On fusion of heart and brain signals for hybrid BCI

Shahjahan Shahid, Girijesh Prasad, and Rakesh Kumar Sinha

Abstract—This paper investigates the fusion of ECG with EEG in devising a hybrid brain-computer interface (hBCI). Effortful motor imagery (MI) based BCI experiments were arranged with a twelve seconds of cue-based MI paradigm on six healthy individuals over two sessions of 160 trials, while ECG and EEG signals were simultaneously recorded. The proposed hBCI uses bispectrum based features from EEG and ECG along with an LDA classifier. The off-line analysis shows an improvement in MI task detection accuracy if both ECG and EEG features are considered together. In addition, the time domain analysis of ECG signal shows that the average heart rate increases during MI state, which clearly shows that the cardiac system responds to MI related tasks.

I. INTRODUCTION

A brain computer interface (BCI) utilizes neurophysiological signal to establish direct communication between human brain and computing devices without the involvement of neuromuscular pathways. Performance of a non-invasive BCI is highly dependent on the separability of cognitive task related features extracted from cerebral electrophysiological signals (e.g., EEG) acquired during psycho-cognitive tasks undertaken by the user. The EEG has highly non-stationary and non-linear dynamic characteristics [1] and, therefore, current BCI systems suffer from limited MI task detection accuracy. Also, some people just do not produce sufficiently separable EEG activities adequate for useful BCI control and are considered ’BCI illiterate’ by some BCI groups [2]. A review of rehabilitation literature [3] suggests that just MI of exercises (mainly involving motor tasks) causes significant changes in the cardiopulmonary autonomic responses consisting of alterations in heart rate, blood pressure, respiration rate, and blood oxygen content. An alteration in heart rate in a two-class MI-based BCI is effectively identified [4]. A study on a large number of healthy subjects [5], supported the hypothesis that the MI is not only associated with the activation of cortical structures, but also with the central commands into the cardiovascular system and their control centre at brain stem in which the slow blood pressure oscillations play a very important role. Therefore, one way of improving the BCI performance maybe using MI correlated hybrid features obtained from multiple modalities such as EEG and sinus rhythm.

Recently, a significant correlation between ECG and $\beta$ oscillation of EEG has been reported in [6]. A successful use of heart rate for the self initiation of an EEG based BCI (actuated control of BCI) has been proposed in [7], [8]. Since, these studies dealt with time domain signal analysis which is generally noise (motion or artifact) sensitive; and therefore, the proposed methods may not be very practical.

In this paper, it is hypothesized that features from ECG may harmonize with MI related EEG and their fusion may enhance BCI performance. To the best of authors’ knowledge, no attempt has been reported in the BCI literature to fuse the features from multiple modalities involving ECG and EEG. The work reported here has twin objectives: (a) to identify MI related autonomic variations, such as instantaneous changes in the heart rate during simple kinesthetic motor imagination tasks; and (b) to devise a hybrid BCI by fusing the features obtained from simultaneously recoded EEG and ECG signals.

II. MATERIALS AND METHODS

A. Subjects, experimental setup and data recording

The experimental study involved six novice young right handed male subjects of average age of 28 years. Before the experiments, it was confirmed that all subjects were physically fit and without a history of any neurological disease. The paradigm (a computer controlled thinking procedure) consisting of two types of effortful kinesthetic motor imagination tasks for left foot and left hand movements along

Fig. 1. A 3-directional cue based paradigm used for data recording
with the rest-state have been used for the data recording. The duration of each trial was 12 s. During the first 6 s, subjects were in a relaxed state and the screen was blank. At 6th s the visual cue in the form of directional arrow was presented on the screen to provide the instruction to perform the assigned task. The arrow pointing left, down and right were set for the imagination of left foot, left hand and rest state, respectively. Random gaps of 1 s to 3 s were kept between two consecutive trials. An operational diagram of the 3- directional cue paradigm is shown in Fig. 1. Before the data recording, all the subjects had given their consents and the data were recorded according to the ethical guidelines for the human experimentations and institutional policies.

Each subject participated in two recording sessions in a controlled experimental environment. In every session, 180 trials (i.e. 60 trials for each class) were recorded. Note that, every session was composed of three runs; where each run consists of 60 trials (20 trials each for effortful left foot and left hand kinesthetic motor imagination as well as for the rest-state). Before recoding signal in any session the subjects were instructed to apply just enough effort/force so that they could experience left foot and left hand movements in a kinesthetic sense without causing any real motion. Three EEG channels (C3, Cz, and C4) were recorded along with the ECG. The recorded data (EEG/ECG) affected with movements and the EMG artifacts, if any, were removed before any processing and analysis.

B. Relative heart rate

The methodology for computing relative heart rate has been adopted from [4]. Firstly, trial-wise ECG was separated as per its task labels (hand/foot/rest). This separation creates 3 sets of dataset. The peaks of QRS complex in filtered (high-pass) ECG were identified and elapsed time between peak to peak (RR-interval) was calculated. A threshold level for finding QRS peaks was decided after applying high-pass filter (5 to 10Hz cut-off frequency) to the raw ECG signal. A linear interpolation method was applied (resampled at 10 Hz) to the computed RR intervals for finding the instantaneous heart rate. The average of instantaneous heart rate (across 60 trials) was calculated from all similar class of recording within a session. Finally, to get the relative changes in heart rate within three class labels, the average of instantaneous heart rate was compared to the mean of 2nd to 3rd seconds’ instantaneous heart rates.

C. Signal processing technique

Since nonlinear and non-Gaussian characteristics are observed in electrophysiological signal, higher order statistics techniques were chosen for feature extraction. A recently developed bispectrum based signal processing technique [9] for BCI has shown to provide significantly higher performance in a multi-subject BCI study. We have adopted same technique but we used it for MI related simultaneously recorded EEG and ECG signals to develop the proposed hBCI. The block diagram of the proposed signal processing technique is illustrated in Fig. 2.

The technique involves the estimation of bispectrum in the feature extraction stage, and Fisher’s linear discriminant analysis (LDA) for classification of the normalized features, which are briefly discussed below. To understand the entire procedure of signal processing, readers can refer to [9].

1) Bispectrum based feature extraction: A bispectrum of a stochastic signal $x(t)$ [$t$ =time index] can be estimated from the expectation of three joint frequencies of the signal. The bispectrum $B_x(k, l)$ can be estimated as [10].

\[ B_x(k, l) = \text{E}\{X(k)\hat{X}(l)X^*(k + l)\} \]  
\[ = \frac{1}{N} \sum_{i=1}^{N} X_i(k)X_i(l)X_i^*(k + l) \]  

where $k, l$ are the discrete frequency indices, $E\{\cdot\}$ denotes the statistical expectation. $X(\cdot) = \text{FFT}[x(t)];$ $*$ denotes the
classified the feature vector $LDA$ decision plane uses the following representation to separate the features into the two different classes. Fisher’s linear discriminant analysis (LDA) method \cite{12} is therefore applied to finds a hyper-plane in the feature space $\vec{B}$ operators for minimum and maximum value computation. feature data in the window; and ‘bandpass filter for ECG signal) electrophysiological signals were considered as $x(t)$. In order to characterize temporal bispectral information, the feature sequences were computed as sum of absolute log-bispectrum as given below.

$$B(m) = \sum_{k,l \in \theta} |\log[B_x(k,l)]| \quad (3)$$

where $\theta$ is the non-redundant region (principal domain) \cite{11} of bispectrum plain, $m$ is a time index related with the time period from which the bispectrum is estimated. The bispectral features in Eq. (3) are used in normalized form. The signal normalization is performed in a sliding window of size 60s that can be expressed as below:

$$\vec{B}(m) = \frac{B^w - \frac{1}{M} \sum_{i=1}^{M} B^w}{\max(B^w) - \min(B^w)} \quad (4)$$

where $\vec{B}(m)$ is the normalized features; $B^w$ is the sliding windowed feature data ($=[B(m-M), B(m-M+1), \ldots, B(m)]$) obtained in Eq. (3); $M$ is the length of feature data in the window; and ‘min’ and ‘max’ are the operators for minimum and maximum value computation.

2) Classification using Fisher’s LDA: The normalized features $\vec{B}(m)$ are often not straightforward to classify. Fisher’s linear discriminant analysis (LDA) method \cite{12} is therefore applied to finds a hyper-plane in the feature space to separate the features into the two different classes. Fisher’s LDA decision plane uses the following representation to classify the feature vector $\vec{B}(m)$ as

$$d(m) = \vec{B}(m)^T w + b \quad (5)$$

where $d(m)$ is the transformed signal, $w$ is the weight vector, $b$ is the bias (threshold). The features are assigned to one class or the other depending on the sign of $d(m)$. The weight vector and bias value can be estimated from an adequate set of training dataset.

D. Performance assessment by classification accuracy

For each time point of the paradigm operation, the classifier’s output (sign of $d(m)$) was compared with actual MI labels (hand/foot/rest) and a confusion matrix (CM) is generated accordingly. The classification accuracy for each class was computed from the formula as below:

Left Accuracy = \frac{\text{True Negative in CM} \times 100}{\text{Number of Actual Left} \times 100} \quad (6)

Right Accuracy = \frac{\text{True Positive in CM} \times 100}{\text{Number of Actual Right} \times 100}

The average accuracy for each time point of the paradigm was computed across the all trials of each class.

III. Result and Discussion

To observe the effectiveness and possibilities of proposed hBCI, we conducted three different analyses: (a) average heart rate distribution during paradigm operation, (b) distribution of average classification accuracy of hBCI over the time course of paradigm period, and (c) the observation of classification accuracy at training and evaluation stage while both sessions use same LDA. The analyses of (b) and (c) were conducted for a BCI operating on EEG only, ECG only, and on fusion of EEG and ECG.

A. Distribution of relative heart rate

Fig. 3 illustrates a typical average heart rate distribution plot for three classes during the time course of the paradigm. As mentioned in computational procedure (see in Sec. II-B), each curve of average heart rates (in Fig. 3) was computed from 60 trials of each class (hand/foot/rest). Note that, the subject was always at rest state during the first 6 seconds of paradigm time course (regardless of the class label). In distribution plot, the relative heart rate during this period was very similar as the rest-state (along base level, i.e. 0%). On the other hand, after six second of paradigm time course, subject either starts to imagine or remains rest. The average heart rate distribution curves (Fig. 3) during this period shows that the heart rate increases up to 10% from the rest-state’s heart rate if the subject imagines any kinesthetic tasks.

![Fig. 3. Typical variation of heart rate over the time course of paradigm (Subject: NEM).](image-url)
observed in all other subjects, if the BCI uses fusion of EEG and ECG signal as input (hBCI). Table I displays the performances of BCI (with different input signal) for all subjects. The overall observation from this analysis and the results in Table I concludes that the fusion of ECG and EEG improves the performances of BCI.

### TABLE I

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<th>C3-C4-Cz-ECG</th>
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C. Performance analysis of BCIs with different modalities

In order to analyze the performance of both traditional and hybrid BCI, we first find the suitable coefficient for (hand or foot). The heart rate tends to come down at the end of the trial period. This observation clearly concludes that cardiac system response gets modulated due to the imagination or nearly execution of motor movement related tasks.

### B. Distribution of average classification accuracy

In order to assess the performance of BCI, we apply three sets of bispectrum based features (computed from EEG only, ECG only, and fusion of ECG and ECG) to the Fisher’s LDA classifier to obtain the classifier’s coefficient; and with best classifier (observed by 5-fold cross validation), the classification accuracy was observed along the time period of paradigm time course. Fig. 4 displays three distribution plots of average classification accuracy for the Subject:FRZ. Each distribution plot displays three curves obtained from when BCI uses EEG only, ECG only and Fusion of ECG and EEG signal. As discussed in the last section, the subject stays at rest for first 6 second of paradigm time course. In all plots, the distribution curves are observed around 50% accuracy in separation of two classes (left/rest, rest/foot and left/foot).

In classification of hand MI vs. rest-state, it is observed that the performance of hBCI (92%) is much better than the performance of the traditional EEG-based BCI (73%). It is also observed that the BCI with ECG performs at a maximum of 85% accuracy only.

In the distribution plot regarding the classification of rest vs. foot MI, we find only slight improvement between traditional BCI and hBCI. The fused features, in this case, only very slightly improve the performances of BCI.

In distribution plot related with the classification of hand MI vs. rest-state, it is observed that cardiac system response gets modulated due to the imagination or nearly execution of motor movement related tasks.

In order to analyze the performance of both traditional and hybrid BCI, we first find the suitable coefficient for REST vs. FOOT MI, and LEFT HAND MI vs. FOOT MI AT TRAINING AND EVALUATION STAGES FOR 6 SUBJECTS.
LDA classifier (at which classifier separates the signal into its MI classes at highest accuracy). Once we had the suitable classifier, we use the classifier to the other session’s signal (evaluation signal) of the same subject and observed the performance of the BCI. We keep evaluation signal out from training stage. Table I displays the performance results at training and evaluation stage. It is a normal expectation that the BCI should work with similar performance as it performs at training stage. We analyze and compare the classification accuracy for traditional BCI with hBCI as below:

In classification of left MI from rest-state: the average accuracy (among six subjects) by traditional BCI was 80% in training stage and 72% in evaluation stage, while the hBCI achieves 92% average accuracy in training stage and 88% in evaluation stage. On fusion of ECG signal with traditional BCI the performance of interface increases in both training and evaluation stages and the variation between these two session decreases.

In classification of foot MI from rest-state: the average accuracy by hBCI improves up to 7% and accuracies observed in training and evaluation stage were consistent.

In classification accuracy of left MI from Foot MI: the average accuracy by traditional BCI was observed 80% in training stage and 75% in evaluation stage, while with hBCI the average accuracy is found 92% in training and 87% in evaluation stage. This comparison directs that hBCI performs better than the traditional BCI.

An overall analysis for the BCI system with ECG only shows that the average classification accuracy is sometimes slightly higher than the traditional BCI. But it is also observed that this type of interface system is not reliable for all subjects, e.g., the accuracy was observed below 70% in classifying left MI from rest stage of ALK’s ECG signal which is much lower than the traditional BCI performance.

The above analysis concludes that the fusion of ECG and EEG features for hBCI enhances the average imagery classification accuracy in training and evaluation stages. Note that, the setup for signal processing was same for any class of signal and for all subjects.

IV. CONCLUSION

Vast majority of non-invasive motor imagery (MI) based BCI systems make use of EEG as the brain signal to extract MI related features. These systems suffer from limited MI task detection accuracy due to non-stationary and non-linear characteristics of the brain signal. Also, it appears that some novice users are unable to produce sufficient EEG activities so that features related with different mental tasks could be classified with an accuracy level sufficient for on-line use. In order to address these limitations, the paper introduces a hybrid brain computer interface by combining ECG with EEG. This interface system is an extension of traditional BCI that uses brain and heart signal as input. The proposed hBCI uses newly developed bispectrum based features. The comparison and analysis of the proposed hBCI concludes that the fusion of ECG with traditional EEG based BCI does enhance the performance of resulting hBCI. Finally, a consistent training and evaluation accuracy is found by hBCI which is a highly desired factor in a practical BCI development.

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