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Sharing Your Mind With A Machine: A Brain-Computer Interface Approach

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ABSTRACT

From Hippocrates who realized 24 centuries ago that the brain is crucial for sensation and intelligence, and Descartes, who analyzed systematically this relationship between mind and body, to recent cortical implants, promising to give disabled volunteers control over their limbs just by using will and imagination, the brain's ability to consciously modulate its interface channels to executive functions has been one of the cornerstones for the continuing progress of the human race.

The real challenge in controlling machines solely by the power of imagination is to generate selectively, capture non-invasively and identify reliably the proper electromagnetic brain patterns corresponding to an optimal dictionary of desired actions. In the past two decades scientists have used two main approaches to establish brain-machine interfaces – the stimulated and the spontaneous command recognition. While the former methods detect subtle changes in the evoked brain responses to relevant / irrelevant stimulations, the latter techniques identify consciously-controlled general states of the mind, most often by measuring the brain activity oscillations or by pattern recognition. Although the stimulated approach requires external stimulation to operate properly, it offers the advantage of higher speed and flexibility.

We propose a new method for a stimulus-driven brain-machine interface, which identifies the conscious modulations by a human operator in one of the fastest sensory systems of the cortex – the visual motion system. This imagination interface has the capacity to deliver up to 10 dual commands per second at high recognition rates. Further research with various types of visual motion has the potential to increase the dictionary volume sufficiently for a practical command system which can bypass the activation of any muscles in the human body.

1. INTRODUCTION

In recent years many Brain-Computer Interface (BCI) studies have achieved progress towards the creation of communications and control devices using only the power of thought and imagination. A Brain-Computer Interface is any human-to-machine communication system, which does not depend on the brain's normal output pathways of peripheral nerves and muscles, according to a definition coined by the First International BCI Meeting in 1999 [1].

1.1. Historical Background

Bypassing the normal executive functions of the body and creating a direct thought-powered connection to a machine has become possible for humankind only after the emergence of several crucial discoveries in the distant past. Hippocrates in ancient Greece was the first to assert that the brain is the control center of the body, involved in sensation and intelligence: "Men ought to know that from the brain, and from the brain-only arise our pleasures, joys, laughter and jests, as well as our sorrows, pains, griefs and tears. Through it, in particular, we think, see, hear and distinguish the ugly from the beautiful, the bad from the good the pleasant from the unpleasant. It makes us mad or delirious, inspires us with fear, brings sleeplessness and aimless anxieties... In these ways I hold that the brain is the most powerful organ in the human body" [2]. Further cornerstones were Galen's fluid-mechanical theory of brain function in the 2nd century, Galvani's first demonstration of bio-electrical forces existing within living tissue in the 18th century [3], Richard Caton's discovery of electrical signals in animal brains in 1875 and Hans Berger's first electroencephalographic (EEG) measurements of electrical waves, including alpha and beta waves, on the surface of the skull in humans in the 1920's [4].

The first BCI studies were initiated at the Laboratory for Neural Control at the U.S. National Institute of Health (NIH) in 1968, and at the Advanced Research Projects Agency of the U.S. Department of Defense in 1970. The first "locked-in" paralyzed human user, implanted with invasive BCI technology in 1996 by Neural Signals Inc [5], was able to control successfully a computer cursor and used initially cognitive load tasking which gradually transformed into a form of free 'operant conditioning'. Other invasive BCI studies have demonstrated the more complex usage of a robotic gripper arm controlled entirely by brain activity optimized by visual feedback [6]. Success in non-invasive BCI in recent years has been more moderate, but still impressive, as illustrated by Pfurtscheller group's ability to replace artificially the hand grasp function in a tetraplegic patient [7]. Beta-wave activity from surface EEG data was recorded and classified in real time while the subject imagined foot movement, after which the output signal directed a functional electrical stimulation (FES) device to help the paralyzed hand grasp a cylinder.

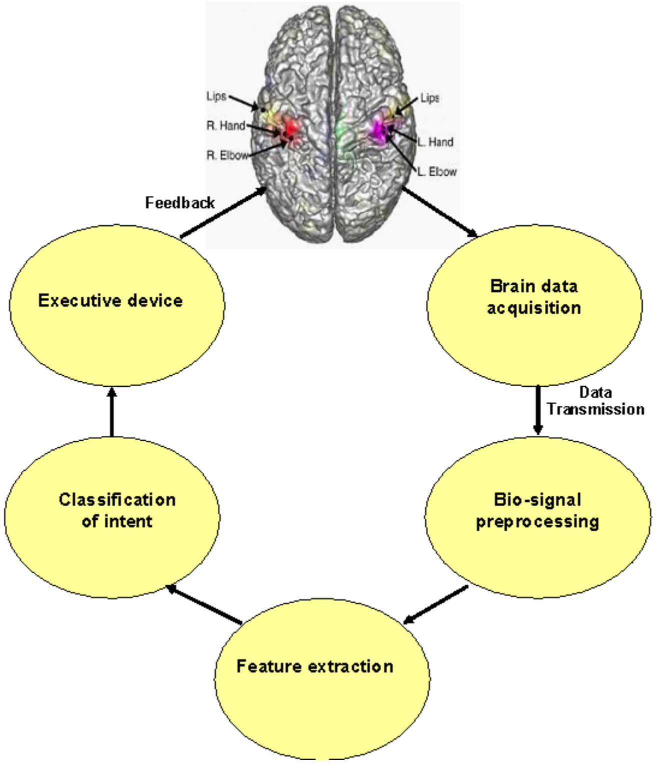

Fig. 1. Basic block diagram of a Brain-Computer Interface device.

1.2. Characteristics of BCI systems

An optimal BCI system should strive to incorporate the following characteristics:

(a) Maximal number of commands (degrees of freedom)

(b) Maximal accuracy of command recognition (noise and artifact resistance)

(c) Maximal speed of command transfer (influenced by stimulus rate, information content)

(d) Maximal comfort for users (influenced by the recording equipment, environment, ease of control of the targeted mental activity)

(e) Maximal resistance to fatigue and emotional states

(f) Maximal resistance to external distractions, passing thoughts

(g) Maximal tolerance to common neurological disorders

(h) Minimal inter-user tuning before usage

(i) Minimal training time for the user, as well as for the machine (with emphasis on special techniques)

(j) Minimal cost of operation

(k) Ability to switch interface on/off and to cancel or recycle commands

(l) Attractive biofeedback graphical user interface for enhanced motivation

1.3. Applications for BCI systems

As the technology improves, Brain-Computer Interfaces find an increasing number of real-life applications:

1.3.1. Applications for “locked-in” users (suffering from ALS, spinal cord injury, brain-stem stroke)

(a) Neuroprosthesis (restoring motor functions in disabled users)

(b) Locomotion assistance (wheelchair control for disabled and elderly users)

(c) Thought-Translation Devices (TTD) (virtual keyboards for email and word processing; control of room lights and TV)

(d) Biofeedback therapy (for example, manipulation of slow cortical potentials in epilepsy patients to prevent a seizure).

1.3.1. Applications for healthy users

(a) Virtual reality control (role play, multi-player games, navigation)

(b) Neural enhancements (additional artificial limbs, memory chip implant)

1.4. Data acquisition modalities for BCI systems

Table 1 shows a comparison of the available data acquisition modalities in current Brain-Computer Interface systems, with their pros and cons.

Since high time resolution is crucial in such systems, the only available measurement methods include non-invasive EEG, invasive intracranial electrocorticography (ECoG) and invasive intracortical neuronal unit recordings.

1.5. BCI experimental approaches

Differences in data acquisition modalities impose also limitations on the experimental approaches to induce reliable and identifiable mental commands. There are two basic types of BCI:

(a) BCI based on stimulated responses - phase-locked / driven brain activity (P300 oddball responses, steady-state visual evoked potentials, slow cortical potentials, visual motion responses [8]).

(b) BCI based on mental states by inducing specific spontaneous brain activity, cue- or internally-paced. Two subtypes of mental-state BCI are based on cognitive load (response modification by feedback, using specific imagination tasks – limb movement, grasping, mental arithmetic) and on 'operant conditioning' (response modification by feedback - no specific cognitive targets, based on the "just do it" principle. Usually, invasive BCI implant users employ initially cognitive load tasking which is gradually transformed into free 'operant conditioning' without the need for biofeedback. After about a year of practice, they do not need to think any more about moving their hands – cursor control is taken over directly by the motor cortex.

TYPE OF SIGNAL	INVASIVE	RESOLUTION	PROBLEMS
EEG / MEG	no	cm^2	Scalp distorts signals; major neuronal synchronization necessary
Intracranial ECoG	yes	mm^2	Requires surgery; some degree of neuronal synchronization necessary
Intracortical neuronal unit activity	yes	single neurons	Requires surgery; Neuronal migration (instability) over time
Time-resolved fMRI	no	mm^2	Low time resolution; metabolism-related
Optical tomography (NIR)	no	cm^2	Low spatial resolution; an emerging technique

Table 1. Comparison of BCI data acquisition modalities

2. VISUAL-MOTION BCI EXPERIMENT

One of the recently emerging and promising branches of BCI is the investigation of imagined-motion brain activity [9]. Visual motion is one of the most common stimuli in everyday life. Cortical responses to visual motion are fast and reliable, which makes them particularly suitable for BCI communication. While 'smooth' motion (SM) perception is the visual processing of natural, gradually-moving objects, 'apparent' motion (AM) corresponds to a series of discrete images shown in rapid sequence, for example on a cinema screen [10]. Smooth and apparent (discreet) motion have been studied extensively for decades, but researchers have had consistent difficulties establishing clearly to what extent the specific cortical processes involved in the perception of apparent motion are similar to those defining smooth motion.

Although both types of stimuli are perceived similarly as motion under proper conditions, some of the early (40-100ms) feed-back or feed-forward pathways the cortex uses to process them may be different [11, 12]. We hypothesized that subjects may be able to voluntarily modify their perception about the particular type of motion that they are experiencing which would correspondingly alter the electrical potentials reaching the surface of the head. In order to address this problem and to investigate just how much visual motion perception could be biased and controlled by imagination and voluntary brain activity, we compared the cortical responses elicited by imagined motion and by 3 types of observed visual motion with increasing ‘smoothness’ and recorded by a high-density EEG array. By using wavelet-packet-preprocessed ICA (Independent Component Analysis), we found that after a short training session, the early single-trial brain activity in motion perception within the first 100ms after stimulus onset could be voluntarily influenced by the subjects to match the responses to a particular type of motion with a success rate of up to 85%. Such a paradigm could be used for constructing fast brain-computer interfaces involving various types of motion.

3. EXPERIMENTAL METHODS

Our experimental setup included a high-density EEG system (EGI Inc., Eugene, Oregon, USA) with a 256 sponge-type electrode array. The subjects were seated in a dark shielded room where the stimuli were projected by two Marquee-type CRT projectors on the left side of a screen located 2.8m in front of them. The visual motion stimulus consisted of a thin vertical white bar on a black background generated by a specialized VSG graphics card (Cambridge Research Inc.). The bar was moved centripetally and centrifugally on the left side of the gaze center at two different displacements in random order - 5 degrees and 10 degrees. The inter-stimulus interval (ISI) between the starting and end points of motion was fixed at 50ms in all three experimental conditions – A) single-jump apparent motion (AM); B) smooth motion (SM) with the same ISI and displacements as in A); C) imagined-smooth motion experiment (IM) in which the subject voluntarily imagined a smooth path of motion to appear on the screen instead of the actual apparent motion stimuli.

Three healthy paid subjects participated in our experiments (2 female and 1 male, 22.3+-4.9 years old).

After data acquisition, we performed standard eye movement and other artifact rejection, after which the EEG data for each subject was segmented into 40 epochs with 1024ms durations and baseline-corrected relative to the stimulus onset. Subsequently, high-frequency noise in the data was removed by using a Mayer wavelet-packet transformation, so that non-stationary waveforms typical for evoked brain potentials were preserved undistorted. Half of the available epochs were averaged and used for defining individually the classification channels. The remaining single epochs for each type of motion were processed individually using independent component analysis (ICA) [13]. Let's assume that the observed signals X are generated by contributions from linearly mixed (H) sources S

$$X = H S + V,$$

where V is a vector of additive noise.

Then the calculated independent components Y can approximate and describe the original sources, so that

$$Y = W X.$$

The effect of selecting just one or several components could be studied by discarding all other undesirable components and reconstructing the signal back.

In that way ICA/BSS algorithms can be used for a number of attractive signal processing applications, including:

(a) ‘Cleaning’ of raw data by removal of undesirable artifacts, noise and interference

(b) Extraction of hidden or weak patterns and features

(c) Decomposition of composite multi-variable signals into independent components

(d) Spatio-temporal decorrelation of correlated signals

(e) Adaptive signal redundancy reduction

In our study we used a method called TQR Thin ICA (TICA), a mixed 2^{nd} and 4^{th} order algorithm employing hierarchical component extraction in order to extract the potentially significant sources of early cortical activity in visual motion - weak, but consistent response peaks with latencies < 100ms, buried into the strong brain noise typical for single-trial data.

3. RESULTS

Our results showed that it is possible to separate most single-trial apparent-motion AM responses from the smooth-motion SM responses in some electrode locations over the inferior parieto-occipital visual cortex (approximately corresponding to standard TP8) within the first 100ms after stimulus onset (motion end). However, observed early imagined-smooth-motion IM responses were closer to those in real smooth motion SM, although the subjects were actually stimulated by AM.

These motion-dependent changes were stronger in centripetal 5-deg displacement trials. In general, early parieto-occipital SM and IM activity was positive while AM responses were more negative. Tests with intermediate 2-stop apparent motion responses exhibited reduced amplitudes, as expected.

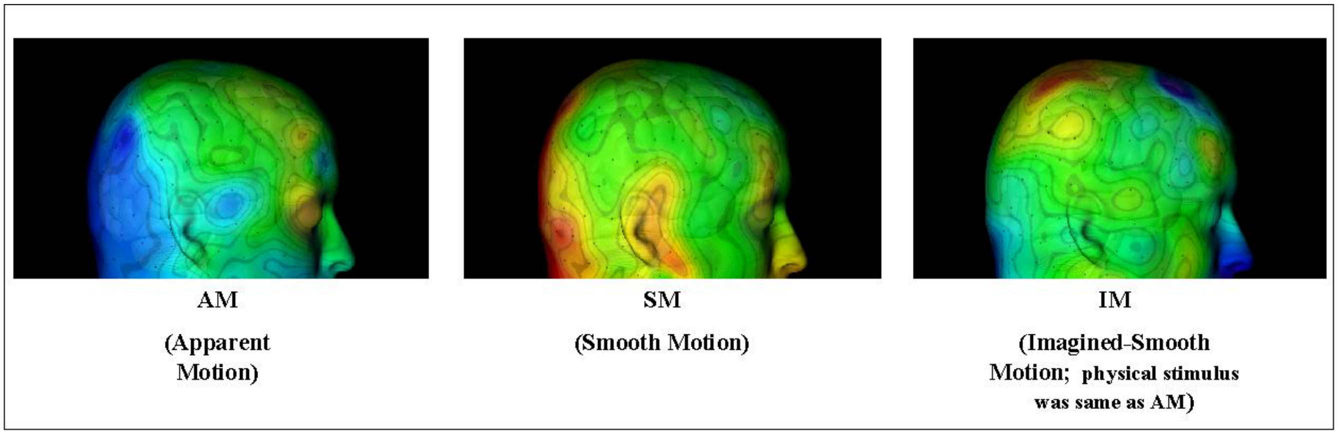

Fig. 2. Parieto-occipital areas in vicinity of MT/V5+ elicited specialized early motion components (40-110ms after stimulation / clue onset): AM: fast negative potentials; SM: fast positive potentials; IM: AM with imagined SM. Example for 256-channel EEG potential distributions for all 3 visual-motion conditions (AM, SM, IM from left to right) at 100 ms (subject A). Potentials were reconstructed from single independent components (combined 2nd- and 4th-order ICA/BSS) for each motion type.

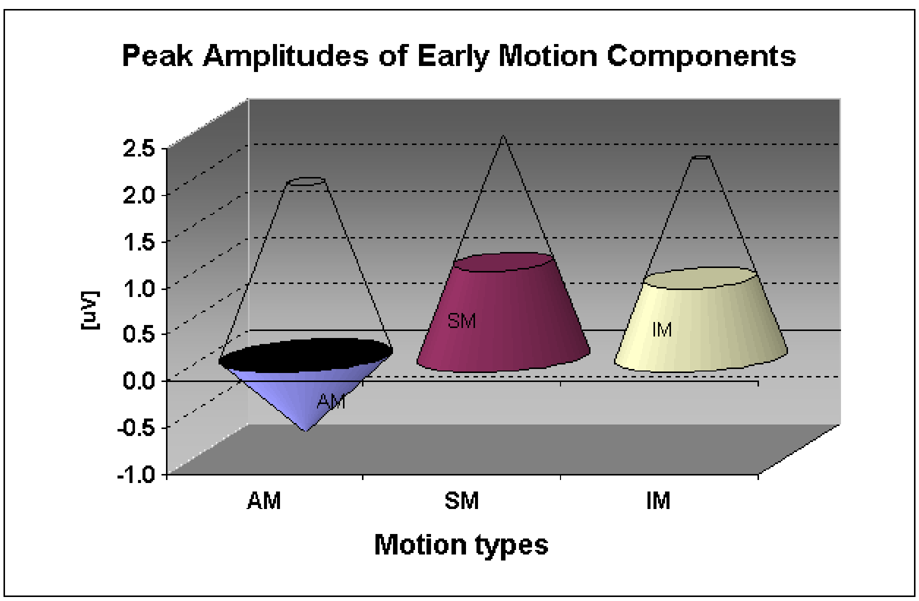

Fig. 3. Mean values and standard deviation for the early motion responses AM, SM and IM. AM peaks had negative amplitudes, while SM responses had positive amplitudes. AM-based IM peaks elicited by motion-responsive cortical areas exhibited modified responses during the imaginary task. IM showed the opposite polarity to that of AM types, even though their physical basis was AM. Note that IM peaks still had weaker peak amplitudes than the actual SM.

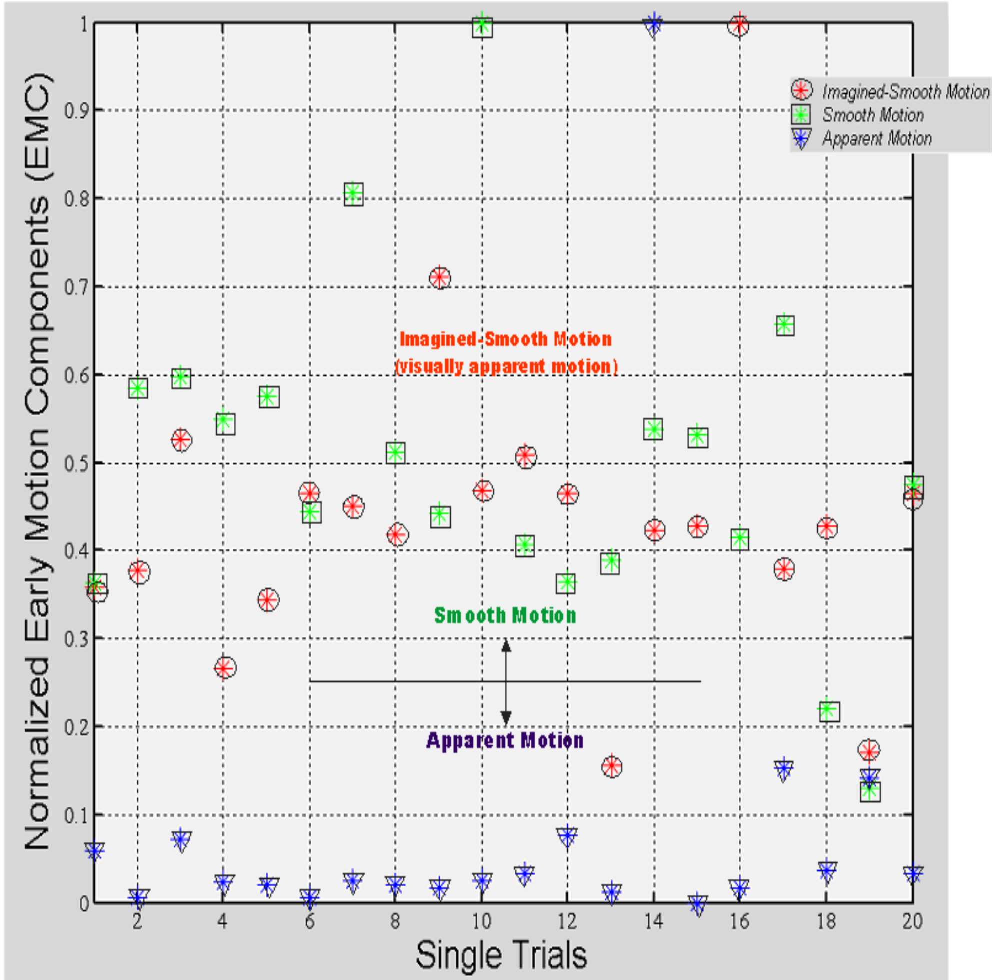

Fig. 4. Separation by polarity (reflecting different dipole orientations) of early evoked-response peaks from reconstructed single-component EEG for all 3 types of motion (smooth, apparent and imagined-smooth) in subject A

The single-trial imagined-smooth cortical responses IM were extracted with a rate of success of up to 85%, so that in most trials the amplitudes of the early IM-response components clustered closer to the corresponding SM than AM components.

The mean correlation for all subjects between IM and SM was 0.74 +- 0.10 and the correlation between IM and AM was 0.31 +- 0.19. Additional tests with 10-deg displacements showed significantly lower IM–SM correlations for two of the subjects which might have been due to the increased IM task difficulty, as well as to the effects of the increased eccentricity. This finding was in agreement with our previous study [14] in which we demonstrated that apparent motion response amplitudes were strongly displacement-dependent.

4. DISCUSSION

The results from these visual-motion BCI experiments demonstrate two main points:

(a) real- and apparent-motion responses can be discriminated on the basis of their electrical patterns on the surface of the brain (given sufficiently high electrode density)

(b) humans can influence their motion responses. How is it possible that near-real-motion responses could be produced by physically discrete apparent-motion stimuli? Although motion-sensitive cortical area hMT^+/V5 is known to be responsible for processing both real and apparent motion, differences and overlaps in cortical activity have suggested that perceived object continuity in apparent motion is supported by the simultaneous interaction with the shape and object processing lateral occipital complex (LOC) [15]. The motion area MT^+/V5 can be modulated substantially by perceptual interpretation [16], as well as by choice and attention, thus creating a perceptual bias [17]. Responses of MT neurons cannot be simply described by a feed-forward sensory activation. It has been shown that their firing patterns are based on retained memory from preceding motion stimuli [18]. As the sequential theory of early visual processing in the brain has been repeatedly challenged, there is now substantial evidence pointing to crucial top-down influences from parietal and frontal areas [19], as well as to the existence of fast motion-processing pathways bypassing the primary visual cortex (V1) and projecting directly to the middle temporal area (MT/V5) [20].

5. CONCLUSIONS

In conclusion, early motion-specific responses can be voluntarily altered by the subjects without using any of 'the brain's normal normal output pathways of peripheral nerves and muscles'. Subjects were able to elicit fast smooth-motion-specific activity in the inferior parieto-occipital cortex even when the actual stimulation consisted of just two flashes of sampled apparent motion.

These results showed, for the first time, that a human BCI operator may be able to modulate very quickly his visual-motion brain responses in order to communicate a simple command to a remote machine. After further investigations, involving various types and parameters of visual motion, these fast controllable imagination-based changes in the brain activity have the potential to increase the degrees of freedom in emerging brain-computer interface communications.

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