A Feasibility Study of Employing EOG Signal in Combination with EEG Based BCI System for Improved Control of a Wheelchair.

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ABSTRACT

For a fully paralysed person, EEG (Electroencephalogram) based Brain Computer Interface (BCI) has a great promise for controlling electromechanical equipment such as a wheelchair. Again EOG (Electrooculography) based Human Machine Interface system also provides a possibility. Individually, none of these methods is capable of giving a fully error free reliable and safe control, but an appropriate combination may provide a better reliability, which is the aim of the present work. Here we intend to use EEG data to classify two classes, corresponding to left and right hand movement, and EOG data to classify two classes corresponding to left and right sided eyeball movement. We will use these classifications independently first and then combine these with different weightage to find if a better and reliable control is possible. For this purpose offline classification of motor imaginary EEG data of a subject was carried out extracting features using Common Spatial Pattern (CSP) and classifying using Linear Discriminative Analysis. The independent EEG motor imaginary data classification resulted in 89.8% of accuracy in 10 fold one leave out cross validation. The EOG eyeball movement produces distinctive signals of opposite polarities and is classified using a simple discriminant type classification resulting in 100% accuracy. However, using EOG solely is not acceptable as there always will be unintentional eye movement giving false commands. Combining both EEG and EOG with different weightage to the two classifications produced varied degrees of improvement. For 50% weightage to both resulted in 100% accuracy, without any error, and this may be accepted as a practical solution because the chances of unintentional false commands will be very rare. Therefore, a combination of EOG and BCI may lead to a greater reliability in terms of avoidance of undesired control signals.

Keywords: EEG, EOG, Data Analysis, BCU, HMI, LDA, CSP, USB Interface.

INTRODUCTION

When a human being interacts with a machine, Human-Machine Interface (HMI) is needed for control and feedback – a two way communication. However, for a person with different degrees of disability, special interfaces are needed, and possibilities unthinkable in the past are coming up with the advent of new technologies. To give mobility to a fully paralysed person, Brain-Computer Interface or BCI is coming up with great promise where an electrical wheelchair may be controlled simply by the thought of the user. BCI may also be used for moving a prosthetic hand or foot. Just imagining an attempted movement of a paralysed limb or a body part may provide the desired control.

A BCI uses recordings of cerebral electrical activity or electrical signals of human brain activity over time, classifies the recorded data to associate these with the desired functions or control and then gives appropriate outputs (Krucoff et al., 2016). These systems provide a direct communication pathway between human brain and an external electronic device. One of the most popular choice for recording of electrical activity of the brain is EEG (Electroencephalogram) recorded from the scalp surface. EEG signals originate from the aggregated neuronal potentials of the brain activity. The signals are of very small amplitude, typically ranging from 10 to 100µV for normal subjects (Aurlien et al., 2004). Surface EEG is suitable for BCI systems because it is non-invasive, has good temporal resolution, portability, user safety and low device setup cost.

For typical BCI, EEG signals from sensorimotor cortex is used to classify a subject's movement, or imagination of movement of various body parts. Since imagination of movement is more appropriate for paralyzed patients the latter has been extensively examined and is commonly known as Motor-Imaginary BCI (Pfurtscheller, 2000). Motor-Imaginary BCI (MI-BCI) mainly focuses on changes in the human µ rhythm, which is an EEG oscillation recorded in the 8-13 Hz range from the central region of the scalp overlying the sensorimotor cortices (Pfurtscheller, 1989). Using imagination of left and right hand movement, the first MI-BCI with high accuracy was reported in 1998 by Guger et al., 2000. In this study, three subjects were used to perform a real time (online) classification. This experiment was conducted to verify the usefulness of a feature extraction method called 'Common Special Pattern' (CSP). The study used 'Linear Discriminant Analysis' (LDA) classification method for classification and resulted in 98%, 94% and 86%

accuracy for the three subjects respectively. However, BCI systems are yet to provide fully reliable outputs working alone. Till date, no BCI system is reported to be 100 % accurate and the classification varies significantly person to person.

Therefore, a combination of BCI with some other body signal may provide a better HMI. One such signal is Electrooculography (EOG) which is the electrical potential that is produced across the cornea and retina due to eyeball movement. The potential arises due to the action potentials from the muscles that are contracted during eyeball movement (Brown et al., 2006; Birndorf et al., 1973, Atique et al, 2006). The EOG signal typically has an amplitude of 1 to 2 mV and has a single peak wave shape with an average time span of 300 to 400 ms. The signal is usually recorded from electrodes placed on the face surrounding the eyes, mainly at the forehead, temple and just below the eyes. Figure 1 shows the electrode placement and corresponding output measurement system for left-right (horizontal) and up-down (vertical) movement of the eyeball.

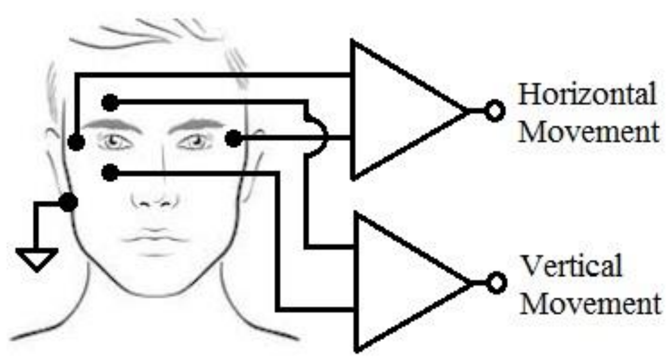

Fig. 1: EOG Recording System

The EOG signals from these different electrodes have very distinct wave shapes for left, right, up and down movement of the eyeball. These wave shapes are easily distinguishable and may be used for Human-Machine Interface (HMI). In several publications, the EOG has been reported for onscreen keyboard controls and for robot control (Usakli et al., 2010a and 2010b; Kumar et al., 2002; Kim et al., 2007). Barea et al. (2002) reported an EOG based electric wheelchair control. However, since unintentional eye movement can result in unwanted control of machine, HMI systems based on EOG only are not fully reliable again.

Summarising the above, EEG based BCI system is not 100% accurate, and control of wheelchair by only BCI can result in unwanted movement. Again, reliability of only EOG based systems have a serious drawback, due to unintentional eye movements. Hence, both systems, used individually, are not fully reliable and may even result in disastrous consequences. On the other hand, a combination of these two different systems may give a better reliability since it is less probable that two signals will have a coincident error. For this reason, it would be interesting to investigate whether combining these two methods in some appropriate way improves the outcome of the desired control, so that 100% correct control is obtained.

The objective of the present study is to produce improved and reliable wheelchair control combining classification results (Class probabilities) of EEG motor imaginary BCI and detectable classes of eyeball movement though EOG. This resulting control signal should not be sensitive to movement of the eyes or in the motor imaginary EEG that are not related to the desired control. In the present work only predicted classes of EEG signals for Left Hand/Right Hand imagined movement and EOG signals for horizontal Left/Right eyeball movement are studied with different weightage to each. The target is to determine if any particular combination of these states improves the overall output than the individual EEG or EOG based HMI, and if such combination of states or classes can be applied to control a wheelchair reliably.

METHODS

EEG Classification for BCI

An offline classification of mental task of imagined movement of Left and Right hand was carried out with a sample EEG data set. The classification procedure involves extracting features by a method called ‘Common Spatial Patterns’ (CSP). The CSP algorithm (Fukunaga, 1990) was first introduced to BCI applications by Graz BCI group (GRAZ BCI, 2017) which is an optimized spatial filter for discrimination of different conditions of human brain activity (Guger et al., 2000). This algorithm is very fast and robust and flexible as it is an adaptive filter which deals with the problem of inter-subject variability and produces complex but physiologically meaningful features. The CSP algorithm was successfully used in motor imaginary BCI tasks, reported in several publications (Blankertz et al., 2007; 2008). The features from CSP algorithm is physiologically meaningful i.e. corresponding to spatial patterns of origin of sensorimotor rhythms (μ and β band). It also effectively reduces the dimension of EEG data to very low dimension of features. Therefore, a simple, light and fast machine learning techniques can be used to classify the motor imaginary states. Thus, after extracting the CSP features, a simple classification method called Linear Discriminant Analysis (LDA) is used for the classification procedure. LDA is a common machine learning techniques for data classification that have been extensively used in BCI applications.

In this present study, the motor imaginary data of one subject corresponding to Left Hand and Right Hand movement were first classified as a Two-class problem (Left/Right Hand). The LDA classifier produces the two state of motor imaginary i.e. left hand and right hand movement imagination class probabilities.

The epoch extraction from the target marker for specific class in the data, signal processing, CSP feature extraction and machine learning methods were carried out using Matlab based tool ‘BCILAB’(BCILAB, 2017). To evaluate the performances of classifiers used in this study, a 10-fold cross-validation with one leave out method is used (Rodriguez, et al., 2010).

Source and type of EEG Data:

Continuous EEG sample data sets were obtained from open source published data; courtesy of Romain Grandchamp, CERCO, Toulouse, France (Grandchamp, 2009). This data contains two class imaginary movements as a sequence of trials in which a subject was instructed to imagine moving either the Left hand or the Right hand. The data have event-markers or time stamps that indicate the timing and type of these instructions including the rest or relaxed conditions. These EEG data were recorded from 29 channels of the standard 10-20 electrode position system. There are total of 128 epochs of which 64 are the left hand and other 64 are of right hand imagined movement.

The CSP Algorithm

The Common Spatial Pattern (CSP) algorithm finds information (i.e., spatial filters) in two distributions of high-dimensional space. The EEG signal is first processed with a bandpass filter in the frequency domain of interest. Then the CSP algorithm maximizes variance for one class and that at the same time minimizes variance for the other class. High or low signal variance reflects a strong and a weak (attenuated) rhythmic activity, respectively.

If a raw EEG data from a single trial constructs a matrix E of elements $N \times T$, where N is the number of channels and T is the measured samples per channel, the normalized spatial covariance of the EEG can be obtained by,

$$C = \frac{EE'}{Trace(EE')} \qquad (1)$$

Where $Trace$ is the sum of diagonal elements of EE'. For each of the two distributions to be separated (for example, Left and Right Hand motor imagery), the spatial covariance $\overline{C_d} \in [l, r]$ is calculated by averaging over the trials of each group. The composite spatial covariance is given as,

$$C_c = \overline{C_l} + \overline{C_r} \qquad (2)$$

C_c can be factored as $C_c = U_c \lambda_c U_c'$, where U_c is the eigenvector matrix and $\lambda_c$is the diagonal matrix of eigenvalues which is assumed to be sorted in descending order. The whitening transformation gives,

$$P = \sqrt{\lambda_c^{-1} U_c'} \qquad (3)$$

Which equalizes the variances in the space spanned by U_c i.e., all eigenvalues of PC_cP' are equal to one. If $\overline{C_l}$ & $\overline{C_r}$ are transformed as,

$$S_l = P\overline{C_l}P' \quad \text{and} \quad S_r = P\overline{C_r}P' \qquad (4)$$

If $S_l$and S_r has common eigenvectors, i.e., if,

$$S_l = B\lambda_l B' \quad \text{then} \quad S_r = B\lambda_r B' \quad \text{and} \quad \lambda_l + \lambda_r = I \qquad (5)$$

Where I is the identity matrix. Since the sum of two corresponding eigenvalues is always one, the eigenvector with largest eigenvalue for $\overline{S_l}$ has the smallest eigenvalue for $\overline{S_r}$ and vice versa. The projection of whitened EEG onto the first and last eigenvectors in B (i.e., the eigenvectors corresponding to the largest λ_l and λ_r) will give feature vectors that are optimal for discriminating two populations of EEG. With the projection matrix $W = (B'P)'$ the mapping of a trial E is given as,

$$Z = WE \tag{6}$$

The columns of W^{-1} are the common spatial patterns and can be regarded as time-invariant EEG source distribution vectors.

Linear Discriminant Analysis (LDA)

The Linear Discriminant Analysis separates the data of different classes by a hyperplane. For a two class classification, the class of the feature vector of the data sample is determined by which side of the hyperplane is the vector resides. The classification of more than two classes is accomplished by more than two hyperplanes.

LDA assumes the data is normally distributed and in case of the simpler version of 'Fisher`s LDA' the data is assumed to have equal covariance matrix for both class. The separating hyperplane is obtained by seeking the projection that maximizes the distance between the mean and minimizing the variance of two classes. For a multiclass BCI, the 'one versus the rest' (OVR) strategy is used which involves in separating each class from all the others. Figure 2 shows graphical view of LDA with simulated data sets with identical covariance matrices.

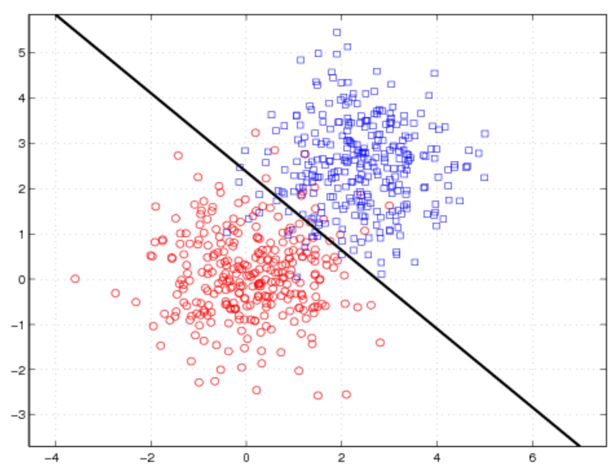

Fig. 2: LDA with Simulated Data sets with Gaussian distribution and Identical Covariance Matrices Between two Classes

For a set of observation that constitute a feature vector set $\vec{x}$ and for each sample of observation corresponds to a known class y, then $\vec{x}$ and y creates a training set that can be applied to classify unknown observations similar or same distribution of samples where $\vec{x}$ is taken from.

LDA solves the problem by assuming that the conditional probability density functions $p(\vec{x}|y=0)$ and $p(\vec{x}|y=1)$ are both normally distributed with means and covariance parameters $(\overrightarrow{\mu_0}|\sum_0)$ and $(\overrightarrow{\mu_1}|\sum_1)$ respectively. Now, Bayes optimal solution is to predict that a sample belongs to second class if the log of the likelihood ratio is bellow some threshold T , that is,

$$(\vec{x}-\overrightarrow{\mu_0})^T \textstyle\sum_0^{-1}(\vec{x}-\overrightarrow{\mu_0}) + ln|\sum_0| - (\vec{x}-\overrightarrow{\mu_1})^T \sum_1^{-1}(\vec{x}-\overrightarrow{\mu_1}) + ln|\sum_1| > T \qquad (7)$$

Equation 7 is called Quadric Discriminant Analysis (QDA). To simplify more, the LDA, makes further assumptions that the class covariances are identical i.e., $\sum_0 = \sum_1 = \sum$ (Homoscedasticity Assumption), and also covariances have full rank. So, the decision criterion in Equation 7 becomes,

$$\vec{w} \cdot \vec{x} > c \qquad (8)$$

Where c is some threshold constant given by,

$$\frac{1}{2}(T - \mu_0^T \textstyle\sum_0^{-1} \mu_0 + \mu_1^T \sum_1^{-1} \mu_1) \qquad (9)$$

and,

$$\vec{w} = \textstyle\sum^{-1}(\mu_0 - \mu_1) \qquad (10)$$

So, the criterion of an input $\vec{x}$ being in a class y is purely a function of this linear combination of the known observations.

EOG Classification for HMI

For the EOG, outputs for only the left-right control (horizontal) were used. The Left and Right side (horizontal) movement of eyeball produces opposite EOG signal outputs, shown in Figure 3 and 4 respectively. This is expected from the placement of the two electrodes on the two sides of the face as shown in Figure 1.

Since the EOG signals from these to eyeball movement produces signal of opposite polarities, these are identified with almost 100% accuracy simply using a discriminant type classification. Therefore, the classes representing intentions for Left and Right movement by EOG usually have no misclassification rate.

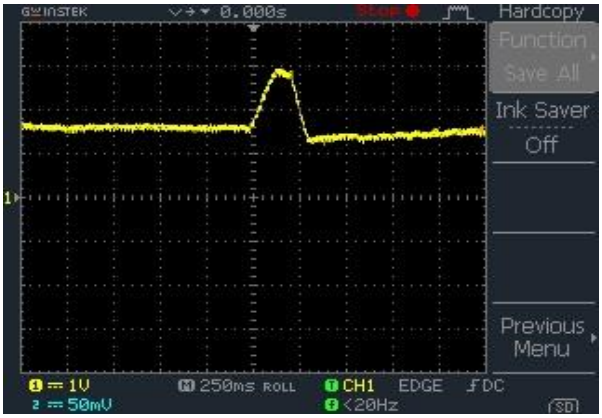

Fig. 4: EOG Signal for Left Sided eyeball Movement

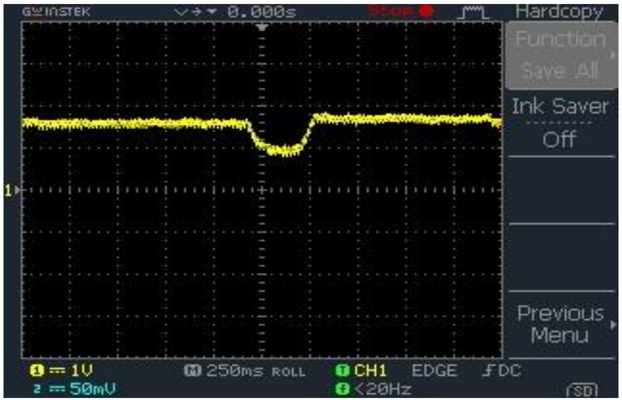

Fig. 4: EOG Signal for Right Sided eyeball Movement

Combination of Class Probabilities Obtained from EEG and EOG:

Different combination of the two classification modalities may result in different magnitudes of improvement. Therefore, the combinations were made with several different weightages. The predicted class probabilities were added percentage wise to have a combined class probability. Different combinations of weighted probabilities were used and the results were compared to improve the insight.

RESULTS AND OBSERVATIONS

Results of different weighted probability combinations are given in Table 1. This shows four combinations of the weightage of BCI and EOG and the corresponding error and accuracy figures. It can be seen that error is ‘0’ and accuracy is 100% for a 50% - 50% weightage percentage of the two parameters.

Table 0: Results of combination of EEG and EOG probabilities

Weight of the BCI Probability %	Weight of the EOG Probability %	Number of wrong prediction among 128 samples	Misclassification Rate (Error) %	Accuracy %
100	0	13	10.2	89.8
70	30	7	5.5	94.5
60	40	4	3.1	96.9
50	50	0	0	100.0

DISCUSSION

It is well known that detectability of EOG alone is almost 100% accurate. The reason of not using it alone is its reliability in control applications, due to movement of the eyes for other purposes. Again, BCI can also lead to inadvertent signals if the user imagines of moving the hands with other intentions. However, probability of having both these maneuvers together for other purposes than the desired control would be very small. Therefore, a combination of EOG and BCI, even though the latter is less accurate, may lead to a greater reliability in terms of avoidance of undesired control signals.

From the above table it appears that a combination of BCI and EOG in the weightage ratios of 60:40 or 50:50 appears to be the best for a reliable and accurate control.

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