DETECTION OF HAND EXTENSION MOVEMENTS IN THE CONTEXT OF A 3-STATE ASYNCHRONOUS BRAIN INTERFACE

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ABSTRACT

The low-frequency asynchronous switch design (LF-ASD) is a direct brain interface (BI) that detects the presence of a specific finger movement in the ongoing EEG. Asynchronous interfaces have the advantage of being operational at all times and not only at specific system-defined periods. In this paper, we present the design of a 3-state asynchronous BI for the detection of two different movements from the ongoing EEG. The proposed 3-state asynchronous BI detects right and left hand extensions. Using data collected from two able-bodied individuals, it is shown that the error characteristics of the new system in detecting the presence of movement are significantly better than the 2-state LF-ASD, with true positive rate increases of up to 22.4% for false positive rates in the 1-2% range. An average performance of 61.5% was achieved in differentiating between left and right hand movements.

1. INTRODUCTION

Over the past decade, several research groups have developed direct brain interface (BI) systems as possible alternative communication and control solutions for individuals with severe disabilities. For a review of the field, see [1]. BI technology aims at mapping the user's cortical activity associated with an intentional control (such as attempted finger movements) directly to application-specific control signals. Thus, control of various devices such as a neural prosthetic is made possible by cognitive processes only, in other words BI systems bypass traditional interface pathways which cannot be used by individuals with severe disabilities.

In developing a non-invasive BI system, the 2-state Low Frequency-Asynchronous Switch Design (the LF-ASD) was first introduced as a BI for asynchronous control applications [2]. Unlike synchronous BI systems, an asynchronous one is operational at any time and not at specific system defined periods. The LF-ASD seeks to recognize the movement related potentials (MRPs) related to *finger flexion movements* in the EEG signal. As an asynchronous BI, it is activated only when a user intends control (Intentional Control (IC) state). It maintains an inactive state output when a user is not meaning to control the device (i.e., the user may be idle, thinking about a problem, or performing some other action). This state of the brain is called the No Control (NC) state.

In this paper, we propose a 3-state asynchronous EEG-based BI system. Unlike the 2-state LF-ASD which detects the presence of a finger flexion from ongoing EEG, the 3-state BI design aims at detecting two different movements. While a 2-state LF-ASD can provide the user with the option to execute only one command (e.g. turn right), a 3-state asynchronous BI would give the user two command options (e.g. turn right or turn left). This has the advantage of allowing the user to activate more devices or giving him/her more flexibility in controlling a device (e.g. turn right or turn left).

The performance of a two-state asynchronous BI system is evaluated using true positive (TP) and false positive (FP) rates. For the evaluation of a 3-state asynchronous BI, the TP and FP rates are not enough and one needs to report the 3×3 confusion matrix of the classifier. A confusion matrix, used to evaluate the performance of a classifier, shows the predicted versus the actual classes of data. In a 3-state asynchronous BI, one needs to detect two different movements from the continuous EEG. This implies that the output can be in one of three states of NC, *movement I* (IC1), or *movement II* (IC2).

The previous design of the 2-state LF-ASD aimed at detecting an attempted right finger flexion. Recent studies with the 2-state LF-ASD have demonstrated an average true positive (TP) rate of 64.7% when the false positive (FP) rate is 2% [3]. Despite these encouraging results, our experience to date indicates that these error rates are too high for most practical asynchronous control applications. In the process of designing a three-state BI, we thought it is prudent to investigate the movements (as the neurophysiologic sources of activating the BI) that may generate stronger MRP patterns in the EEG. If so, the detection of such patterns would be easier and may yield improvements in the performance of the system.

Many studies by the neurophysiologic research community that explore the effects of different movements on EEG have been conducted. These studies show that the movements that involve more parts of the body (e.g. hand movement) or movements that need more effort (e.g. finger extension) generate stronger patterns in the ongoing EEG compared to other movements (e.g. natural finger flexion) [4,5,6]. At the same time, it has been reported that right and left movements (regardless of what the movement is) generate patterns in different locations of the brain [7]. Thus, we decided to pick two movements that a) involve more parts of the body, b) need more effort to execute, and c) generate patterns in different locations of the brain. Specifically, right hand and left hand extensions are used. These two movements may generate more discriminative patterns during the movement than finger flexions. If that is the case, then using these movements would improve our BI's performance in detecting the presence of a movement. These two specific movements have not been studied before in the context of a BI system.

This paper reports on the preliminary evaluation of a 3-state asynchronous BI that aims at detecting right and left hand extension movements in an asynchronous manner. We used two detectors to detect the presence of the left or right hand movements from the ongoing EEG. The first detector determines whether or not a movement is present and the second one determines whether the right hand extension or the left hand movement is executed.

The performance of the design is evaluated using EEG recordings of right and left hand extension movements of two able-bodied individuals. The goal of this paper is two fold: the first is to evaluate the performance of the system in detecting the presence of the new set of movements. The second is to introduce a design of a 3-state asynchronous BI.

In Sections 2 and 3 of this paper, the experimental paradigm, the latest design of our BI system and the evaluation method are presented. The results and conclusions are followed in Sections 4 and 5, respectively.

2. EXPERIMENTAL PARADIGM

The EEG data used in this study were recorded from 15 mono-polar electrodes positioned over the supplementary motor area and the primary motor cortex (defined with reference to the International 10-20 System at F1, F2, F3, F4, Fz, FC1, FC2, FC3, FC4, FCz, C1, C2, C3, C4, and C5). Electro-oculographic (EOG) activity was measured as the potential difference between two electrodes, placed at the corner and below the right eye. The ocular artifact was considered present when the difference between the EOG electrodes exceeded an operator defined threshold. All signals were sampled at 128 Hz.

The subjects used in this study consisted of two able-bodied subjects. Both subjects were male, right handed and 28 years old on average. Subjects were seated 150 cm in front of a computer monitor. The data were collected while the subjects were performing a guided task. At random intervals of mean 7 seconds, a target window was displayed on the subject's monitor. A box moves from the right side to the left side of the screen. When the box reached the target window, the subject tried to activate the custom-made switch by extending his right or left hand. An arrow, pointing to left or right on the moving box shows the subject whether to move his right or left hand. For each subject, an average of 150 trials from each movement was collected in two sessions at the same day.

3. STRUCTURE OF THE PROPOSED ASYNCHRONOUS BRAIN SWITCH DESIGN

Fig. 1 shows the block diagram of our proposed design. This design includes two major blocks: a) *Detector I* which determines whether a movement is performed or not, and b) *Detector II* which determines whether the movement is right hand or left hand extension. The details of both detectors are explained as follows.

Fig. 2 shows the structure of *Detector I* [2]. *Detector I* uses features extracted from the 0-4Hz band in six bipolar EEG channels (defined with reference to the International 10-20 System at F1-FC1, Fz-FCz, F2-FC2, FC1-C1, FCz-Cz, and FC2-C2). After amplification, a low-pass FIR filter (0-4Hz) is used to decrease the interference with the features in the high-frequency band.

Previous studies show that when a movement is performed, a bipolar pattern similar to the one shown in Fig. 3 is generated in the ongoing EEG [2]. A feature extraction method based on the one employed in [2] is implemented. It generates large feature values when there is such a pattern in the spontaneous EEG. The delay parameters ($\alpha_i, \alpha_j, \beta_i, \text{and} \beta_j$), shown in Fig. 3, determine the shape of the pattern that needs to be detected. Thus, these delay parameters need to be properly determined so

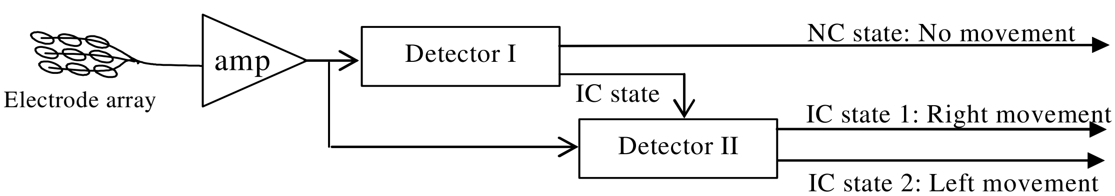

Fig. 1. Structure of the new 3-state asynchronous BI design

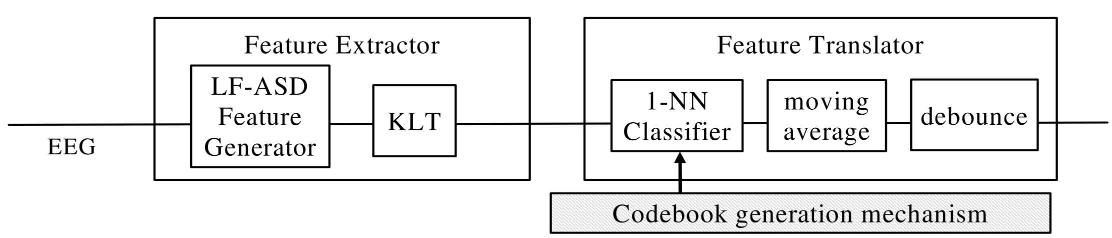

Fig. 2. Structure of Detector I, where KLT = Karhunen-Loève Transform, and 1-NN = 1-Nearest Neighbour.

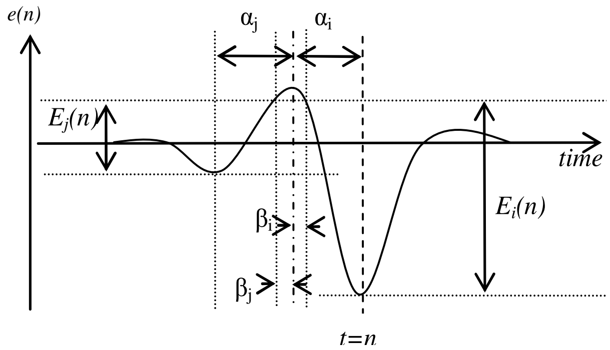

Fig 3. Description of delay terms ($\alpha_{\mathrm{i}}, \alpha_{\mathrm{j}}, \beta_{\mathrm{i}}, \beta_{\mathrm{j}}$)

as to detect the presence of a specific movement. In this study, the same delay parameters used in the original design of the LF-ASD are used. Specifically, α_{i} was set to 36 and α_{j} was set to 16. For simplicity reasons the delays of all channels were equally set and β_{i}andβ_{j} were set to zero. The procedure of feature extraction is repeated for each of the six bipolar channels. The resulting feature vector is a six-dimensional vector, with each dimension reflecting the value of the feature in each channel.

The Karhunen-Loève Transform (KLT) component is used to reduce the 6-dimensional feature vector to a 2-dimensional feature vector. A 1-NN (1-nearest neighbour) classifier is used as the feature classifier. Finally, a moving average and a debounce block are used to further improve the classification accuracy of *Detector I* by reducing the number of false switch activations (for details, see [2] and [3]). *Detector I* classifies the input patterns, at every 1/16th of a second, to one of the two classes, No Control (NC) or Intentional Control (IC) states.

Studies show that cortical activation related to movement preparation and execution desynchronizes the Mu (8-12Hz) rhythm of the EEG. This is known as event related desynchronization (ERD) [7]. ERD of a hand movement is more prominent over contralateral sensorimotor areas during motor preparation and extends bilaterally after movement initiation [7,8]. However, some studies show that the frequency band of ERD patterns varies from subject to subject [9]. *Detector II* contains a feature extraction block which calculates the power spectral density (PSD) features of the EEG. Specifically, Welch's Periodogram method [10] is used to extract the PSD features. Note that two different designs of *Detector II* are evaluated. The first design extracts the difference between PSD features of C3 and C4 electrodes in the Mu (8-12Hz) band. The second design extracts subject specific ERD frequency bands that lead to more discrimination between the two classes of left and right movements. Specifically, we employ the stepwise linear discriminant analysis (LDA) method [11] to select the subject specific ERD frequency bands. For both designs, window lengths of 128 samples with 90% overlap were used to extract the features. A 1-NN (1-nearest neighbour) classifier is used as the feature classifier. To generate codebooks for the 1-NN classifier, the k-means algorithm [12] with 3 vectors per class is used to generate initial clustering of each class. This is followed by Learning Vector Quantization (LVQ3) [12] to find the final codebook. Finally, if *Detector I* detects a movement in the ongoing EEG, *Detector II* classifies the input patterns to one of the two classes of right hand movement (IC1) or left hand movement (IC2).

3.1. Evaluation

For the evaluation of the system, approximately 40% of the data were used to train the classifier and the rest were used for evaluation. Instead of reporting the whole 3×3 confusion matrix, we report the performance measures that are important for our application. Thus, the ability of the subjects to control the BI system was performed by evaluating the performance of each detector. Two measures, described below, were used.

The first measure reports a) the percentage of correct movement detection (regardless of which movement is performed) during IC states (true positives, TPs) and b) the percentage of false switch activations during NC states (false positives, FPs). Specifically this measure reflects the performance of *Detector I*. A TP was identified if the BI system was activated at least once in a time window spanning 0.25 seconds before and 0.5 second after the expected time of the movement, a method similar to that employed in [13]. FPs were assessed in the periods before the box reached the target and after the end of the target window (as explained in Section 2). Periods during which ocular artifacts occurred were not evaluated.

The second measure which shows the performance of *Detector II,* reports the confusion matrix of *Detector II*. *Detector II* differentiates between right and left hand extensions.

4. RESULTS

The performance of *Detector I* in detecting the presence of left and right hand movements from the background EEG is shown in Table 1. The performance of *Detector I* is compared to the previous design (LF-ASD) for a debounce period of 16 (as used in previous studies [3]). In Table 1, we show the TP rates at fixed FP rates of 1% and 2% for the two designs. While, the latest design of the 2-state LF-ASD detects finger flexions from spontaneous EEG, *Detector I* detects left and right hand movements from spontaneous EEG. The results show that *Detector I* outperforms the latest design [3] of the 2-state LF-ASD by approximately 21% for both subjects.

Table 2 shows the performance of *Detector II*. Specifically, the confusion matrix of the classifier of D*etector II* when the FPs of *Detector I* were fixed at 2%, is reported. The confusion matrix is reported for two settings of *Detector II*: 1) PSD features extracted from traditional Mu band, and 2) PSD features extracted in subject specific frequency bands using stepwise LDA. As an example, for subject 1 and for the case that the Mu band features are used, 64% and 54% of the right and left hand movements are correctly classified. On average, the differentiation rate between right and left hand extensions using traditional Mu band PSD features and subject specific frequency bands are approximately 55.7% and 61.5%, respectively. Using subject specific frequency bands improves the performance of the system by approximately 5.8%.

Table 1. TP rates at fixed FP rates of 1% and 2% for the latest LF-ASD and Detector I.

Subject	Latest LF-ASD		Detector I		TP (%) Improvement at	
	TP (%) at		TP (%) at		FP=1%	FP=2%
	FP=1 %	FP=2%	FP=1%	FP=2%		
Subject 1	41.2	64.7	58.3	83.6	17.1	18.9
Subject 2	41.2	64.7	69.0	84.4	24.8	19.7
Average	**41.2**	**64.7**	**63.6**	**84.0**	**22.4**	**19.3**

Table 2. Confusion matrix for discrimination between left and right hand movements. The values are estimated for FP rate of Detector I set to 2%.

Subject	Confusion matrix (%)	
	Mu band features	Subject specific frequency bands
Subject 1	$\begin{bmatrix} 64 & 36 \\ 46 & 54 \end{bmatrix}$	$\begin{bmatrix} 66 & 34 \\ 41 & 59 \end{bmatrix}$
Subject 2	$\begin{bmatrix} 52 & 48 \\ 47 & 53 \end{bmatrix}$	$\begin{bmatrix} 61 & 39 \\ 40 & 60 \end{bmatrix}$

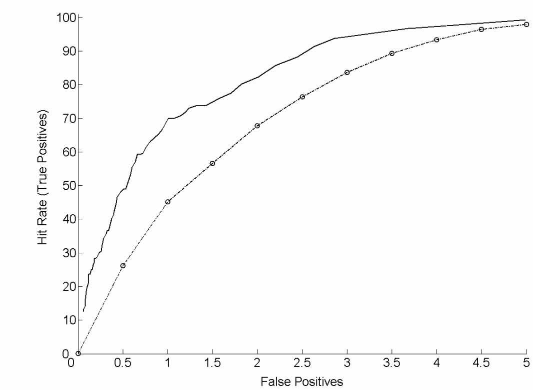

Fig. 4. Truncated ROC curves for the latest LF-ASD (Dashed line with circles) and our proposed design for subject 2 (Solid line).

Fig. 4 shows the receiver operating characteristic (ROC) curves of *Detector I* for two cases: 1) the latest LF-ASD design [3], and 2) our proposed hand-movement-based BI design for subject 2. As we are interested in lower FP rate levels, only those FP values below 5% are shown in the ROC curves. As the figure show, for every fixed FP rate level, our proposed BI system generates much better TP rates than the previous design.

5. CONCLUSIONS

In conclusion, the error characteristics of the system in detecting the *presence* of hand movements are significantly better than the previous system which aimed at detecting a single finger movement. The true positive rate increased by approximately 21% for false positive rates in the 1-2% range.

The performance of the proposed asynchronous BI system in differentiating between the left and the right hand movements was approximately 55.7% and 61.5% for the two Mu band features and subject specific frequency band features, respectively. It is also shown that the use of subject specific frequency bands yield 5.8% better discrimination between right and left hand movements in average. Although the results of differentiating between right and left hand movements are promising, more improvements are needed. The use of different feature extraction methods, self-learning classification schemes, selection of proper electrode locations and evaluating the performance of the system on a larger subject pool are in the scope of our future directions.

6. REFERENCES

[1] T.M. Vaughan, “Guest editorial brain-computer interface technology: a review of the second international meeting,” *IEEE Trans. Neural Sys. and Rehab. Eng.*, vol. 11, no. 2, pp. 94 – 109, June 2003.

[2] S.G. Mason and G.E. Birch, "A Brain-Controlled Switch for Asynchronous Control Applications", *IEEE Trans. Biomed. Eng.*, vol. 47, no.10, pp. 1297-1307, Oct. 2000.

[3] J.F. Borisoff, S.G. Mason, A. Bashashati and G.E. Birch, “Brain Computer Interface (BCI) Design for Asynchronous Control Applications: Improvements to the LF-ASD Asynchronous Brain Switch,” *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 985-992, June 2004.

[4] G.H. Yue, J.Z. Liu, V. Siemionov, V.K. Ranghanatan, T.C. Ng, and V. Sahgal, "Brain activation during human finger extension and flexion movements," *Brain Research*, vol. 856, no. 1-2, pp. 291-300, Feb. 2000.

[5] S. Slobounov, J Johnston, H. Chiang, and W. Ray, "Movement-related EEG potentials are force or end-effector dependent: evidence from a multi-finger experiment," *Clin. Neurophysiol.*, vol. 113, no. 7, pp. 1125-1135, July 2002.

[6] A. Stancak, and G. Pfurtscheller, "Event-related desynchronisation of central beta-rhythms during brisk and slow self-paced finger movements of dominant and nondominant hand," *Cognitive Brain Research*, vol. 4, no. 3, pp. 171-183, Oct. 1996.

[7] G. Pfurtscheller, and F.H. Lopes da Silva, "Event-related EEG/MEG synchronization and desynchronization: basic principles," *Clin. Neurophysiol.*, vol. 110, pp. 1842-1857, 1999.

[8] G. Pfurtscheller, C. Neuper, C. Andrew, and G. Edlinger, "Foot and hand area mu rhythms," *International J. of Psychophysiol.*, vol. 26, no. 1-3, pp. 121-135, 1997.

[9] M. Pregenzer, and G. Pfurtscheller, "Frequency Component Selection for an EEG-Based Brain to Computer Interface," *IEEE Trans Rehabil. Eng.*, vol. 7, no. 4, pp. 413-419, Dec. 1999.

[10] P. D. Welch, “The use of the fast Fourier transform for the estimation of power spectra,” *IEEE Trans. Audio Electroacoust.*, vol. AU-15, pp. 70–73, 1967.

[11] Peter A. Lachenbruch, “Discriminant Analysis,” Hafner Press, NY, 1975.

[12] T. Kohonen, “The self-organizing map,” *Proceedings of IEEE*, vol. 78, pp.1464-1480, 1990.

[13] S.P. Levine, J.E. Huggins, S.L. BeMent, R. K. Kushwaha, L.A. Schuh, M.M. Rohde, E.A. Passaro, D.A. Ross K.V. Elisevich, and B.J. Smith: "A Direct Brain Interface Based on Event-Related Potentials." *IEEE Trans. on Rehab. Eng.*, vol. 8, no. 2, pp. 180-185, 2000.