An Adaptive EEG filtering approach to maximize the classification accuracy in motor imagery

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***Abstract* – We propose in this paper a novel approach of adaptive filtering of EEG signals. The filter adapts to the intrinsic characteristics of each person. The goal of the proposed method is to enhance the accuracy of the home devices system controlled by the thoughts related to two motor imagery actions. μ-rhythm and β-rhythm are the specific returned bands that contain the information. The main idea of the proposed method is to preserve the frequency bands of interest with a different value of the SNR on the stop-band. Our experimental results show the benefits of a suitable tuning of the filter on the accuracy of the classifier on the output of the EEG system. The proposed approach outperforms significantly performances reported in the literature and the effectively enhancement of the classification accuracy can reach up to 40% based only on filtering tuning.**

Keywords – brain computer interface (BCI), ElectroEncephaloGram (EEG), EEG filters optimization, Motor imagery.

I. INTRODUCTION

A Brain Computer Interface (BCI) is an interface which can improve the life quality of people with severe disabilities and make people capable to control and communicate with outside using only their thoughts. According to the non-invasive technique, EEG signals are captured from EEG headset based on Ag/cl sensors. This acquisition technique provides a fine temporal resolution, ease of use, portability and low set-up cost. EEG based BCI has become the mainstream of brain computer interface.

In order to control a BCI, user have to provide different brain activity patterns which will be identified by the system, processed and translated to actuators and control devices. The captured activity pattern is always accompanied with noise due to several causes like bad electrode location, electrode impedances, etc [7]. Hence it is very valuable to remove all artifacts and enhance the accuracy of the EEG signal processing by adjusting signal to noise ratio (SNR) related to the filtering component. Due to the big size of the EEG signal trials and the no-stationary character of such signal, filtered data is followed by feature extraction techniques, before being classified by one of the appropriate classifier.

Nowadays, several BCI researchers continue to improve and to find solutions for practical implementation of processing algorithms. Their works are focused on feature extraction and classifying EEG records to desired classes of mental tasks [12]. Despite the significant improvements that have been achieved in this area, the obtained results are still limited without deep analysis of filtering blocks which have an important impact on the system performance [19]. Few works in the literature analyze the filter block effect, and alert BCI researchers to study raw data for a simple element. If the filtering process must be used, we should be careful when choosing the filter parameters [22] [8]. In this respect, we conduct a study of the effect of pre-processing techniques on the improvement of the accuracy for different subjects. The feature extraction and the classification algorithms are out of the scope of this study.

As the filtering block seems to be a useful preprocessing step for removing artifacts, improving stationary, and increasing the accuracy, a design exploration of the filtering techniques is required [3]. It looks that digital filters are widely used for EEG signals without deep analysis of their effect on different trials and different data-set leading to a decrease in the system performance for many subjects [1]. In this work, our objective is to find the suitable parameters of the most common used filter for motor imagery domain including: Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) techniques. Some parameters of the filter, as stop band (SB), pass band (PB), bandwidth (BW) and transition width (TW) should be accurately tuned to reduce filter order while increasing the classification accuracy of the motor imagery system. Most of the published works considered FIR and IIR techniques with order ranging from 4 to 8 without any analysis and justification for their choices [6] [5] [7]. By using the Matlab filter design tool, we checked these filters and noticed that the predefined features (SB, PB, BW and TW) are not well tuned for the motor imagery data sets. That is why we conduct extensive investigations on filter design for different subjects to find the optimal SNR bandwidth for each subject which leading to an improvement of the classification accuracy.

The remainder of this paper is organized as follows. In section II, we describe the data-set used in our experiments. In section III, we review the feature extraction and classifiers algorithm and present the chosen one. Section IV mentions the existing filtering algorithms for BCI and presents the problem related to the motor imagery area. Experimental results and analysis are discussed in section V. Section VI is dedicated to describe the proposed method. Section VII shows our experimental results. And finally, concluding remarks are drawn in section VIII.

II. Data Set Description

In all of our experiments, we use three public data sets of BCI competition IV (1 data set) and BCI competition III (2 data sets) provided by Graz University of Technology. These three data sets contain motor imagery EEG signals recorded from seventeen subjects performing two different motor imagery tasks (Left Hand “LH” and Right Hand “RH”). Below, the description of these data sets.

1. Data set IIa [18], from BCI competition IV constitutes EEG data from nine subjects performing four different motor imagery data, i.e., LH, RH, foot and tongue. The recording was done with 25 Ag/cl electrodes; three of them contain EOG artefacts, and was sampled with 250 Hz, and filtered between 0.5 and 100 Hz. Each subject recording contain 288 trials, for this study we use only EEG signals corresponding to left and right hand Motor Imagery (MI) tasks.

2. Data set IIIa [4], from BCI competition III contains EEG signals from three subjects performing four different motor imagery data i.e., LH, RH, foot and tongue. The data were acquired through 60 electrodes, was sampled with 250 Hz and filtered between 1 and 50 Hz. The recoding comprises 60 trials for each class. For the purpose of our study, only EEG signals corresponding to LH and RH were used.

3. Data set Iva [4], from BCI competition III comprises data set from five healthy subjects performing two different MI data, i.e., RH, foot. EEG was recorded using 118 electrodes. Signals were band-pass filtered between 0.05 and 200 Hz and then digitized at 1000 Hz. Each subject recording contain 280 trials.

For the three data-sets, trials are extracted in reference to the Trigger. Based on some experiments, the epoch (window) had duration of 2 seconds for data set (IIIa, IIa) and 0.2 second for data set IVa [13]. Figure 1 depicts an example of two trials for one subject for each data set. The presented signals are taken from C3 and C4 channel which are characterized by the appearance of rhythmic activity of the motor imagery movement [21].

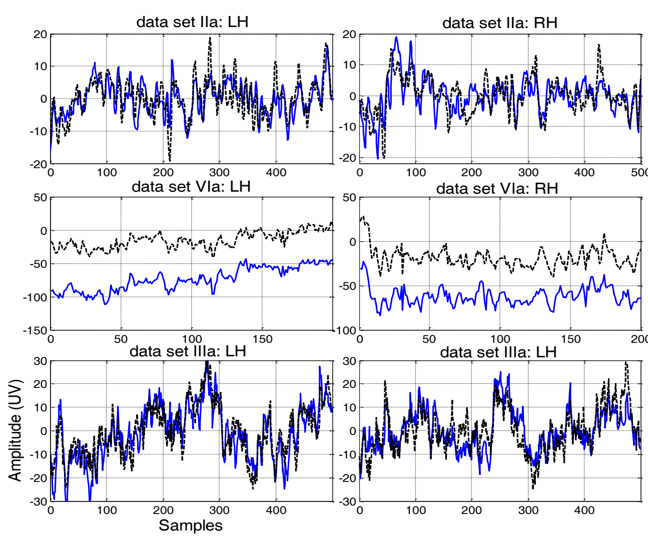

Figure 1: Example of raw EEG signal

III. Overall Brain computer interface description

In this paper, we report on the offline analysis of the two class BCI experiment to be used by the finite state machine of the home devices controller. General structure of the motor imagery detection system is depicted in Figure 2. At the beginning of the chain, we start by extracting trials from the recorded EEG signals which are referenced by a trigger.

Before applying features extraction, we conducted a deep analysis of the filter block which will be presented later on the next section. Regarding the signal enhancement process, several feature extraction techniques are proposed to examine the long EEG signals which require rapid and automatic methods to provide fundamental features to be used in subsequent automatic analysis. Many techniques have been reported including power spectral density [7], Short-Time Fourier transform STFT [2], CSP [3] and wavelet analysis [2] etc. The choice of any technique will affect the accuracy of the associated classifier. In this respect, we will consider the CSP technique which seems to be the best spatial filter algorithm for the motor imagery from the effectiveness point of view to extract ERD/ERS effect. The main idea of this technique is to design a pair of spatial filters such that the filtered signal's variance is maximal for one class while minimum for others [1]. For comparison purpose, we use also other variants from the CSP which are SRCSP (Spatially regularized CSP), CCSP1 (Composite Common Spatial Pattern) and DLCSPauto (Diagonal Loading CSP automatic) [13].

A classifier algorithm is applied to check the classification accuracy using the selected feature. A comprehensive review of classifiers for BCI is presented in [14] with many classifiers such as Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), Neural Networks (NN), Hidden Markov Models (HMM) and Mahalanobis distance (MD). Also the choice of any classifier technique will affect the performance of the BCI-based system. For this reason, we propose to use the LDA technique which is a simple and robust classifier. Despite its good performances, it was used in a widely cited paper [9].

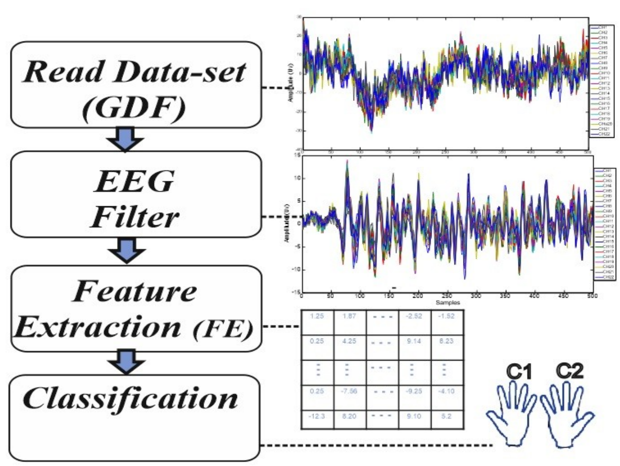

Figure 2: System block diagram of EEG chain

IV. EEG FILTER DESIGN

It is critical to ensure that preprocessing steps do not introduce spurious information, as do not remove interesting data which can result in system performance degradation. To avoid any of these symptoms, the unwanted signals should be carefully removed through one of the appropriate techniques. The most effective and widely used algorithms of EEG data filtering are Finite Impulse Response (FIR) and Infinite Impulse Response (IIR). FIR filters may be realized by non-recursive structures which are simpler and more convenient for programming on dedicated digital signal processing platform. These structures are always stables and guarantee the phase linearity of the signal. The main disadvantage of the FIR filer is the high orders for simple filtering operation. On the other hand, IIR digital filters require a reasonable order compared to the FIR, leading to an important reduction in resources and timing saving. It seems that IIR-based techniques are well adapted for embedded and real-time implementation. However, IIR filters don't have a linear phase, which can be corrected by cascading it with a pass filter [6]; or applying the filter in forward and reverse direction to give zero-phase distortion [15] [17].

The frequency of the received data is in the range [0.5 100] Hz and [0.05 200] Hz for the data set (IIa, IIIa) and (IVa) respectively. For this range of frequencies, these data should be processed through one of the above mentioned filter techniques to keep the interesting frequency of the system in its bandwidth. In our case, the theoretical frequency response for the MI area is located on the μ-rhythm [8-13] Hz and β-rhythm [14-30] Hz [2]. In our case, the only known parameter is the attenuation band which should be close to zero decibel to avoid any distortion of the EEG information [16]. For the pass band frequency it's on μ and β-rhythm. But in reality it differs from one subject to another [10] [20], making the selection of proper frequency bands one of the most challenging problem in BCIs.

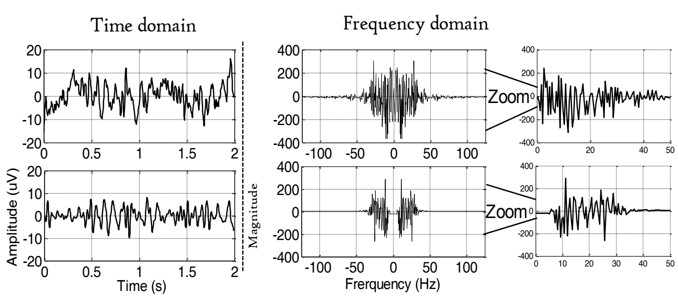

Figure 3: Frequency response for Butterworth (Order=4)

To filter the motor imagery data, many works have been reported in [6] [5] [3] which proposed using of Butterworth filter with an order ranges from 4 to 8. These low filters order are insufficient to remove the unwanted frequencies located outside the band of interest. Figure 3 depicts the frequency response of the Butterworth filter with an order four (2^{nd} row), and it shows clearly the presence of the undesirable information outside μ and β band which can be among factor of system performance deterioration. Also the uniformly attenuation of the rejected EEG data lets the diagnosis of the system more complicated to locate the information close to the pass band frequencies. These experiments prove this filter with fewer weights, in general, passes a few activity in the pass bands and more activity in the outside of the band [1]. To filter the usual band motor imagery band, a minimum filter order should be defined as depicted in Figure 4. These orders at least guarantee the removal of the unwanted signal and kept just μ and β band. The calculation of these filter orders is based on the SNR value, transition width which is equal to 1Hz on both pass band and stop band. We notify that more these constraint are complex, the filter order is increasing, by consequent the filter implementation requires more execution time. Using one of the filter order will keep the frequency in question and will facilitate the localization of the information related to each subject.

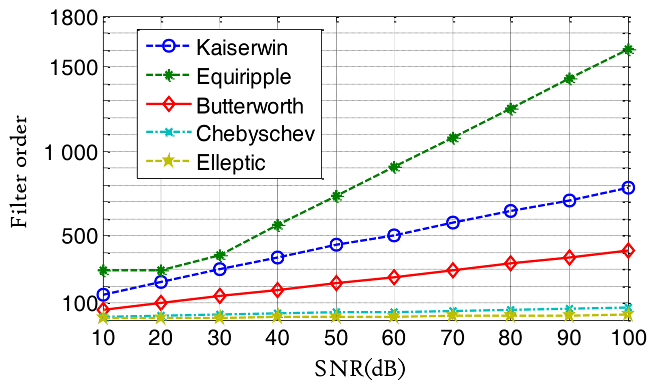

Figure 4: Minimum Filter order for MI-EEG data

A lot of researchers in the literature, mentioned the uses of μ and β bands for motor imagery applications and demonstrate that the most responsive frequency bands vary according to each subject [11] [10] [20]. These two major points are totally different and each one should be treated alone. From this point of view, to process motor imagery data under the first hypothesis, we should keep, before filter parameters, all frequencies outside these two bands. Under the second hypothesis, the main question how to apply a band pass filter with guarantee that the information isn't affected. In [20], it was propose to identify the informative frequency band based on ERSP (Event-Related Spectral Perturbation) method but this step was done after performing a band pass filter which can already affect the interesting data. This motivates us to make deep analysis of the filter block which is not yet well studied in the EEG literature.

V. PRELIMINARY OBSERVATIONS AND DISCUSSIONS:

To show the effect of the filter parameters on the BCI chain, we propose to evaluate the system performance based on filter parameters for each subject. For comparison purposes with other results, we use the criterion of kappa score metric [18]. As example, in figure 5, we present the accuracy of subject number "one" of data set IIa depending on the filter type and the SNR value. The same treatment is made for all other

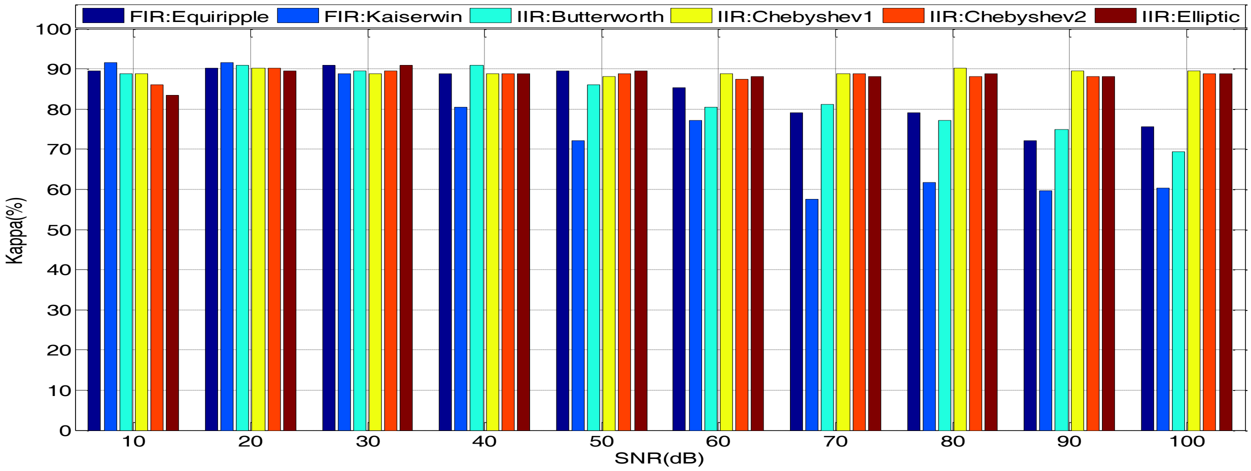

Figure 5: Performance in term of kappa using different filter type for (subject1, data set IIa)

subjects of three data sets (but not showed here) and we noticed the same dependence of classification accuracy to the SNR values and the filter type.

In Table 1, we summarize the best and the worst results for each subject and the couple of filter type and SNR value corresponding to each result. It is clear that there's no specified filter algorithm or specified filter parameters that provides always better accuracy for any subject. This confirms the variability of frequency domain due the intrinsic characteristic of subject's EEG signals [11]. Moreover, in some cases we noted that filtering deteriorated dramatically the classification accuracy relative to non-using of filter: for example for subject number B3 of data set IIIa, using Kaiserwin filter with SNR of 70 dB decreases the performance of the system by more than 50%. This recalls the presence of the motor imagery information outside μ and β bands. In this special case, it is better to work on unfiltered signals, or change the pass band of the subject.

For example, filtering EEG data of subject number C9 with an Elleptic filter and for a SNR value of 50 dB enhance the kappa value by only 0.7% (see Table 2). In this case, we have to consider a trade-off between the execution time and the classification accuracy improvement.

VI. PROPOSED APPROACH

The main idea of our proposed system is to find the suitable filter type and filtering parameters by subject. We recall here that the used basic metric in our studies is the SNR which has an effect on the filter order: when the SNR value is too high, then the filter order is too high, consequently the EEG data is very well filtered and all unwanted frequencies are removed. This may causes a problem for people having motor imagery frequency outside μ and β bands. To solve this problem and avoid the suppression of the useful data, the proposed system is depicted on Figure 6.

At the beginning, we divide the data-set of each subject into two parts: the first part is used for the training step, and the second for the test phase. Each part will be filtered through EEG filter block commanded automatically by a multiplexer (to select the filter parameters). These parameters are $P_{1...n}$ corresponding to the filter type (6 filters) and the SNR value (vary from 10 to 100 dB). Hence, there are generally sixty parameters to apply for the data of each subject. Thereafter, optimal spatial filters are extracted through the CSP block. Hence the signal size will be reduced that overload the work of the next step which is the training classification. Once the training process is performed, we apply the obtained test feature and measure the kappa performance (X %) corresponding to each parameter. After finishing the computation for each subject, an automatic process will be launched to select the best parameters giving the maximum accuracy P(max(X%)). The returned parameters will be used in runtime by this subject. Finally it will be very interesting to auto-calibrate the system during the online approach, by feedback the information to the system at each bad classification (accuracy under desired threshold).

			Accuracy in term of kappa (%)			
			Min	**Filter (SNR dB)**	**Max**	**Filter (SNR dB)**
BCI competition IV	**IIa**	C1	57.63	Kaiserwin (70)	91.66	Kaiserwin (10)
		C2	47.22	Kaiserwin (70)	67.36	Butterworth (90)
		C3	52.08	Kaiserwin (100)	96.53	Elleptic (20)
		C4	45.18	Kaiserwin (80)	73.61	Equiripple (10)
		C5	43.75	Kaiserwin (70)	68.06	Chebyschev1(70)
		C6	51.39	Kaiserwin (90)	73.61	Chebyschev1(50)
		C7	48.61	Equiripple (90)	79.16	Chebyschev1(10)
		C8	59.02	Kaiserwin (90)	99.30	Chebyschev1(80)
		C9	69.44	Kaiserwin (100)	93.75	Elleptic (50)
BCI competition III	**IIIa**	B1	51.11	Kaiserwin (90)	97.77	Equiripple (10)
		B2	53.00	Kaiserwin (90)	71.66	Butterworth (30)
		B3	33.33	Kaiserwin (70)	100.0	Elleptic (50)
	IVa	A1	38.39	Equiripple (60)	67.14	Kaiserwin (80)
		A2	46.42	Butterworth (50)	98.21	Elleptic (20)
		A3	45.40	Butterworth (50)	58.16	Equiripple (10)
		A4	42.41	Chebyschev1(80)	51.33	Butterworth (10)
		A5	44.84	Chebyschev1(30)	56.75	Kaiserwin (50)

Table 1: Resume of the accuracy for each subject.

			CSP			SRCSP			CCSP1			DLCSPauto		
			Without filter	Butter Order 4 [18]	proposed	Without filter	Butter Order 4[18]	proposed	Without filter	Butter Order 4[18]	proposed	Without filter	Butter Order 4[18]	proposed
BCI competition IV	IIa	C1	77.08	88.89	**91.66**	72.22	88.89	**93.75**	72.22	88.89	**92.36**	75.69	88.89	**91.66**
		C2	52.08	51.39	**67.36**	51.38	63.19	**70.13**	52.08	54.17	**68.05**	52.77	51.39	**68.05**
		C3	89.58	96.53	**96.53**	92.36	96.53	**96.53**	92.36	96.53	**96.54**	91.66	96.53	**96.52**
		C4	56.25	70.14	**73.61**	65.97	66.97	**72.22**	66.66	**70.83**	68.10	56.25	70.14	**73.61**
		C5	50.00	54.86	**68.06**	50.00	63.19	**68.05**	50.00	62.50	**78.47**	50.00	56.94	**68.06**
		C6	56.94	71.53	**73.61**	56.94	63.89	**70.83**	56.94	67.36	**79.17**	56.94	71.53	**73.61**
		C7	59.72	**81.25**	79.16	70.14	78.47	**79.16**	59.94	81.25	**99.31**	58.33	**81.94**	79.17
		C8	95.13	93.75	**99.30**	95.83	95.83	**98.61**	95.83	95.87	**99.31**	96.52	93.75	**99.30**
		C9	93.05	93.75	**93.75**	92.36	92.36	**93.75**	91.66	91.67	**92.36**	93.05	93.75	**93.75**
BCI competition III	IIIa	B1	94.44	95.56	**97.77**	93.33	96.67	**98.88**	92.22	98.89	**98.88**	94.44	94.44	**98.88**
		B2	51.66	61.67	**71.66**	51.66	53.33	**80.00**	50.00	56.67	**66.66**	50.00	63.33	**75.00**
		B3	85.00	93.33	**100**	90.00	93.33	**100.0**	85.00	93.33	**100.0**	88.33	95.00	**100.0**
	IVa	A1	47.32	66.07	**67.14**	55.35	**72.32**	57.14	52.67	**71.43**	57.14	49.10	**66.96**	53.57
		A2	75.00	96.43	**98.21**	85.71	96.43	**100.0**	75.00	96.43	**98.21**	58.92	96.43	**98.21**
		A3	55.10	47.45	**58.16**	48.46	**60.20**	55.61	54.08	**63.27**	55.10	55.10	46.94	**57.14**
		A4	53.12	**71.88**	51.33	55.80	**77.68**	58.48	51.78	**71.88**	69.64	54.46	**71.43**	57.58
		A5	52.38	49.60	**56.75**	48.80	**86.51**	64.68	42.86	**86.90**	66.66	53.17	50.00	**54.36**
Mean			67.28	75.53	**79.06**	69.19	79.16	**79.87**	66.74	75.84	**78.73**	67.13	79.28	**81.52**

Table 2: Classification accuracies obtained for each subject for different feature extraction methods.

VII. EXPERIMENTAL RESULTS

To show the effectiveness of the suggesting approach, we integrate our proposed methods on the framework proposed in [13] to keep the same environment. Table 2 reports the classification accuracies obtained on data sets for different couples of feature extraction and filters. Our results show a clear improvement in performance and an effective way to address the problem of classifying the Motor Imagery system actions. The success degree of the proposed approach is depending from the data set; and it reaches 100% for the data set IIIa, 91.66% for data set IIa and 50% for the last data set. These heterogeneous of the accuracy are due to many factors such as the recording equipment, environment and degree of subject's interaction with the system.

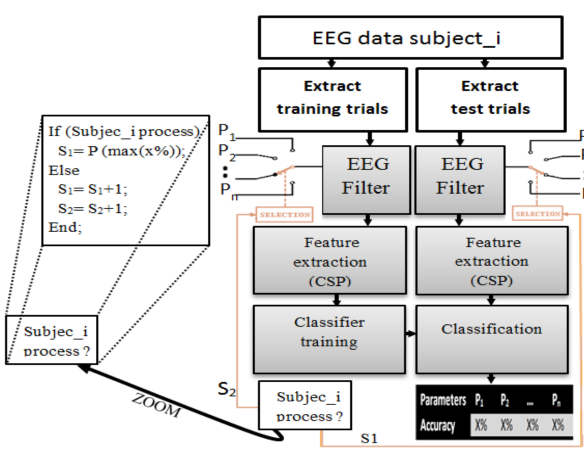

Figure 6: Proposed EEG filter design approach

Although, the system become more accurately, the home device controller is accompanied with an increasing on the consuming time and the complexity. During training steps, the proposed EEG filter design will consume 1.19 seconds to process EEG trials. Anyway, this task will be executed just one time, after that the home device system will take almost 0.02 second to process EEG trials captured through 22 electrodes.

VIII. CONCLUSION

The EEG filter design described in this study proposes an adaptive EEG-filter platform capable to avoid any decrease of the system performance. Instead of using unified filter parameters for BCI system users, filter parameters should be well tuned during the training phase of the home devices system. Our proposed approach are tested and validated on the three public data-set and we prove that accuracy can be significantly increased based only on the adaptive filtering implementation with respect to each user. Our system performance can reach an enhancement of more than 40% for some subject. Hence, the results obtained in this study encourage the use of the proposed adaptive filter. Our future work targets an embedded System on Chip (SoC) implementation of our BCI system to integrate it in the new generation of low power wireless EEG headsets.

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