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Feature Vectors Combination to Increase the Efficiency of a Brain-Computer Interface (BCI) System

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ABSTRACT

Brain-computer interface (BCI) system as a modern way of communication between brain and external device has got much attention in the recent decades. The basis of BCI is to record brain signals using one of the invasive (such as ECoG) or non-invasive (such as EEG) methods,to interpret different states of the brain and to make control orders for external devices.Preprocessing, feature extraction, feature reduction and data classification are the stages of processingbrain signals which are of great importance in a BCI system. In this paper, by implementing the stages of processing brain signals, the type of movement imagery is determined and using the method of features combination and superior features selection, the error rate of predicting the type of movement is optimized. It must be mentioned that in this paper, the dataset number IIB of the brain-computer competitions (2008), recorded from nine persons,is used. After preprocessing and eliminating signal artifacts, feature vectors are extracted by the parametric model of AR, AAR, wavelet transform and CSP filter. The main goal of this paper is to investigate the efficiency offeature vectors separately and to provide a method for BCI system efficiency increase; to achieve this goal, first the feature vector effects for each person are investigated using SVM classifiers; then by combining feature vectors the BCI system is tested and to increase its efficiency the methods of superior features selection are used. Investigating tables and figures we will conclude that by combining feature vectors, brain signals classification precision related to movement imagery may be increased.

KEYWORDS: brain-computer interface (BCI), feature, classifier, SVM, feature selection.

1. INTRODUCTION

Research on and development of the relationship between human and machine has beena subject in focus in the recent decades. There is some information in the brain signals by which the mental states of a person (such as movement imagery) can be converted into control orders for external devices; this process is called brain-computer interface (BCI) system [1]. BCI systems based on movement imagery have been studied many times to help the disabled (controlling wheelchair).

The first stage to process the brain signals is to record brain data. There are different methods to record brain data. The most common method is Electroencephalogram (EEG) which because of low cost, high time resolution and non-invasive parameters (ease of installation) is used more [2 , 3].

To determine brain signals and to control an external device, extracting effective features and classifying data enjoy ahigh significance.The challenge the researchers face in this path is to make a proper feature vector with the intended BCI system and to reduce data classification precision.

Pfurtscheller and Aranibar indicated that the amplitude of signals in alpha and beta band is accompanied by changes duringmovement imagery which are called ERD and ERS [3]. This characteristic can be used as a feature to determine the type of movement imagery; there are different methods to extract this type of feature, including frequency band power, AR parametric model, wavelettransform, common spatial pattern (CSP), power spectral density (PSD), statistical characteristics etc. [4].

In the sources [2, 5, 6] CSP method has been applied to extract feature; the source [7] has used AR and PSD methods to make feature vector and the source [8] also has used wavelet method.

In the stage of extracted feature vectors classification, the sources [9 , 5] have applied FDA and LDA. Also, the sources [7, 10, 11] have used KNN and SVM to classify the brain data.

In this paper, we showed that one type of feature is not sufficient to determine the type of movement imagery in different people, and by making a feature vector consisting of several types of feature BCI system efficiency can be increased to determine the type of movement imagery. To investigate the effect of each one of feature vectors, we have used one type of classifier; also, because of reference to the relative high efficiency of the classifier SVM in the articles, we have applied this classifier.

In section 2 we will deal with brief investigation into the techniques of feature extraction, and this section will ends with introduction to the suggestedfeature vectors. In section 3, the results arising from the suggested feature vector will be explained and finally conclusion and suggestions will be presented.

2.METHOD

To show the changes the special mental activities make in the signal frequency feature, EVENT-RELATED Desynchronization and EVENT-RELATED Synchronization are used; these changes are visible in the form of increase or

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decrease in frequency band power [12]. Left and right hand movement imagery is usually accompanied by ERD and ERS in the frequency band mu (8-12 Hz) and beta (13-28 Hz). During imagery of movement toward right, signal power in alpha band is more in right hemisphere of the brain compared to that of theleft hemisphere (channel C3), and duringimagery of movement toward left, signal power in alpha band is more in left hemisphere of the brain compared to that of the right hemisphere (channel C4) [13]. Figure 1 shows the average of C3 and C4 channel power from training data in alpha frequency band in time realm. ERD and ERS show that by extracting time and frequency features of the signal, good results can be achieved; we have used the methods AR, AAR and wavelet for ERD and ERS detection. A brief explanation of these methods will be presented in the next sections.

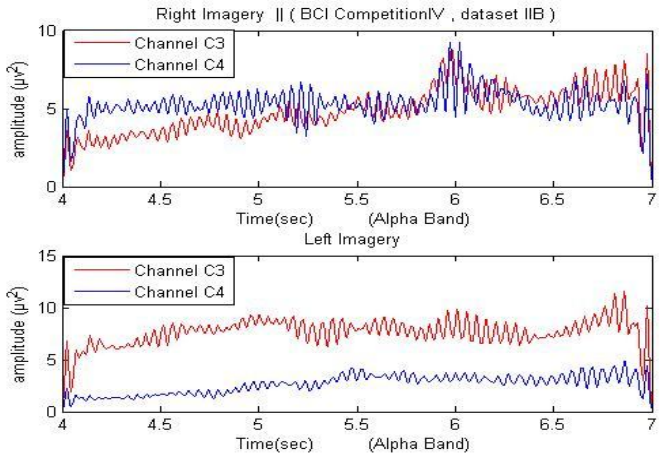

Fig. 1. signal power difference in alpha frequency band between channels C3 and C4 from right and left movement imagery data

2.1. Wavelet transform

In BCIs, the ability of extracting feature from rhythm changes in EEG signal, when occurring mental operations, is very important. Discrete wavelet transform (DWT) is one the common methods to extract feature which is very powerful for time-frequency features extraction and very effective to show ERD/ERS [14]. It must be mentioned that because of brain signals being non-static, time-frequency analysis is used.

Decomposing EEG signals into approximation and detail information, discrete wavelet analyses signal in different frequency ranges and time precisions. The mechanism of discrete wavelet is shown in figure 2;with discrete signals, by crossing signal from high-pass filter and reducing sampling rate to half, detail coefficients are made and also by crossing signal from low-pass filter and reducing sampling rate to half, approximate coefficients are made [15, 16] and by computing statistical parameters of these coefficients feature vectors are also made.

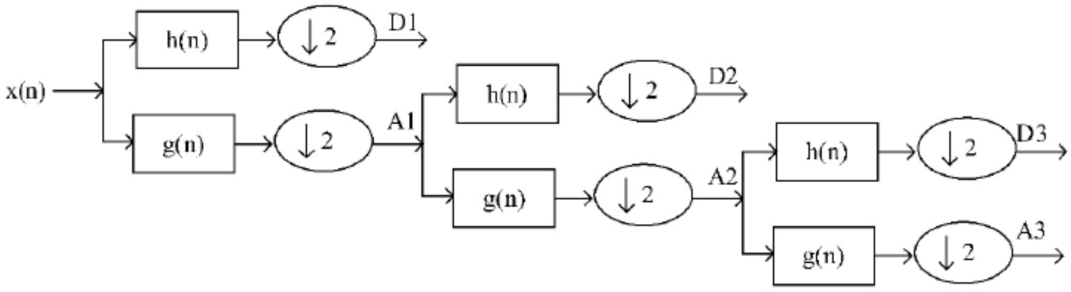

Fig. 2. sub-bands resulting from discrete wavelet transform

2.2. Common spatial pattern

In 1995, Koles introduced a modern method for spatial filters. The main idea of this method was to maximize the difference between variances of different classes and it was introduced by the name common spatial pattern 1 [17]. To increase the variance difference of two classes of CSP, the following relation is used.

$$Y = W^T X \qquad (1)$$

X is a matrix with the dimensions $K \times n$, where n is the number of EEG record channels and K is the number of training data sampling points in each channel, W is the CSP projection matrix, and W matrix rows which are the very spatial filters are determined in a way that make the greatest difference for variance of the two classes, and Y is the EEG signal resulting from CSP filter.Signal features are extracted by the relation (2) of CSP features in which Zp is the first and last row of the matrix W [18] and in our paper m=2.

$$f_p = Log\left(\frac{VAR(Z_p)}{\sum_{i=1}^{2m} VA(Z_i)}\right), P = 1, \dots, 2m \quad (2)$$

2.3. Autoregressive

Sometimes, meeting some conditions, a signal can be put equivalent to a parametric model and parameters of this model can be estimated; these parameters can be applied as a feature in classification.

Linear combination result from signal in the previous instant accompanied by the effect of a white noise (E) is called AR parametric model. AR model with order P is obtained from the following relation; the coefficients of this relation are used as the features of the model AR:

$$X[n] = C + \sum_{i=1}^{P} a_i X[n-i] + E[n] \quad (3)$$

The other method to estimate the signal is AAR. This method is like AR with the difference that estimating adaptively the AR parameters using LMS method it operates more optimized and reduces signal prediction error. In figure 3,auto adaptive predictor diagram block is seen.

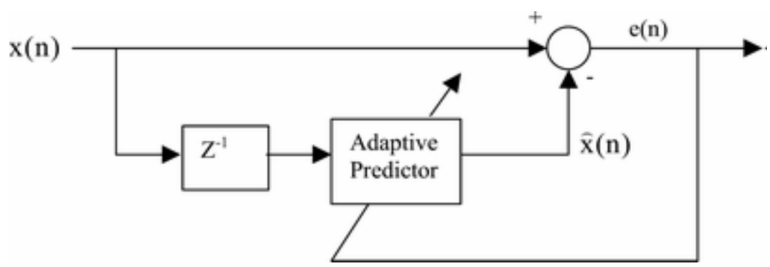

Fig. 3. Auto adaptive predictor diagram block

2.4. The suggested feature vector

According to the stated matters in the previous sections, we have suggested and investigated the following feature vectors.

- CSP features and AAR model features
- AR model in the method of BURG and order of 10
- AR model in the method of BURG and order of 20
- AR model in the method of YULE and order of 10
- AR model in the method of YULE and order of 20
- Statistical parameters from the sub-bands (D2, D3) arising from wavelet transform with the main function of db2
- Statistical parameters from the sub-bands (D2, D3) arising from wavelet transform with the main function of db4
- Statistical parameters from the sub-bands (D2, D3) arising from wavelet transform with the main function of db6
- Combining all the above feature vectors

3. RESULTS

The data under experiment

In this paper, we have used the dataset number IIB of the brain-computer competitions (2008). This collection has been gathered by informatics department of medical engineering institute of Graz University of Technology and includes the recorded EEG data from nine persons who have done two mental activities of right hand movement imagery and left hand movement imagery.

Brain data record has been in the way that the person under experiment sits on an armchair opposite the monitor; at the beginning of the experiment (t=0 s) a "+" sign appears on the computer monitor, after elapsing 2 seconds (t=2 s) a short beep sound is broadcasted in the environment and in the third second (t=3 s) a showing arrow whose direction is random appears toward right or left and is displayed for 1.25 seconds on the monitor. This arrow notifies the person that according to its direction s/he must imagine the intended motion in his/her mind and continues this action for 7 seconds.

To record brain signal in EEG method in these experiments, three electrodes have been used in bipolar method. According to the standard 10-20 the names of these three electrodes are C3, C4 and CZ. Sampling frequency is 250 Hertz [19].

3.1.Preprocessing

Pfurtscheller in his studies showed that usually there is proper information to separate brain signals in the frequency range less than 30 Hz and also alpha (8-12 Hz) and beta (13-22 Hz) frequency band contains useful information to separate hand movement signals and hand movement imagery [20]. Therefore, in this paper, to separate EEG signal in the intended frequency band, a mid-pass FIR filter with high cutoff frequency of 27 Hz and low cutoff frequency of 7 Hz have been

used. This of two-frequency range includes alpha and beta. Also, to reduce calculations, sampling rate has been reduced to half (125 Hz).

3.2.Classification precision for each one of feature vectors

In this section, the effect of each one of extracted feature vectors for each person is investigated and the conclusion will be stated. Figure 4 shows the classification results using separate feature vectors. In this figure it is observed thatone type of feature vector is not useful for all persons, in other word, the effect of one feature vector is not the same for all persons; that is why the average classification precision is low for nine persons. For example, column 1 indicates classification precision in lieu of the feature vectornumber 1, and it is above column 2 (feature 2) for the first person, but for the second person it is reverse. Table 1 shows the average classification precision for nine persons and in lieu of each feature vector; as it is seen, the feature vector number 6 (statistical features from db2 wavelet transform coefficients) provides the highest precision meaning 74.27%.

Table 1. Average classification precision for nine persons and in lieu of each one of feature vectors

	Feature Vector Index							
	1	2	3	4	5	6	7	8
Accuracy(%)	73.50	70.72	70.43	70.65	68.51	74.27	73.14	73.56

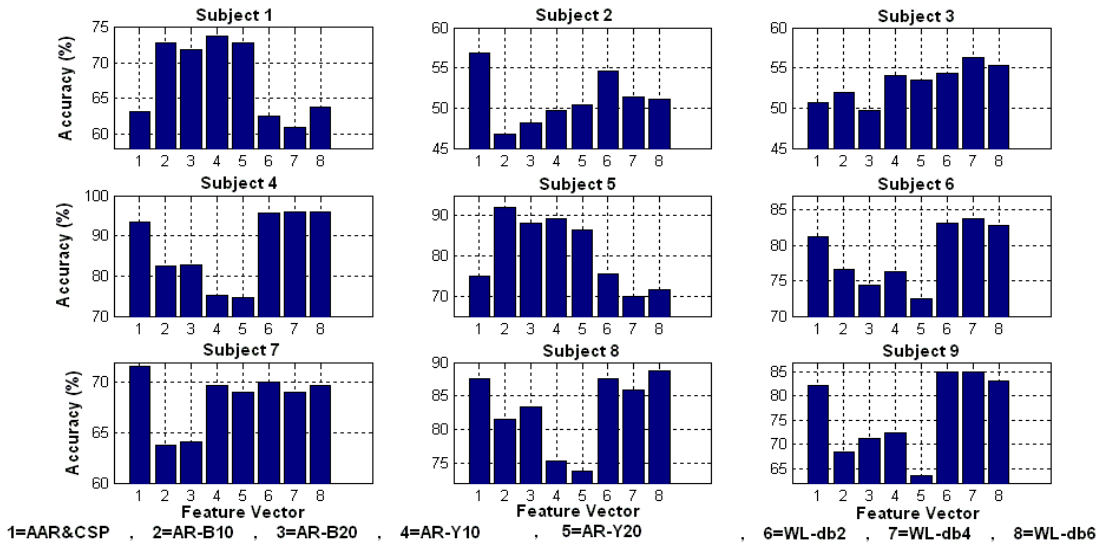

Fig. 4. Classification precision in lieu of each feature vector for nine persons in a separate manner _ the numbers 1 to 8 in the horizontal axis are related to the number of feature vector, and the type of feature vector corresponding to each number has been showed in the ending line of the figure

3.3. Combining feature vectors

Regarding the obtained results in the section 3.3 it was seen that classification precision for one type of feature vector will not be high for all the subjects. For example, for the person number 4, classification precision using db4 wavelet transform is 95.63%, while using Yule method with the order 20 we will achieve the precision of 75.3%.On one hand, for the person number 1, classification precision using db4 wavelet transform is 62.5%, while using Yule method with the order 20 we will achieve the precision of 73.7%. Therefore, we can conclude that combining all these feature vectors may provide the classifier with more useful information and causeincrease inSVM classifier precision. In this section, applying all the feature vectors combination, one unit feature vector has been made and is given as an input to SVM; in table 2, the average classification precision for nine persons is showed.

Table 2. Classification precision from feature vectors combination and SVM classifier

	Subject									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Mean**
Accuracy(%)	59.69	55.71	56.25	95.94	71.56	82.50	70.63	86.25	82.19	73.41

3.4. Reducing feature vector dimension

Regarding the obtained tables in the previous sections, we concluded that combining all feature vectors could be useful, but by combining them the result was not improved. One examinable reason can be put in the way that the final feature vector dimension (combining all the features) is very high and by using dimension reduction algorithms the desirable result can be achieved.

To reduce feature vector dimension and in fact, to select better features to separate movement imagery signals, the class separability criteria (CSC) and t-test method have been used. From among 268 features available in the final feature vector, using CSC method the features having the highest order were selected. The number of intended features for each stage is obtained by the formula (4), where L is the number of the stage. In this section, L=50 has been selected so that the selected feature vector dimension is not more than 250.

$$Number\ OF\ Feature = 5 + (L * 5)\ 5) \qquad (4)$$

Figure 5 shows the results from classifiers in 50 stages of feature selection. As it was expected, the obtained results have been improved compared to the previous states and at best, in the stage 50, the classifier precision is 76.86% (table 3).

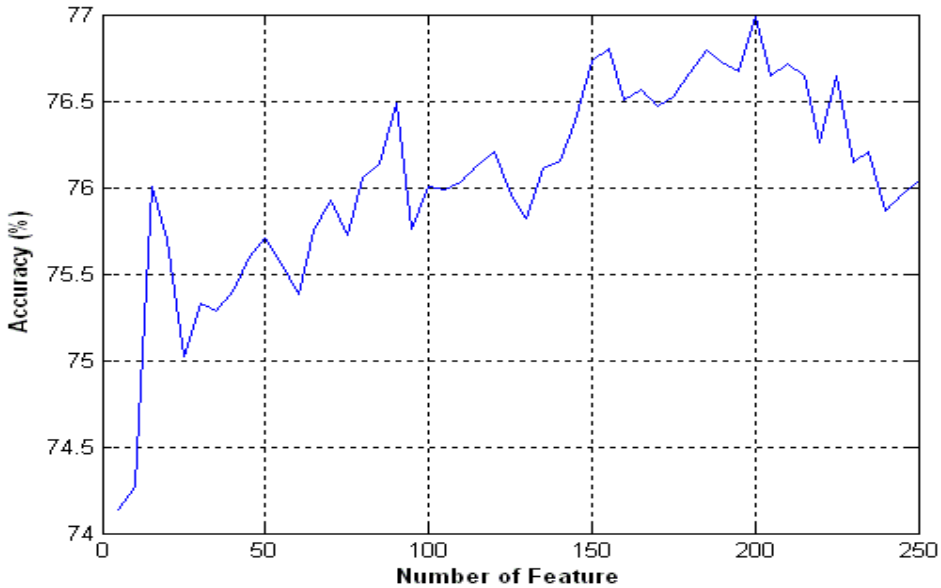

Fig. 5. Classification precision for superior features selection using t-test method

Table 3. The highest classification precision from combining feature vectors and selecting 200 superior features and the classifier SVM

	Subject									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Mean**
Accuracy(%)	70.00	52.86	59.06	94.06	86.88	84.06	72.19	91.56	82.19	76.98

Conclusion

In this paper, the necessary processing has been done on dataset IIB from BCI competition (2008).The main goal of this paper was to investigate the effect of varieties of feature vector on nine subjects and to present a suggestion to improve results. Give the provided results in the section 3.3 it was seen that the effect of one type of feature vector is not the same for classifying different people's brain data, and the useful information obtained from different feature vectors extraction can be used. Thus, first 8 types of feature vector were made and by combining them one unit feature vector was considered.

According to the tables and results presented in the previous sections, it is seen that the suggested combined feature vector in this paper operates well, and EEG data classification precision related to the movement imagery has significantly increased. Our suggested method to use combination of several types of feature vector instead of using one type of feature caused increase in the intended BCI system efficiency. The considered feature vectors are among the feature vectors used in the sources [5,6,7,8] having been applied separately; combining these vectors and using the technique of reducing feature vector dimension, we increased classification precision.

In this paper, the main focus is on the step of extracting feature from the stages of signal processing, therefore it is suggested that to achieve more efficiency using the introduced feature vector in this paper, more attention be paid to the classification stage. The obtained results show that by using the methods of optimizing classifiers and also applying the methods of combining classifiers, the system efficiency can be increased.

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