A BRAIN–CONTROLLED 3D SONAR SCANNER

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ABSTRACT

We present a non–invasive brain–machine–interface (BMI) prototype system which allows the simple control of a switch. The main goal of the system, based on electroencephalogram (EEG) recordings, is to create mechanical action from brain activity. Experimental work presented in this paper outlines the operation of a system which is a crude imitation of an ultrasound echolocation based vision mechanism, commonly used by bats and dolphins, which is controlled by brain activity. Simple time–frequency–space domain signal analysis methods are employed to generate the electrical control–signal, while the sonar transducer is mounted on a robotic arm capable of scanning the upper hemisphere.

***Index Terms*—** brain to machine interface, biomedical acoustics, signal processing.

1. INTRODUCTION

Until recently, transforming ones thoughts into physical actions and machine responses was possible only in the science fiction novels. However, a neologism "techlepathy" defines the exchange of information from one mind to another with the assistance of technology. Strictly speaking the term, as defined, includes even an ordinary cell–phone conversation. For purposes of reporting on brain–machine–interface (BMI) research, techlepathy refers specifically to technologies which rely upon readings and processing of electrical signal that have been generated at the neuron level.

Over the last decade, interest in research and development of an effective BMI interface has grown rapidly [1], with two main interfacing techniques being invasive and non–invasive. Invasive BMI techniques are driven by the need to somehow help patients with severe disabilities to operate computers, prosthetics, wheelchairs and enable meaningful communication with other humans [2]. However, this line of application is inherently limited to the clinical environment, which implies limited availability to a general engineering population due to the involvement of human subjects who are already in a need for medical attention, as well as high cost of the equipment and required support. Although some of the clinical experiments use non–invasive techniques, most of the published clinical works employ some degree of invasive techniques [1].

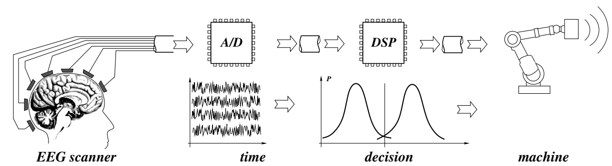

Fig. 1. EEG based BMI system architecture.

Application of BMI technology for healthy subjects is pursued much less then the clinical applications, simply because it is still far more convenient to use ones own senses combined with the current technology for communication. However, once a simple technology is developed, for example in a form of a simple "thinking hat", a wide range of possible industrial applications will open. It is not far fetched vision to imagine the thinking hat becoming the main form of a bidirectional communication device among humans and machines, replacing, for example, today's cell phones. In that vision, not only traditional voice message would be transmitted bidirectionally, but also various aspects of the human brain, such as emotions, alertness or concentration, as well as signals form visual and audio cortex.

Machine vision is also one of the contemporary mainstream research areas. However, for number of years, researchers who focused on camera based systems neglected sonar detection as a method for machine vision systems. However, it appears that there is renewed interest in revisiting the problem of how echolocation is used in nature with intent to create biologically inspired systems which are suitable for short–range low–speed applications [3].

The main objective of our research is to develop a simple EEG based BMI development platform, which includes both hardware and software components, leading into a low cost brain interface intended for a general, healthy population. In this paper we report initial results from our pilot BMI project aiming to create a brain–controlled 3D sonar vision system, and explore possible applications.

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Fig. 2. Electrode setup.

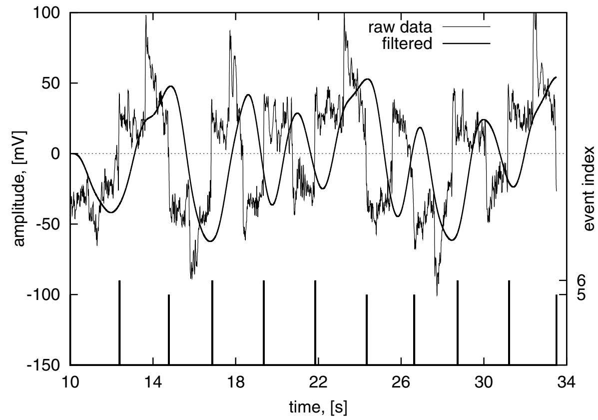

Fig. 3. Partial time domain waveform diagram of a signal recorded by the electrode 32 showing both the raw data and waveform after a 1Hz low–pass filter applied; the event index is on the right side y–axis.

An overview of the paper follows. In Section 2, the experimental setup of the system is presented. In Section 3, an visually evoked potentials stimuli plan is outlined. Space–time–frequency experimental results are discussed in Section 4. Details of sonar transducer implementation are shown in Section 5. Concluding remarks are in Section 6.

2. EXPERIMENTAL SETUP

The block diagram of our BMI system prototype is shown in Fig. 1. The system employs high–impedance electrodes, as shown in Fig. 2, which need to be checked individually for good contact. At the beginning of the experiment, the actual impedances of individual electrode values are measured and stored in a file, so that the subsequent power level calculations could be normalized accordingly. The raw data was sampled at a conservative 500Hz sampling rate. Furthermore, the data is filtered by a 30Hz low-pass filter.

The data processing channel paths are as follows. Scalp–recorded EEG activity is collected by means of a 128 channel EEG scanner, (plus the reference electrode). The time domain waveforms are first amplified and sampled by a bank of A/D converters, then processed in the discrete domain by signal processing algorithms. Once the decision is made, the control signal is sent to an external machine, in this case a 3D sonar scanner device, which then performs preprogrammed action.

The initial set of experimental data was collected from two participants, a young female and an older male, totalling 10 blocks each being five minutes long, split into three experiments over two separate days. Hence, the first two experiments used non–trained ("naive") participants. Since our intention was to develop a pilot BMI platform prototype, we opted to limit the number of participants in order remove subject to subject variations during this early phase of the project. Therefore, the third experiment was repeated with one of the two participants, who now was considered trained.

3. VISUALLY EVOKED POTENTIALS

The two healthy subjects who participated in this project were seated at a normal reading distance from a computer monitor. The subjects received on–screen instructions at the beginning of each of the five minutes long sessions. Our stimuli plan consisting of seven different events were defined and accompanied with the following on–screen instructions:

1. event 0: if there is no other stimuli, focus on a white cross at the centre of the screen,
2. event 1: white square at the left side of the screen, do not move eyes from the centre and ignore the event,
3. event 2: white square at the right side of the screen, do not move eyes from the centre and ignore the event,
4. event 3: white square at the left side of the screen, do not move eyes, just imagine the eye movement,
5. event 4: white square at the right side of the screen, do not move eyes, just imagine the eye movement,
6. event 5: white square at the left side of the screen, move eyes and focus on the square until it disappears,
7. event 6: white square at the right side of the screen, move eyes and focus on the square until it disappears.

The paradigm used in the present investigation was chosen because it is easy to administer and is known to evoke distinct lateralized evoked potentials. Visual stimuli presented lateral to a central fixation point evoke a contralateral negativity most pronounced at central and parietal recording sites approximately 80–100ms post–stimulus onset. This negativity can be dissociated from an evoked negativity related to eye

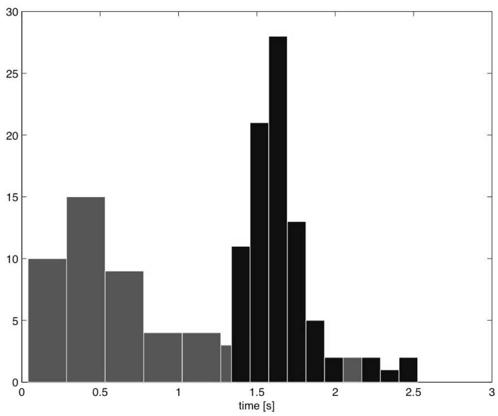

Fig. 4. Decision making triggering distribution for untrained (grey) and trained (black) sessions of the same subject.

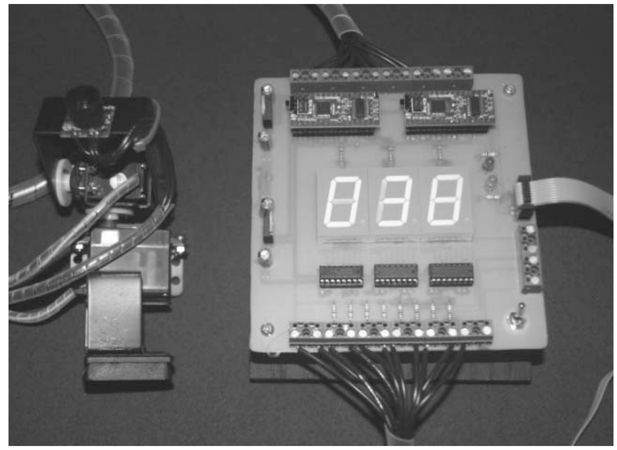

Fig. 5. 3D sonar scanner; transducer mounted on a rotating head and control electronics are shown.

movement control commands that evolves in similar regions but later in time, approximately 140–160ms post–stimulus, see Fig. 8 in [4].

Latency encountered in this kind of experiment is considered acceptable for controlling a machine with relatively slow dynamics, such as our scanner. For example, a full scan of the upper hemisphere by the sonar scanner takes up to 10 minutes.

4. SIGNAL ANALYSIS

In the current analysis, the signal from the electrode 32 is used. Figure 3(top, raw data) depicts time domain realizations of the electrode for several events. Closer examinations reveals interesting patterns. For the event 5, the electrode 32 shows a large negative value. Similarly, for the event 6, the electrode 32 has a large positive value.

The analysis consisted of three separate experiments. In the first experiment, a 2.3 seconds long running window is used. The width of the window is derived from initial analysis which considered the distance between consecutive events. Provided the running window, a mean value is calculated for each data block. If the mean value is greater than zero, it is assumed that the event 6 occurred, otherwise event 5. In the second experiment, the signal from electrode 32 is processed with a low-pass filter with a cutoff frequency of 1 Hz. A sample realization is shown in Fig. 3(top, filtered). The signal is fed through a comparator. If the signal is greater than zero, a rising edge is detected. Otherwise, for the signal values less than zero, a falling edge is detected. Based on the detected edges, a decision is made. If a rising edge occurred, it is assumed that event 6 occurred, otherwise event 5. These two experiments represent asynchronous detection. The last experiment assumes synchronous detection, i.e., the exact location of the events is known. Given that the exact locations are known, a mean value is calculated between two successive events. If the mean value is greater than zero, it is assumed that the event 6 occurred, and otherwise event 5.

The results of the analysis are summarized in Table 1. The worst performance is achieved in the first experiment. Even though, the events appear approximately every 2 seconds, they still appear randomly. Therefore, due to this randomness, the fixed window length approach does not provide good results. The third experiment provides the smallest error, however, a complete knowledge about the events is required. In reality, this approach might not be feasible. Therefore, the second experiment provides a promising path for future research. The current results indicate that the error is around 30 %. Nevertheless, these results can be further improved by incorporating adaptive equalization.

A comparison of decision making triggering distributions for trained and untrained sessions of the same subject (with delay times due to the LP filter included), Fig. 4, shows that in the case of trained subject the decision triggering impulses follow the input stimuli very closely, as oppose to very unfocused response in the first session.

Table 1. Results for the three conducted experiments.

Detection	Error Percentage	
	Untrained	Trained
Experiment 1	56.30 %	44.55 %
Experiment 2	55.46 %	29.75 %
Experiment 3	42.02 %	14.05 %

The future research will also examine the rest of the electrodes using the time-frequency analysis [5, 6]. The need for time-frequency analysis stems from the two facts. First, the EEG signals are highly nonstationary [1]. Second, such an

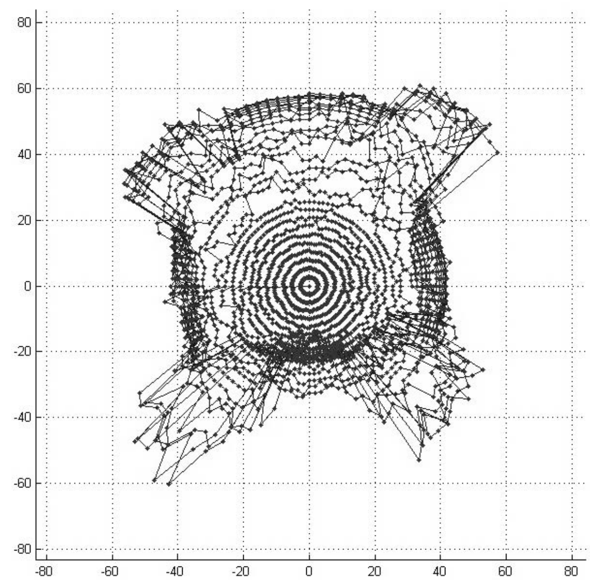

Fig. 6. 3D scan with edge detection.

analysis will reveal electrodes, and hence parts of the brain, which are affected by events 5 and 6.

5. MACHINE VISION

At the receiving end of our BMI system we have a machine vision system based on a single commercially available ultrasonic sensor, Fig. 5. We chose to control the vision system because we think that ultrasound vision is a good alternative to camera based systems, if we can learn how to "see" by using a sound in the same way the bats and dolphins do [3]. In other words, how to deal with reverberation artifacts associated with sonar probing of the environment.

The ultrasonic mapping system was designed as an electronically controlled mechanical platform which can generate 3D maps within the upper hemisphere. Absolute angular control of the platform is accomplished through the use of a single ultrasonic sensor mounted on a servo controlled omnidirectional platorm. Internal control logic can be set to scan the full upper hemisphere, Fig. 6, where the readings are processed in polar coordinates. Figure 6 shows an example of a 3D scan of a room, where corner effects are clearly visible. Alternatively, the scanned scene can be processed so that it emulates the human vision field. An example of a human face in front of a wall scan is shown in Fig. 7 using depth resolution of about 5cm within 6.5m range. Effects due to corners and various materials is clearly visible, indicating the need for better processing techniques, which is a subject of our future publications.

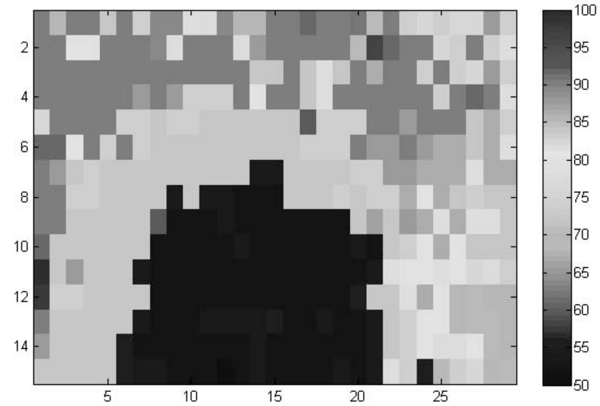

Fig. 7. Machine vision – a human face in front of a wall.

6. CONCLUSIONS

We presented an overview of our prototype BMI system capable of generating the simple on–off commands needed to control a 3D ultrasound vision system. Initial results, where we achieved about 86% accuracy in the second experiment, are certainly encouraging. Further development of more complex space–time–frequency algorithms applied to all 128 waveforms, as well as improvements in the vision algorithms, will certainly lead into a more sophisticated BCI artificial machine vision system.

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