on average (A) no difference was found. ***D)*** Decoding performance during the two baseline conditions: motor imagery without visuo-tactile stimulation and motor imagery with only tactile stimulation. The addition of tactile stimulation to the hands led to a significant decrease in decoding performance (difference between black and grey bars). In all panels, * indicates $P < 0.05$ (*two-tailed, paired t-test, corrected*). Error bars represent standard error of the mean.

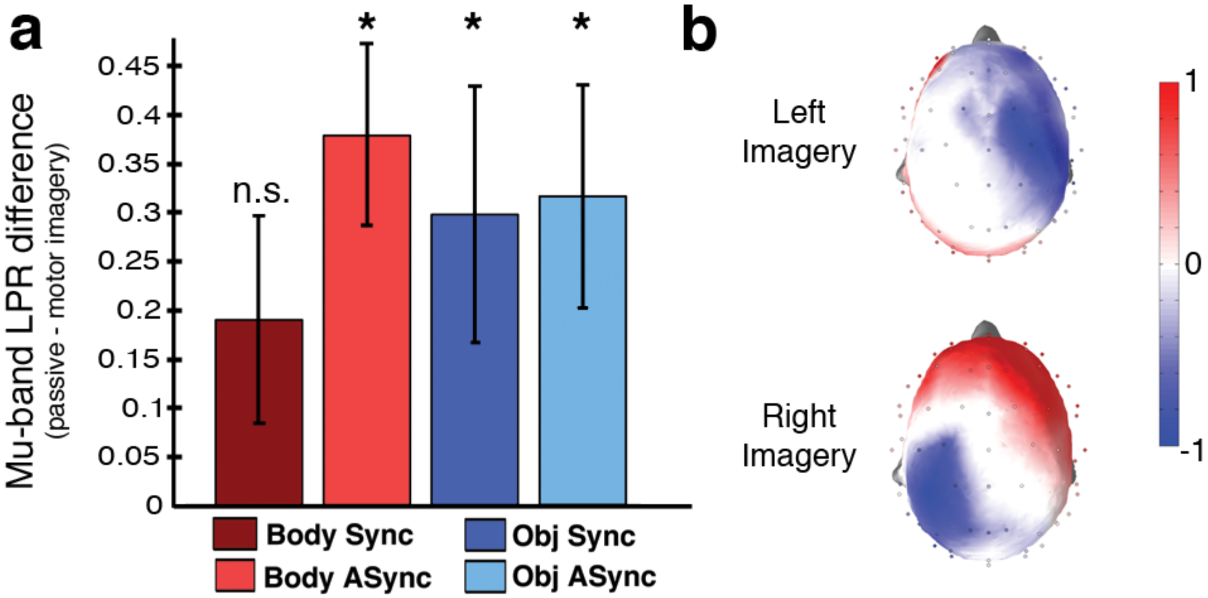

Figure 2. Mu-band changes during motor imagery during visuo-tactile stimulation. ***A)*** Mu-band log power differences between passive visuo-tactile stimulation (data from Evans & Blanke, 2012) and visuo-tactile stimulation during motor imagery for each condition. As mu-band power was found to be suppressed during visuo-tactile stimulation, positive differences represent a move toward an LPR of 0 (i.e. toward the baseline). Statistical contrasts for each condition against the 0 line (*i.e.* no difference) showed no different in the illusion condition (synchronous, body stroking) but that all other visuo-tactile stimulation conditions were associated with significant mu-band differences. ***B)*** Normalized spatial filter weights obtained from common spatial patterns analysis (see *Methods*) were projected onto the scalp for left and right motor imagery during the illusion condition. Note that the absolute magnitude of the weight is a statistically-derived indication of the importance of that electrode to the decoder, and that electrodes contralateral to the imagery side were of greatest importance.

3.3

Computational embodiment of a virtual limb

Computational embodiment of a virtual limb

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Abstract

When looking at our hand, we simultaneously feel it based on tactile and proprioceptive cues. However, seeing a fake hand being touched while our real hand is touched (but hidden from view), we experience the fake hand as belonging to us (ownership) and recalibrate our perceived hand position. Using computational modeling and data collected from a fully automated experimental setup, we extracted, on a subject-by-subject basis, the maximal distance between the real and fake hands (threshold) and the stimulation conditions that subjects tolerate before the recalibration of perceived hand position breaks down. The model predicts, and experiments confirm, that ownership breaks down discontinuously near this threshold, such that subjects sometimes perceive their hand close to the fake hand, and sometimes close to the real hand. By computing the limits of ownership and limb position perception, our model paves the way for computational approaches to embodiment of neuroprosthetic limbs.

Introduction

One goal of neuroprosthetics[1–4] is to design artificial limbs that feel and move, ideally like real limbs. Most research has focused on movement control of artificial limbs[1,2,5], although for a limb to be functionally useful, one must also be able to perceive somatosensory signals from the artificial limb such as touch and proprioception[3,4,6,7]. Recently, artificial limbs have been interfaced to the peripheral nervous system[7,8] or the somatosensory cortex[9] in order to provide somatosensory feedback[10–12]. Yet, despite these achievements, many amputees continue to reject current artificial limbs because users must rely on visual instead of tactile and proprioceptive signals to interact with objects[13].

An interesting avenue for improvement of artificial limbs arises from cognitive neuroscience research in amputees[14] and patients with related neurological conditions[15], as well as in healthy subjects[16–18]. A widely used paradigm to study bodily experience and perception of one's upper limb is the rubber hand illusion[16] (RHI) where participants watch a fake hand being stroked in synchrony with stroking on their own (occluded) hand. This manipulation alters tactile perception and induces the illusion that touch is felt on the fake hand and that the fake hand feels like one's own hand[16–18]. These subjective effects are often accompanied by a shift in the perceived position of one's own hand towards the fake hand (drift) as well as physiological changes[19,20], which are absent or weaker when the stroking provided to the real hand and the fake hand is not synchronous[16–19,21]. The illusion is reduced or abolished when the fake hand does not match the real hand's posture[18], when the rubber hand is placed too far from the real hand[22], or when the stroking is applied in different directions[23]. The potential importance of inducing body ownership for prosthetic limbs was recently demonstrated by showing that upper limb amputees experience an artificial hand as part of their own body when synchronous touches were applied to the artificial hand and their (occluded) stump[24]. These findings were extended using a robotic tactile interface allowing for greater stimulation control and reproducible conditions[25].

Although it has been speculated[26–28] that illusory hand ownership and perceived hand position occur as the brain's perceptual systems attempt to interpret the conflicting visual, tactile, and proprioceptive information, there is currently no computational account of the RHI and the role of visual, tactile, and proprioceptive stimulation parameters (*e.g.* duration, synchrony, and limb position) on illusory hand ownership and perceived hand position. Since systematic changes in illusory hand ownership can also be induced in virtual environments[29], we used automatized, machine-controlled stroking in a novel virtual-hand setup to investigate whether computational modeling can account for measured drifts of perceived hand position. We show that a Bayesian model of causal inference can predict the conditions under which humans fuse proprioceptive with visual information during the RHI. Fusion does not occur if the distance between the real hand and the virtual hand is too large or if both hands are stimulated asynchronously for a long time. Our model and data suggest that, for intermediate distances between the virtual and real hand, perceived hand position switches discontinuously between the fused and a non-fused, proprioception-dominated position. We argue that fusion of sensory cues from the virtual hand with those from the participant's real hand is reminiscent of another case of multisensory integration, the ventriloquist effect, where visual and auditory signals from extrapersonal space are perceived as coming from one location only if the fusion of sensory information is plausible[30–32] .

Results

In order to gain systematic control over the stimulation parameters in RHI experiments, we developed an automated stimulation method in a Virtual Reality environment, where the fake hand was presented visually on a head-mounted display (Fig. 1). Participants saw a three-dimensional virtual hand on the screen while the skin of their real hand (resting on a table in front of them) was stimulated by a set of four small electric vibrators (Fig. 1A). Tactile stimulation of the participant's hand with vibration motors (Fig. 1E) was provided simultaneously with animation of lights on the virtual hand and induced illusory hand ownership (Fig. S1B). Illusory hand ownership was comparable to that described in earlier studies using experimenter-applied stroking on a physical rubber hand[16,18,19] or on a virtual hand[29]. In particular, participants reported illusory ownership for the virtual hand (that was located at a distance of 17cm from the hidden real hand) during synchronous stroking in a congruent hand position ($p<0.01$, *Post-hoc Wilcoxon matched-pairs test*; Fig. S1), but not during asynchronous stroking or if the fake hand was in an incongruent position (all $p>0.05$).

Going beyond traditional RHI studies, our automated setup enabled us to systematically vary, on a trial-by-trial basis, the distance between the virtual and real hand (visuo-proprioceptive separation) and the delay between tactile stimulation and visual stimulation via animations on the virtual hand (visuo-tactile delay, Fig. 1E). If participants were not at all influenced by the position of the seen virtual hand, the perceived hand position, as reported by the subjects, would be independent of the position of the virtual hand. Instead, the reported position exhibited a systematic drift towards the virtual hand that increased with the magnitude of visuo-proprioceptive separation. We found a mean drift of 5±3cm for separations from 0 to 10cm, and a mean drift of 10±5cm for separations of 10 to 20cm. Additionally, we found a significant correlation between drifts and visuo-proprioceptive separation in the interval 0-20cm ($F_{1,1446}$=30.16, p=4e-8), suggesting that the participants' perceived hand position was influenced by visual information from the virtual hand (Fig. 2A).

How does visuo-tactile delay modulate perceived hand position? If the visuo-proprioceptive separation was less than 10cm, the tested delays of 0-1s (between tactile stimulation and the visual animation on the virtual hand) had no significant influence on the perceived hand position. For separations between 20 and 30cm, however, the perceived hand position drifted towards the virtual hand for near-synchronous stimulation (visuo-tactile delay < 0.2s) by a significantly larger amount than for asynchronous (delays from 0.6s to 1s) stroking (p=0.003, two-tailed T-test; Fig. 2A). The largest drift was found for near-synchronous stroking when the virtual and real hands were approximately 15 to 25cm apart. Importantly, the drift of perceived hand position towards the virtual hand under conditions of near-synchronous stroking was induced reliably (variance of perceived drift ≈ 7cm) for visuo-proprioceptive separations smaller than 20cm. By contrast, we found a broad distribution of perceived hand positions when the visuo-proprioceptive separation was between 20 and 30cm, indicating that drift induction was much less reliable for larger separations (Figs. 2A and 2B).

In order to understand the distribution of perceived hand positions, we developed a model of how subjects integrate sensory information from vision (arising from the virtual hand on the head-mounted display) and proprioception (hand position as estimated from proprioceptive signals stemming from the subject's real hand). Additionally, we incorporated into our model how this integration is influenced by ownership as manipulated through additional visuo-tactile stimulation (stroking of the virtual and real hands with different visuo-tactile delays). If the real hand is at position Q, the position of the hand as estimated by proprioceptive cues is formulated as $X_p = Q + \eta_p$, where the noise η_p is assumed to be Gaussian distributed with a standard deviation σ_p that reflects the lack of precision of the proprioceptive information (Fig. 3A). We estimated the precision of proprioceptive information ($\sigma_p \approx 7.2$ cm) from the present data set using large visuo-proprioceptive separations (>30 cm) because participants are known to disregard visual signals and rely solely on proprioceptive signals if the fake hand is placed far away from the real hand[22]. In analogy to the imprecision of proprioceptive cues, we modeled noise in the visual information channel with a standard deviation σ_v. Models of sensory fusion suggest that the brain combines the two sources of noisy information probabilistically[33–35]. Using the data for small visuo-proprioceptive separations (<10cm) where subjects are known to fuse sensory cues[33], we deduced the precision of visual information stemming from the virtual hand in our head-mounted display ($\sigma_v \approx 3.8$cm; see *Methods*).

Yet, in contrast to classical sensor fusion paradigms[33–38], the RHI paradigm has the additional feature that the source of visual information may or may not overlap with the subject's own hand. Therefore, we formulated our model in such a way that visual information influences perceived hand position only if the participant experiences the virtual hand to be their own hand (Fig. 3A), in which case they ought to also expect a nonexistent, or at most a very short, delay between the tactile and the visual strokes. The task of the subject is to infer the position of their real hand (Fig. 3B) from the three sources of sensory information (*i.e.*, proprioception, vision, visuo-tactile delay). To do so, visual and proprioceptive sources are only combined if the subject has reason to believe that both vision and proprioception relate to the same object in the world, *i.e.* that it is their own hand. More precisely, we hypothesized that the participants assign a probabilistic ownership variable to the seen virtual hand that can take one of two states (Fig. 3B): 'own=1' indicates that the virtual hand is 'mine' (*i.e.* the same hand as the participant's real hand) and 'own=0' indicates that the virtual hand is 'not mine' (*i.e.*, not the participant's real hand).

Based on the aforementioned estimates of the precision in the visual and proprioceptive channels (obtained exclusively from empirical data at very short and very large separations), our model assigns a probability of perceived ownership over the full range of visuo-proprioceptive separations from 0 to 40cm, for both near-synchronous and asynchronous visuo-tactile stimulations (Fig. 3C; *cf. Methods* for fitting procedure and Bayesian prior). We found that for near-synchronous stroking at distances below 20cm the model reliably generates the percept of owning the virtual hand, whereas distances above 30cm do not normally give rise to ownership (Fig. 3C). The transition threshold (defined as 50 percent probability of ownership) was found at approximately 25cm.

Moreover, the model accurately predicts the distribution of drifts in perceived hand position across the large range of visuo-proprioceptive distances that we measured in our participants (Figs. 2B and S2). In particular, it predicts that for near-synchronous stimulation and visuo-proprioceptive separations of 20 to 30cm, the distribution of perceived drifts has two peaks: a sharp peak for large drifts caused by the data points where our model assigns hand ownership (and therefore fuses visual and proprioceptive information) and a much broader peak around zero-drift generated by the data points where our model does not assign ownership for the virtual hand (Fig. 2B). Evidence for the double-peaked distribution was found by fitting a Gaussian Mixture Model to the data (see *Methods*) in the interval 20-30cm with one (log-likelihood=-1571, BIC=-780) and two components (log-likelihood=-1560, BIC=-769). Using these BIC indices, we computed the Bayes Factor between single- and double-peaked distributions and found that a Gaussian Mixture Model with two components is 245 times more probable to fit the observed data than a model with one component.

The double-peaked structure in the histogram could be caused by inter-individual differences concerning the thresholds of ownership such that at a separation of 25cm, some subjects assign ownership whereas others do not. Alternatively, it could arise intra-individually in subjects who, for the same stimulus, sometimes assign ownership and sometimes do not. Consistent with both explanations, our model shows that the ownership threshold varies between and within single subjects (Fig. 3D), and that the response is double-peaked for visuo-proprioceptive separations that are close to the threshold of 50% ownership probability (Fig. 4A).

Previous work on the RHI employing manually applied stroking has used a large variety of different stroking durations (Table S2), but has rarely investigated whether longer trials with more strokes would be more efficient to induce illusory hand ownership and stronger drifts of perceived hand position than shorter trials. We investigated this issue for perceived hand position and found no significant effect between short trials (fewer than 40 strokes) and long trials (more than 45 strokes) during near-synchronous stroking. For asynchronous stroking, however, long trials at large visuo-proprioceptive separations (20-30cm) induced significantly less drift than short trials (p=0.003, *two-tailed T-test*; Fig. 4B). Thus, in long trials subjects are more likely to detect the inconsistency between the visual and tactile information caused by the visuo-tactile delay than in short trials. Our model also accounts for these experimental results and suggests an interpretation in terms of refused ownership of the virtual hand for long asynchronous trials, but not for short trials.

Discussion

A fully-automated RHI setup has allowed us, for the first time, to perform a systematic analysis of how the relation and weighting of two major sensory modalities (vision and proprioception) as well as the impact of ownership (as manipulated through additional visuo-tactile cues) contribute to perceived hand position. Earlier work has studied ownership and perceived hand position with virtual hands presented on a distanced rear projection screen[29], on a monitor[39], or on a video-projector[40]. Here, we built upon these earlier approaches and projected an immersive virtual reality scenario onto a head-mounted display showing virtual hands seen as extending from our participants' bodies in stereoscopic vision. More traditional RHI studies[16,18] revealed that perceived hand position is sensitive to various parameters such as visuo-tactile delay[18,41], visuo-proprioceptive separation[22], and virtual hand posture[23]. Yet, in the large majority of these studies, the experimenter applied the visuo-tactile stroking manually at fixed visuo-tactile delays and fixed visuo-proprioceptive separations while only testing single or few trials per condition. The present RHI setup was automated and programmable, thus permitting the chosen stimulation-related parameters to be continuous, explicit, experimenter-independent, and reproducible within and across individuals. Certain effects sensitive to precise timing, such as the frequently employed experimental factor of visuo-tactile delay, can only be systematically tested using systems like the present automated paradigm. Automation additionally allowed us to perform a large number of trials in a comprehensive and controlled fashion, which improved comparability across conditions and individuals and was a necessary prerequisite for the comparison with the computational model.

In contrast to previous studies using binary, factorial designs[16,18,19], our design tested the effects of separation[22], delay and duration in a continuous fashion across a large continuous range (Table S2). Importantly, the present data show that the often used visuo-proprioceptive separation of approximately 15-25cm[16,18,19] is optimal to induce changes in perceived hand position that depend on visuo-tactile delay. At small (<10cm) separations, we found that drifts were independent of delay[41], while large separations (>30cm) induced small drifts with a large variability that reflects the unreliability of proprioceptive signals. Extending data from a recent behavioral RHI study[41], we found that prolonged stimulation did not boost, but significantly decreased the drift in perceived hand position during asynchronous stimulation with large visuo-proprioceptive separations (20-30cm), whereas no effects of duration were observed during near-synchronous stimulations. Our model explains these data in terms of refused ownership of the virtual hand in long versus short asynchronous stimulations.

Although the perceived hand position drifted towards the virtual hand for all separations between 0-40cm on average, a large drift was induced most reliably under conditions of near-synchronous stroking for separations of 10-20cm. For separations of 20-30cm, the drift was also large, but unreliable (Fig. 2B) and subject-dependent (Fig. 3D). Our hierarchical Bayesian inference model accounts not only for the average drift in perceived hand position as a function of separation and delay, but also for the observed variance, or unreliability of the drifts within and across subjects[16]. In particular, our model suggests that the distribution of drifts in perceived hand position should be double-peaked (or at least have a large variance caused by a shoulder in the distribution) for visuo-proprioceptive separations that correspond to an ownership probability of about 50%. Our experimental data confirmed this prediction, showing this critical visuo-proprioceptive separation to be approximately 20-25cm when averaged across subjects (Fig. 2B). Importantly, this threshold can be extracted for each individual subject (Fig. 3D), representing significant progress beyond earlier experimental settings that relied on averaging across large subject samples[18,41]. The threshold value is important for three reasons. First, perceived hand position is strongly and reliably influenced by visuo-tactile delay for separations close to the threshold. Second, for separations around the individual threshold for a given subject, our model shows that the subject assigns hand ownership and therefore fuses visual and proprioceptive information for some trials (peak at large drift values), but generates zero drift and refuses ownership for the other trials (shoulder at smaller drift values in the distribution, Fig. 2B, 4A). Third, for separations significantly below this threshold, our model systematically assigns hand ownership and therefore predicts reliable fusion of visual and proprioceptive information whereas for separations significantly above the threshold, it predicts that subjects refuse ownership and therefore rely only on proprioceptive signals. Previous computational models of visuo-proprioceptive integration tasks[33,34] did not incorporate the possibility of assigning body ownership and therefore fail to explain the variability of the drift and changes in the mean drift across the full range of visuo-proprioceptive separations.

The present model is reminiscent of a causal inference model that has been developed to account for illusory perceptions during a visuo-auditory illusion called the ventriloquist effect[30,32] . Both the RHI and the ventriloquist effect concern the misperception of the location of an object. In the former, the object is the position of the subjects' touched, own hand in relation to the fake hand that is seen as being touched (visuo-proprioceptive conflict). In the latter, it is the position of the ventriloquist's mouth with respect to the seen "speaking" puppet (visuo-auditory conflict). In both illusions, the observer has to decide whether the different signals (visual and proprioceptive for the

RHI; auditory and visual for the ventriloquist effect) arise from one single cause (fake hand; "speaking" puppet) or from two separate causes (real or fake hand; ventriloquist or puppet). The parallels between the present RHI model and previous causal inference models[30,32], and the analogy to earlier models of cue integration and fusion[33–38], suggest that probabilistic inference processes are powerful tools to understand multisensory perception and subjective experience. However, our RHI model also includes distinct features of bodily processing related to the self as the misperceived object is part of the observer's body and the occluded real hand gives rise to additional tactile signals that are not available in the ventriloquist effect.

One of the advantages of a computational model for own body illusions is that it can be used to design, for individual patients, the optimal stimulation patterns for inducing hand ownership for artificial limbs (*e.g.* Fig. 3D). The application of synchronous touches to an artificial hand and the (occluded) stump of an upper limb amputee[24,25] has already been shown to induce illusory ownership for the artificial hand. Based on these previous and the present findings, we argue that illusory hand ownership and hand position perception using automated visuo-tactile stimulation on the prosthetic hand and the stump or chest regions (containing skin regions with referred hand sensations[7,14]) may contribute to the design of artificial limbs that feel like real limbs. Moreover, for most current artificial limbs, amputees rely on visual instead of tactile and proprioceptive signals to interact with objects[13], although somatosensory feedback has also successfully been integrated into prostheses[10–12]. Our data suggest that such forms of visual and somatosensory feedback can be empowered by additional automated visuo-tactile feedback that generates ownership for the prosthesis when interfaced with the skin[25], the peripheral[42], or the central nervous system[4,5]. Combining visual and somatosensory feedback with ownership automation is likely to boost tactile perception in amputees[43], may induce the sensation that foreign, touched objects are a part of the amputee's body (and not just a prosthesis), and may decrease the rejection rate of current artificial limbs due to the feeling that they are too heavy and alien.

Methods

Participants

18 healthy, right-handed participants (10 females; aged: 24 ± 5.8 years; *mean*±*SD*) were recruited for the main study. In addition, for a pilot study where we investigated illusory touch and hand ownership using the current setup (see Supplementary Fig. S1), 11 healthy right-handed participants (4 females, aged: 23.5 ± 4.9 years; *mean*±*SD*) were recruited. All participants reported

having normal or corrected-to-normal vision and gave informed consent prior to partaking in the two studies. The studies were undertaken in accordance with the ethical standards as defined in the Declaration of Helsinki and was approved by the local ethics research committee at University of Lausanne.

Visuo-tactile Stimulation

The general experimental setup is shown in Figure 1. Tactile stimulation was provided via a set of four, button-style vibration motors (Precision Microdrives, London, UK) affixed in a line to the top of the participants' right hand. The vibration motors were 12mm in diameter, with a weight of 1.7g, and vibrated at a maximum of 9000rpm. The motors were programmed to vibrate in sequence to simulate a continuous, stroke-like movement lasting 600ms (100ms per motor; 50ms inter-motor vibration pause). This type of sequence was chosen to automatize the stroking patterns that are generally used to manually stroke the participants' hand during the RHI[16,17]. The direction of the stroking sequence was either to the left or to the right (randomized across participants). An inter-stroke interval of 600ms was inserted between strokes to aid in perceiving the sequence of vibrations as a single motion (Fig. 1E, top). Visual stimuli were rendered with XVR (VRMedia, Pisa, Italy) on a Fakespace Wide5 head-mounted display (HMD; Fakespace Labs, Mountain View, CA, USA). The HMD displayed a stereoscopic virtual scene with a tabletop and four spheres on a virtual right hand (Fig. 1B) representing the four vibration motors on the real right hand (Fig. 1A). Visual "vibrations" were represented by animating the virtual motor to jitter and by changing its color from white to red. Synchronization between visual and tactile stimuli was controlled with a custom-made program (precision of ~0.1ms).

General Procedure

Participants saw a 3D virtual hand on the screen of the HMD while the skin of the participants' real hand (resting on a table in front of them) was stimulated by a set of four small electric vibrators (Fig. 1A). We addressed the issue of whether the hand is perceived at the position of the real hand, at the position of the virtual hand, or somewhere in between. Participants were seated in a fixed chair ~10cm in front of a table (Fig. 1A). The HMD was individually fit to each subject to ensure the real and virtual tables were aligned and to create a close perspective correspondence between the real and virtual scenes. Furthermore, the head was restrained with a chin rest to stabilize the virtual scene. The HMD fully blocked the participants' vision of the table, their real hand, and the rest of the room. To eliminate the possibility that participants perceived auditory cues from the vibrators, white noise was provided through a set of headphones. The participants' right hand (palm down) was placed on the table with the tip of the middle finger at one of three pre-defined proprioceptive hand positions. A virtual hand was projected at different positions on the virtual tabletop (see below). Participants were asked to fixate on the virtual hand and to remain still while visuo-tactile stimulation was administered.

Main Experiment

The HMD, the virtual scenario including virtual hand and table, and the visuo-tactile stimulation methods were as described above. We tested subjects' responses for a large range of different stimulation configurations across three main parameters: (1) visuo-tactile delay, (2) duration of stimulation, and (3) visuo-proprioceptive separation. We adopted a continuous experimental design, in which each trial was defined by fixing the three parameters. The visuo-proprioceptive separation ranged from 0 to 40cm, trial duration from 5 to 90 strokes (with 1 stroke = 1.2s), and visuo-tactile delay from 0 to 1s. All parameters were selected randomly on a trial-by-trial basis with uniform probability. This setup allowed us to administer computer-controlled, automatized visuo-tactile stimulation across a large range of stroking durations as well as visuo-tactile delays (from near-synchronous to many different levels of asynchronous stimulation). Throughout the experiment, the proprioceptive hand position was fixed by the experimenter and changed after five trials by displacing the subjects' right hand to one of three randomly selected positions (17, 26, or 35cm to the right of the body midline). These parameter ranges were determined from pilot studies with the aim of focusing the collected data on regions where the subjects were found to be more sensitive on average.

Each trial involved a visuo-tactile stimulation period (see *General Procedure)* followed by a darkened virtual scene without the virtual table and the virtual hand. Next, the virtual scene reappeared with a virtual ruler (with centimeter precision) spanning the virtual table (Fig. 1C). Participants were instructed to verbally provide the label of the tick on the virtual ruler corresponding to the perceived position of the tip of the real right hand's middle finger (adapted from[18]). Labels for the ticks on the virtual ruler were randomly selected on a per-trial basis.

Of the eighteen participants recruited for this experiment, fifteen performed 62 ± 4 ($mean \pm SD$) trials and the remaining three participants performed 163 ± 37 trials. We recorded a larger number of trials for these three participants in order to contrast our proposed model with competing models on a per-subject basis. For the group analysis, a total of 1341 trials were pooled across all eighteen participants.

Model Description

We test whether a Bayesian ideal observer model with access to visual, tactile, and proprioceptive cues provides a reliable explanation of the perceived hand position in the RHI. We hypothesize that the perceived hand position during the RHI is a combination of prior beliefs (top-down influence) and sensory input to three sensory modalities (vision, proprioception, touch). The model relies on three assumptions: (i) incoming visual and proprioceptive information is independent, *i.e.* the firing of primary visual neurons and proprioceptive neurons are statistically independent of one another for a given sensory stimulus; (ii) visuo-tactile synchrony conveys information about the ownership of the hand; and (iii) prior to integrating visual and proprioceptive information, the subject makes a (likely unconscious) top-down decision as to whether the virtual hand is one's own hand or not (hand ownership). Assumptions (ii) and (iii) are based on findings from previous RHI studies demonstrating that visuo-tactile synchrony modulates hand ownership and that top-down information can influence the RHI.

Our model of perceived hand position in the RHI paradigm is composed of two sub-models. First, a *perception model* is described to model how the participants form and maintain their internal percepts of their hand position as well as ownership of the virtual hand. Second, a *response model* is constructed to capture how subjects will report when asked about his or her percept. In analogy to the model proposed in[44], our perception model is an encoder of sensory related information, while our response model is a decoder that exploits the representation formed by the encoder in order to produce meaningful decisions.

PERCEPTION MODEL

Suppose that the subject believes that the virtual hand is his or her own hand and that the real hand is located at position Q. The subject should then expect that both the visual (X_v) and proprioceptive (X_p) position signals fluctuate around this real hand position. We model this using assumption (i) and define the stimulus likelihood:

$$p(X_p, X_v \mid Q) = \mathcal{N}(X_p; Q, \sigma_p)\mathcal{N}(X_v; Q, \sigma_v) \quad (1)$$

where $\mathcal{N}(x; \mu, \sigma)$ is a Gaussian evaluated at x, with mean μ and standard deviation σ. This simple model has been successfully used to explain visuo-auditory, visuo-spatial, and visuo-proprioceptive integration tasks[33–38].

In our experiment, the visuo-tactile synchrony is defined by the delay Z, between the visual and vibrotactile stroking patterns. Perfect synchrony requires a visuo-tactile delay of 0s, but due to noise in the sensory systems, the perceived delay may fluctuate around 0s with a small variance σ_Z. Since the visuo-tactile delay is always positive, we model its likelihood with an exponential distribution $E(Z,\sigma_Z)$ defined by $E(Z,\sigma_Z) = \exp\left(-\frac{Z}{\sigma_Z}\right)/\sigma_Z$. Taking into account this visuo-tactile likelihood term, we extend the visuo-proprioceptive likelihood in Eq. (1) to:

$$p(X_p,X_v,Z \mid Q) = \mathcal{N}(X_p;Q,\sigma_p)\mathcal{N}(X_v;Q,\sigma_v)E(Z,\sigma_Z) \qquad (2)$$

This equation defines the distribution of the perceptual measurements from the three sensory systems (vision, proprioception and visuo-tactile delay) that one *should expect* if he or she believes that their hand to be at position Q and that the seen hand is their own hand. If the subject does not believe the seen hand to be his or her own hand, the visual position signal will no longer fluctuate around the real hand position, but rather around a mean $\bar{Q}$, whose value is unknown to the subject.. Analogously, the visuo-tactile delay also fluctuates around an unknown mean $\bar{Z}$. Because $\bar{Q}$ and $\bar{Z}$ are both unknown, we marginalized both variables over a large window in both the visual and visuo-tactile delay domains using a flat prior, $p(\bar{Q},\bar{Z}) = \vartheta$, where ϑ is a constant. If the size of this window is much larger than the size of the visual modality's standard deviation (σ_v) and the visuo-tactile standard deviation (σ_Z), the marginalized likelihood can be well approximated by: $\iint p\left(X_v,X_p,Z,\bar{Q},\bar{Z} \mid Q\right)d\bar{Q}d\bar{Z} \approx N\left(X_p;Q,\sigma_p\right)\vartheta$.

Given this, the general likelihood function that accounts for both possible ownership beliefs is defined as:

$$p(X_p,X_v,Z \mid Q,own) = \begin{cases} \mathcal{N}(X_p;Q,\sigma_p)\mathcal{N}(X_v;Q,\sigma_v)E(Z,\sigma_Z) & \text{if } own = 1 \\ \mathcal{N}(X_p;Q,\sigma_p)\vartheta & \text{if } own = 0 \end{cases} \qquad (3)$$

where the binary variable '*own*' models the belief that the subject has about the ownership of the virtual hand. The resulting model can be seen as an extension of previously proposed models for causal inference[31,32,45], though in contrast to previous models, our model accounts for three sensory modalities rather than two. Because the brain has no direct access to either the real hand position Q

or the ownership assignment of the virtual hand (*own*=0,1), it must deduce both values from sensory cues.

For an *ideal observer* who receives a multisensory stimulus $\{X_v\ , X_p\ , \mathrm{Z}\}$, the knowledge about the variables $\{\mathrm{Q}, own\}$ is contained in the posterior distribution using Bayes formula:

$$p(Q,own \mid X_p, X_v, Z) = \frac{p(X_p, X_v, Z \mid Q, own)\, p_0(Q, own)}{\sum_{own} \int dQ\, p(X_p, X_v, Z \mid Q, own)\, p_0(Q, own)} \qquad (4)$$

where $p_0(Q, own)$ is the prior knowledge that the subject has about the latent variables.
The quantity $p(Q,own \mid X_p, X_v, Z)$ is also known as the *belief state* as it provides a measure of how much the ideal observer believes that a particular pair (Q, own) corresponds to the true hand position and to the true ownership state. The model summarized in Eq. (4) differs from standard multisensory integration models[33–38] because it incorporates the concept of ownership and takes into account three sensory modalities: vision, touch and proprioception.

In the main experiment, subjects report the perceived hand position. However, we do not know their internal state of ownership assignment. By marginalizing over the ownership variable, we obtain:

$$p(Q \mid X_p, X_v, Z) = \frac{\sum_{own} p(X_p, X_v, Z \mid Q, own)\, p_0(Q, own)}{\sum_{own} \int dQ\, p(X_p, X_v, Z \mid Q, own)\, p_0(Q, own)} \qquad (5)$$

Henceforth we assume the prior $p_0(Q, own)$ to be flat for *Q,* but for consistency and generalization purposes, we consider the prior over the ownership variable to be adaptive and parameterized as $p_0(Q, own = 1\ ) = \mathrm{c}$, where $c\ \in\ [0,1]$.

Substituting $p_0(Q, own)$ into (5) and solving the integral over Q, we obtain the final probability density function in the form of a *Gaussian Mixture Model* with a mixture coefficient α that is also a function of the perceptual stimuli:

$$
\begin{aligned}
p(Q|X_v, X_p, Z) &= \alpha \mathcal{N}(Q; X_p, \sigma_p) + (1-\alpha)\mathcal{N}\left(Q; \lambda X_v + (1-\lambda)X_p, 1/\sqrt{\frac{1}{\sigma_v^2} + \frac{1}{\sigma_p^2}}\right) \\
\alpha &= 1/\left[1 + \mathcal{N}\left(X_v - X_p; 0, \sqrt{\sigma_v^2 + \sigma_p^2}\right) E(Z, \sigma_Z) \frac{c}{\vartheta(1-c)}\right] \qquad (6) \\
\lambda &= \sigma_p^2 / (\sigma_v^2 + \sigma_p^2)
\end{aligned}
$$

The first term on the right-hand side in the first line of Eq. (6) accounts for the situation where the subject does not believe that the virtual hand he or she sees is their own hand and therefore relies only on proprioceptive cues. This case contributes to the final estimate with a weight α. The second term (weight: $(1-\alpha)$) describes a Gaussian with a center that represents a weighted average between visual (weight λ) and proprioceptive information (weight $(1-\lambda)$). Note that the constants ϑ and c need not be considered as different parameters but can rather be merged into a single parameter $\eta = c/[\vartheta(1-c)]$ without a loss of generality. Thus, the set of free parameters of our model is $\{\sigma_v, \sigma_p, \sigma_z, \eta\}$.

Note that the variable α has a particularly important meaning as $(1-\alpha)$ is the *posterior probability of the ownership* of the virtual hand given the prior and the sensory input, namely: $(1-\alpha) = p(own = 1|stimulus)$. If ownership of the virtual hand is certain, *i.e.* $p(own = 1|stimulus)$=1, then the position $\lambda X_v + (1-\lambda)X_p$ (*cf.* Eq. (6)) is equivalent to the *Maximum Likelihood Estimate* (MLE) of the perceived hand position in the case where the subject fuses both vision and proprioception.

RESPONSE MODEL

Our perception model is defined by the distribution *p(Q|X_v,X_p,Z),* that is, the distribution of perceived hand positions *Q* given the multisensory input as described by Eq. (6). Next, we specify how a subject makes their decision when reporting their perceived hand position. Here, we assume that the subject draws a *single sample* from the distribution *p(Q|X_v,X_p,Z) and reports the resulting Q-value.*

In general, a given subject's decision making strategy depends on their individual cost functions[46]. For instance, if the cost function of the subject is based on the mean squared error (MSE), the optimal policy consists of reporting the *posterior mean* of the belief state. However, in disagreement with this hypothesized cost function, our results rather suggest that a mixture of *two*

Gaussians provides a better explanation than a single Gaussian for the observed proprioceptive drifts at visuo-proprioceptive separations in the range 20-30cm (as measured by the *Bayesian Information Criterion*, see *Significance Tests* below). Alternatively, if the cost function is assumed to be a Dirac-delta on the correct answer, the optimal policy is to report the *maximum a posteriori* (MAP). As it has been shown that subjects may use approximations to the MAP estimate based on few samples from the posterior[47], our response model can be interpreted as an extreme approximation to the MAP strategy based on a single sample from the posterior distribution of perceived hand positions.

Parameter Optimization

The four free parameters $\{\sigma_v, \sigma_p, \sigma_z, \eta\}$ in Eq. (6) were fit using the following step-by-step procedure for both the group (*e.g.* Fig. 2B) and individual data sets (*e.g.*, Figs. 3D, 4A):
(i) For visuo-proprioceptive separations larger than 30cm, we first measured the standard deviation of perceived drifts from the data. This defined the parameter σ_p, which remained fixed throughout the rest of the fitting procedure.

(ii) For visuo-proprioceptive separations smaller than 10cm, we measured the standard deviation of perceived drifts from the data. This defined the standard deviation $1/\sqrt{\frac{1}{\sigma_v^2}+\frac{1}{\sigma_p^2}}$ under the assumption of fusion of two independent Gaussian signal channels[33], represented by vision and proprioception in our setup. Since (i) provided the value of the parameter σ_p, we could deduce σ_v, which also remained fixed subsequent steps.

(iii) The delay parameter σ_z was inconsequential for our analysis leading to Figs. 2B, 4A, and 4B. Thus, for these fits, we only considered one free parameter (η) that reflects the Bayesian prior in the full model described in Eq. (6). We determined a distribution $p(\eta \mid Data)$ of plausible parameter values by using a Markov Chain Monte Carlo (MCMC) procedure[48], under the assumption of a flat prior $p_0(\eta \mid Data)$ on a finite interval ($\eta \in [0,4000]$). We computed 10,000 steps of MCMC resulting in 10,000 possible choices of the parameter η where a specific value η_k appears with a probability $p(\eta \mid Data)$. This probability is itself proportional to $p(Data \mid \eta, \sigma_p, \sigma_v)$, where '*Data*' represents the reported drifts *Q* for a given X_p and *Xv* for the real and virtual hands, respectively, and η, σ_p, σ_v defines the set of free parameters of the model described in Eq. (6). We proceeded analogously for our analysis leading to Figs. 3C and 3D except that we treated the two free parameters $\theta = \{\sigma_z, \eta\}$ in parallel (with a flat prior over σ_z in the interval [0s, 1s]).

(iv) The full model from Eq. (6) is plotted in Figs. 2B and 4A, evaluated at the data points for each range (*e.g.*, visuo-proprioceptive separations between 10cm and 20cm), adding the contributions of all 10,000 possible choices of θ:

$$p(Q \mid X_v, X_p) = \int d\theta\, p(Q \mid \theta, X_v, X_p)\, p(\theta \mid data) \approx \frac{1}{S}\sum_{s=1}^{S} p(Q \mid \theta_s, X_v, X_p) \qquad (7)$$

Analogously, for Fig. 3C and the insets of Fig. 3D, we plot the inferred ownership $(1-\alpha) = p(own = 1|stimulus)$ as a function of the visuo-proprioceptive separation, summing over all 10,000 parameter choices $\theta = \{\sigma_z, \eta\}$ that result from the MCMC method. For the threshold values in Fig. 3D, we first determine the ownership curve $(1-\alpha) = p(own = 1|stimulus)$ separately for each of the 10,000 parameter choices and then find the value of visuo-proprioceptive separation (threshold) for which the ownership curve passes through the value of 0.5. In Fig. 3D, the mean and standard deviation of the resulting threshold values are shown.

Significance Tests

In each visuo-proprioceptive range in Figs. 2A and 4B, there are a finite number of data samples, *N*. We therefore computed whether a sample of *N* data points drawn from the model looked similar to, or statistically differed from, the observed *N* experimental data points. To this aim, we drew 4000 samples from the model's predictive distribution as defined in Eq. (7) for each visuo-proprioceptive separation range (*e.g.* 10-20cm, 20-30cm, *etc.*). These predictive samples were then compared to the experimentally observed distribution of drifts in the same range. Finally, we computed the respective histograms (bin size=3cm) and performed a two-sample χ^2-test.

In order to test whether a Gaussian Mixture Model with one or two components better explained the drifts in the visuo-proprioceptive separation interval of 20-30cm, we fit both models and compared them using the *Bayesian Information Criterion*[49] (BIC). The BIC is defined in terms of the model's log-likelihood $p(Data \mid \theta)$, the number of free parameters in the model d, and the amount of data seen by the model N as: $BIC = -2\ln p(Data \mid \theta) + d \ln N$. Thus, models with smaller BIC values indicate better, more parsimonious descriptions of the data. The *Bayes Factor*

$BF = p(M_1 \mid Data) / p(M_2 \mid Data)$ between two models M_1 and M_2 can be approximated with their respective BIC values as: $BF \approx \exp[-(1/2)BIC_1 + (1/2)BIC_2]$. Given the computed BIC values from the single and double-peaked Gaussian Mixture Models (see *Results*), we found a BF of approximately 245, indicating that a mixture model with two components is 245 times more probable to fit the observed data than a model with one component.

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Figure Captions

Figure 1

Automated setup to induce hand ownership for a virtual hand.

(**A**) Experimental setup: the participant's right hand is stimulated by small vibrotactile motors while looking at a virtual scene on a head-mounted display that occludes vision of their hand. (**B**) Subjects see a virtual hand with virtual representations of the vibrotactile motors on their real hand. (**C**) Following visuo-tactile stimulation, a virtual ruler was presented for participants to report perceived hand position. (**D**) Illustrative case where visual, proprioceptive, and perceived hand positions differ from one another. (**E**) Representative temporal sequence of visuo-tactile stimulation on the hand for a given trial. Vibrotactile motors "stroked" the hand with a sequence of four vibrations either in synchrony with a visual counterpart (synchronous) or with an injected delay *Z* (asynchronous). Individual motor colors added for graphical representation only. Note that all virtual scenes are shown in a monocular view though participants saw stereoscopic scenes.

Figure 2

Empirical data on perceived hand position depend on visuo-proprioceptive separation and visuo-tactile delay.

(A) Each point represents an individual trial with a given visuo-proprioceptive separation (y-axis) and the drift as reported by the participants (x-axis; where drifts are +/- absolute value of the 'reported hand position' - 'real hand position'). Positive drifts indicate a shift of perceived hand position towards the virtual hand. To avoid overlap of trials with identical parameter settings, a small Gaussian jitter ($\mu = 0cm$ and $\sigma = 0.2cm$) was added for visualization purposes. Small visuo-tactile delays ($Z < 0.2$s) are shown in red, large visuo-tactile delays ($Z > 0.6$s) are in blue. Colored vertical bars indicate mean drift averaged over all trials within a visuo-proprioceptive separation range of 0-10cm, 10-20cm, 20-30cm, and 30-40cm (from bottom to top). The mean of synchronous trials (red bar) and asynchronous trials (blue bar) are provided in these ranges (shaded regions: SEM). Vertical solid line at zero-drift indicates perceived hand position responses that are independent of visual cues (and thus rely exclusively on proprioceptive cues). The dashed diagonal line outlines the contrary situation, where responses are influenced exclusively by visual cues. **(B)** Histograms of the experimental distribution of perceived drifts for each of the four ranges in *(A)*. The solid black curve indicates the distribution prediction from the model. Note the broad distribution for visuo-proprioceptive separations >20cm that is well captured by the model. The vertical solid line and dashed diagonal lines represent the visual- and proprioceptive-dominated responses, as in *(A)*. Between 0–30cm of visuo-proprioceptive separation, the model does not significantly differ from the empirical data (χ^2-test: 0-10cm, df=112, p=0.18; 10-20cm, df=180, p=0.03; 20-30cm, df=312, p=0.16; 20-30cm, df=234, p=0.1).

Figure 3

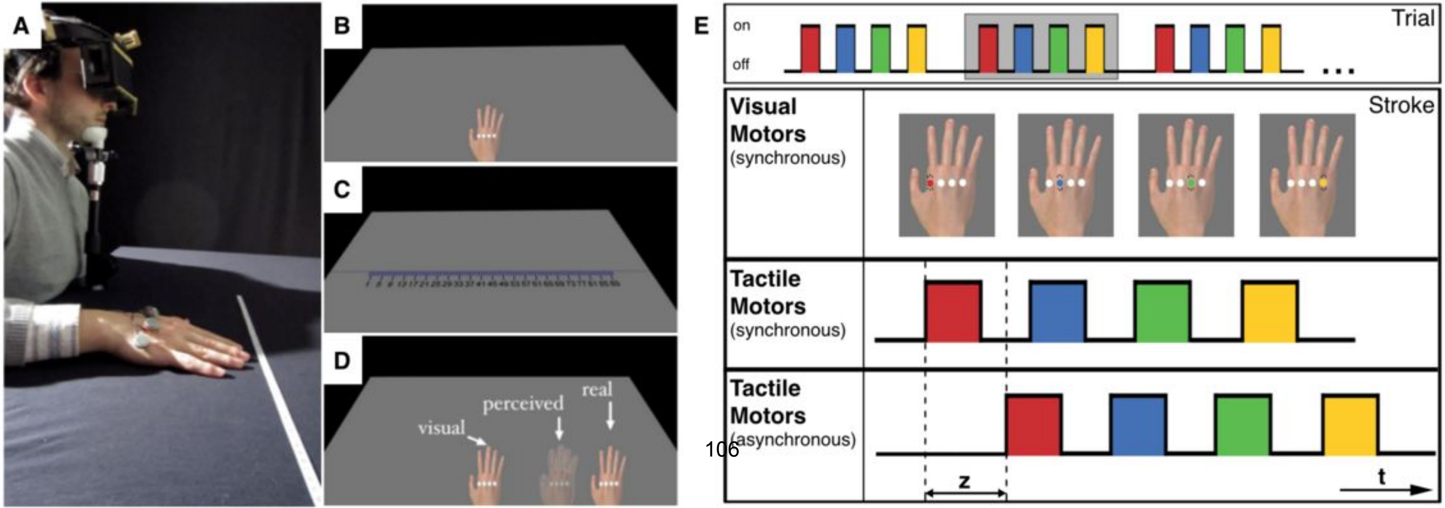
Three-sense Bayesian model of the rubber hand illusion.

(**A**) Causal diagram representing the sensory variables (proprioceptive position, visual position, visuo-tactile delay) and their dependencies upon the causes in the external environment. The rubber hand illusion setting contains a real hand at position *Q* (top left) that is either one's own hand (*own*=1, top right) or not (*own*=0). (**B**) Perceived hand position (top left) and probability of ownership (top right) are inferred from the sensory variables X_p, X_v, and *Z*. (**C**) Model-predicted probability of ownership for the virtual hand as a function of the visuo-proprioceptive separation for synchronous ($Z = 0.1$s, red) and asynchronous ($Z = 0.7$s, blue) visuo-tactile stimulation. Ownership thresholds (dashed arrows) are defined as the visuo-proprioceptive separation that yields a probability of ownership of 0.5 (dashed horizontal line). (**D**) Ownership thresholds (mean and standard deviation) for synchronous ($Z = 0.1$s, red) and asynchronous ($Z = 0.7$s, blue) visuo-tactile stimulation for individual subjects, as extracted by the model. *NA* indicates that the ownership threshold was ill defined for that subject. Insets: Model-predicted probability of ownership (as in *(C)*), for three individual participants.

Figure 4

Detailed data analysis: Single subject and trial duration.

(A) Histograms of the empirical distribution of drifts and the model prediction (as in Fig. 2B) for an individual participant (subject 18). For visuo-proprioceptive separations between 0 and 30cm, the model was not found to significantly differ from the empirical data (Z-scores: 0-10cm, z=0.074; 10-20cm, z=0.11; 20-30cm, z=1.59; 30-40cm, z=2.12). **(B)** Long trials (>45 strokes, dark blue) and short trials (<40 strokes, light blue) during asynchronous stroking. Each point represents an individual trial (*cf.* Fig. 2A). Vertical bars indicate average mean drift (shaded regions: standard deviation) over all trials within a visuo-proprioceptive separation range (from bottom to top: 0-10cm, 10-20cm, 20-30cm, and 30-40cm). For separations between 20 and 30cm, long trials of asynchronous stroking induced significantly less drift than for short trials (p=0.003, *two-tailed T-test*).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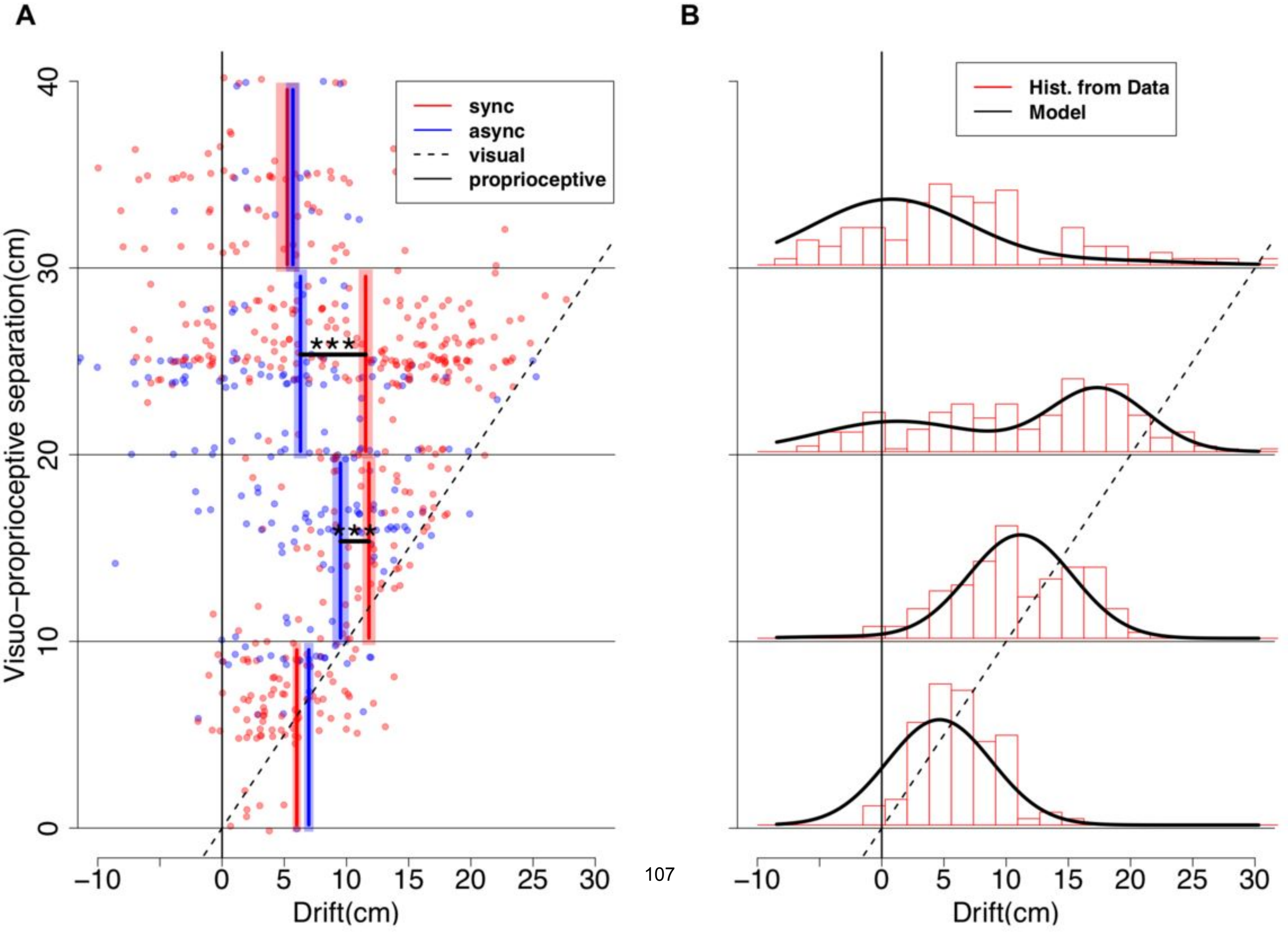
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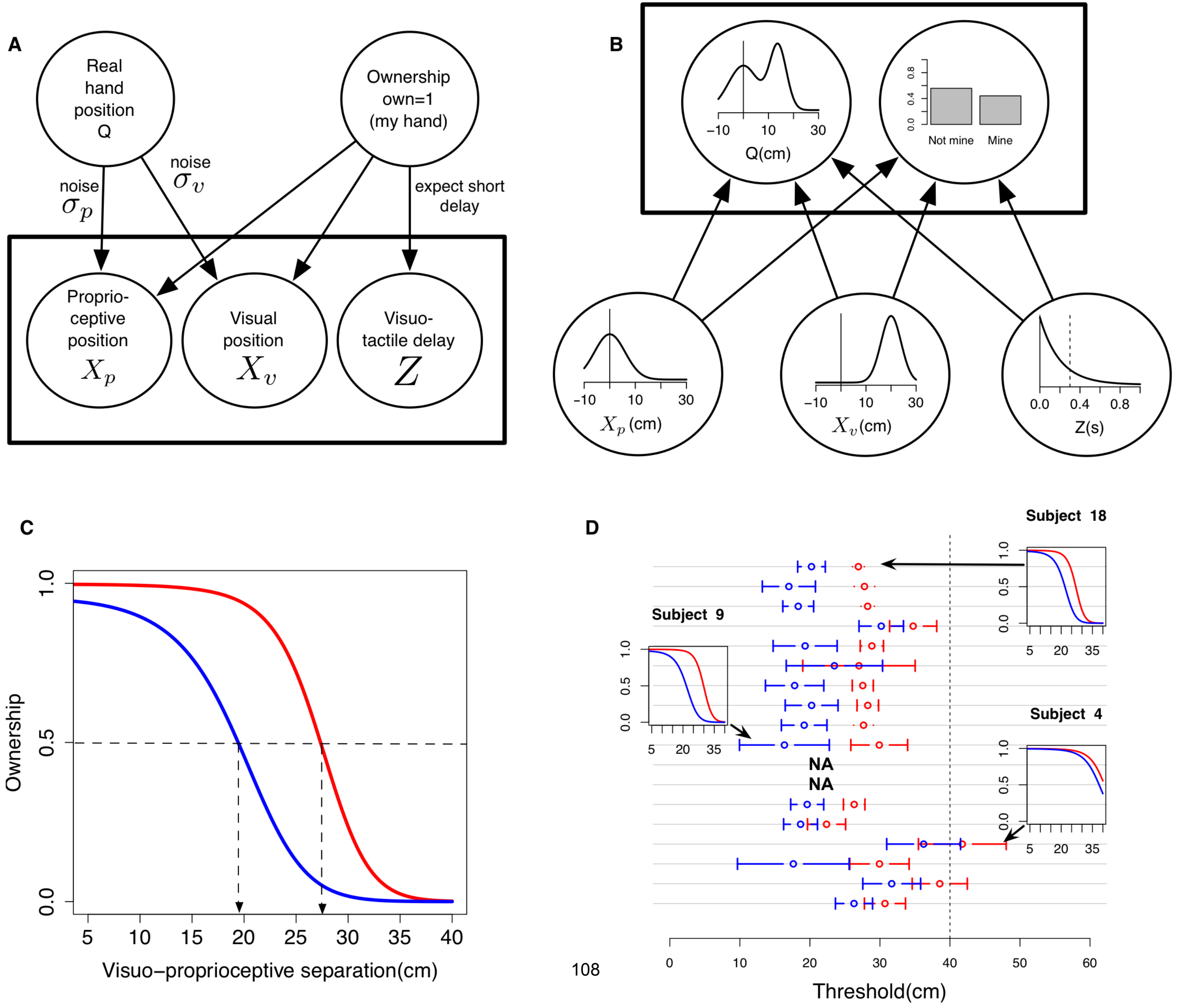
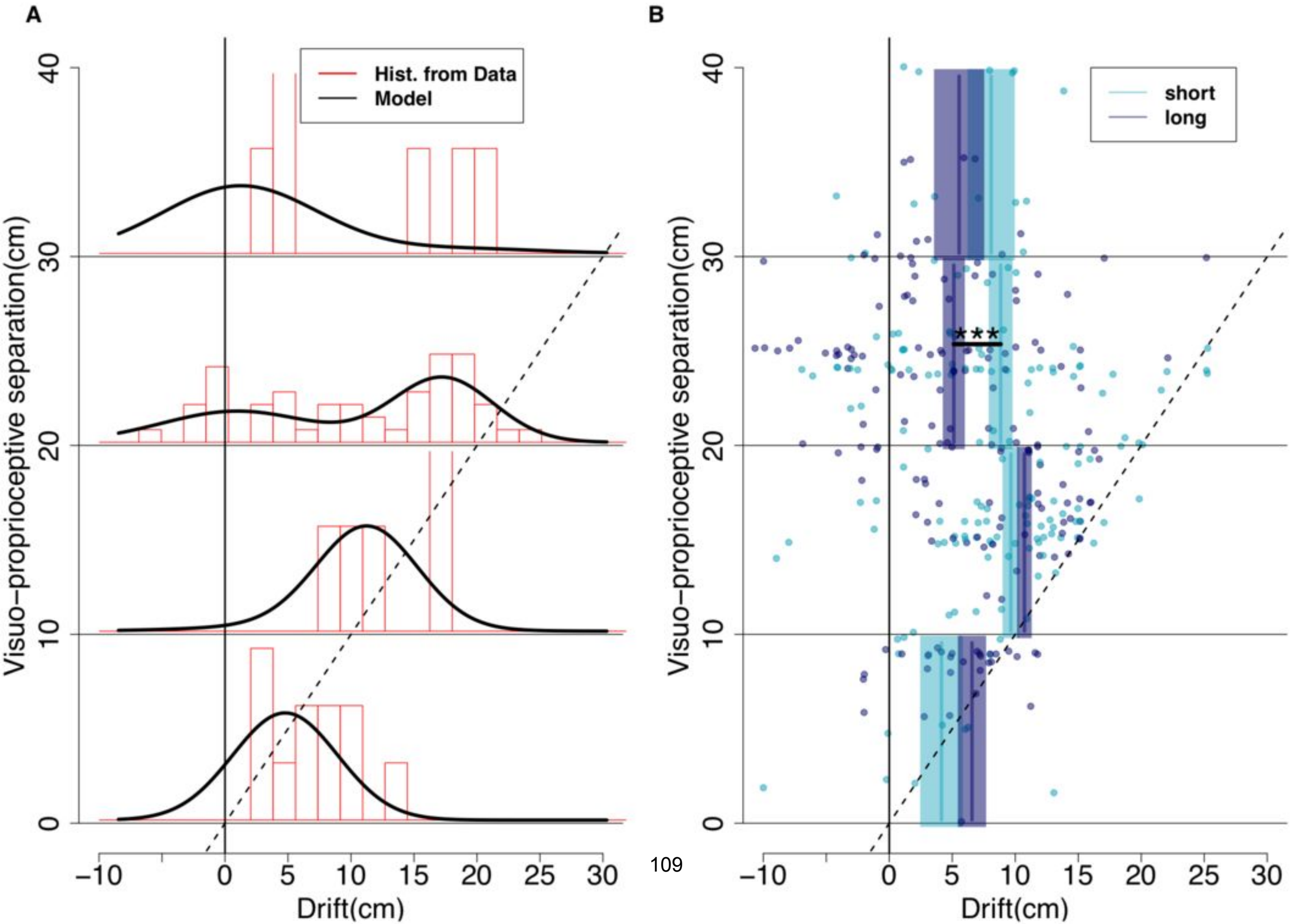
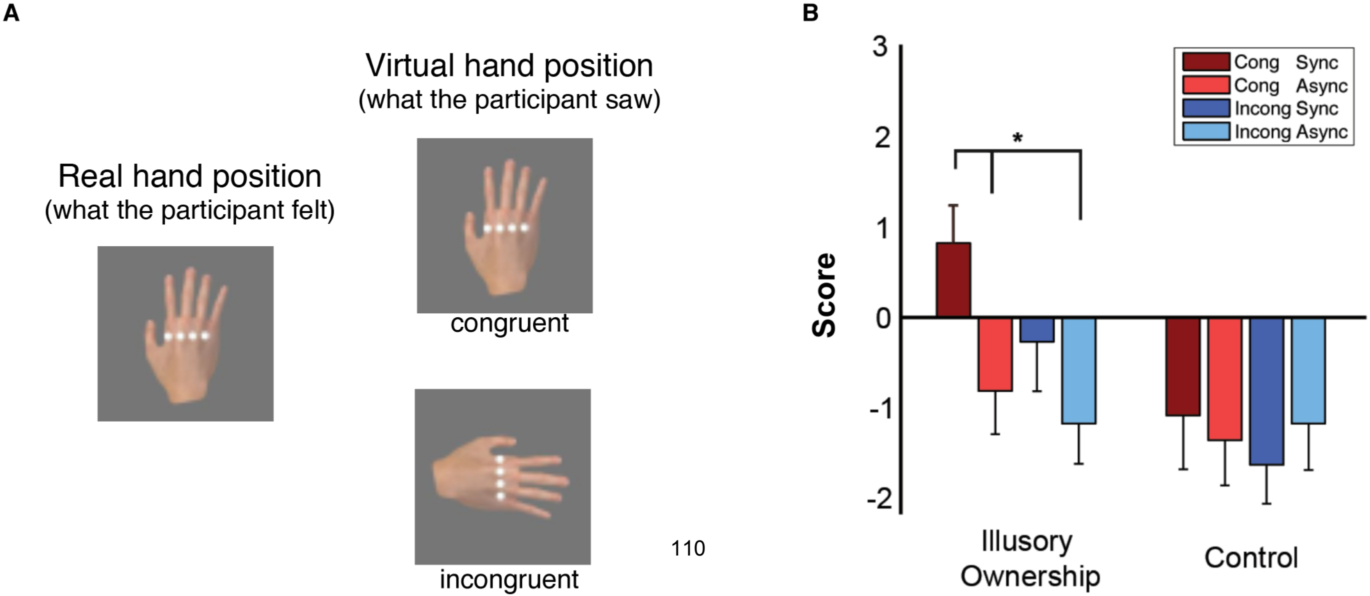
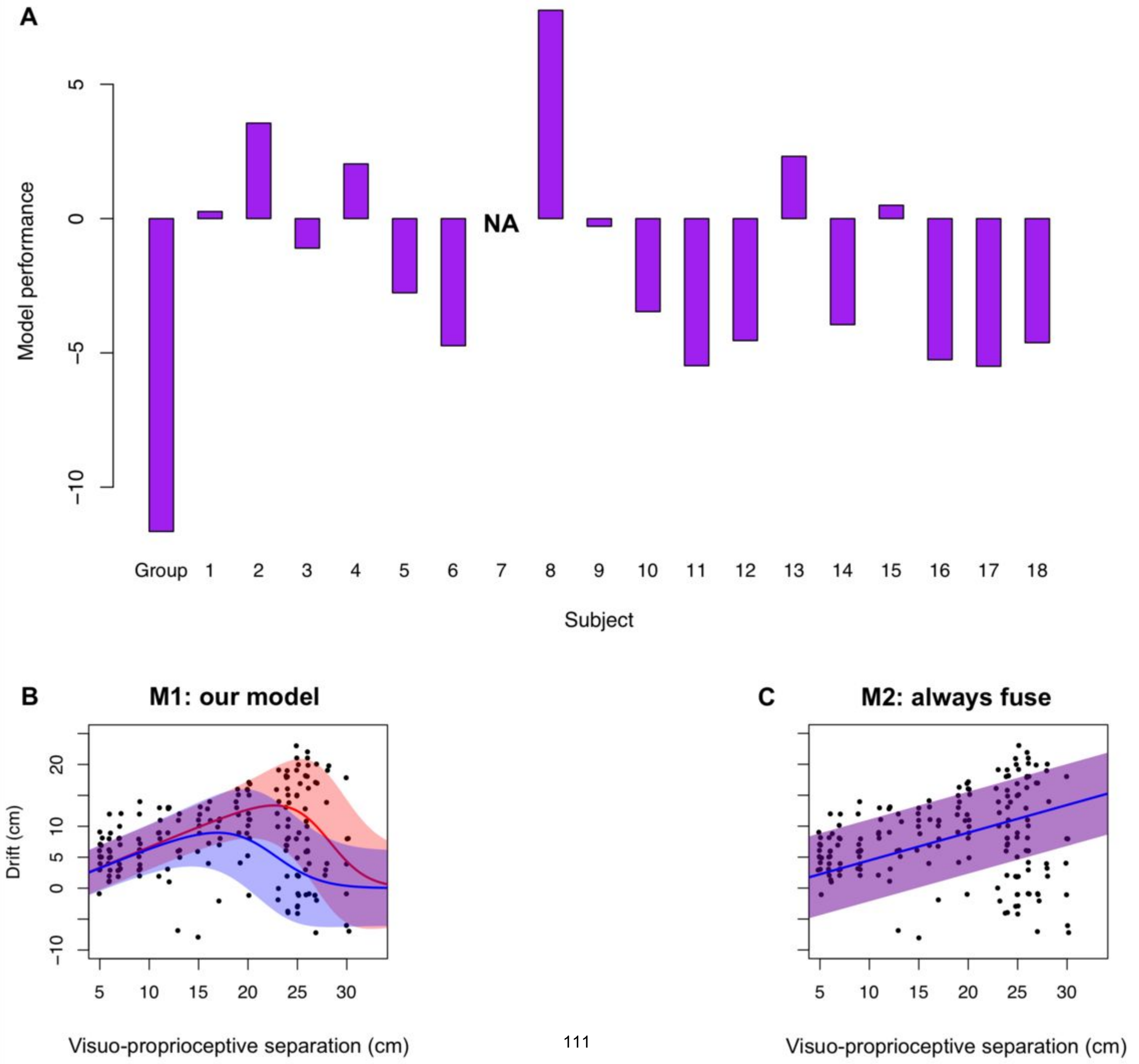
10
15
20
25
30
Drift(cm)
−10
0
5
10
15
20
25
30
Drift(cm)


A
Real hand position Q
Ownership own=1 (my hand)
noise σ_p
noise σ_v
expect short delay
Proprio-ceptive position X_p
Visual position X_v
Visuo-tactile delay Z
B
Q(cm)
Not mine
Mine
X_p (cm)
X_v (cm)
Z(s)
C
Ownership
Visuo–proprioceptive separation(cm)
D
Subject 18
Subject 9
Subject 4
NA
NA
Threshold(cm)


A
B
Hist. from Data
Model
short
long
Visuo−proprioceptive separation(cm)
Drift(cm)
0
10
20
30
40
−10
0
5
10
15
20
25
30
***


A
Virtual hand position
(what the participant saw)
Real hand position
(what the participant felt)
congruent
incongruent
B
3
2
1
0
-1
-2
Score
*
Cong Sync
Cong Async
Incong Sync
Incong Async
Illusory Ownership
Control


A
Model performance
5
0
−5
−10
NA
Group
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
Subject
B
M1: our model
Drift (cm)
20
10
5
0
−10
5
10
15
20
25
30
Visuo-proprioceptive separation (cm)
C
M2: always fuse
5
10
15
20
25
30
Visuo-proprioceptive separation (cm)

Supplementary Figure Captions

Supplementary Figure 1. Experimental design and self report scores for the induction of illusory ownership. In this experiment, we used a 2x2 factorial design with the factors Stroking and Posture. Visuo-tactile stroking was applied for one minute either synchronously (no visuo-tactile delay) or asynchronously (visuo-tactile delay of 400ms). The virtual hand position was fixed 17 cm to the left of the real hand[1,2] and its orientation was either congruent to the real hand posture or incongruent[3] (virtual hand rotated 90° toward the body midline). Immediately following the visuo-tactile stimulation, participants were given a questionnaire composed of ten questions (7-item Likert scale) to gauge the strength of the RHI in each condition (see Supplementary Table 1 for the complete list of questions). The order of the experimental conditions was randomized and balanced across subjects. For this experiment, 11 healthy right-handed participants (4 females, aged: 23.5 ± 4.9 years *mean±SD*) were recruited. **(A)** Experimental design illustration showing hand positions for the real hand and the virtual hand in congruent and incongruent posture conditions. **(B)** Illusory hand ownership scores (item Q3 from Supplementary Table 1) and scores for a control question (item Q5). Scores from the 7-item Likert scale were normalized between -3 and 3. Post-hoc Wilcoxon matched-pair tests revealed a body-selective, synchrony-dependent modulation of illusory hand ownership question (p=0.005). Importantly, this result was absent for the control conditions with incongruent visual hand postures, as well as for the control question (all p > 0.05).

Supplementary Figure 2. Comparison of our proposed model with a linear model that always fuses vision and proprioception[4]. Model comparison is performed using the *Deviation Information* Criterion (DIC)[5], defined as $DIC := -2\left[2\left\langle \ln p(Data \mid \theta)\right\rangle_{p(\theta \mid Data)} - \ln p(Data \mid \left\langle \theta \right\rangle_{p(\theta \mid Data)})\right]$, where $\left\langle f(\bullet)\right\rangle_{p(\bullet)}$ is the expectation of a function $f(x)$ under the density $p(x)$ and θ is the set of free parameters of the model. *Small DIC values indicate stronger models*. DIC values are estimated using *Markov Chain Monte Carlo,* MCMC. The MCMC procedure produces samples from $p(\theta \mid Data)$ that are necessary for the estimation of DIC values (10^4 samples, using 10^3 burning steps and a thinning of 10 steps). **(A)** Relative model performance between our model and the linear model, defined as $performance = (DIC_{proposed} - DIC_{linear}) / \sigma_{diff}$, where σ_{diff} is the estimated standard deviation of the difference between DIC scores. Relative performance measures are shown for data collapsed across participants (group) and for each individual subject. *NA* indicates subject data that led to ill-defined DIC scores. We found our model to outperform the linear model (negative relative performance values) in the large majority of individual subjects and at the group level. **(B)** Empirical drift measurements for an individual participant (black dots; Subject 18) with the model prediction for synchronous (red curve) and asynchronous (blue curve) trials. Shaded regions correspond to the predicted standard deviation of the mean. **(C)** Linear model predictions for synchronous and asynchronous trials on the same participant's data. Note that without the third sensory modality (tactile), no distinction is made between predictions for synchronous and asynchronous trials.

Question	Synchronous Congruent	Asynchronous Congruent	Synchronous Incongruent	Asynchronous Incongruent
Q1: It seemed as if I were feeling the vibrations in the location where I saw the virtual hand being vibrated.	2.09 ± 0.37	-0.82 ± 0.57	2.23 ± 0.29	-0.55 ± 0.57
Q2: It seemed as though the virtual vibrations I felt were caused by the vibrations I saw on the virtual hand.	1.27 ± 0.39	-0.91 ± 0.51	0.55 ± 0.59	-0.73 ± 0.55
Q3: I felt as if the virtual hand were my own hand.	0.82 ± 0.44	-0.82 ± 0.48	-0.27 ± 0.55	-1.18 ± 0.44
Q4: It felt as if my (real) hand was moving/drifting towards the virtual hand's position.	-1.09 ± 0.45	-1.55 ± 0.45	-1.18 ± 0.49	-1.64 ± 0.41
Q5: It seemed as if I might have more than one right hand or arm.	-1.09 ± 0.60	-1.36 ± 0.50	-1.64 ± 0.43	-1.18 ± 0.51
Q6: It seemed as if the vibrations I felt originated from somewhere between my own hand and the virtual hand.	-0.91 ± 0.51	-0.91 ± 0.65	-1.27 ± 0.58	-0.27 ± 0.59
Q7: It felt as if my (real) hand was becoming 'virtual'.	0.64 ± 0.45	-0.82 ± 0.60	-0.36 ± 0.58	-0.64 ± 0.53
Q8: It appeared (visually) as if the virtual hand was drifting towards my (real) hand.	-0.55 ± 0.39	-1.82 ± 0.44	-1.45 ± 0.45	-0.55 ± 0.57
Q9: The virtual hand began to resemble my own (real) hand in terms of shape, skin tone, freckles, or some other visual feature.	-1.0 ± 0.53	-1.18 ± 0.49	-0.91 ± 0.49	-1.73 ± 0.32
Q10: I felt as if I were fully immersed in the virtual environment.	0.27 ± 0.47	-0.64 ± 0.49	-0.09 ± 0.55	-0.36 ± 0.62

Supplementary Table 1. Questionnaire scores from the illusory ownership pilot experiment. Scores correspond to a 7-item Likert scale normalized between -3 and 3. Questions were adapted from classical questionnaires gauging illusory effects during the RHI[6,7].

Paper	Duration of visuo-tactile stimulation (s)	Visuo-tactile delay (ms)	Visuo-prorioceptive separation (cm)
Present work	{15.7,31.5,56.7 85.0,113.4,141.7 170.1,226.8, 283.5}	[0,800]	[0,35]
Botvinick et al. (1998) [6]	NA	NA	NA
Tsakiris & Haggard (2005) [1]	240	[500,1000]	17.5
Moseley et al. (2008) [8]	450	NA	NA
Kammers et al. (2009)[9]	90	NA	15
Lloyd (2007) [2]	60	NA	{17.5,27.5,37.5,47.5,57.5,67.5}
Ehrsson et al. (2008) [10]	60	NA	26
Slater et al. (2008) [7]	300	NA	20
Rohde et al. (2011) [11]	{420,[0,10,40,120]}	NA	17
Sanchez-Vives et al. (2010) [12]	NA	NA	20
Tsakiris et al. (2008) [13]	2.3	NA	17.5
IJsselsteijn et al., (2006) [14]	450	NA	30
Hohwy et al. (2010) [15]	{10,30,60}	[500,1000]	NA
Durgin et al. (2007) [16]	120	NA	15
Ehrsson et al. (2005) [17]	{30,60}	NA	15
Morgan et al. (2011) [18]	300	NA	15
Shimada et al. (2009) [19]	180	[100,600]	15
Dummer et al. (2009) [20]	600	NA	NA
Ocklenburg et al. (2010) [21]	180	NA	17.5
Schütz-Bosbach et al. (2006) [22]	NA	NA	NA
Zopf et al. (2011) [23]	120	NA	20
Tsakiris et al. (2007) [24]	125	[500,1000]	15
Lopez et al. (2010) [25]	60	NA	24.5
Mean ± SD	174 ± 168	650 ± 200	25 ± 14
{Min, Max}	{2.3,600}	{100,1000}	{15,67.5}

Supplementary Table 2. Comprehensive summary of experimental parameter ranges used in previously reported rubber hand illusion setups as well as in the present work. Note that the range of parameters used in the present study encompasses most of the previous setups. *NA* indicates that the corresponding information was not provided by the article or was unclear from the methods description. The bottom row summarizes the distribution of the parametric ranges (ignoring *NA* values).

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3.4

The psychology of brain-machine actions

The psychology of brain-machine actions

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Abstract

The feeling of controlling our movements (sense of agency, SOA) is of major legal and ethical importance. Investigating SOA for brain-machine "actions", where sensory consequences were generated without any body movements using a brain-machine interface, we describe the limits of conscious control when humans are merged with a machine.

Human action is associated with a sense of agency (SOA) characterized by the feeling that one’s movements and their consequences are self-generated*(1)*. SOA has been related to moral responsibility *(2)* and is of major legal and ethical importance as societies hold individuals responsible for their actions and consequences. Recent advances in brain-machine interfaces (BMI) have made it possible to decode cortical activity to generate machine-controlled actions without concomitant bodily action*(3,4)*. Though it is likely that in the future many patients and healthy individuals will be fitted with BMIs to restore and augment movement capacity*(5)*, we currently lack understanding of whether such machine or BMI-actions rely on the same brain mechanisms as those described for body-driven actions and whether similar legal accountability ought to be ascribed. As SOA has been shown to decrease when spatial and temporal conflicts are inserted between bodily actions and their sensory consequences*(6)*, here we test the SOA while introducing conflicts between decoded brain activity (using a real-time, non-invasive, BMI*(7)*) and its resultant sensory consequences (a visual feedback signal).

To test SOA for BMI-actions, participants were trained to imagine left or right hand clasping to move a visual cursor to the left or right of a screen, respectively. In a first experiment, we injected a delay (six delays ranging from 0-3750ms at 750ms intervals) between the decoded cortical activity and its visual consequences on a trial-by-trial basis (“visuo-neural delay”). We additionally tested spatial conflicts by manipulating the direction of the cursor to be either congruent or opposite (incongruent) to the trained directional association (*e.g.* for incongruent trials, participants imagined left hand clasping but the cursor moved to the right). For each trial, we measured real-time classification performance and gauged SOA for the BMI-action*(7)*.

We found that SOA is high for congruent and low for incongruent feedback and that SOA depends differently on delay for congruent and incongruent trials ($F_{(5,7)}$=5.76;P=0.001;Fig.1A). Namely, SOA significantly decreased from 84% to 58% with increasing delay for congruent trials (P=0.001), but was not significantly modulated for incongruent trials (20-34%;P=0.13). These results show that humans report feeling a SOA for congruent BMI-actions, but that SOA decreases as a function of visuo-neural delay and is strongly diminished in the presence of prominent spatial conflict (in a delay-independent manner). These findings are comparable with studies introducing visuo-motor delays and spatial conflict upon bodily actions*(8)*, suggesting common brain mechanisms for body-driven and BMI-actions.

Average BMI classification performance remained high and showed no difference across experimental conditions (M=76.7,SEM=3.1,$F_{(5,7)}$=1.36;P>0.25; Fig.1B). EEG analysis on the statistically-derived classification features and frequency power changes showed that participants modulated the expected mu-/beta-band oscillations over bilateral sensorimotor cortex to control the cursor movements in all experimental conditions (Fig.1C;Fig.S1). Thus, the changes in SOA cannot be accounted for by differences across conditions in the decoder performance.

Next, we tested if there was a relationship between classification performance and SOA on a trial-by-trial basis. Applying methods from psychophysics*(7)*, we fit psychometric SOA curves to classification performance for the two extreme delay conditions (separately for congruent and incongruent trials;Fig.1D). For congruent trials, this analysis revealed that low classification performance was associated with low SOA and high performance with high SOA. For any fixed classification performance, delay insertion led to a decrease in SOA (point of subjective equality (PSE) shift: 43.4% to 62.1%;P=0.015;Fig.1E). Thus, for participants to report an equivalent SOA in delayed trials, they needed to remain longer in the brain state associated with the learned BMI-action consequence. Furthermore, delay insertion resulted in higher SOA variance (decrease in the absolute slope of the psychometric curve; P=0.03). Incongruent trials showed the reversed pattern (low classification performance: high SOA; high performance: low SOA), though delay had similar effects on the PSE (shift: 50.7%-62.9%; P=0.02;Fig.1E) and variance of SOA responses (absolute slope decrease; P=0.04). Taken together, this shows that although classification performance was not influenced by visuo-neural delay (Fig.1B), delay alters the trial-by-trial relationship between classification performance and SOA (Fig.1D). These data for incongruent trials also show that low classification performance can be associated with high SOA. This suggests that SOA for incongruent BMI-actions may be based on congruence between the actual and the intended (cued) cursor direction rather than comparison between one's brain state and the resultant sensory consequences, and highlight a potential importance of reconstructive accounts of SOA*(1)* for BMI-actions.

As SOA for bodily actions is normally tested for delays <1s, we next tested in an independent subject sample whether our findings extend to shorter visuo-neural delays (6 delays: 0-1s in 250ms intervals and 3.75s). This analysis confirmed the effect of delay on SOA ($F_{(5,6)}$=7.82;P=0.0001;Fig. S2A), but showed that delays below 1s do not modulate SOA judgments, as is observed for body-driven actions. Again, classification performance did not vary across the tested delays and BMI control was driven by mu-/beta-band modulation over bilateral sensorimotor cortex (Fig.S2B-C). Additional EMG recordings excluded that SOA judgments for BMI-actions were associated with minor limb movements or covert muscle contractions (Fig.S2D).

Avoiding earlier confounds related to proprioceptive and motor signals that accompany bodily actions, our data show that BMI-actions that are driven by decoded brain activity are associated with a robust SOA. Although, the SOA pattern generally followed that for bodily actions, it was less sensitive to delay (if compared to body-driven actions) and in some incongruent BMI-actions associated with low classification performance. These similarities and differences in the psychology of BMI-actions need to be investigated and may inform societal decisions pertaining to legal responsibility as well as ethical concerns as humans progressively merge with machines in the quest for repair, substitution, and augmentation.

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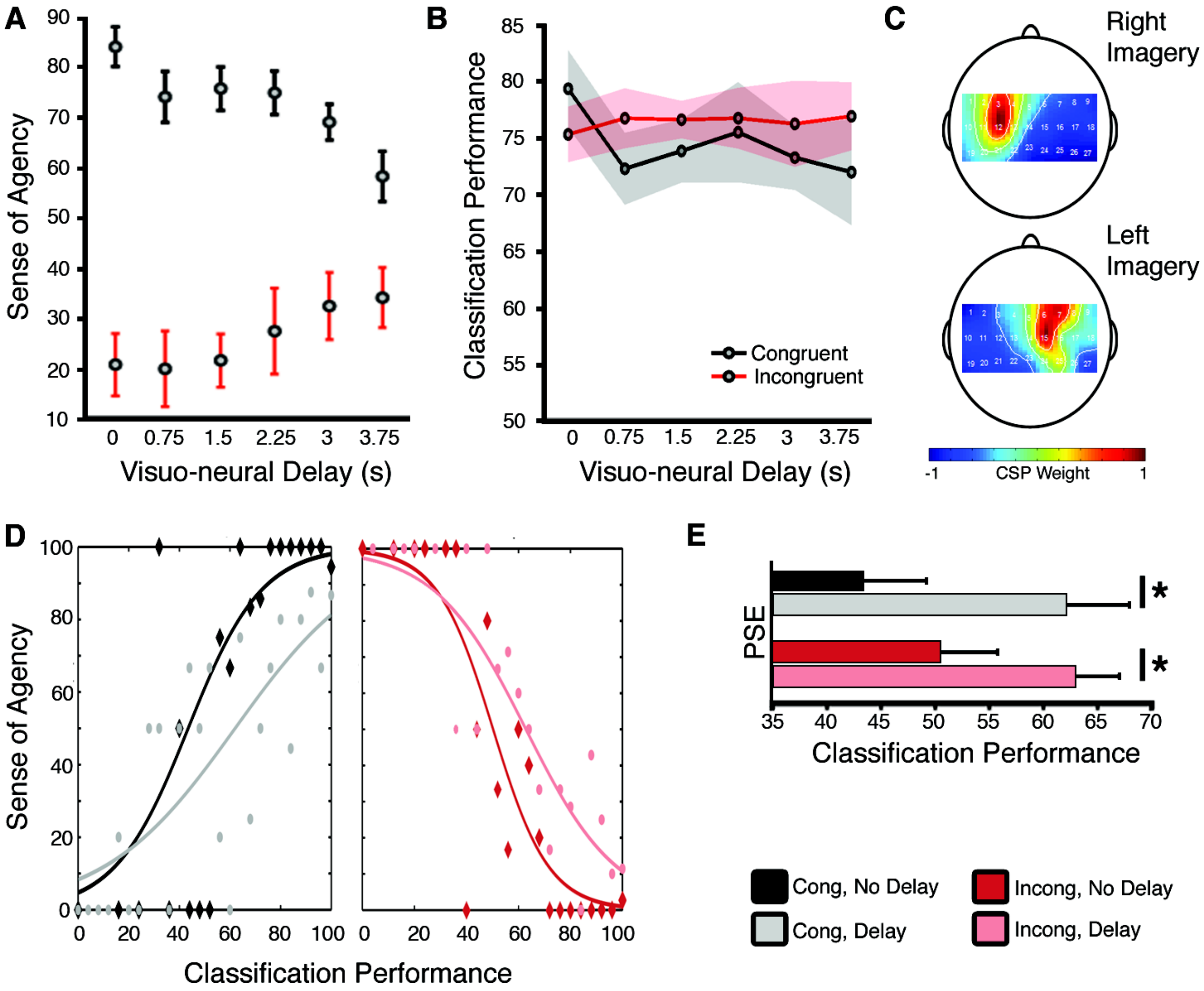

Figure 1. **(A)** Sense of agency (SOA) and **(B)** classification performance (CP) as a function of visuo-neural delay and congruency. **(C)** Normalized, per channel spatial pattern weights for left and right motor imagery in a prototypical participant. **(D)** SOA as a function of CP at zero and high (3.75s) delay for congruent and incongruent trials. Data points represent mean SOA across all participants in 4% CP bins. Curves indicate best-fit logistic regression. **(E)** Point of subjective equality for each psychometric curve in (D). In all panels, error bars and shaded regions indicate SEM. * indicates difference (*p<0.05*) between two conditions.

Supplementary Materials

Brain-machine interface training procedure

Participants (study 1: N=8, 2 females, all right handed, aged 26.5 ± 3.5 years *mean±SD;* study 2: N=7, 7 males, 1 left-handed, aged 26 ± 2.3 years) first trained to perform a lateralized motor imagery task without visual feedback (*9*). A left or right directional cue (40 trials: 20 left, 20 right) indicated to imagine clasping the left or right hand, respectively. Coefficients for a binary linear classifier were computed and used in a second training phase with visual feedback in which participants were instructed to move a cursor to the cued edge of the screen using the trained motor imagery association. After each training block of 40 trials (20 left cues, 20 right), sufficient control of the cursor was judged by measuring real-time classification performance (percentage of time steps classified in the direction of the cue) on a trial-by-trial basis. If participants were unable to achieve >75% mean performance across trials in the training block and did not verbally report that they felt able to move the cursor in a desired direction, the full training procedure was repeated until these criteria were met (generally 1 to 4 training blocks of 40 trials). This procedure was repeated up to five training blocks, after which participants still unable to sufficiently control the cursor were dismissed and did not take place in the experiments (study 1: two participants; study 2: six participants).

EEG data processing

27-channel electroencephalography (EEG) was sampled at 128 Hz (*g.tec*, Schiedelberg, Austria). Electrodes were centered over sensorimotor cortex, grounded with an additional electrode placed on the forehead, and re-referenced to an electrode attached to the right earlobe. Electrode placement and data processing methods are described in further detail elsewhere (*10*).

Offline Classifier Computation

EEG data from the motor imagery period of the classifier training session were visually inspected for eye blink and muscular artifacts and trials with artifacts were removed. In study 2, we combined non-artifacted trials from the two most-recent classifier training sessions to further increase the robustness of the classifier. Thus, the number of artifact-free trials used to train the per-subject classifiers was 38 ± 2 (*mean* ± *SD*) for study 1 and 51 ± 14 for study 2.

Data from the training session was used to compute common spatial patterns (CSPs) for each subject (*11*). In study 1, CSPs were computed for motor imagery data from a fixed window (0.25 – 1.25s following the directional cue). In study 2, we further optimized the CSPs by selecting a per-subject window position that maximized the classification performance on the training set (from a 1.5s window at 0.5s intervals, between 0.25 – 4.25s following the cue).

Next, feature vectors were constructed by bandpass filtering the raw EEG in the α/μ and β frequency bands (8 to 30 Hz), re-projecting the data through the first two and last two CSPs, and then computing the log variance in each dimension of the filtered signals. The per-subject classifiers (linear discriminant analysis (*12*)) and per-subject CSPs were only computed during the classifier training phase without visual feedback and were held fixed throughout the remainder of the experiment.

Real-time Preprocessing, Classification, and Visual Feedback

Real-time EEG data were bandpass filtered, projected through the offline-computed CSPs, and log variance was taken (Simulink, Mathworks, Natick, Massachusetts, USA). Visual feedback was provided in the form of a cursor that could move to the left or right of its current position with a velocity proportional to the magnitude of the distance of the feature vector from the linear decision boundary (*13-14*). The cursor trajectory was additionally smoothed by applying a sliding mean (1s window) to the log variance. Features were computed for each

EEG sample and fed to the classifier, resulting in classifier output (translated to a new cursor position) every ~8 ms.

In both studies the visual consequences were manipulated experimentally by inserting a buffered delay on the real-time classifier output (study 1: 0 – 3750ms at 750ms intervals; study 2: 0 – 1000ms at 250ms intervals and 3750ms). Thus, the cursor position was updated at every time step, but could be updated from classifier output representing ongoing brain activity from up to 3750ms prior to the current time step. In study 1, an additional manipulation of cursor direction was made: for incongruent trials, classifier output was multiplied by negative one, resulting in an inverted velocity mapping between classifier output and cursor position with respect to the learned directional association.

Verification of BMI Control Signals

To ensure that participants used sensorimotor rhythm modulation rather than non-EEG artifacts to control the cursor, we plotted topographies of the statistically derived common spatial pattern filter weights for single subjects (Fig. 1C, S1A, S2C). For all individual subjects and in both studies, the resulting spatial filters showed focalized importance of electrodes C3 and C4 (located over left and right sensorimotor hand regions) in discriminating between left and right motor imagery (for more on spatial interpretation of CSPs see (*11*)).

We next verified the presence of classical electrophysiological neuromarkers of motor imagery during real-time cursor control, namely the suppression of sensorimotor mu/beta band-power (8 – 30 Hz) in contralateral versus ipsilateral imagery (*9*). To do so, we first computed the mu- and beta-band power spectral density for all participants (Fast Fourier Transform; Matlab, Mathworks, Natick, Massachusetts, USA) during the cursor control period separately for left and right imagery trials and in electrodes lying in close proximity to sensorimotor hand regions (C3 and C4) as well as in a central control electrode (FCz). Next, we computed the log power ratio (LPR) of contralateral versus ipsilateral imagery trials and took the mean across participants (Fig. S1B). Thus, the LPR indicates the relative power modulation between right imagery trials as compared to left imagery trials (at electrode C3) and left imagery trials as compared to right imagery trials (at electrode C4). The LPR at the control electrode was taken as left imagery versus right imagery. Finally, since a LPR of 0 indicates no difference in the PSD between contralateral and ipsilateral motor imagery trials, we performed two-tailed t-tests (Bonferonni corrected for multiple comparisons) of the LPR distributions against a distribution with mean 0. This analysis showed suppression in contralateral imagery trials as compared to ipsilateral trials, as evidenced by suppressed LPRs in channels C3 (-1.08±0.24 *mean±SEM*; $P = 0.003$) and C4 (-1.02±0.33 *mean±SEM*; $P = 0.018$), but not in the control electrode FCz (0.098±0.14 *mean±SEM*; $P = 0.5$).

Finally, we verified by visual inspection and electromyography (EMG; study 2) that cursor control was not based on limb muscle artifacts. EMG activity was sampled at 128Hz from electrode pairs placed on the left and right forearm flexor muscles midway between the wrist and elbow. The EMG signals were rectified and an average amplitude ratio was constructed against maximum voluntary contraction (MVC) for left and right directions (*14*). The resulting EMG ratios are plotted in Figure S2D and shows low ratios for all participants, suggesting that overt muscle contractions were not used to control the cursor. Moreover, for illustrative purposes, Figure S2E displays single EMG traces during cursor control (motor imagery) and overt movements (MVC) for participant 2 in sample left- and right-cued imagery trials.

Measurements and statistical analyses

SOA was gauged on a trial-by-trial basis with a two-alternative, forced-choice response (yes/no) to: "*I felt as if I were controlling the cursor I saw on the screen.*" Binary responses were transformed into a percentage of yes answers, resulting in a single percentage per subject, per experimental condition. Classification performance was taken as the percentage of time steps the real-time classifier output corresponded to the cued direction during cursor control, regardless of where the (potentially) manipulated visual cursor was displaced. Thus, classification performance can also be considered as an indicator of the percentage of time that participants spend in the brain state associated to the learned coupling between BMI-action and consequence.

Statistical Analyses

Differences in SOA responses and classification performance across experimental conditions in study 1 were assessed using a 2x6 repeated-measures ANOVA with factors Direction x Visuo-neural Delay. After observing a significant interaction, we separately analyzed congruent and incongruent trials with 1x6 repeated-measures ANOVAs to test for an effect of delay. For any main effects we used post-hoc two-tailed, paired t-tests to test for differences across individual experimental conditions. Statistical results from studies 1 and 2 can be found in Table S1.

To reconfirm the effect of delay on SOA, we also performed linear regression separately on congruent and incongruent trials and found that SOA decreases with increasing delay for congruent ($r^2 = 0.25$, $P < 0.001$), but not for incongruent trials ($r^2 = 0.08$, $P > 0.05$).

Psychometric analyses

To test for an explicit relationship between SOA and classification performance on a trial-by-trial basis, trials were pooled across participants and binned (2% classification performance width) such that each SOA response was paired with its corresponding classification performance in four conditions: 1) congruent, no delay; 2) congruent, high delay (3.75 s); 3) incongruent, no delay and 4) incongruent, high delay. For study 2, only the first two conditions were considered. Psychometric curves were then fit to the binned group data in these four conditions using binomial, logistic regression (glmfit logit function, Matlab, Mathworks, Natick, Massachusetts, USA).

For each of the four conditions, two measurements were collected from the psychometric fits. First, the point of subjective equality (PSE) was taken as the classification percentage closest to 50% SOA (resolution 0.001%). Second, we measured the sensitivity (slope) of the psychometric fit *(15)*. Standard errors on these values were obtained using the bootstrap method with 10,000 iterations and statistical differences across conditions were assessed using a one-tailed bootstrap test (*16*).

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Supplementary Tables

Table S1. Statistical results for sense of agency measures in Study 1 and Study 2. All statistical contrasts used to assess differences across experimental conditions in SOA judgments (see *Statistical Analyses* above for details). For all pairwise T-test contrasts, only significant differences ($P < 0.05$) are reported.

Study 1	**F / t**	**P**		**Study 2**	**F / t**	**P**
2 x 6 ANOVA Interaction Direction Delay	5.76 43.3 --	0.001 < 0.001 > 0.6		1 x 6 ANOVA effect of delay (congruent trials)	7.817	0.0001
1 x 6 ANOVA effect of delay (congruent trials)	5.33	0.001		T-Tests: 0 > 3.75s 0.25 > 3.75s 0.5 > 3.75s 0.75 > 3.75s 1 > 3.75s	all > 2.86	all < 0.03
1 x 6 ANOVA effect of delay (incongruent trials)	1.87	0.125				
T-Tests: congruent > incongruent (at all delays)	all > 3.77	all < 0.007				
T-Tests: (within congruent) 0 > 3s 0 > 3.75s 1.5 > 3.75s 2.25 > 3.75s 3 > 3.75s	all > XXX	all < 0.03				

Supplementary Figures

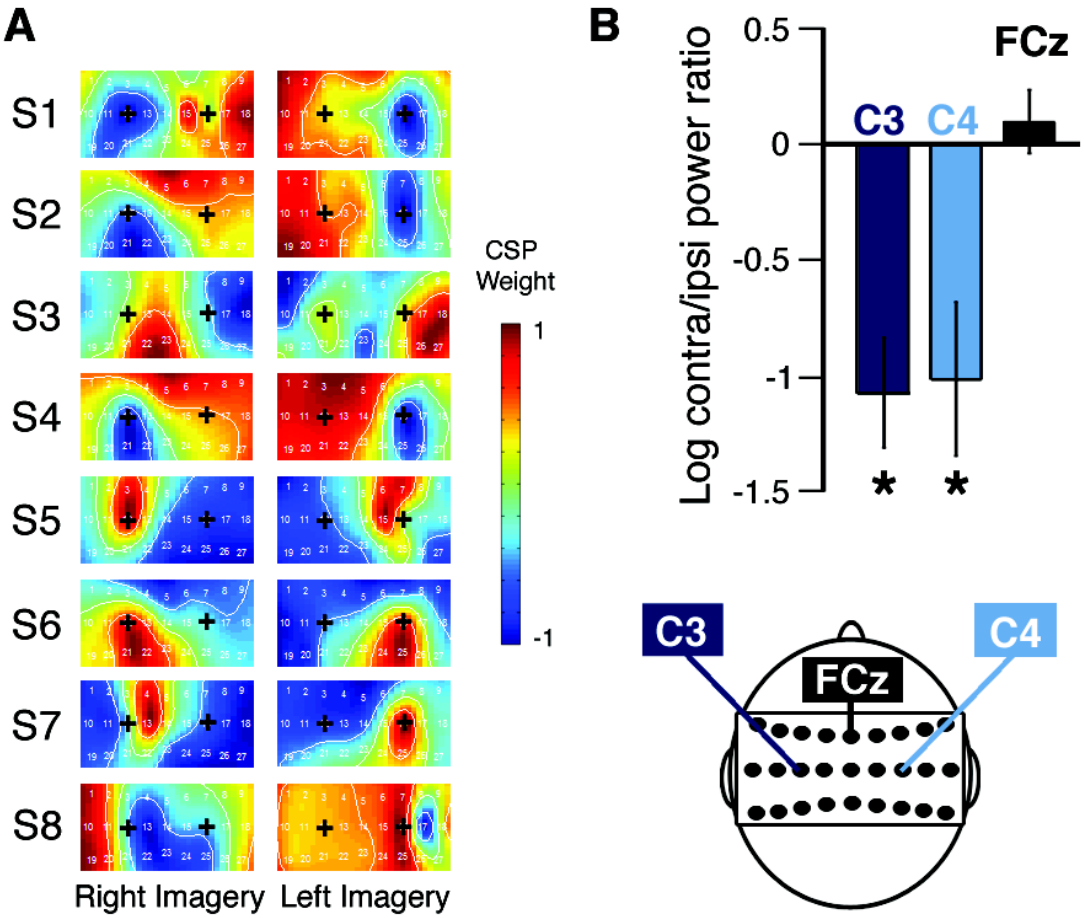

Fig. S1.

Cursor control driven by bilateral sensorimotor mu- and beta-band modulation. (A) Normalized common spatial pattern weights for each electrode during left and right motor imagery for each participant (S1-S8) in study 1. On each map, '+' labels are placed over electrodes C3 and C4 for orientation. **(B)** Contralateral divided by ipsilateral power ratios (LPR) for 8 – 30 Hz oscillations at electrodes C3, C4, and control electrode FCz. * indicates significant suppression ($P < 0.05$; *two-tailed T-test*) with respect to an LPR of 0 (*i.e.* no difference between ipsilateral and contralateral power). Error bars represent SEM.

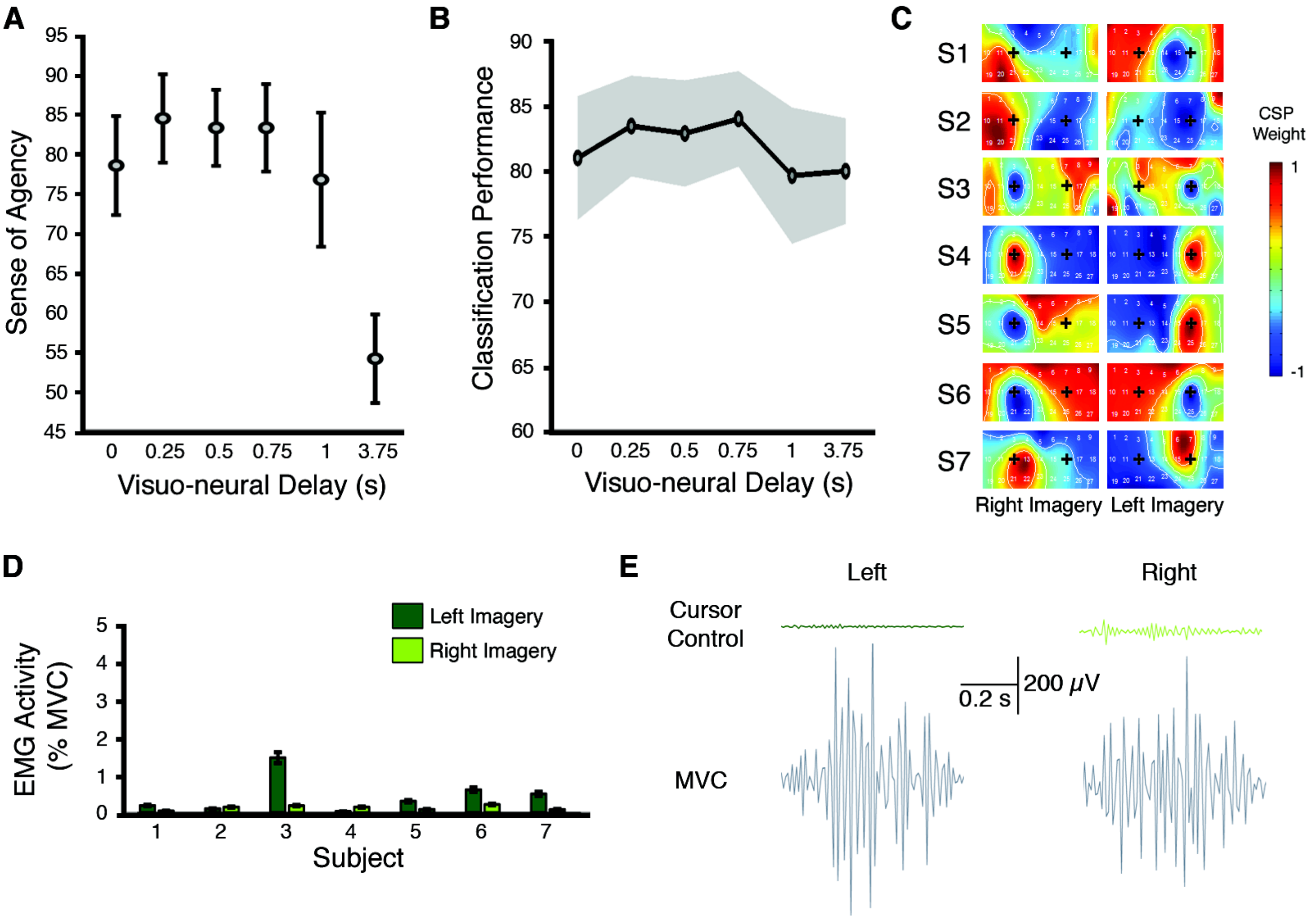

Fig. S2.

Study 2 results. (A) Sense of agency and **(B)** classification performance as a function of visuo-neural delay. **(C)** Per-subject, normalized spatial filter weights for each electrode during left and right motor imagery for study 2. On each map, '+' labels are placed over electrodes C3 and C4 for orientation. **(D)** Mean electromyographic (EMG) activity of left and right forearm flexor muscles during motor imagery. Activity was averaged across trials and conditions for each subject and a ratio was computed to their maximum voluntary contraction (MVC), resulting in very low ratios (all < 2%). **(E)** Sample EMG traces from participant 2 during left and right cursor control and during MVC trials. In all panels, error bars and shaded regions indicate SEM.

4. General Discussion

In this final chapter I begin with a summary of the cumulative results presented in the adjoined scientific articles. I then take a quick detour to introduce ongoing research and preliminary results from studies that I believe to be of additional relevance to the methods and message of this thesis. Next, I provide a more in-depth discussion, exploring the present findings and their relationship to ownership and agency in different or complementary contexts than those discussed in the articles. Along the way, I hint at unresolved issues and propose specific follow-up experiments that could address these open questions. Lastly, I finish with an outlook on future research directions emerging from an established link between cognitive neuroscience and BMIs.

4.1 Summary of main results

One critical step of this thesis involved the **design and implementation of an automated, virtual reality setup to induce the RHI**. In three independent subject samples (Study 1: pilot and main studies; Study 3) we verified that our novel technical setup induced the effects associated with traditional RHI setups, such as proprioceptive drift and changes in ownership as measured by subjective reports (Botvinick and Cohen, 1998; Tsakiris and Haggard, 2005; Makin et al., 2008; Blanke, 2012). These encouraging results led to a series of experiments on illusory ownership that exploited the advantages of a programmable setup, including simultaneous induction of illusory ownership over two hands (Study 1 and Study 2) and systematic manipulation of sensory cues for testing a probabilistic model (Study 3).

Using this setup, we measured electrical brain activity while inducing the RHI and found that **illusory hand ownership** led to **body-selective** and **synchrony-dependent** modulation in **mu-band** activity over **bilateral fronto-parietal regions** (Study 1; Evans and Blanke, 2012). In the same participants, we measured EEG activity during a **lateralized motor imagery** task and found it to elicit a classical pattern of **mu-** and **beta-band** changes over **bilateral**

sensorimotor cortex (Pfurtscheller et al., 1997a; Pfurtscheller and Neuper 2001). Finally, **overlap analysis** showed illusory ownership and motor imagery to recruit **shared anatomical networks** and to be characterized by **similar electrophysiological signatures**.

We then extended this study to assess whether induction of **illusory ownership** over the virtual hands **altered the ability to decode single-trial motor imagery** in a traditional non-invasive BMI task (Study 2; Evans and Blanke, *in preparation*). Indeed, **classification performance was boosted** in the illusion condition as compared to asynchronous stimulation on visual control objects and this effect was found for the majority of individual subjects. Despite these promising results, classification performance was globally maximal in a baseline condition where no visuo-tactile stimulation and no ownership induction was provided during motor imagery.

Again exploiting our automated setup to record a **large number of hand localizations** across a **wide range of systematically varied parameters**, we were able to show the most comprehensive view to date of the complex relationship between trimodal sensory cues (visual, proprioceptive, tactile) and the recalibration of perceived hand position as measured in the RHI (Study 3; Rezende et al., *submitted*). Our rich data set showed that perceived hand position is biased by visual or proprioceptive cues if the visuo-proprioceptive hand separation is small or large, respectively. Importantly, at intermediate visuo-proprioceptive separations, the ownership illusion breaks down discontinuously such that sometimes they perceive their hand near where they see their hand, and sometimes near where they feel their hand. We additionally described a **hierarchical, Bayesian multisensory integration model** to explain the computational underpinnings of the emergence of illusory ownership in the RHI. This model accurately predicted both the mean and variance of the empirically measured proprioceptive drifts and allowed us to extract the stimulation conditions necessary for the recalibration of perceived hand position, on a subject-by-subject basis.

In a second series of experiments, we investigated the **sense of agency** (SOA). By injecting a delay between decoded cortical activity and its visual consequences (using a real-time, BMI-controlled cursor), we demonstrated that **SOA extends to machine-generated BMI-actions**. Furthermore, BMI-actions -- actuated in the **absence of proprioceptive and tactile reafferent signals** -- were found to be sensitive to the comparison between predicted and actual consequences and therefore **resemble SOA for bodily actions** (Study 4; Evans et al., *submitted*).

4.2 Sense of agency when effects precede actions: ongoing work

In ongoing work, we manipulated the temporal ordering of motor movements (finger deflection) and their visual sensory consequences (virtual finger deflection) to probe the SOA for a wide range of action-consequence temporal couplings (Evans et al., *in preparation*).

Motivation and Background

By injecting delays between bodily movements and their sensory consequences, several studies have demonstrated that SOA depends on the temporal coherence of the action and its effect (Fourneret and Jeannerod, 1998; Sato and Yasuda, 2005; Sato, 2009). Relatedly, previous work in the time perception of volitional movements has confirmed a shift in the temporal perception of actions towards their effects and vice versa (intentional binding; Haggard et al., 2002; Eagleman and Holcombe, 2002; Ebert and Wegner 2010; Cravo et al., 2009; for a review see Moore and Obhi, 2012). However, to our knowledge, all previous paradigms investigating SOA and the perception of the temporal relationship between actions and their sensory consequences have assumed a particular causal relationship: that actions lead to effects. Here, we wondered whether SOA could be felt for movements in the artificial case where this ordering is inversed; namely, when sensory effects precede their corresponding movement. To test this, we predict voluntary motor movements (finger deflections) and provide visual sensory consequences that precede them (negative delay). Furthermore, in the same participants, we test the standard temporal ordering, investigating trials where motor movements precede their visual consequences (positive delay). By performing hundreds of trials per participant and utilizing methods from psychophysics, we fully characterize SOA as a function of the temporal offset between visuo-motor actions and effects, offering a comprehensive view of the dependence of SOA on the temporal coherence of action and effect.

Methods

Participants sat at a table and placed their right hand on a block containing a haptic sensor. This sensor allowed for detection of an index finger deflection at millisecond precision (movement onset time). Vision of their real hand was occluded by a stereo monitor that projected a virtual hand co-localized with their real hand (Figure 14). The virtual hand could be animated to produce a finger deflection (visual onset time).

Figure 14: Testing sense of agency when sensory consequences precede their corresponding actual movement. Subjects sat at a table and saw a 3D arm projected co-localized with their (occluded) real hand. Participants performed voluntary finger deflections and saw visual consequences (animated finger deflections). Using a haptic sensor and predictive algorithms, some trials resulted in movement onsets preceding the visual consequences (positive delay) and others where the visual consequences preceded the movement (negative delay). After each trial participants answered whether or not the movement they saw corresponded to the movement they made.

In a short training block, participants learned to make finger deflections that mirrored the velocity and amplitude of the animated finger. In these trials, no delay was inserted between the finger movement and the animation. In the main experiment, participants (behavioral study 1: *N=14,* 300 trials per subject; EEG study 2: *N=10*, 600 trials per subject) were instructed to lift their finger at the time of their choosing. Using dynamic predictive algorithms based on per-subject movement history profiles, we anticipated the movement onset time with the intention of providing visual consequences just prior to that moment. If participants moved prior to the visual onset triggered by the predictive algorithm, the visual consequence was presented within a small window (0 to 750 ms). For each trial, participants answered a forced-choice (yes/no) question about whether the movement they saw corresponded to the movement they made. To summarize, a given trial consisted of both a visual and a movement onset time and the corresponding SOA response.

Results

We reasoned that if SOA is influenced by the causal ordering of action and effect, the function defined by SOA and the difference in onset time between the movement and visual animation (ΔT; negative values indicate visual cues precede movement, positive values indicate the inverse) would not be a symmetric. Said differently, we hypothesized that psychometric SOA responses would not be mirrored across the moment of

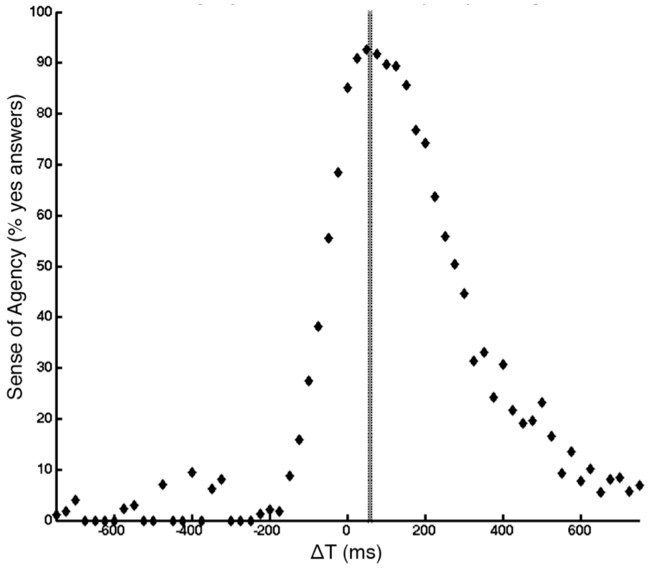

Figure 15: Sense of agency as a function of visuo-motor delay. SOA (% yes answers; binned at 25 ms) as a function of ΔT for Study 2. ΔT is taken as the difference in time between their movement onset and the visual consequences (where negative values indicate visual precedes movement, positive values indicate the inverse). A line is drawn at peak SOA for this group data.

perfect visuo-motor coherence (ΔT=0). To test for this, binary SOA responses were binned (25 ms width) and transformed into percent yes answers (Sato and Yasuda, 2005; Figure 15). Two analyses were then conducted to test for symmetry. First, we found the ΔT that corresponded to the per-subject SOA peak. This analysis revealed that maximum SOA for all subjects across both studies was shifted to positive ΔT, that is, peak sense of agency was experienced when finger movements preceded their visual consequences (Figure 16). This observation was statistically confirmed as we found ΔT to be significantly shifted from ΔT=0 (study 1: 82±13 ms *mean±SEM*; P < 0.0001; study 2: 73±17ms; P = 0.002; *two-tailed t-test*).

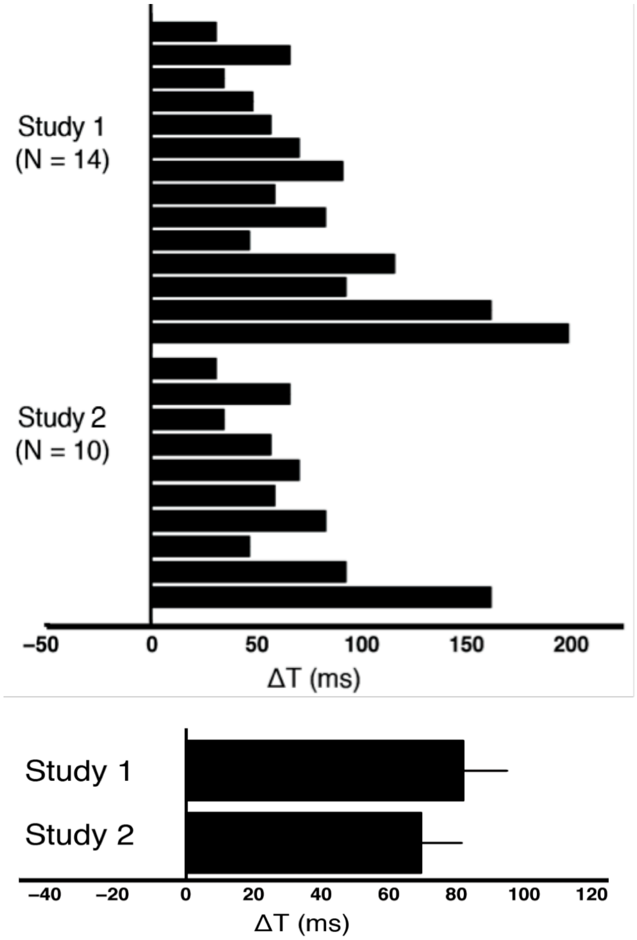

Figure 16: Peak sense of agency experienced when movements precede their sensory consequences. We found maximum SOA responses to occur with a delay with respect to the objective simultaneity of the visual and motor events. *Top:* Per-subject ΔT corresponding to their peak sense of agency (SOA). All participants showed peak SOA values shifted from simultaneous (ΔT=0) toward positive ΔT, and *Bottom:* mean values across both studies show a significant positive shift from ΔT=0. Error bars represent SEM.

Next we assumed that the peak SOA found in the first analysis corresponded to participants perceived simultaneity between the two sensory cues (motor, visual). Under this assumption, we split the data into events happening before this moment of unity (negative delays) and those happening after (positive delays) to test whether the perceptual SOA responses were more sensitive to causal order. By fitting psychometric curves to negative and positive delays separately (Figure 17 left) we found a significant change in sensitivity (absolute slope; $P < 0.0001$; Figure 17 right). This result indicates that participants' SOA is more sensitive to negative delays (reversed causal order) than positive delays, and that there is less variance in perceptual SOA responses when sensory effects precede their causes.

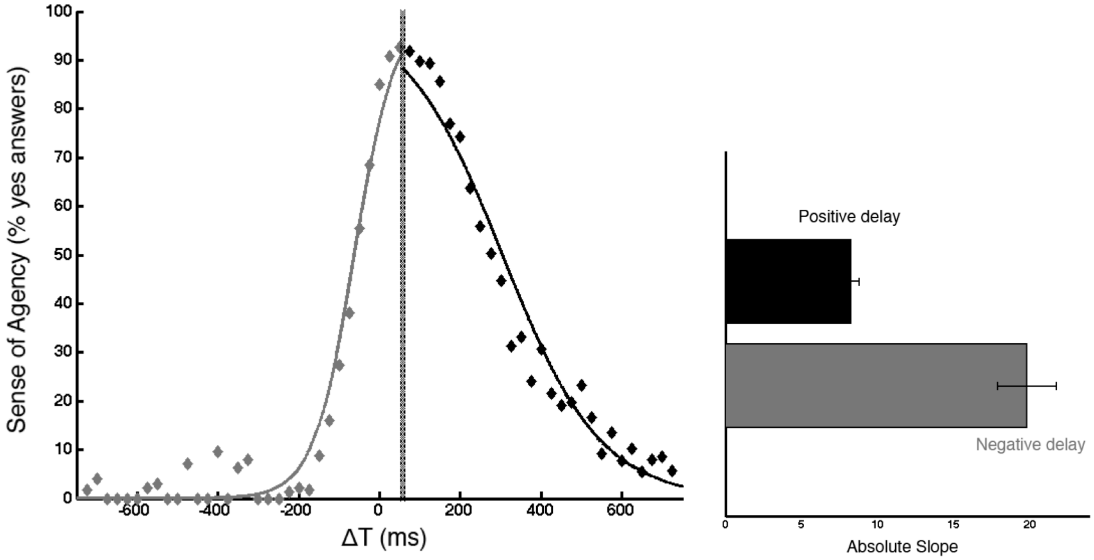

Figure 17: Sense of agency is sensitive to causal ordering. *Left:* Psychometric fits (binomial logistic regression) to group data from Study 2. Negative delays are defined as events where visual sensory consequences occur before perceived simultaneity (peak SOA) and positive delays where they occur afterward. Psychometric responses for positive delays show characteristic responses (Farrer and Jeannerod, 2008), namely that SOA decreases as a function of increasing ΔT. *Right:* Absolute slope obtained from the fit coefficients for negative and positive delays in Study 2. Error bars represent SEM. Negative delays show a much larger slope, indicating that SOA is sensitive to the causal ordering of action and effect.

Summary

Using predictive algorithms, haptic sensors, and virtual reality feedback, we were able to show that SOA can also be felt for movements in the artificial case where the visual consequences of voluntary finger deflections temporally precede the actual (proprioceptive) movement (henceforth referred to as negative delay).

In two independent subject samples, we showed that SOA is asymmetric and dependent on the temporal order and delay between actions and their consequences. In particular, **peak SOA** was found to be **significantly shifted from zero visuo-motor delay**, corresponding to the trials where movements preceded their sensory consequences (by approximately 75 ms). Interestingly, we also found that participants **exhibit a SOA for movements** in the artificial situation **when sensory effects precede the actual movement** (negative delay; 50% agency at 100 ms), but that the perceptual mechanisms of SOA for these negative delays are much more sensitive than for positive delays. Though further study is needed to characterize the observed temporal ordering asymmetry of SOA, this work demonstrates the potential for combining novel techniques and technologies compatible with electrical neuroimaging to generate implausible experimental settings in order to test the limits of SOA.

4.3 Towards precise and programmed experimental setups in the cognitive neuroscience of bodily self-consciousness

One of the main contributions of this thesis is its emphasis on mixing haptic and virtual reality technologies toward designing novel illusory hand ownership and agency paradigms, supporting recent interest in virtual reality and robotics as multipurpose tools for psychological and neuroscientific research (Bohil et al., 2011; Lenggenhager et al., 2011; Slater et al., 2008; Sanchez-Vives and Slater, 2005; Tarr and Warren, 2002; Riva, 2007; Ionta et al., 2011). In addition to eliciting comparable effects to those reported with previous setups that induced unilateral hand ownership with experimenter-applied, manual visuo-tactile stimulation (Botvinick and Cohen, 1998; Ehrsson et al., 2004; Tsakiris & Haggard, 2005; Lloyd, 2007; but see Schütz-Bosbach et al., 2009), our setup allowed us to move beyond the limitations of manual stimulation toward difficult or otherwise impossible to achieve stimulus configurations. For instance, using our setup we could apply bilateral or multiple hand stimulation, or to systematically manipulate multiple sensory cues over hundreds of trials with millisecond and centimeter precision (as in Study 3). Furthermore, automated setups require explicit definition of stimulation-related parameters. Well-defined spatio-temporal parameters will facilitate precision as well as the comparison between experimental conditions, subjects, and future studies from different laboratories (see also *Section 4.6.3*).

Concerning the efficacy of our automated setup, previous literature reports proprioceptive drifts of around 2 to 3 cm (Tsakiris and Haggard, 2005; Tsakiris et al., 2007; Slater et al., 2008), whereas our setup elicited strong recalibrations of perceived hand position of up to 12 to 13 cm (Study 3). Despite these achievements, future work might investigate how to boost the magnitude of illusory ownership and agency (as measured by subjective reports and objective measures) by providing additional or enhanced sensory feedback. For example, ownership experience or agency over virtual or robotic devices may be boosted by combining real-time hand tracking with visual animations to provide dynamic visuomotor congruencies (Sanchez-Vives et al., 2010), or by selectively activating different or additional cutaneous mechanoreceptors via haptic and robotic interfaces that apply pressure, tapping, or continuous brush sensations (Marasco et al., 2011; Schütz-Bosbach et al., 2009). The immersive quality of visual virtual stimuli can be enhanced by closer collaboration between cognitive neuroscientists, graphical animators and 3D modelers that use advanced shading, texturing, and 3D rendering techniques (Sanchez-Vives and Slater, 2005). However, it should be noted that given our results and those mentioned above, perfect visual realism does not seem to be a prerequisite to induce illusory ownership (Study 1, 2, and 3) or agency (Study 4; our ongoing work).

4.4 Hand ownership

4.4.1 Neural mechanisms of hand ownership and their relationship to non-invasive BMIs

One of the main contributions of this thesis was the use of common motor imagery paradigms to bridge ideas in cognitive neuroscience and BMI research. Oscillatory activity in the mu-band over central sensorimotor regions was investigated (Study 1) and exploited (Study 2) as a shared neural signature between illusory hand ownership and motor imagery. Moreover, central mu-band activity was used as a control signal for a non-invasive BMI to test SOA for covert, machine-mediated actions (Study 4).

Our results from Study 1 reinforce previous findings by linking electrophysiological modulation due to illusory hand ownership to bilateral premotor and posterior parietal cortex (Ehrsson et al., 2004, 2005, 2007) as well as the postcentral gyrus (Lloyd et al., 2006; Schaefer et al., 2006a, 2006b; Ehrsson et al., 2005; Tsakiris et al. 2007; see also Schaefer et al., 2007). Moreover, they show that illusory ownership leads to oscillatory modulations in same frequency band (mu-band) and same regions (fronto-parietal cortices) implicated during imagination of motor movements (Pfurtscheller et al., 1997a, 1997b, Pfurtscheller & Neuper, 1997; Miller et al., 2010; for a review see Hari and Salmelin, 1997).

Though these overlap analyses revealed strong anatomical and spectral similarities in the neural signatures of hand ownership and motor imagery of hands, our results hint at three important issues that could be addressed in future research. First, future work might explore the relationship between hand ownership and other traditional behavioral mental imagery tasks (*e.g.* mental hand rotation; Parsons, 1994; Kosslyn, 2001). Recent data suggest that illusory ownership modulates the capacity to imagine hand rotations (Ionta et al., 2012). Therefore, it may be interesting to see how these behavioral changes are reflected in fronto-parietal mu oscillations. Second, paradigms that provide visual feedback corresponding to imagined motor movements may investigate the additional role of visuo-motor contingencies during motor imagery and hand ownership (Mercier et al., 2008). Finally, the present work analyzed oscillatory effects in an offline situation, averaged across multiple participants. Future research is needed to find reliable, online neural indicators of ownership. Our work suggests mu-band oscillations to be a likely candidate (Study 1 and 2), but it remains to be seen if ownership experience can be predicted at the single-trial level or detected in spontaneous, ongoing EEG activity. Such online detection would aid in the design of ecological neuroprosthetic devices that adjust control to account for ongoing neural measures of ownership (see also *Section 4.6.3*).

4.4.2 Boosting BMI performance with multimodal feedback

By applying our experimental paradigm from Study 1 to a BMI motor imagery setting, we found illusory ownership to significantly alter offline, single-trial decoding performance (Study 2). Applying limb ownership manipulation in BMI contexts represents a first step toward the use of paradigms inspired by cognitive neuroscience to inspire the engineering of BMIs. Recent advances in engineering have taken permitted researchers to provide closed-loop feedback in BMIs (Figure 18), resulting in a growing body of evidence that multimodal, visuo-proprioceptive feedback can boost BMI performance over unimodal visual feedback in invasive BMIs for monkeys (Suminski et al., 2010) and in non-invasive BMIs in humans (Ramos-Murguialday et al., 2012; Gomez-Rodriguez et al., 2011). Importantly, these studies stress that performance is only increased if visual and proprioceptive cues are spatially and temporally coherent, and are thus in line with findings from cognitive neuroscience showing both limb ownership (Makin et al., 2008; Blanke, 2012) and agency (de Vignemont and Fourneret, 2004) to depend on both the spatial and temporal coherence of visual, proprioceptive, and tactile cues (see also Study 3). Though these engineering advances can be explained by findings from a large literature in the cognitive neuroscience of body ownership and agency, further collaboration is needed

Figure 18: Boosting illusory ownership and agency with meaningful sensory feedback. Contemporary setups using brain-machine actions to "close the sensorimotor loop" and move the body via external devices. Future complex systems will continue to build upon techniques from robotics, neuroimaging, and perhaps brain stimulation to provide closed-loop control with brain-machine interfaces. *Left:* A haptic device to clench the actual hand during motor imagery of hand movement (from Ramos-Murguialday et al., 2012). *Center*: A haptic robot designed to flex the arm during motor imagery of arm movement (from Gomez-Rodriguez et al., 2011). *Right:* Direct brain stimulation to somatosensory regions to provide artificial tactile sensation in monkeys (from O'Doherty et al., 2011).

between engineers and neuroscientists to fully characterize the perceptual and subjective consequences of such closed-loop control.

4.4.3 Probabilistic computational models of hand ownership

Most studies investigating illusory ownership employ parametric designs that manipulate unimodal sensory input and discuss its effects on the RHI. In an alternative approach, we consider sensory input to be a set of continuous trimodal sensory input parameters that, once processed by an optimal Bayesian observer, results in the perceptual, illusory effects of the RHI. This approach is inspired by evidence that humans optimally integrate sensory information in a large range of sensorimotor and perceptual tasks (Körding and Wolpert, 2006; Ernst and Bülthoff, 2004; Chater et al, 2006) and represents a more systematic approach to the conceptual understanding the RHI wherein future empirical results can be tested against, assimilated into, or compel revisions to our integrative model.

Alongside analogous models applied to visuo-auditory perceptual illusions such as the ventriloquist effect (Körding et al., 2007), this approach offers direct insight of how to computationally describe other bodily illusions as studied in the cognitive neuroscience of bodily self-consciousness such as full body or body-swap illusions (Lenggenhager et al., 2007; Petkova et al., 2011; Blanke, 2012), numbness illusions (Dieguez et al., 2009), or deformed body part illusions (Schaefer et al., 2007). Moreover, as Bayesian theory has been proposed as a framework to understand the sense of agency (Moore and Haggard, 2008), explicit causal probabilistic inference models such as ours may be described and tested against empirical data to validate conceptual hierarchical comparator model theories of agency (Pacherie, 2008; Moore and Obhi, 2012).

Concerning model improvements, it remains to be tested how accurately our model can predict ownership sensation given an individual subject's multisensory history (Bayesian prior) and the parametric configuration of sensory cues. Though our computational model already attributes the likelihood that one experiences ownership over an artificial limb on a trial-by-trial basis (for applications see also *Section 4.6.1*), our experimental design split subjective reports of ownership (questionnaires) from measurements of perceived hand position (proprioceptive drift). Thus, future work may measure both subjective reports and hand localizations on a per-trial basis to directly test model-predicted ownership against empirical ownership probabilities as well as to test whether subjective reports influence hand localization or vice versa.

4.5 Agency

4.5.1 Sense of agency for brain-machine actions

Consistent with studies that perturb SOA by injecting spatial and temporal deviations between bodily actions and their sensory consequences (Fourneret and Jeannerod, 1998; Farrer et al., 2008; Sato and Yasuda, 2005), in Study 4 we found **SOA for BMI-actions to be sensitive to both spatial and temporal visuo-neural conflicts**. Furthermore, for both types of action, SOA is highest in the experimental condition without inserted spatial or temporal conflict. These findings therefore suggest that our sense of causal authorship for both types of action is based on a set of common mechanisms that do not require direct comparison against reafferent proprioceptive and tactile signals (see *Section 4.5.2* below).

On the other hand, we observed **two important differences between SOA for bodily and BMI-actions**. First, in our experiments, SOA for unperturbed BMI-actions (*i.e.* congruent, no visuo-neural delay) was found to be around 80-85%, whereas most studies report entirely unperturbed SOA (*i.e.* 100%) for bodily movements in the same experimental condition (Fourneret and Jeannerod, 1998; Sato and Yasuda, 2005 Farrer et al., 2008). Second, the temporal sensitivity of SOA for BMI-actions was lower with respect to that for bodily actions. In our experiments, participants remained insensitive to visuo-neural delays of less than 1s (second study in Study 4), whereas in the aforementioned studies on agency for bodily actions, visuo-motor or visuo-auditory delays of approximately 300 ms are already sufficient to perturb SOA.

One potential explanation for these observed differences is that the signal-to-noise ratio is much lower for BMI-actions than for everyday, over-trained bodily actions (such as a reaching movement). A low signal-to-noise ratio for BMI-actions can be due to both the novelty of the task and to imperfections in the neural decoding process. Indeed, recent studies have shown that SOA for bodily actions increases with learning of novel motor tasks (van der Wel et al., 2012), but these findings remain to be tested for SOA over BMI-actions. For instance, by testing naïve BMI users against expert users, future work may find differences in the magnitude of SOA and in temporal sensitivity to visuo-neural conflicts.

It could also be possible that the observed dissimilarities in SOA between bodily and BMI-actions are due to differences in the neural systems underlying representations of such actions. To test this, future studies may investigate and directly contrast the electrophysiological consequences of SOA manipulation for bodily and BMI-actions. Alternatively, one might use our paradigm to manipulate agency with combined EEG and fMRI technologies to measure BOLD responses during EEG-based BMI control (Halder et al., 2011; Hinterberger et al., 2005) and during bodily control for a similar task. Any revealed dissociation in the neural structures underlying both types of action may explain the observed SOA differences in Study 4.

4.5.2 Theoretical ramifications

Tapping into cortical motor representations may be a way of accessing a physiological substrate of the transformation process between intention and action (Decety, 1996). Decoding and generating actions directly from cortical activity creates a novel situation in which experimental paradigms such as those presented in Study 4 can test SOA in the absence of re-afferent proprioceptive and tactile information. Our approach facilitates the experimental decomposition of SOA into its relevant, constituent sensory and neural systems and thus provides new potential for the neuroscientific investigation of SOA. In addition, measuring agency for BMI-actions can provide a new perspective on the engineering of BMIs, namely by guiding technological advances with an understanding of the perceptual and subjective experience of BMI control (see *Section 4.6.2*).

Do our findings provide deeper insights to the current theoretical models of sense of agency? To our knowledge, all previous empirical work on agency has focused on testing SOA with respect to bodily movements (Repp, 2005, 2006; Repp and Knoblich, 2007; Knoblich and Repp, 2009; Daprati et al., 1997; Daprati and Sirigu, 2002; van den Bos and Jeannerod, 2002; Nielsen, 1963; Fourneret and Jeannerod, 1998, Franck et al., 2001; Haggard et al., 2002; Knoblich et al., 2004; Synofzik et al., 2006; Kanape et al., 2010) and several theoretical accounts have been put forth to explain these diverse empirical findings on SOA for bodily actions (Wegner, 2002; Blakemore and Frith, 2003; Knoblich and Repp, 2009; see also introduction *Section 1.1.4*).

The **sensorimotor comparator model** inherently assumes the body's involvement in action generation: SOA depends on the degree of congruence between bodily movements (motor commands in efference copies) that are

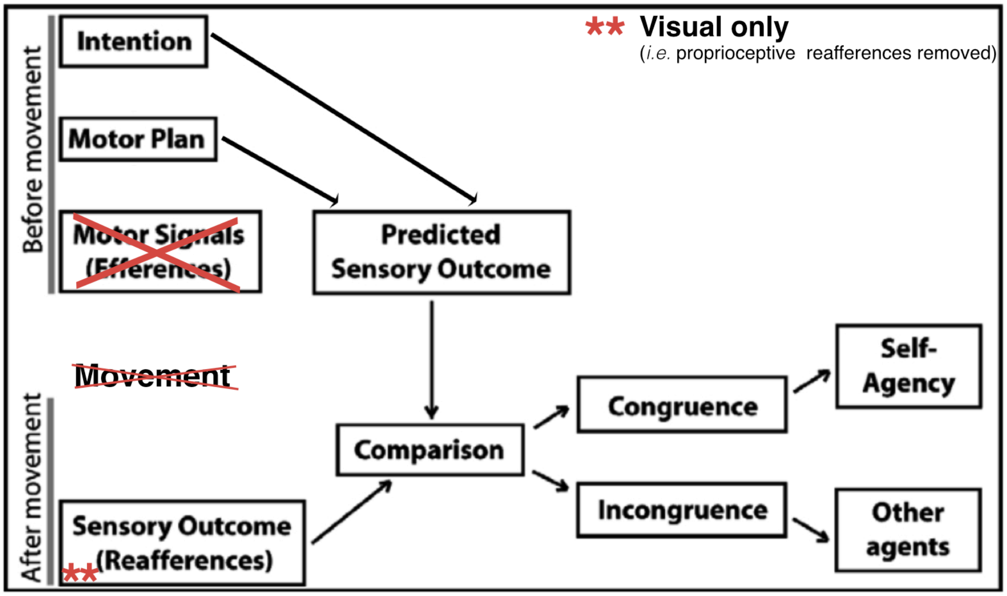

Figure 19: A modified sensorimotor comparator model in the context of BMI-actions. We tested SOA for machine-mediated actions without accompanying overt bodily movement. According to the comparator model, SOA for these BMI-actions must have been generated by comparing predicted outcomes against actual outcomes. But where can this prediction arise in the absence of bodily movement? We outline here the possibility that participants compared their motor intention or plan directly against the re-afferent visual information (cursor movements). Figure adapted from David et al., 2008.

matched against re-afferent sensory feedback. Our results for actions without an associated bodily movement are partially compatible with this account. We found SOA for BMI-actions to depend on the degree of visuo-neural delay, paralleling findings for visuo-motor (Fourneret and Jeannerod, 1998) or visuo-auditory delays (Sato and Yasuda, 2005). Furthermore, the sensorimotor account predicts that improved performance should result in higher SOA, as this yields a better match between predicted and actual sensory consequences. In line with this prediction, our psychophysics results demonstrated that improved classification performance was strongly coupled to increased SOA.

On the other hand, our findings also suggest the **need to modify** to the sensorimotor comparator model to allow for the case where motor signals without accompanying bodily movement (*e.g.* voluntary neural modulation via motor imagery) are compared with re-afferent sensory effects (Figures 19 and 20). In addition, as it stands, the sensorimotor comparator model cannot explain the

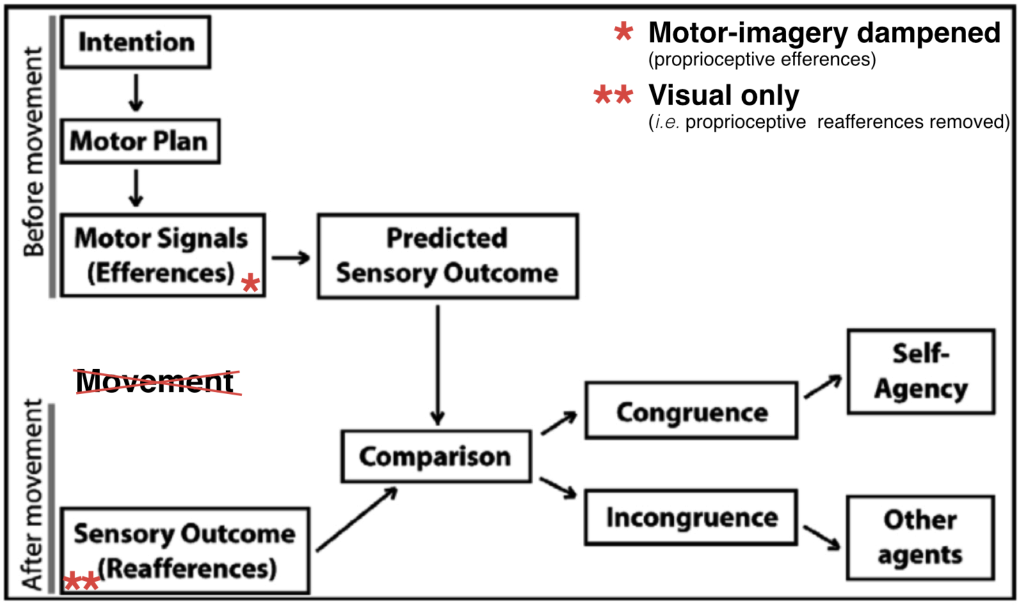

Figure 20: A modified sensorimotor comparator model in the context of BMI-actions. We outline here the possibility that participants compared efference copies that were dampened (due to motor imagery) against re-afferent visual information (cursor movements). Figure adapted from David et al., 2008.

everyday case where SOA is attributed to action representations that are formed but no movement is executed and no re-afferent sensory feedback is present (*e.g.* thoughts, action observation, or motor imagery; Jeannerod, 2007; Georgieff and Jeannerod, 1998).

Perhaps speaking more to the present data, the **theory of apparent mental causation** (Wegner, 2002) does not require bodily movements to feel SOA for actions. In the context of our experimental setup, this model predicts that a post-hoc judgment of SOA is made according to whether one's thought to move the cursor left was consistent with the subsequent outcome (*e.g.* the visual cursor went to the left). Evidence supporting this theory may come from our psychometric analyses for incongruent trials where the visual cursor moved opposite to the learned association. In these trials, participants reported a high SOA when classification performance was low. Low classification performance indicates that the brain activity modulation would normally yield cursor movements opposite to the cued direction, yet because we inverted the direction of the classifier output, the visual cursor displacements were coincidentally consistent with cued direction. Thus, despite this discrepancy between their neural activity and its corresponding sensory consequences, participants reported high SOA. This suggests that SOA in these trials could not be due to an explicit, low-level comparison of the visual and neural signals, as it appears that participants lack insight into their own internal neural states.

Despite these consistencies, our data cannot fully be explained by the theory of apparent mental causation. According to the theory, interpretation of the source of the action's outcome is subject to the so-called exclusivity principle. This principle holds that SOA arises only in settings where action consequences can be interpreted without a potential alternative cause. Given our experimental setup, this prerequisite to unperturbed SOA is violated; participants were aware that the visual feedback was generated from an imperfect decoding of neural activity. Thus, discrepancies between one's thought and the subsequent visual cursor displacement could have been interpreted as stemming either from poor task performance by the subject or from the computer and its algorithmic and hardware flaws.

Finally, given that our results for SOA over BMI-actions are partially compatible with both of the above accounts, it is worth considering our results in the context of more-recent, multifactorial theories that allows for comparisons between action predictions and consequences to occur at both sensorimotor and perceptual levels (Pacherie, 2008; Knoblich and Repp, 2009; Moore et al., 2009). This **hierarchical comparator model** posits that a conglomeration of motor, perceptual, and distal cognitive factors all influence SOA. Our data on SOA for BMI-actions fits favorably within this umbrella of a conceptual framework, as we found SOA to be dependent on low-level congruence between neural signals and corresponding visual re-afferences, but also to dissociate under the artificial case where the decoder output was inverted. This model has been used to explain how a sense of agency can emerge for joint actions for human dyads (van der Wel, 2012), a situation that closely resembles the joint action between brain and machine necessary for BMI-actions.

In summary, using **BMIs as a platform to research the sense of agency** opens up a large number of potential research possibilities and provides a novel theoretical perspective to help shape conceptual models of SOA. Future studies on SOA for BMI-actions can borrow from a considerable literature on SOA for bodily actions. For example, studies may test SOA for BMI-actions in schizophrenic patient populations, or investigate SOA for BMI-actions in alternative or additional sensory re-afferent systems (auditory or proprioceptive; *e.g.* Ramos-Murguialday et al., 2012).

4.5.3 Sense of agency when effect precedes cause

If SOA can indeed be felt for a movement for which no motor efference copy yet exists (*Section 4.2*), our findings imply that any strict temporal ordering of efferent motor signals and their subsequent sensory consequences implicit to the sensorimotor comparator model must be false. These results seem to rather suggest that any predictive comparison mechanism behind SOA must be temporally flexible to allow for either efferent or re-afferent signals to arrive first and serve as a predictor for the other. On the other hand, we demonstrated that SOA is strongly skewed toward positive delays (movement preceding visual consequences), and this preferred temporal ordering might be informative of the computational mechanisms underlying SOA. Further analysis of electrical neuroimaging data captured during this study may reveal neural mechanisms that reflect this asymmetry in SOA perceptual judgments.

4.5.4 Agency in artificial contexts: Implications on legal and moral systems

Responsibility in human moral and legal systems is intrinsically tied to the intention of actions, and therefore, the sense of agency (Haggard and Tsakiris, 2009; Moretto et al., 2011). Societal discourse has begun to acknowledge legal liability with respect to the consequences of unconscious bodily movements or actions lacking a sense of authorship (Beran, 2002; Mahowald et al., 1990).

Parallel to these concerns of responsibility and agency for bodily actions, our current trend toward technologies that transfer bodily action to machines is generating additional ethical and legal challenges. One contemporary issue of relevance concerns the push toward military technologies such as drones that translate human action into remote, machine-controlled actions. Lethal combat in these distanced, disembodied contexts may have strong effects on the psychology of killing (Miller, 2012). Yet, of even more significance to the work in this thesis, are the ramifications of the blurred boundary between brain and machine in BMI technologies. In BMIs, intentions can be translated into potentially dangerous machine-generated actions without any associated overt, bodily movement and therefore may present entirely new challenges for moral agency (Clausen, 2009; Blanke and Aspell, 2009) and personal identity (Lucivero and Tamburrini, 2008). These questions will need to be addressed by experimental investigations that directly test our sense of agency for brain-machine actions for real-time (Study 4) and for future, predictive controllers such as those described in our ongoing work on agency. Work in this thesis contributes to psychological and neuroscientific research on the brain mechanisms of causal authorship, which alongside findings from emerging fields such as neuroethics (Farah, 2005) and robotic ethics (Capurro et al., 2009), must inform future moral, ethical, and legal stances toward robotic control and BMIs.

4.6 Knowledge transfer between cognitive neuroscience and BMIs

Work throughout this thesis has demonstrated examples of the crosspollination of ideas between cognitive neuroscience and the neuroengineering of BMIs. Here I summarize the mutual benefit of research platforms that take this cross-disciplinary perspective and I then speculate on how the findings in this thesis could be combined into a practical application: cognitive motor neuroprosthetic controllers.

4.6.1 A new approach to cognitive neuroscience

BMIs offer cognitive neuroscience a unique platform to study brain function, providing a novel situation for the multisensory study of action and motor representation wherein potentially confounding re-afferent proprioceptive signals can be selectively removed from experimental setups. They permit neuroscientists to utilize neuroimaging as a tool to provide real-time feedback of neural activity, thus providing subjects with insight into their own brain activity (Sitarem et al., 2007). Throughout this thesis I have shown how borrowing technological and methodological approaches from BMI paradigms, as well as related engineering disciplines such as virtual reality and haptics/robotics, benefits cognitive neuroscience with enhanced experimental precision and reproducibility (Study 1 and 3; see also *Section 4.3*) and creates novel experimental scenarios (Study 4; ongoing work in *Section 4.2*). It has been stated that engineering approaches to studying the cognitive neuroscience of bodily self-consciousness will be of increasing importance for translational research on motor neuroprosthetic devices (Rothschild, 2010) and neurorehabilitation (Kwakkel et al., 2008), where the detailed description of stimulation parameters may be critical for robustness, reproducibility and testing.

4.6.2 A new approach to brain-machine interfaces

Research in BMIs is dominated by an engineering approach where advances are generally driven by boosting performance metrics over previously reported methods. In an orthogonal approach, cognitive neuroscience attempts to understand the neural and behavioral mechanisms of human cognition and phenomenology, often by experimentally perturbing normal performance. Despite its selective and destructive effects on task performance, these types of experimental manipulations shed light on the involved brain mechanisms and can yield results that suggest how better performance can be achieved in novel ways. Given this, what do the results from the studies in this thesis suggest? Can they be synthesized into a realizable system that can be embedded into the design of future neuroprosthetic devices?

4.6.3 Design of cognitive motor neuroprosthetics

Based on the present findings, I argue that the automated induction and online measurement of illusory hand ownership (Study 1, 2, and 3) as well as agency (Study 4, ongoing work in *Section 4.2*) may be used to guide or improve control of external devices including robotic arms using BMI technology as well as to control prosthetic arms that are interfaced with the peripheral nervous system and employ targeted reinnervation (Marasco et al., 2011; Navarro et al., 2005). More specifically, I foresee the need for these devices to be driven by complex algorithmic controllers that embed a hierarchical system of probabilistic models that account for signals at multiple tiers: sensorimotor, perceptual, and cognitive levels. To achieve this, sensors must measure current sensory configurations (*e.g.* proprioceptive, visual, and tactile states), and using probabilistic models such as those described in Study 3, may ascribe an online limb ownership probability. This information can be combined directly with data from brain sensors that capture ongoing neural measures of ownership (such as mu-rhythm oscillations; Study 1 and 2), agency (theta-rhythm activity (Cavanagh et al., 2010); or insights from our ongoing work), and additional cognitive signals (Musallam et al., 2004). Finally, to close the loop and further boost performance, there will be a need for artificial feedback stimulators (tactile, proprioceptive, visual), that may be realized by direct cortical stimulation (O'Doherty et al., 2011), robotics (Suminski et al, 2010), vibrotactile (Study 2), or pressure-based haptic devices (Marasco et al., 2008).

To calibrate these controllers, rigorous perceptual training schemes utilizing psychophysics (Study 4; ongoing work in *Section 4.2*) and Bayesian techniques (Study 3) may be further exploited. Important to this calibration procedure will be a focus on the human experience of embodiment of such limbs, including the cognitive and perceptual effects of using the device. A human-centric approach on neuroengineering may steer the development of algorithms that aim toward optimizing limb ownership and the sense of agency for the prosthetic device.

Several major challenges remain to the utopian vision of cognitive motor neuroprosthetic controllers presented above (Lebedev and Nicolelis, 2006). Of critical importance will be the discovery of robust features obtained by the sensors (external sensory and neural) that reflect limb ownership and agency. In contrast to most of the work in this thesis describing phenomena observed with offline analysis, and often collected across multiple subjects and in cued designs, these features will need to be reliably detected at the single-subject level from spontaneous, ongoing signals.

Finally, given the current limitations of neural decoding, it is likely that a paired emphasis will need to be placed on shared control via hardware controllers (Millán et al., 2010). Using online, predictive algorithms based on learning models of an individual's natural movement statistics (Ingram et al., 2008) may yield hardware controllers that predict ahead of time where the user is intending to move, independent to neural activity. In these novel contexts, research such as our ongoing work on SOA when actions precede consequences may better inform the limits of SOA for such machine-generated actions. We can imagine that these hardware devices may even improve on the imperfections of normal human motor behavior, preventing users from everyday clumsiness knocking over objects or stumbling.

4.7 Conclusion

As we progressively blur the lines between man and machine in our developments of technology-assisted tool use, tele-presence systems, medical robotics, and brain-machine interfaces, there is an increasing need to understand the neuronal, perceptual, and cognitive consequences of such a synergy. To work toward this end, I established a link between research in cognitive neuroscience and in brain-machine interfaces, concentrating on the two conceptual notions of ownership and agency. Furthermore, I strengthened the tie between these domains with methodologies including motor imagery paradigms, analytical techniques from psychophysics, machine learning, and Bayesian modeling, as well as technologies including haptic motors and sensors, virtual reality, neuroimaging, and real-time BMIs. I have outlined how future research using this approach can guide the design of cognitive motor neuroprosthetic devices that may restore lost motor function and aid in rehabilitation of patients suffering from limb loss, stroke, or paralysis. Moreover, I have highlighted how our work on the sense of agency for brain-machine actions is of strong impact to society for its implications on legal and moral systems.

Cross-disciplinary research always comes with the associated risk of scientific compromise in both disciplines (Horlick-Jones and Sime, 2004; Wickson et al., 2006; Klein, 2008). However, by using standard paradigms from both the cognitive neuroscience of bodily self-consciousness and the neuroengineering of brain-machine interfaces, I argue that the work in this thesis stays close to established standards while independently advancing ideas in both domains. Importantly, I believe that this work is of general scientific and societal interest and that future research can take inspiration from my approach toward the design of ecological and functional neuroprosthetic devices and toward a better understanding of how the human brain generates experiences such as owning a body and being the author of one’s actions.

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Abbreviations

BMI = brain-machine interface

RHI = rubber hand illusion

BOLD = blood- oxygen level dependent response

PET = positron emission tomography

EEG = electroencephalography

MEG = magnetoencephalography

fMRI = functional magnetic resonance imaging

NIRS = near infrared spectroscopy

SEP = somatosensory evoked potential

MNI = Montreal Neurological Institute

SOA = sense of agency