# A Novel Effective Feature Selection Algorithm based on S-PCA and Wavelet Transform Features in EEG Signal Classification

Saadat Nasehi
Department of Electrical Engineering,
Najafabad Branch, Islamic Azad University,
Isfahan, Iran
st_nasehi@sel.iaun.ac.ir

Hossein Pourghassem
Department of Electrical Engineering,
Najafabad Branch, Islamic Azad University,
Isfahan, Iran
h_pourghasem@iaun.ac.ir

***Abstract*— There are various methods to extract feature from EEG signals but the effective feature selection is an issue. In this paper, a novel effective feature selection based on Statistical-Principal Component Analysis (S-PCA) and wavelet transform (WT) features in medical and BCI application is proposed. In this method, we decompose the signals to six sub-bands by four mother wavelet (sym6, db5, bior1.5 and robio2.8). Then five features (such as the number of zero coefficients, the smallest and largest coefficients, the mean and standard deviation of coefficients) extract from each sub-band as feature vector. In this algorithm, S-PCA is used to select ten effective features from among WT features. Finally, we use KNN classifier and seven different signals of brain activities to evaluate the proposed method. The results indicate the improvement of the classification performance in comparison with current methods.**

***Keywords- Statistical-Principal Component Analysis, EEG signal, wavelet transform, feature extraction, KNN classifier.***

## I. INTRODUCTION

The microvolt-sized signals are produce on the scalp that results from neuronal activity within the brain. These signals can be measured by placing electrodes on the scalp. Record and analyses those can help to human in various fields such as medicine (epilepsy [1,2], depression [3], Alzheimer's disease [4,5]) and brain computer interface (emotion recognition [6,7]). Two basic steps must be performing to analysis the EEG signals: feature extraction and signals classification.

Feature extraction can be calculated based on statistical characteristics or syntax description. Components of domain, frequency and time can be used to extract features from EEG signals. Spectrum amplitude of signals in five frequency bands delta (2-4HZ), alpha (4-8HZ), beta (8-15HZ), theta (15-30HZ) and gamma (30-90HZ) is a traditional algorithm to extract features in simple application. But it can not make the distinction between the different signals when frequency components of signals (classes) are too much similarity together. i.e., Shoeb presented a patient-specific seizure onset detection algorithm [8]. Shoeb's algorithm uses the eight features derived from 0-25 HZ frequency spectrum range by means of a 3 HZ bandwidth filter. It trained on two or more seizures form each patient and could detect seizures with a median detection delay of 3 seconds and a median false detection rate of 0.07 false detections per hour. But false detection was large for some patient, because frequency spectrum of seizures and non-seizures signals have large similarity together and the extracted feature could not make the distinction between them. In these conditions, Wavelet transform can be use to extract the various features.

Wavelet transform is a powerful mathematical tool that can be used to analysis of non-stationary signals such as EEG [9,10]. It has property of time-frequency resolution and can be apply to extract various features [11]. For example, Murguppan presented a human emotions recognition algorithm based on wavelet transform features [12]. Murguppan's algorithm uses wavelet transform to decompose the EEG signals into five frequency bands (delta, theta, alpha, beta and gamma). Then statistical features derived from all those five bands to classify five emotions (happy, surprise, fear, disgust and neutral).

Many features can be obtained by applying wavelet transform but the effectiveness of features is an issue that always has been emphasized. The non-effective features increase computational cost. As well as, they may be decrease performance of classification. On the other hand, the effective feature selection is difficult, supervisory when the number of features is too much. Thus we need a non-supervisory tool to select effective feature from among several features. This paper proposes a novel method based on Statistical-Principal Component Analysis (S-PCA) to do it.

## II. STRUCTURE OF THE PROPOSED ALGORITHM

Outline of the proposed algorithm is shown in Fig 1. In this algorithm, each class divides to smaller category that called epoch. Next, wavelet transform apply on each epoch to extract various features. Then effective features are select from among them by S-PCA. Finally, K- nearest neighbor (KNN) classifier is used to classify several different EEG signals and brain activity recognition.

The proposed algorithm can satisfy three important goals in EEG signals classification: making the maximum distinction between the different classes, reducing the computational cost and improving the performance of classification.

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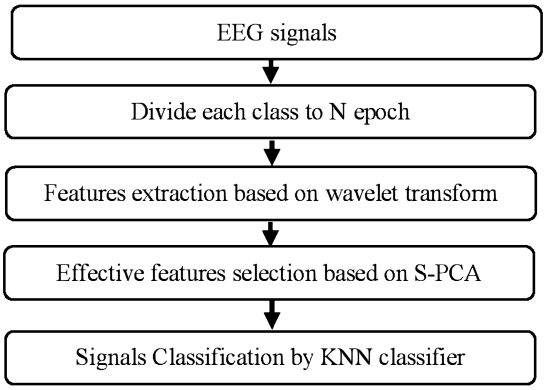


Figure 1. Outline of the proposed algorithm for EEG signal classification.

### *A. Feature extraction based on wavelet transform*

Wavelet transform is achieved by correlation between frequency content of signal and mother wavelet function at different scales [13,14]. So signal is decomposed into several signals that each new signal belongs to a frequency band. These new signals (sub-bands) are specified with its coefficients. These coefficients are used here to extract the features of EEG signals.

The following steps are proposed to extract the features based on wavelet transform from EEG signals. This process is shown in Fig. 2.

1. Dividing every class to N epoch.
2. Appling the wavelet transforms on each epoch and calculating the coefficients at six sub-bands and four mother wavelet function (sym6, db5, biorl.5 and robio2.8). So 24 coefficients (batch) obtain for each epoch. The used mother wavelets are shown in Fig. 3.
3. Extracting five features for each batch such as the number of zero coefficients, the smallest and largest coefficients, the mean and standard deviation of coefficients. So 120 features obtain for each epoch.

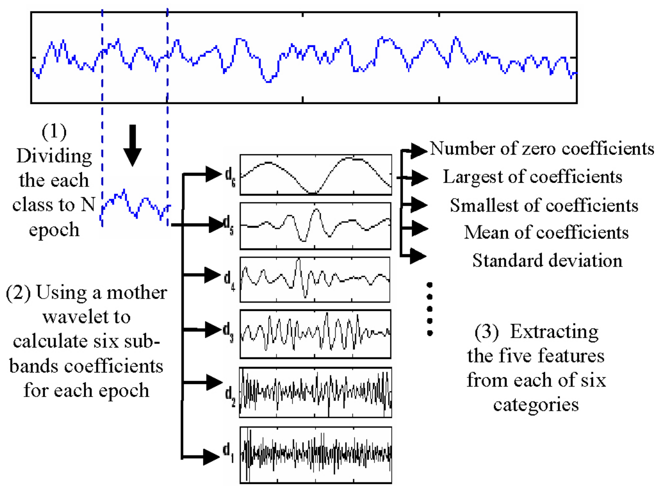


Figure 2. The process of feature extraction based on wavelet transform.

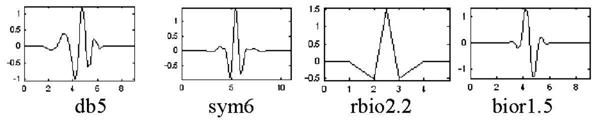


Figure 3. Four used mother wavelets.

### *B. The effective feature selection based on S-PCA*

Many of obtained features (in previous section) may be not making the distinction between different classes. Thus, features with two following properties must be finding from among them.

- Dispersion of feature being small for training samples within classes.
- Dispersion of feature being large for training samples between classes.

Feature selection with this two property is difficult, supervisory when number of features are too much. Thus non-supervision tool to remove non-effective features is needed. Following algorithm to select the effective feature is proposed (Fig. 4).

1. Selecting the *j*th training epoch from each class and extracting the all of feature based on wavelet transform.
2. Mapping the Values of all features to interval [0 1] by Eq (1). So values of all features set in a certain range.

$$x_{new} = \frac{x_{old} - x_{\min}}{x_{\max} - x_{\min}} \qquad (1)$$

3. Applying PCA and selecting the effective features to distinguish the *j*th training epoch of each class.
4. Repeating the steps (1,2,3) for $j$=1,2,…,M. (M is number of training epoch)
5. Selecting the some features that have had the most statistical presence in step (3).

The obtained features at step (5) are effective to use in signal classification and brain activity recognition. In this algorithm, PCA [15] is transforming a feature vector with large dimension to a feature vector with lower dimension so that can reconstructed primary vector with minimum error [16]. The algorithm of PCA is shown in Fig 5.

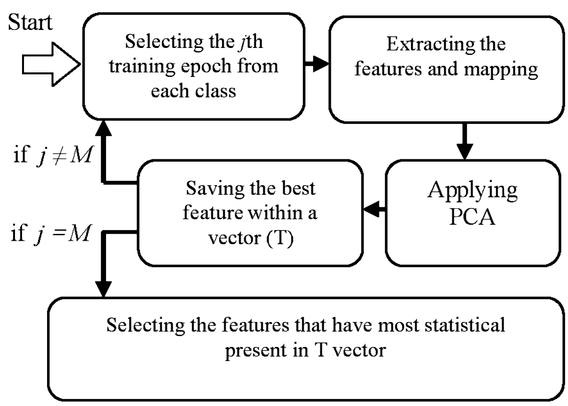


Figure 4. The proposed algorithm (S-PCA) to select effective feature.

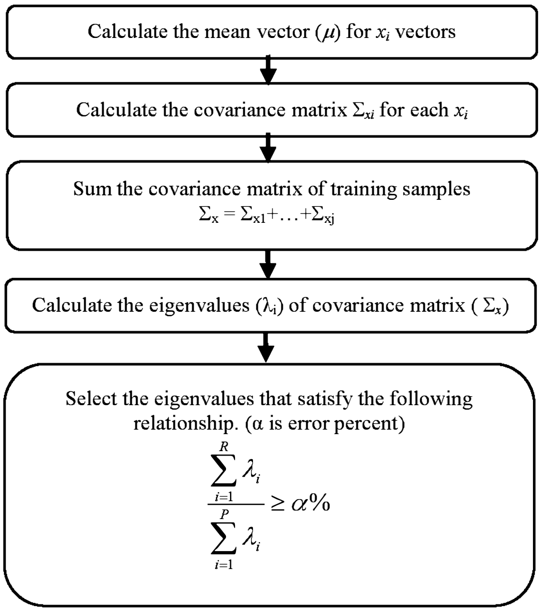


Figure 5. PCA algorithm.

## C. EEG signal classification using KNN

We use KNN classifier to test of the proposed algorithm and classify several EEG signals. KNN algorithm [17] specifies the class of test sample in three steps:

- Distance of test sample with all classes be calculated based on one of metrics: Euclidean, City Block or Manhattan.
- Closest of training samples to test sample be specified based on K-th nearest neighbour.
- Class of test sample equal with the class that have maximum training sample in K-th nearest neighbor.

# III. SIMULATION

The algorithm implement in MATLAB to classify several EEG signals whit different feature and evaluate two following subject:

- Ability of features based on wavelet transform comparable whit features based on five band frequency to make the distinction between classes
- Ability of effective features to improve the performance of classification.

## A. EEG database

Seven different brain signals (measured by g.MOBIlab [18]) are used to evaluate the proposed algorithm. Signals are measured by two bipolar channels whit sampling rate of 256HZ and sensitivity of 100μv. Each signal (class) contains 16000 samples with resolution of 16 bits. We divide each signal to N = 80 epoch (every epoch including 200 samples). 75 and 5 epoch at each class is used to train and test, respectively.

## B. Classification results

In the first experiment, five features are extracted from spectrum in Δ, θ, α, β and γ frequency bands. In this state, KNN classifier (K = 4) could correctly determine 8 cases from 35 test epoch. In the second experiment, the entire 120 feature based on wavelet transform is extracted. In this state, 28 cases correctly are diagnosed. In the third experiment, ten effective features are selected with S-PCA from among 120 features based on wavelet transform. In this state, 32 cases correctly identified. Ten selected effective features shown in Table 1. In all experiment Cityblock distance is used for KNN classifier. Table 2 shows the classification accuracy for K = 4, 9, 13. The results comparison shows that effective features can improve the classification performance.

Mean of training epochs for seven classes and five effective features shown in Fig 6. Difference of means indicate the ability of effective feature to make the distinction between classes.

TABLE I. TEN SELECTED EFFECTIVE FEATURES BY S-PCA FROM AMONG 120 FEATURES EXTRACTED BASED ON WAVELET TRANSFORM

| Features | Mother wavelet | Sub-band | Type of feature |
|---|---|---|---|
| 1 | sym6 | d1 | Standard deviations |
| 2 | sym6 | d5 | Standard deviations |
| 3 | db5 | d1 | Number of zero |
| 4 | sym6 | d1 | Mean of coefficient |
| 5 | db5 | d1 | Mean of coefficient |
| 6 | sym6 | d1 | Smallest of coefficient |
| 7 | db5 | d1 | Smallest of coefficient |
| 8 | bior1.5 | d1 | Standard deviations |
| 9 | sym6 | d2 | Number of zero |
| 10 | sym6 | d1 | Number of zero |

TABLE II. THE RESULTS OF EEG SIGNAL CLASSIFICATION WITH DIFFERENT FEATURES (IN ALL CASES, CITY BLOCK DISTANCE IS USED FOR KNN CLASSIFER)

| Epoch of test | | The number of correct identify for different features and K | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Exp 1 | | | Exp 2 | | | Exp 3 | | |
| Classes | The number of test epoch for each class | Use of five extracted feature based on frequency spectrum | | | Use of 120 extracted feature based on wavelet transform | | | Use of ten effective feature based on S-PCA | | |
| | | K=4 | K=9 | K=13 | K=4 | K=9 | K=13 | K=4 | K=9 | K=13 |
| Class 1 | 5 | 1 | 0 | 1 | 3 | 4 | 3 | 5 | 5 | 5 |
| Class 2 | 5 | 2 | 1 | 2 | 4 | 2 | 3 | 3 | 4 | 4 |
| Class 3 | 5 | 0 | 0 | 1 | 4 | 3 | 2 | 4 | 0 | 1 |
| Class 4 | 5 | 5 | 4 | 4 | 2 | 3 | 3 | 5 | 4 | 4 |
| Class 5 | 5 | 0 | 1 | 0 | 5 | 5 | 5 | 5 | 5 | 5 |
| Class 6 | 5 | 0 | 1 | 1 | 5 | 5 | 5 | 5 | 5 | 5 |
| Class 7 | 5 | 0 | 0 | 0 | 5 | 5 | 5 | 5 | 5 | 5 |
| Classification efficiency | | 22% | 20% | 25% | 80% | 77% | 74% | 91% | 80% | 82% |

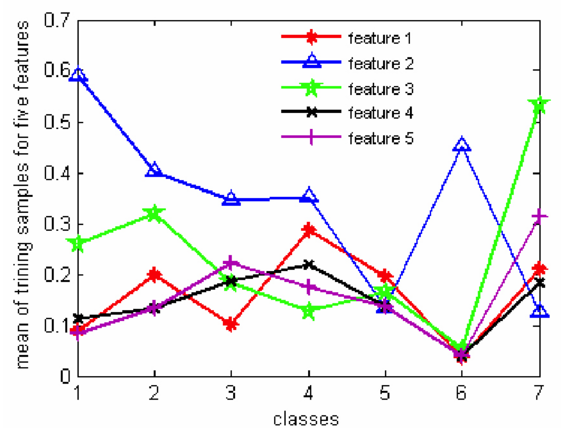


Figure 6. The mean of training epoch for five features in Table 1

## IV. Conclusions

There are various methods to extract feature from EEG signals. But the effective features selection is an issue of interest because it plays an important role to improve the classification performance. The selected features must be able to make maximum distribution between classes. Wavelet transform can be use to extract various features from EEG signals and S-PCA can be used to select effective features among them, non-supervisory. This algorithm also reduces the computational cost and can be use in different application such as seizure onset detection and emotion recognition.

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