EEG-EMG based Hybrid Brain Computer Interface for Triggering Hand Exoskeleton for Neuro-Rehabilitation

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ABSTRACT

Traditionally a Brain-Computer Interface (BCI) system uses Electroencephalogram (EEG) signals for communication and control applications. In recent years different biological signals are also combined with EEG signals to produce hybrid BCI devices to overcome the limitation of lower accuracy rates in BCI. This paper presents a new approach of combining EEG and Electromyogram (EMG) signals using the spectral power correlation (SPC) to create a hybrid BCI device for controlling a hand exoskeleton. The proposed method was tested on 10 healthy individuals for measuring its performance level in terms of accuracy. The EEG-EMG SPC based hybrid BCI was trained to classify the grasp attempt and resting states of the user. Upon successful detection of a grasp attempt, the hybrid BCI triggers the hand exoskeleton to perform a finger flexion-extension motion. The proposed EEG-EMG SPC method is also compared with the conventional only EEG based method which uses common spatial pattern (CSP) based spatial filtering. The results have shown that the proposed EEG-EMG SPC method yielded an average accuracy of 90±4.86% while the conventional EEG-CSP method yielded 79.75±5.71%. This significantly ($p<0.02$) improved performance in terms of classification accuracy indicates that EEG-EMG SPC based hybrid BCI is a better alternative than the conventional EEG-CSP based BCI to generate hand exoskeleton based neurofeedback.

Keywords

EEG; EMG; SPC; Hybrid BCI; Hand Exoskeleton.

1. INTRODUCTION

Every year a large number of people get affected by stroke in India, which is also one of the major reasons of disability. Recent population based studies have shown the incidence rate of stroke to be 119-145/1000,000 [1]. Therefore, developing advanced techniques of neuro-rehabilitation have become an active area of research these days. Stroke survivors are often found with severe forms of disability, which hampers their daily life activities drastically. As the conventional clinical therapies provided by the physiotherapists are proving to be less effective in patient recovery, a new thrust towards the technology driven rehabilitation techniques are coming into picture [2]. These include, EMG signal based systems and EEG-based BCI systems, which provides neuro-feedback to the patients, through virtual reality platform or using hardware like powered exoskeletons. However, several rehabilitation systems don't use biological signals, but few sensor based technique are used to assist the person in their limb movement using exoskeletons. These assistive devices along with neuro-feedback helps in reorganizing the neural connections around the affected areas of the brain to enable the patient to re-learn their motor controls, which is also termed as neuro-plasticity [3].

There are many BCI systems which uses EEG, magnetoencephalography (MEG), Electrocorticography (ECoG) or functional magnetic resonance imaging (fMRI) technology for controlling or communicating with external devices. But due to high temporal resolution, non-invasive nature and portability of EEG based data acquisition makes it a popular choice in developing neuro-rehabilitation applications [4]. EEG based BCI devices were also implemented in powered wheelchairs, prosthesis and exoskeletons [5]. However EEG signals also suffers from several drawbacks such as low spatial resolution due to volume conduction and lower accuracy due to low signal to noise ratio. On the other hand, the EMG signals are frequently used to control prosthetic devices and exoskeletons [6, 7]. However, using EMG signal alone depends on the amount of residual muscle activity which is subject to fatigue, especially in case of older people and stroke patients. To overcome these drawbacks, different biological signals are also fused with the EEG signal for improved performance [6, 8]. In recent years several methods of fusing EEG and EMG signals have become popular to build hybrid BCI systems [9]. Such hybrid BCI systems combines the features extracted from both EEG and EMG signals to detect the user's movement intent. Although the hybrid BCI approach is gradually becoming popular there are very few studies which deal with the bio-robotics applications. Studies have shown that the combined multimodal data from EEG and EMG enhances the movement intention prediction rate with increased reliability [10]. Leeb *et al.* [11] has also shown that the fusion of EEG and EMG signals resulted in higher accuracy than solely using either signal in generating neurofeedback.

In this paper we present a novel approach of combining EEG and EMG signals by fusing these two signals. Unlike the previous approaches which calculates the EEG and EMG features separately and then merge them to generate the feature vector, our method uses the spectrum power correlation between the EEG and EMG signals for different channel combinations and forms the feature vector on the basis of the correlation coefficients. The conventional only EEG based feature extraction which uses spatial filtering by CSP algorithm was also taken into account in our study to compare the proposed EEG-EMG SPC method for its performance in terms of classification accuracy.

The rest of the paper is structured as follows. First we discuss about the experimental protocol and the basic overview of the whole hybrid BCI setup. Then the EEG-EMG SPC method will be discussed in detail with brief description of the conventional EEG-CSP method, with which our proposed method is compared. After that the experiments and results will be discussed. And

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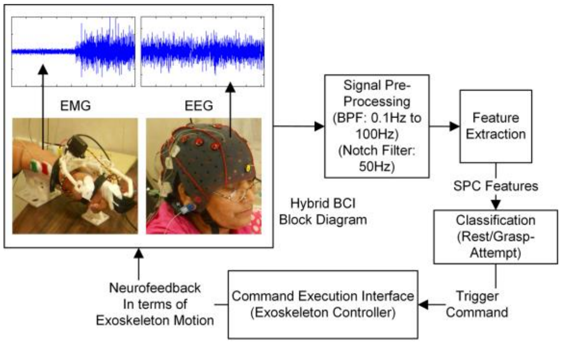

Figure 1. Basic block diagram of a Hybrid BCI system using EEG and EMG signals

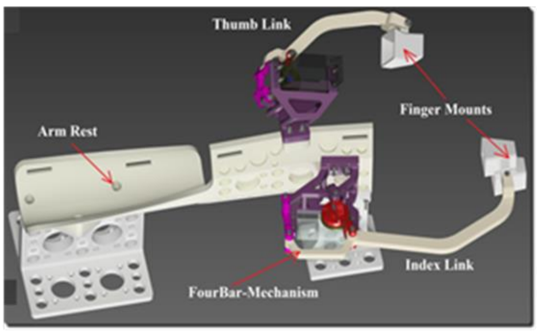

Figure 2. The CAD model of the hand exoskeleton

finally the discussion and conclusion about the current study is presented.

2. MATERIALS AND METHODS

2.1 SYSTEM OVERVIEW

The basic block diagram of the proposed hybrid BCI system is shown in Fig.1. The signals extracted from the users brain and muscle was pre-processed using an amplifier. The biosignal amplifier used here was the *g.USBamp* from g.tec™, Graz, Austria, for signal amplification. The EEG Cap was also from g.tec™ and Ag/AgCl gel based electrodes were used along with the cap for sensing the EEG activity on the scalp. Suface EMG (sEMG) electrodes were used for sensing the muscle activity and signals were amplified using the same amplifier. After preprocessing the signals were uploaded to the data processing unit through user datagram protocol (UDP). The data processing unit is basically a homegrown GUI based platform built in MATLAB/SIMULINK™, which was running in a Dell Precision 7510 mobile workstation. In the data processing unit the combined EEG-EMG features were extracted and translated into binary command (on/off) to trigger the hand exoskeleton. The commands were sent to the exoskeleton controller through RS-232 based serial communication.

The hand exoskeleton, used for our study was also built in-house, which can support the motion of three fingers, thumb, index and middle. Here, the middle and index fingers are driven together using a single finger of the exoskeleton and the other finger of the exoskeleton drives the thumb. Each finger of the exoskeleton is mounted on a four bar linkage, which was optimally designed to follow the human finger flexion and extension trajectory [12]. The participants fingers were inserted inside a cap attached to the end of each finger of the exoskeleton so that the fingers could move

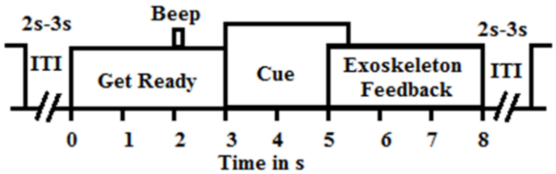

Figure 3. The timing diagram of a trial in feedback

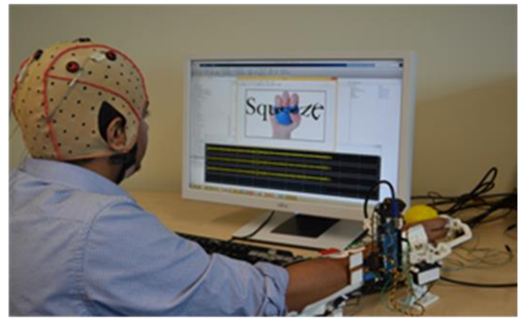

Figure 4. The physical realization of the experimental environment; A participant is getting online BCI feedback by means of the hand exoskeleton

according to the exoskeleton's movements. Two four-bar linkages are actuated by HS-5685MH digital servo motors from Hitec™ which were capable of producing 12.9 Kg-cm torque at 7.4 V. The exoskeleton controller was built on a ATmega328P microcontroller based embedded system. The whole system was powered by an 11.1V Lithium-polymer battery and a LM338T based variable voltage regulator. The CAD model of the developed exoskeleton is shown in Fig.2.

2.2 EXPERIMENTAL PROTOCOL

The experimental process was divided between two phases; the BCI calibration phase and the BCI feedback phase. The calibration phase consists of two runs and the feedback phase consists of one run. In each run there are total 40 trials. The trials are of two types; rest and grasp-attempt. These two types of trials are randomly distributed in a particular run, which means that within the 40 trials 20 are of rest and 20 are of grasp-attempt. The timing diagram of a particular trial is shown in Fig.3. The entire length of the trial is 8s. Within that period first 3s is the preparatory phase where a "get ready" command appears on the computer screen to make the participant alert about the upcoming task. After 3s a cue appears on the screen indicating the participant what task to perform in that particular trial. The cue may instruct the participant to rest, i.e. not to attempt any hand movement or the cue may instruct the participant to make a grasp attempt by showing a picture of a squeezed ball, as shown in Fig.4. In the calibration phase this cue lasts from 3s to 8s, but in the feedback phase the cue is shown for 2s after that the participant get the neurofeedback. After the calibration phase the data was used to train a support-vector-machine (SVM) based pattern classifier, which is used in the feedback phase for instructing the exoskeleton according to the task performed by the user. The calibration phase takes only 16min to complete. This calibration time is comparatively short as compared to other BCI systems commonly in use and a desirable characteristic for practical BCI application as long calibration time may cause mental fatigue for the participant and BCI performance may reduce due to that. In the period between 3s and 5s, the feature

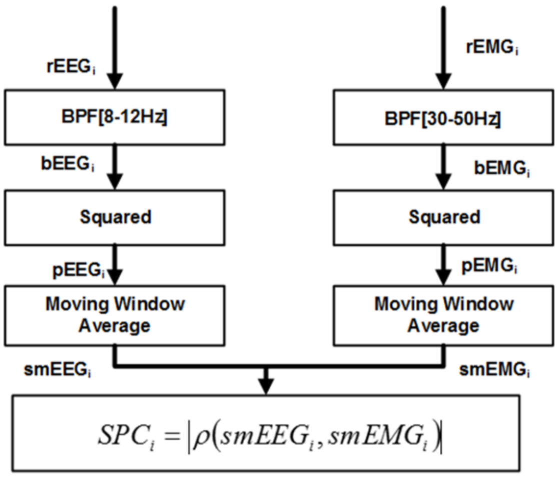

Figure 5. The block diagram of the SPC Index calculation process

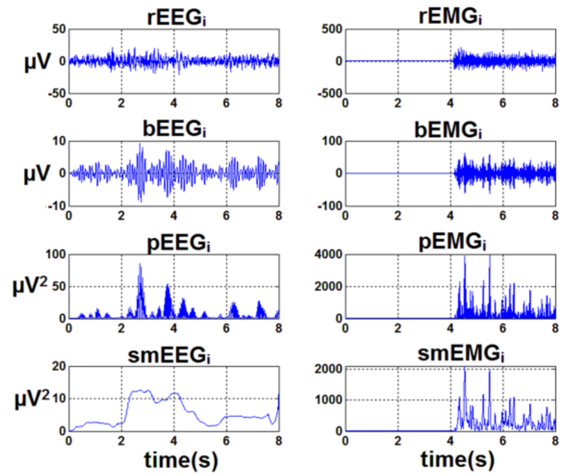

Figure 6. The signal transformation of EEG and EMG during the SPC index calculation steps

extraction process runs in the background on the acquired EEG and EMG data and then the features were classified as rest or grasp-attempt. If the classifier detects a grasp-attempt then the data processing unit sends a command 1 to the embedded controller of the exoskeleton to start the motion. The embedded controller, upon receiving the command 1, executes one flexion and extension motion of the exoskeleton arm and then stops. This means that the participants fingers goes from fully open to fully closed state and back to the fully open state along with the exoskeleton arms. Again, if the classifier detects a rest state then it sends command 0, and no movement of the exoskeleton is performed, i.e. the participants hand remains in the resting state. It is to be noted that we have used EEG-EMG SPC method in the online BCI for generating exoskeleton based feedback. Later, we have also processed the data offline using conventional EEG-CSP method. The accuracy computed from both the methods was then compared. A Wilcoxon signed rank test was used for comparing the statistical significance of the difference in performance between the two methods, as both the methods were applied on the same population.

2.3 DATA ACQUISION

Neurologically it is well established that the sesori-motor-rhythm (SMR) in the primary motor cortex (M1) is mainly associated with different physical movements [13]. For the placement of EEG channels on the scalp there is a 10-20 international system which locates the position of the electrodes on the scalp. It is found that the event related desynchronization and synchronization appearing in C3 and C4 channels (as designated by 10-20 system), is associated with hand movements. Therefore, we have acquired scalp EEG data from C3, C4 and also from Cz in bipolar mode. The EMG signal was acquired from the flexor-digitorum-superficialis (FDS) muscle of the right forearm, in bipolar mode. All the signals were sampled at 512Hz and they were initially filtered by the biosignal amplifier with a pass band frequency between 0.1-100Hz with a notch filter at 50Hz.

2.4 Participants

The participants were all healthy and right handed; aged between 20 and 30. They were seated upright with screen parallel to their eye, while undergoing the experimental process. They were wearing the hand exoskeleton in their right hand, while the left hand was resting comfortably in their lap. The experimental process was approved by institute ethics committee, IIT Kanpur.

2.5 METHODS

In this paper we have compared two methods. One of them is based on both EEG and EMG signals and the other one is based only on EEG signal. We will first discuss the EEG-EMG approach which uses SPC between the two signals. The calculation of the SPC based EEG-EMG feature will be presented here. Then we will discuss the conventional only EEG based method which uses CSP based filtering for feature extraction.

2.5.1 EEG-EMG SPC Method

The co-ordination between the brain and muscle activity can be measured in several ways. Here we are using the spectrum power correlation between these two signals to extract the combined EEG-EMG features, rather than calculating their features separately. The basic idea behind this approach is that the change in the EEG and EMG signal related to a certain event or stimuli can occur at different frequency bands. Therefore, if we can calculate power variation of EEG and EMG signals and then calculate the correlation between them then an estimate of simultaneous activation of EEG and EMG can be obtained, which could be used to differentiate between two events. The process of SPC index for a particular trial is discussed as follows and it is also shown in a block diagram in Fig.5. First we designate the raw EEG and EMG signal acquired within the 3 to 5s of i-th trial as $rEEG_i$ and $rEMG_i$ respectively. As we know that the ERD occur in EEG signal at μ band, (i.e. 8-12Hz) during hand movement, therefore the $rEEG_i$ is band pass filtered between 8-12Hz and the filtered signal was designated as $bEEG_i$. Similarly, it is known that EMG signal below 15Hz could be contaminated by noise therefore we have band pass filtered the $rEMG_i$ between 30-50Hz to get the muscle activity related to the grasp attempt. The band passed EMG is denoted as $bEMG_i$. Now to get the power variation of the EEG and EMG signals, $bEEG_i$ and $bEMG_i$ are squared to the power signals $pEEG_i$ and $pEMG_i$ respectively. But even after band pass filtering the signals could be jittery; therefore to smooth it out each data point of $bEEG_i$ is averaged by its preceding 1s time window and each data point of $bEMG_i$ is averaged by its preceding 30ms time window. The EEG and EMG signals after smoothing are designated as $smEEG_i$ and $smEMG_i$ respectively. Next the Pearson's correlation co-efficient

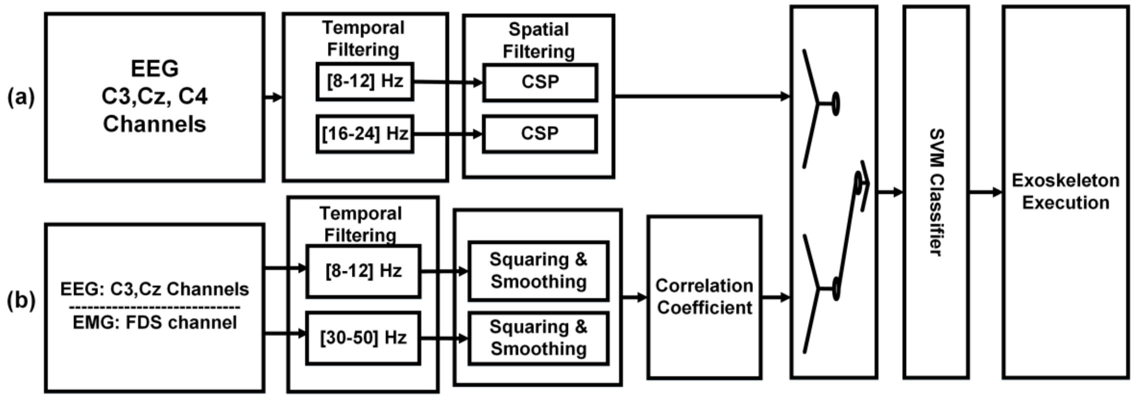

Figure 7. Signal processing flow chart showing the difference between (a)EEG-CSP and (b)EEG-EMG SPC

$\rho(\mathrm{smEEG_i}, \mathrm{smEMG_i})$ between $smEEG_i$ and $smEMG_i$ is calculated using the following formula,

$$\rho(\mathrm{smEEG_i}, \mathrm{smEMG_i}) = \frac{\mathrm{cov}(\mathrm{smEEG_i}, \mathrm{smEMG_i})}{\sigma_{\mathrm{smEEG_i}} \cdot \sigma_{\mathrm{smEMG_i}}} \quad (1)$$

where, the covariance between $\mathrm{smEEG_i}$ and $\mathrm{smEMG_i}$ is denoted as $\mathrm{cov}(\mathrm{smEEG_i}, \mathrm{smEMG_i})$, and $\sigma_{\mathrm{smEEG_i}}$ and $\sigma_{\mathrm{smEMG_i}}$ are the standard deviation of $\mathrm{smEEG_i}$ and $\mathrm{smEMG_i}$, respectively. Finally the SPC index of the i-th trial denoted as $\mathrm{SPC_i}$ can be obtained from the absolute value of $\rho(\mathrm{smEEG_i}, \mathrm{smEMG_i})$, i.e. $|\rho(\mathrm{smEEG_i}, \mathrm{smEMG_i})|$. But calculating the correlation coefficient alone is not enough. We also need to calculate the p-value of this correlation, alongside it, to measure the statistical significance of the correlation. If the p-value is greater than 0.05 then the correlation is considered insignificant and it is replaced by zero, to avoid any misleading consequence. The $\mathrm{SPC_i}$ can be calculated for any different pair of EEG and EMG channels, where one component is an EEG channel and another component is an EMG channel. In the current study we have calculated $\mathrm{SPC_i}$ for C3-FDS and Cz-FDS channel combinations. Therefore, the feature vector for each trial is composed of two elements, which are basically the SPC index of C3-FDS and Cz-FDS channel combinations.
The modification in the EEG and EMG signals after each step of the SPC index calculation process is shown in Fig.6 from an example within the acquired data set.

2.5.2 EEG-CSP Method

The EEG-CSP method relies on the temporal and spatial filtering of the EEG signal only for extracting the features. The filtering process and the feature vector generation are discussed below.

2.5.2.1 Temporal Filtering

Before spatial filtering using CSP we need to apply temporal filtration in specific bands. Studies have found that μ band and the upper β band ERD/ERS of the EEG signal has stable relationship with the hand movement activity [13]. Therefore, the temporal filtering on EEG signals was done for μ band [8-12Hz] and β band [16-24Hz] using a 4^{th} order Butterworth filter.

2.5.2.2 Spatial Filtering

To calculate the spatial filters which maximize the discrimination between two classes, CSP is most commonly used in BCI. CSP diagonalizes the corresponding covariance matrices of two different classes, calculated from multichannel EEG data [14].Due to volumetric conduction EEG signal often gets contaminated by the signal sources within the brain which is not associated with the task under consideration. Hence CSP algorithm is found to be good to separate out unwanted signal sources by designing spatial filters. CSP maximizes the variance of one class and minimizes the variance of the other class to increase the separability between the two classes [15]. The supervised decomposition of signals is parameterized by a matrix $W \epsilon R^{c \times c}$ (C: number of channels). It is used to project the original sensor space E ϵ R^c into the surrogate sensor space $Z \epsilon R^c$, using eq.(2)

$$Z = WE \quad (2)$$

where, $R^{C \times T}$ is the EEG measurement of a single-trial and T is the number of samples per channel. CSP projection matrix is denoted as W, while the rows of W are the spatial filters and the columns are the common spatial patterns.

Normally m first and m last rows of Z, i.e. Zt, where $t \epsilon \{1 \ldots\ldots 2m\}$, are used to compute the CSP features. And the feature vector x_t is derived from Zt by eq.(3) as,

$$x_t = log\left(\frac{var(Z_t)}{\sum_{i=1}^{2m} var(Z_i)}\right) \quad (3)$$

Here, m is taken to be 1 and 3 EEG channels were used. Hence the feature vector was composed of 4 elements. The first two elements were the first and second best features of μ band and the second two elements were the first and second best features of β band.

The basic difference between the feature-extraction processes of the two methods are also shown in Fig.7.

3. RESULTS

Table 1. Classification Accuracy Comparison

Sub ID	EEG-CSP		EEG-EMG SPC	
	10CV_Tr_Acc (%)	Feedback_Acc (%)	10CV_Tr_Acc (%)	Feedback_Acc (%)
S01	73.75	80.00	95.00	87.50
S02	73.75	85.00	91.25	87.50
S03	88.75	90.00	97.50	100.00
S04	83.75	75.00	92.50	87.50
S05	73.75	75.00	97.50	90.00
S06	77.50	75.00	90.00	92.50
S07	70.00	82.50	98.75	87.50
S08	66.25	85.00	88.75	95.00
S09	65.00	77.50	93.75	90.00
S10	67.50	72.50	97.50	82.50
Mean	74.00	79.75	94.25	90.00
Std	7.63	5.71	3.55	4.86
p-value(Between Feedback Acc of EEG-CSP and EEG-EMG SPC)				0.002

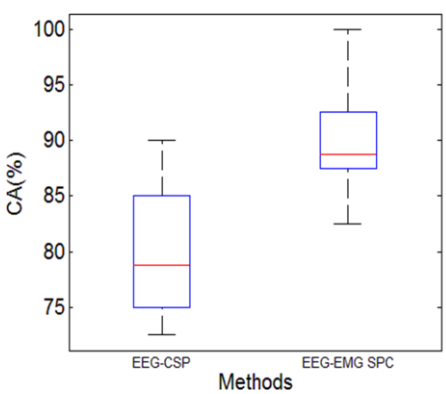

Figure 8. Classification accuracy comparison of the methods in feedback phase

The performance of the developed hybrid BCI system was measured in terms of classification accuracy. The classification accuracy is defined by the percentage of correctly classified trials in the feedback phase. The classifier used in the current study is an SVM classifier with linear kernel. The advantage of using the linear kernel over a quadratic or radial basis function (RBF) kernel is that it reduces the over fitting problem while transitioning from training to feedback phase. This is a crucial factor to consider as the EEG data is non-stationary in nature and its distribution varies from session to session. After the calibration phase the SVM classifier was trained on the acquired features of the two classes and the goodness of the classifier was measured using a 10-fold cross validation accuracy. Then the same classifier

Table 2. SPC Index comparison

Sub ID	Feedback Phase			
	Rest (C3-FDS)	Grasp (C3-FDS)	Rest (Cz-FDS)	Grasp (Cz-FDS)
S01	0.23	0.49	0.25	0.52
S02	0.22	0.31	0.24	0.32
S03	0.27	0.47	0.26	0.44
S04	0.25	0.38	0.27	0.37
S05	0.26	0.42	0.27	0.47
S06	0.28	0.31	0.28	0.37
S07	0.25	0.29	0.21	0.31
S08	0.23	0.52	0.24	0.47
S09	0.21	0.37	0.24	0.39
S10	0.22	0.41	0.25	0.38
Mean	0.24	0.40	0.25	0.40
Std	0.02	0.08	0.02	0.07

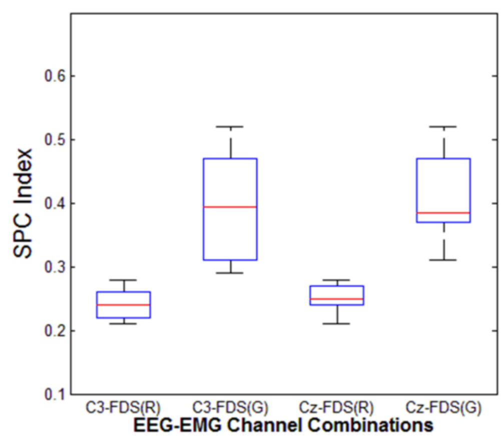

Figure 9. SPC index distribution of different channel combinations in rest(R) and grasp-attempt(G) classes in feedback phase

was applied in the feedback phase for predicting the classes of each trial. The results of the classification accuracy of the two methods are shown in Table 1. Here we see that the average accuracy in the training phase for EEG-CSP is 74±7.63% while it is 94.25±3.55% for EEG-EMG SPC. In the feedback phase also the average classification accuracy of the EEG-EMG SPC is 90±4.86, which is significantly ($p<0.02$) higher than the average accuracy of the EEG-CSP which is 79.75±5.71. Participant S03 achieved highest accuracy in feedback phase both in case of EEG-EMG SPC and EEG-CSP, which are 100% and 90% respectively, while participant S10 achieved the lowest accuracy in both EEG-EMG SPC and EEG-CSP, which are 82.5% and 72.5% respectively. The comparison of the performance of the two methods in the feedback phase is also shown in Fig.8, in terms of the distribution of classification accuracy across all the subjects.

The SPC indexes of different combinations of EEG and EMG channels are shown in Table 2. The average SPC indexes of the two different classes (rest and grasp-attempt) are shown side by side for each participant, during the feedback phase. The average SPC index for C3-FDS combination is found to be 0.24±0.02 in rest and 0.40±0.08 in grasp-attempt. In case of Cz-FDS combination the average SPC index is found to be 0.25±0.02 in rest and 0.40±0.07 in grasp-attempt. The distribution of the SPC indexes is also shown in Fig.9.

4. DISCUSSION AND CONCLUSION

In this paper we have proposed a novel technique of feature extraction for BCI based applications based on fusion of EEG and EMG signals. We have compared our method with the conventional only EEG based method which popularly uses CSP based spatial filtering approach. The results have shown that the proposed EEG-EMG SPC method performed significantly better than the conventional EEG-CSP method in terms of classification accuracy. The distribution of the SPC indexes for rest and grasp-attempt classes are also significantly ($p<0.02$) discriminable which proves that the EEG-EMG SPC features are relatively stable. All the participants were able to trigger the hand exoskeleton using the online hybrid BCI system based on the EEG-EMG SPC method with an average accuracy of 90% which is quite higher than the recommended of 70% for communication and control. Hence the proposed hybrid BCI technique has the potential to be applicable for the rehabilitation of poststroke hand disability. The EEG-EMG correlation based feature is selected out of other possible features as it may provide deeper insight about the brain-muscle co-ordination with higher accuracy which is important when an external device such as an exoskeleton is used for neurofeedback. Although there could be different possible hand motion, grasping is very fundamental and related to most of our daily living activities, that is why our current work is targeted for hand grasping. Further work will include the experimentation on hemiplegic stroke patients and the method will be modified for continuous control of the hand exoskeleton. The most important aspect of the proposed method is that deals with the interaction between the brain and muscle signal which is often ignored while designing BCI based neuro-rehabilitation applications.

The results proved feasibility of a novel hybrid BCI approach using EEG-EMG SPC in controlling a hand exoskeleton device on healthy participants, which outperformed the conventional only EEG based BCI approach. The proposed system has also a bright prospect to be used for neuro-rehabilitation of stroke patients.

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