Online Adaptive Filters to Classify Left and Right Hand Motor Imagery

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Abstract: Sensorimotor rhythms (SMRs) caused by motor imagery are key issues for subject with severe disabilities when controlling home devices. However, the development of such EEG-based control system requires a great effort to reach a high accuracy in real-time. Furthermore, BCIs have to confront with inter-individual variability, imposing to the parameters of the methods to be adapted to each subjects. In this paper, we propose a novel EEG-based solution to classify right and left hands(RH and LH) thoughts. Our approach integrates adaptive filtering techniques customized for each subject during the training phase to increase the accuracy of the proposed system. The validation of the proposed architecture is conducted using existing data sets provided by BCI-competition and then using our own on-line validation platform experienced with four subjects. Common Spatial Pattern (CSP) is used for feature extraction to extract features vector from μ and β bands. These features are classified by the Linear Discriminant Analysis (LDA) algorithm. Our prototype integrates the Open-BCI acquisition system with 8 channels connected to Matlab environment in which we integrated all EEG signal processing including the adaptive filtering. The proposed system achieves 80.5% of classification accuracy, which makes approach a promising method to control an external devices based on the thought of LH and RH movement.

1 INTRODUCTION

Today, the number of patients suffering from CereBroVascular Accident (CVA), Spinal Cord Injury (SCI) and other similar illnesses is growing every day. Improving the life quality of these persons is one of the most challenging task in front of the Brain Computer Interface (BCI) technologies. These technologies are used according to the non-invasive mode (Hajimani et al., 2013), which is based on capturing directly the Electroencephalogram (EEG) signals from the scalp using the Ag/cl electrode and without any surgery operation. EEG-based control system can be conducted by different SMRs Rhythm such as: Event Related Desynchronization/Synchronization (ERD/ERS) (Duan et al., 2014), Event Related Potential (ERP) (Cai et al., 2013), P300 speller (Koo et al., 2014), etc. By using these techniques, many applications can be developed to control home equipments, bed nursing, multimedia devices, games, driving assistance cars, etc.

A typical EEG chain is used in online approach as depicted in Figure 1. According to the 10-20 system standard, the eight electrodes of the OpenBCI acquisition system are fixed on the scalp on these position: (C1, C2, C3, C4, FC2, CPZ, CZ, FCZ, CPZ, OZ, Ground electrodes are placed on the ear). EEG signals are registered using an OpenBCI 32-bit acquisition board based on the ADS1299 Analog front end device. EEG digital signals are then sent to the host through RFduino module allowing users to interact freely without any discomfort. The acquired EEG signal are processed to remove all unwanted signals. These undesired frequencies are removed based on adaptive filters due to the intrinsic variability of EEG signals in each subject (Belwafi et al., 2014). Once the EEG signals is well filtered, we proceed to the extraction of the main characteristic of each trials by applying the Common Spatial Pattern algorithm; which is the most effective spatial filter algorithm to extract ERD/ERS effects (Kais et al., 2014). The obtained feature is then classified using the Linear Dis-

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criminant Analysis (LDA) classifier, which uses linear function to distinguish between LH and RH tasks (Lotte et al., 2007).

Even if the off-line validation of the proposed EEG-based architecture is very interesting using existing data sets, the on-line validation remains the best validation one providing a real-time interaction which represents the feedback aspect in the BCI-chain (Yu et al., 2015). To proceed for classification of LH and RH movements using the on-line approach, we proposed to use the headset of OpenBCI with eight channels connected to Matlab environment in which we developed all EEG signal processing including adaptive pre-processing.

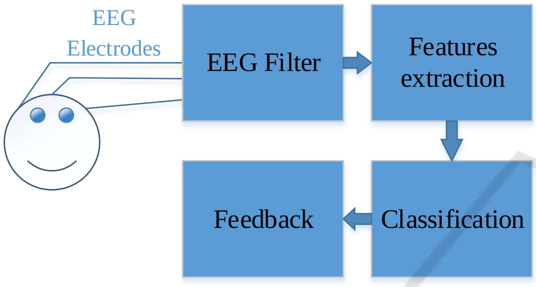


Figure 1: Brain computer interface chain.

The remainder of this paper is organized as follows. In Section 2, the fundamentals of BCI theory is described. The data recording and processing explained in section 3. Section 4 presents the results and realization of the system. The conclusion and future research plans are discussed in Section 5.

2 EXPERIMENTAL SETUP

The block diagram of the proposed EEG-based system is depicted in Figure 2. Eight EEG channels are used and placed on the scalp according to the 10-20 system. The spatial distribution of the electrodes is depicted in Figure 3. As above mentioned, EEG signals are acquired using an openBCI32 bit board. The conversion from analog to digital is done by the ADS1299, followed by an amplification stage with a factor of 24. The sampling frequency is fixed to 250 Hz. Notch filters are configured and applied to all eight channels as a first pre-processing action. The acquisition board will send continuously EEG data through the RFduino module to the Matlab environment via a USB interface (see Figure 4). An automatically script will be launched to check the frames permanently, converts it to the corresponding value and stores them into a matrix to be subsequently processed. Four volunteers participated in this experiment whereas two of them are familiarized with these experiments. The participants are informed by the recording scenario to avoid the risk of suffering due to the long time of recording (Onishi and Natsume, 2013), which can exceed half hour. In total, 260 trials are recorded during these experiments (140: for training and 120 for test). After launching the process by press start button, the participant has to imagine the left hand or the right hand movement according to the picture appearing on the bottom of the interface as illustrated in Figure 4.

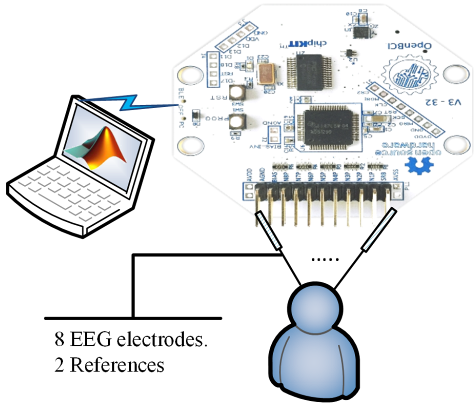


Figure 2: Experimental setup.

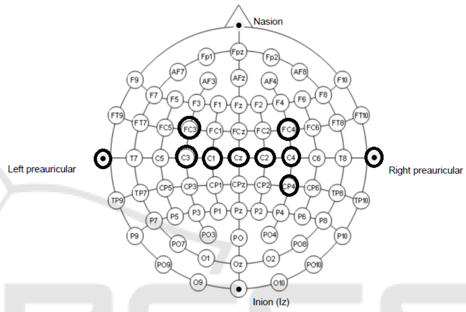


Figure 3: Electrode positioning.

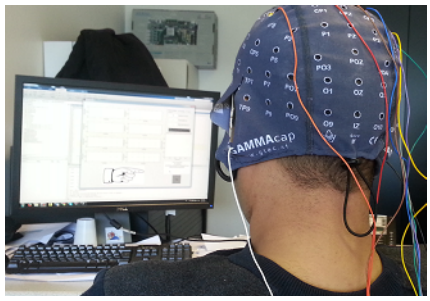


Figure 4: The interface of the proposed system.

3 METHOD

Signal processing was performed to keep just the frequencies related to left and right hand motor imagery which are represented by μ-rhythm and β-rhythm (Lotte and Guan, 2011). Recently, a new approach is proposed to select automatically the best filters parameters that guarantee the removal of all unwanted signals, and adapts to the intrinsic individual characteristics of EEG signals for each person (Belwafi et al., 2014). This method is based on the variation of the Signal-to-Noise Ratio (SNR) on the stop band that has an explicitly effect on the pass band frequencies. Increasing the SNR will increase the filter order leading to a modification of the transition band to be close to the cut-off frequency where the signal becomes very well filtered. Furthermore, the applied adaptive filtering techniques are based on the Finite Impulse Response (FIR) and Infinite Impulse Rate (IIR).

Once the EEG signals are filtered, their size should be minimized as much as possible keeping only useful information contained in each trials. Many techniques are reported in literature including power spectral density, Short-Time Fourier transform STFT, CSP and wavelet analysis (Duan et al., 2014), etc. The CSP algorithm is strongly recommended for feature extraction of EEG signal in motor imagery. This algorithm computes the discrimination between features of two classes according to the distribution of their topographic patterns (Robinson et al., 2011). Formally, CSP computes the normalized covariance matrices by applying the following equation (Equation 1):

$$C_i = \frac{EE^T}{trace(EE^T)} \qquad (1)$$

where trace(x) is the sum of diagonal elements of x, 'i' is the index of class (LH, RH) and E is data of each trials of dimension given by Number of channel x Number of samples. Then, the overall composite spatial covariance matrices is calculated by adding the covariance matrices of each classes. In the next step, the composite matrices (C_c) is decomposed according to the following equation(Equation 2):

$$C_c = U_c \lambda_c U_c^T \qquad (2)$$

where U_c is the matrix containing eigenvector and λ_c is the diagonal matrix containing the eigenvalue sorted in the ascending order. According to the equation (Equation 3), the whitening transform will be computed to equalize the variances in the space that is created by U_c.

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

A simple test can be done to check that all above operations are done successfully. The multiplication of of P, (U_c) and P transpose respectively, should give one. The transformed covariance matrices $S_{i\in\{1,2\}}$ is obtained according to the equation (Equation 4):

$$S_i = PC_iP^T = B\lambda_i B^T \qquad (4)$$

Then, the projection matrix W is obtained according to the following equation:

$$W = B^T P \qquad (5)$$

The feature vector which optimally discriminate the two classes are the (N/2) smallest and (N/2) largest eigenvector of Z (see Equation 7), where N is the number of feature that should be retained. In our case, the number of feature is fixed to six.

$$Z = WE \qquad (6)$$

Finally, the returned feature vectors is calculated based on the following equation:

$$F_i = log(\frac{var(Z_i)}{var(Z_1) + var(Z_2)}) \qquad (7)$$

To predict the class of each trials, LDA classifier is applied on the extracted features. The goal of LDA is to separate the data representing the two classes by an hyper-planes as depicted in Figure 5. The equation of the hyper-plane (L) is mentioned on the same figure, where Q and b are the hyper-plane coefficients which will be estimated during the training phase.

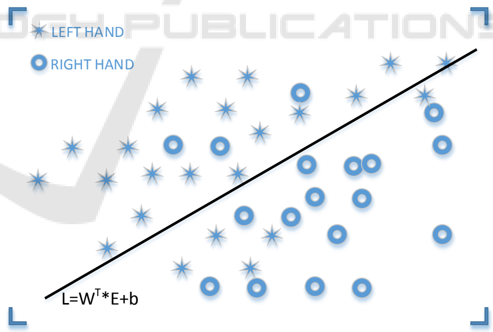


Figure 5: A Hyper plane separating LH and RH.

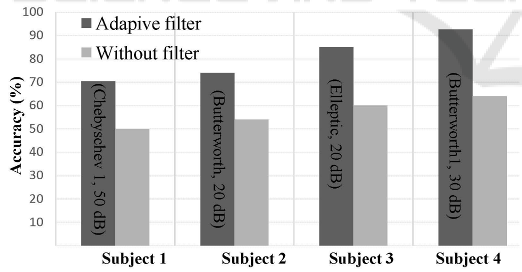
Depending on the sign of L, the classifier will assort each feature. If the hyper plane (L) of an action is strictly negative, then the action should be a RH. Similarly the corresponding actions strictly positive then is LH.

4 RESULTS

Two sessions are recorded during the evaluation of the system. One recording session is used for training, and the other one for testing. As depicted in Figure 6, the accuracy of the two class motor imagery actions increases when we integrate the adaptive filtering techniques for all subjects. In fact, the proposed BCI chain is able to discriminate RH and LH EEG signals with a high accuracy reaching 92% for subject 4 for example. The mean performance of all subjects is close to 80% using adaptive filtering techniques. Figure 6 shows clearly a significant improvement in the system accuracy by just tuning the filters parameters. The adaptive filter is done automatically during the training phase for each subject and the best parameters were fixed during the test phase. Furthermore, the enhancement of classification accuracy over traditional classifiers based on one fixed filter is significant and can reach u;p 25%. The filters parameters are heterogeneous among subject. For example for subject one the best filters is Chebyschev1 with an SNR of 50 dB, that implies motor imagery frequencies of this subject are inside μ and β bands. In others cases for example, for subject two the LH and RH frequencies are outside these theoretical bands. Information Transfer Rate (ITR) is used to evaluate the proposed system according to the following equation:

$$ITR = L[plog_2(p) + log_2(N) + (1-p)log_2(\frac{1-p}{N-1})] \quad (8)$$

Let consider L is the number of decisions in one minute, and p is the accuracy of the subject in making decisions among N targets.



Subject	Adapive filter	Without filter
Subject 1	70.50	50.00
Subject 2	74.00	54.00
Subject 3	85.00	60.00
Subject 4	92.50	64.00
Mean	**80.50**	**57.00**

Figure 6: Classification accuracy for four subjects.

The ITR for all subjects is 8.64 bits/min which is very interesting result compared to a similar work. For example, in (Sannelli et al., 2010), the ITR computed for three subjects is 3.56 bits/min. The system proposed in (McFarland et al., 2003) dedicated for controlling the mouse using two motor imagery actions reaches 7.4 bits/min as ITR for eight subjects. For comparison purpose with the offline approach, the same algorithms are used in the off-line context and a small increase of only 1% of accuracy. Our results show that adapting filtering is very interesting to be integrated into the on-line validation of the EEG-based motor imagery application to reach a high accuracy.

5 CONCLUSION

The proposed EEG chain shows a clear improvement of the performance of the system leading to good discrimination between LH and RH motor imagery tasks for online validation. In order to improve the performance of the proposed system, adaptive filter was used to remove the maximum of the unwanted signals, and to tune the pass band which contain μ and β band. The proposed method shows that the combination of the adaptive filter with CSP as features extraction and LDA as classifier improves the classification accuracy using the online approach. Furthermore, the ITR of the system is very interesting comparing with those obtained from equivalent existing systems.

Our future work target is to extend the proposed procedure to a multiclass paradigm in order to classify three tasks that will be used with a state machine to control home devices equipment. In addition, it will be interesting to implement the proposed procedure in real time embedded system.

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