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Performance monitoring for brain-computer-interface actions

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A B S T R A C T

When presented with a difficult perceptual decision, human observers are able to make metacognitive judgements of subjective certainty. Such judgements can be made independently of and prior to any overt response to a sensory stimulus, presumably via internal monitoring. Retrospective judgements about one's own task performance, on the other hand, require first that the subject perform a task and thus could potentially be made based on motor processes, proprioceptive, and other sensory feedback rather than internal monitoring. With this dichotomy in mind, we set out to study performance monitoring using a brain-computer interface (BCI), with which subjects could voluntarily perform an action – moving a cursor on a computer screen – without any movement of the body, and thus without somatosensory feedback. Real-time visual feedback was available to subjects during training, but not during the experiment where the true final position of the cursor was only revealed *after* the subject had estimated where s/he thought it had ended up after 6 s of BCI-based cursor control. During the first half of the experiment subjects based their assessments primarily on the prior probability of the end position of the cursor on previous trials. However, during the second half of the experiment subjects' judgements moved significantly closer to the true end position of the cursor, and away from the prior. This suggests that subjects can monitor task performance when the task is performed without overt movement of the body.

1. Introduction

Studies of performance monitoring necessarily involve the performance of a task, and performance of a task, where performance is measured, invariably involves movement of the body (in order to register a response), even if only a single finger. Even without experimentally-delivered feedback the subject will at a minimum have proprioceptive and tactile feedback, and likely also visual (e.g. seeing one's own finger press a button) and auditory feedback, and any one of these could be used to infer which response was given and/or how well the task was performed.

In studies of perception of weak or ambiguous stimuli, on the other hand, it is possible to ask subjects, "how sure are you of what you just saw/heard/felt?". This kind of "second-order" judgement can be made independently of and prior to any feedback, and presumably requires internal evaluation of the quality of the neuronal evidence, also referred to as metacognition (Fleming, Dolan, & Frith, 2012; Metcalfe, 1996; Metcalfe & Greene, 2007; Miele, Wager, Mitchell, & Metcalfe, 2011; Smith, Shields, & Washburn, 2003; Yeung & Summerfield, 2012). Previous research has looked at metacognition of somatosensory perception (Hilgenstock, Weiss, & Witte, 2014) and attention (Kerr, Sacchet, Lazar, Moore, & Jones, 2013; Whitmarsh, Barendregt, Schoffelen, & Jensen, 2014), but not motor imagery, and not in the context of brain-computer interface (BCI) control.

Theorists have raised the distinction between decisional and post-decisional loci of metacognition in the context of an evidence-accumulation framework (Yeung & Summerfield, 2012). The primary task involves accumulation of sensory evidence up to a threshold, which, when reached, gives way to an overt response. In decisional-locus models, the very same information encoded by the neuronal decision variable (DV) is used to make both the first-order response and the second-order (metacognitive)

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judgement. Post-decisional locus models hold that processing of stimulus information continues even after the decision threshold is reached, leading potentially to changes-of-mind (Kaufman, Churchland, Ryu, & Shenoy, 2015) and, importantly, contributing to retrospective judgements of decision confidence (Murphy, Robertson, Harty, & O'Connell, 2015).

While it has been argued that performance monitoring and metacognition are governed by common principles, previous authors have suggested that a distinction be drawn between the two, and in particular the metacognition of agency (Haggard & Tsakiris, 2009; Metcalfe & Greene, 2007; Miele et al., 2011; Synofzik, Vosgerau, & Newen, 2008). Importantly, confidence judgements are thought to rely on neural processing in the lateral and medial prefrontal cortex (PFC) and possibly in areas of the parietal cortex as well (Kiani & Shadlen, 2009), whereas error monitoring has been reliably linked to activity in the anterior-cingulate cortex (ACC) (Dehaene, Posner, & Tucker, 1994). With these details in mind it is instructive to distinguish between two kinds of self monitoring:

(1) Monitoring of one's own bodily movements or bodily state. For example, one estimates one's own reaction time by monitoring the delay between stimulus onset and proprioceptive signals from the responding hand. (2) Monitoring of one's own brain activity, without relying on any signals from the body. For example estimating the quality of sensory evidence by directly probing neural activity in the relevant areas of sensory cortex. We set out to ask whether the latter kind of self monitoring, which is possible for sensory-evoked processes (metacognition for perception), is also possible for neural activity that is endogenously and voluntarily generated (performance monitoring for BCI action).

We posed this question using a motor-imagery-based (MI-based) brain-computer interface (BCI), with which subjects could voluntarily perform an action (moving a cursor on a computer screen) without any movement of the body and in the absence of any movement-related somatosensory feedback. Importantly, cursor-movement feedback was only visible to subjects during a pre-experiment practice session. No on-line visual feedback was given during the actual BCI experiment, during which the true final position of the cursor was only revealed to the subject at the end of each trial, after s/he had estimated where s/he thought the cursor had ended up after 6 s of BCI control.

Results show that during the first half of the experiment (minimum 120 trials) subjects based their assessments on the prior probability of the end position of the cursor on previous trials. However, during the second half of the experiment subjects' judgements moved significantly closer to the actual end position of the cursor, and away from the prior. This suggests not only that subjects can monitor performance of a task performed without movement, but also that this capacity can be learned. We conclude that internal monitoring is possible, not only for sensory-evoked neural activity (Fleming, Huijgen, & Dolan, 2012; Fleming, Weil, Nagy, Dolan, & Rees, 2010; Kiani & Shadlen, 2009; Pleskac & Busemeyer, 2010; Yeung & Summerfield, 2012), but also for voluntarily generated patterns of brain activity used in BCI control.

2. Materials and methods

2.1. Participants

For as yet unknown reasons, a substantial proportion of people who attempt to control a motor-imagery-based BCI are unable to do so – a phenomenon known as "BCI illiteracy" (Vidaurre & Blankertz, 2010). With this in mind, we pre-screened seventeen potential participants for their ability to control the BCI after an initial training session. Of these, four were not able to perform the task well enough (see below under "Practice with real time visual feedback") and another six were unable to perform the task at all (the BCI classifier was unable to adequately fit the training data). This left seven subjects, all males, right handed, aged 27.4 ± 2.9 years old (*mean ± SD*). 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 standard as defined in the Declaration of Helsinki and was approved by the local ethics research committee at the University of Lausanne.

2.2. Electroencephalography (EEG) recordings

Electroencephalography (EEG) was recorded from a 27-channel montage centered over the sensorimotor cortex at a sampling rate of 256 Hz (*g.tec*, Schiedelberg, Austria) as used previously (Evans, Gale, Schurger, & Blanke, 2015; Marchesotti et al., submitted for publication). Electrodes were grounded by an additional electrode placed on the forehead, and then re-referenced to electrodes attached to the earlobes. Data were processed in real-time using a custom Simulink model (*Mathworks*, Natick, Massachusetts, USA), with 256 classifier decisions per second smoothed by taking the average within a 1-s sliding window. Real-time BCI data processing methods are described in detail elsewhere (Guger et al., 2000).

2.3. Protocol and paradigm

The experiment took place during a single recording session of about 1–2 h (two recording sessions on two consecutive days for S1). During all recordings, subjects were comfortably seated about 50 cm away from a computer display with their hands on their laps (palms up).

2.3.1. BCI training procedure

Participants first performed a lateralized motor imagery task without visual feedback (Fig. 1). The data from this task were used to train the classifier. Subjects performed 2 blocks of 40 trials each (20 with left cue and 20 with right cue, randomly interleaved). The subjects had to alternatively perform left- and right-hand motor imagery (MI): While staying completely immobile and keeping their gaze on a fixation cross, the subjects had to imagine the sensation of moving their right (or left) hand (e.g. squeezing an imaginary ball) for 6 s according to a visual cue (arrow) pointing to the right (or left). Subjects were made aware of the difference between forming a visual image of their hand moving and imagining the somato-motor sensation associated with moving their hand, and were asked to do the latter.

Each trial started with the appearance on the screen of a fixation cross and a cue (an arrow pointing to the right or to the left) which remained on for 2 s (Fig. 1). Then the arrow disappeared cueing the subject to initiate MI. After 6 s, the fixation cross disappeared, indicating to the subject that s/he can relax (move, blink, etc.) for 3–3.6 s (drawn randomly from a uniform distribution). Then a new trial started with the appearance of the fixation cross and the cue on the screen.

We used the Common Spatial Patterns (CSP) decomposition (Blankertz, Tomioka, Lemm, Kawanabe, & Muller, 2008) for dimensionality reduction and feature selection, and used linear discriminant analysis (LDA) to train the classifier (Parra, Spence, Gerson, & Sajda, 2005). We used the first two and last two spatial patterns in the ranking returned from the CSP procedure as inputs to the classifier, and hence our feature space had four dimensions.

2.3.2. Practice with real-time visual feedback

After training the classifier, subjects performed 1 or 2 practice blocks of 40 trials each (20 with left cue and 20 with right cue)