MULTI-CHANNEL SIGNAL SEGMENTATION AND CLASSIFICATION

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ABSTRACT

Multi-channel sensors and multi-channel signal analysis form a specific area of general digital signal processing methods with applications in medicine, environmental signal analysis or technology. The paper is devoted to general mathematical methods related to initial signal de-noising, detection of its principal components and segmentation to find its specific parts. Feature detection includes the use of discrete wavelet transform (DWT) and discrete Fourier transform (DFT) for estimation of features invariant to signal shift to form clusters of close data segments. The self-organizing neural networks are then used for signal segments classification. Results are numerically evaluated by statistical analysis of distances of individual feature vector values from the corresponding cluster centers. Proposed methods are used for electroencephalogram (EEG) signal segmentation based upon detection of changes of signal spectral components applied to its first principal component, signal segments feature extraction and their classification. Results achieved are compared for different data sets and different mathematical methods used to detect signal segments features. Numerical results are compared with experience of experts specialized to EEG data analysis to allow further correlation with MR images. Proposed methods are accompanied by the appropriate graphical user interface (GUI) designed in the MATLAB environment.

KEY WORDS

Multi-channel signal proceesing, discrete wavelet transform, principal component analysis, feature extraction, biomedical signal and image analysis

1 INTRODUCTION

Multi-sensor processing of noisy non-stationary observations [16] form an important area of digital signal processing. Wavelet functions including dual-tree complex wavelet transform [14, 1, 4] form an efficient mathematical tool for processing of such signals. While the use of wavelet functions for multi-dimensional signals is described in many papers already their use for multi-channel signals is still not so extensively studied.

The paper presents the use of wavelet functions in combination with the principal component analysis [2, 15] allowing their application for signal segments feature extraction. The task of signal segments classification is solved by neural networks [8, 5] in many cases. The paper presents wavelet signal features classification by self-organizing neural networks and it presents appropriate graphical user interface proposed.

The information content of EEG signals [13, 12] is fundamental for brain analysis and in connection with magnetic resonance methods it forms one of the most complex diagnostic tools. To analyse extensive EEG observations it is necessary to use efficient mathematical tools for fast enough data processing. Digital filtering using finite impulse response (FIR) filters or discrete wavelet transform can be used in the EEG signal preprocessing stage to remove power frequency from the observed signal and to reduce its undesirable frequency components at first. Fig. 1 presents a sample of an observed EEG signal segment with results of its filtering in Fig. 2.

Signal segmentation methods related to change-point detection can are usually applied to a given time series using Bayesian method [6] detecting changes of its statistical properties or it is possible to detect changes in signal frequency components important for EEG signal processing. Owing to the multi-channel basis of EEG signals this method has been applied after the principal component analysis (PCA) of an observed and preprocessed multichannel signal to its first principal component.

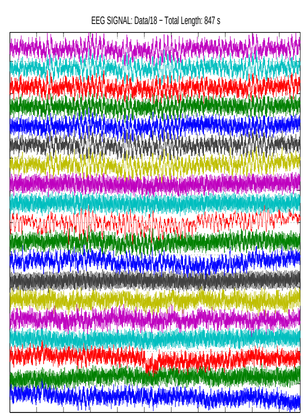

Figure 1. Original EEG signal recording presenting 19 channels with the additive noise of $50\ Hz$

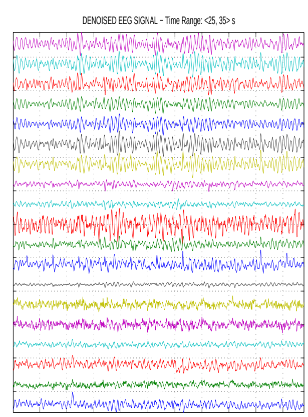

Figure 2. De-noised EEG signal after the removal of the signal noise components

2 PRINCIPAL COMPONENT ANALYSIS

Principal component analysis [15] resulting from applied linear algebra allows to reduce the dimension of a matrix $\mathbf{X}_{N,M}$ containing multi-channel data. In the case of EEG records each its column $j = 1, 2, \cdots, M$ represent channel index and its row $i = 1, 2, \cdots, N$ stand for observations. It is possible to transform this matrix into a new one using matrix $\mathbf{P}_{M,M}$ to find values

$$\mathbf{Y}_{N,M} = \mathbf{X}_{N,M}\ \mathbf{P}_{M,M} \tag{1}$$

In the case of principal component analysis matrix $\mathbf{P}_{M,M}$ is orthonormal evaluating columns of matrix $\mathbf{Y}_{N,M}$ with the decreasing variance. Assuming that signal-to-noise (SNR) ratio is defined by relation

$$SNR = \frac{\sigma^2_{signal}}{\sigma^2_{noise}} \tag{2}$$

it is possible to assume that this analysis finds signal components with decreasing SNR. Proposed algorithm presented in Fig. 3 includes multi-channel signal filtering to reject signal component of $50\ Hz$ and to preserve signal frequencies in the range of $\langle 0.5, 60\rangle\ Hz$ and the following evaluation of principal components.

```
%% EEG Data Filtering %%%
   b1=fir1(M,[48 52]/Fs,'stop');
   b2=fir1(M,[0.5 60]/Fs,'bandpass');
   X=filter(b2,1,filter(b1,1,EEG));
%% Principal Component Analysis %%%
   P = princomp(X);
   Y=X*P;
```

Figure 3. Algorithm of multi-channel FIR filtering (of order M) of an EEG signal observed with the sampling frequency F_s and its following principal component analysis

Results of PCA for a selected segment of EEG observations after their de-noising is presented in Fig. 4 together with resulting signal variances.

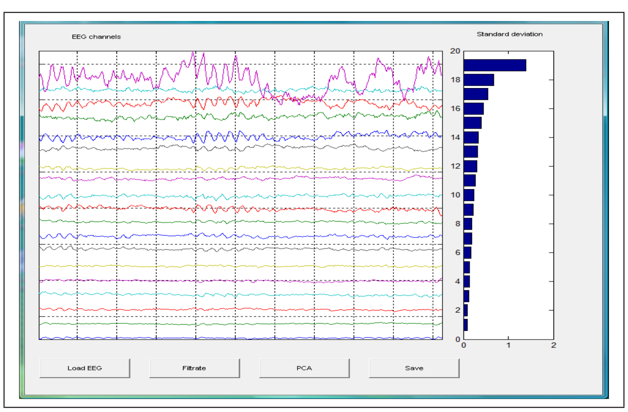

Figure 4. Graphical user interface for principal component analysis of the set of observed EEG channels and evaluation of results

3 SIGNAL SEGMENTATION

The first principal component of the multi-channel signal can be used for segmentation of the whole set of observed time-series. While Bayesian methods can be used for this purpose [6] it is more efficient in the case of EEG signals to detect changes of spectral components in the given signal. The proposed method uses two sliding overlapping windows and the whole algorithm is based upon detection of changes of spectral components in given frequency bands. Fig. 5 presents the proposed graphical user interface designed to find signal segments of similar properties in the frequency domain.

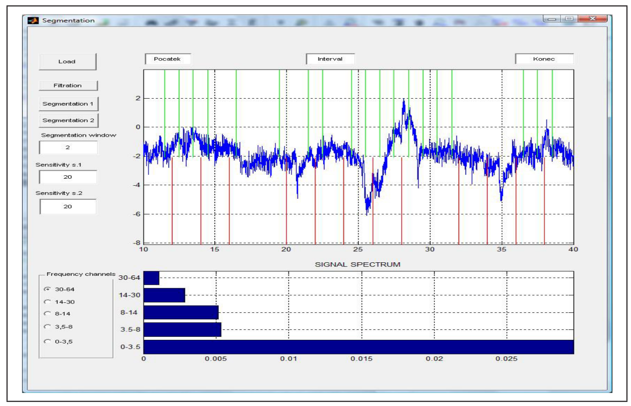

Figure 5. Graphical user interface for segmentation of the EEG signal and average frequency energy of the selected segment in given frequency bands

4 WAVELET FEATURE EXTRACTION

Discrete wavelet transform (DWT) forms a general mathematical tool for signal processing with many applications in EEG data analysis [7, 9, 14, 3] as well. Its basic use includes time-scale signal analysis, signal decomposition and signal compression.

The set of wavelet functions is usually derived from the initial (mother) wavelet $h(t)$ which is dilated by value $a = 2^m$, translated by constant $b = k\ 2^m$ and normalized so that

$$h_{m,k}(t) = \frac{1}{\sqrt{a}}\ h(\frac{t-b}{a}) = \frac{1}{\sqrt{2^m}}\ h(2^{-m}\ t - k) \tag{3}$$

for integer values of m, k and the initial wavelet defined either by the solution of a dilation equation or by an analytical expression [11]. The initial wavelet can be considered as a pass-band filter and in most cases half-band filter covering the normalized frequency band $\langle 0.25, 0.5)$. A wavelet dilation by the factor $a = 2^m$ corresponds to a pass-band compression.

The set of wavelets define a special filter bank which can be used for signal component analysis and resulting wavelet transform coefficients can be further applied as signal features for its classification. Signal decomposition performed by a pyramidal algorithm is interpreting wavelets as pass-band filters. Another approach [11] is based upon a very efficient parallel algorithm using the fast Fourier transform.

The proposed algorithm is based upon the wavelet decomposition of the signal segments and evaluation of its coefficients for their classification. Fig. 6 presents application of this method to EEG signal segments and their analysis by a harmonic wavelet transform [11] resulting in features standing for scales 1, 2 and 3 respectively covering three frequency bands with different time-scale resolutions. Another approach proposed [14] is based upon the dual tree complex wavelet transform (DTCWT) use to reduce poor shift sensitivity of the original DWT. The basic idea of this method is based upon the signal decomposition running in two parallel trees using real filters to generate real and imaginary parts of complex coefficients.

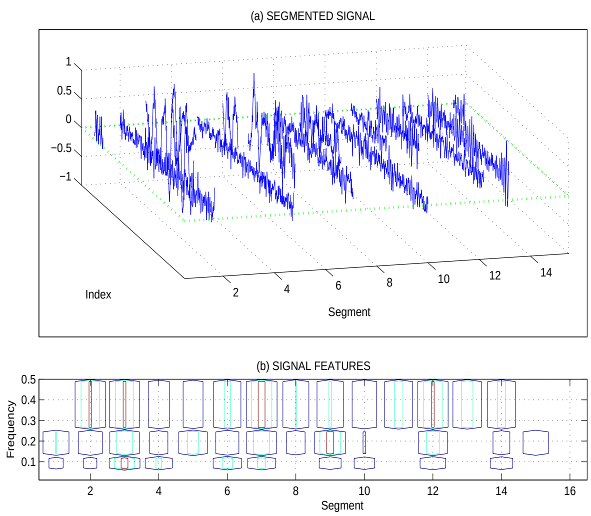

Figure 6. Results of feature extraction presenting **(a)** EEG signal segments and **(b)** their wavelet features resulting from a harmonic DWT on scales $1, 2, 3$

5 CLASSIFICATION

Classification of signal segments into a given number of classes using segments features can be achieved by various statistical methods. Another approach is based upon the application of self-organizing neural networks using features as patterns for the input layer of neural network. The number of output layer elements is equal to signal classes and must be either defined in advance or it can be automatically increased to create new classes [5]. During the learning process neural network weights are changed to minimize distances between each input vector and corresponding weights of a winning neuron characterized by its coefficients closest to the current pattern. In case that the learning process is successfully completed network weights belonging to separate output elements represent typical class individuals.

Results of signal classification into four classes by a self-organizing neural network are given in Fig. 7 for two selected signal features allowing a simple visualization of segmentation results and visualization of typical class representatives with their features closest to the corresponding cluster centers.

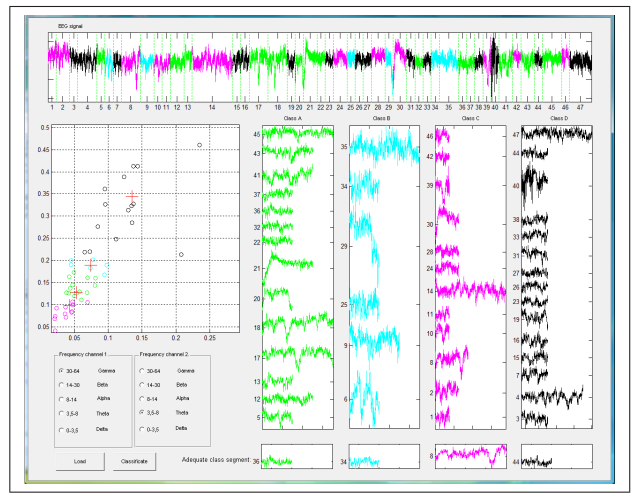

Figure 7. Graphical user interface for signal segments classification into the given number of classes and detection of typical signal segments closest to cluster centers

Numerical results of classification of Q signal segments with feature matrix $\mathbf{P}_{R,Q} = [\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_Q]$ for the selection of different sets of $R = 2$ features and $C = 4$ classes are compared in Tab. 1. Each class $i = 1, 2, \cdots, C$ can be characterized by the mean distance of column feature vectors $\mathbf{p}_{j_k}$ belonging to class segments j_k for $k = 1, 2, \cdots, N_i$ from the class centre in the $i-$th row of matrix $\mathbf{W}_{C,R} = [\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_C]'$ by relation

$$ClassDist(i) = \frac{1}{N_i} \sum_{k=1}^{N_i} dist(\mathbf{p}_{j_k}, \mathbf{w}_i) \qquad (4)$$

where N_i represents the number of segments belonging to class i and function $dist$ is used for evaluation of the Euclidean distance between two vectors. Results of classification can be numerically characterized by the mean value of average class distances related to the mean value of class centers distances obtained after the learning process according to relation

$$crit = mean(ClassDist)/mean(dist(\mathbf{W}, \mathbf{W}')) \qquad (5)$$

This proposed Cluster Segmentation Criterion (CSC) provides low values for compact and well separated clusters while close clusters with extensive dispersion of cluster vectors provide high values of this criterion. It is obvious that classification parameters achieved and summarized in Tab. 1 both by the DFT and DWT provide similar results but slightly better in the case of wavelet features selection.

Table 1. Comparison of signal segments classification into four classes using two features resulting from a chosen signal segments analysis

Features	*Cluster Segmentation Criterion*			
	Set 1 *(Q=21)*	*Set 2* *(Q=36)*	*Set 3* *(Q=71)*	*Set 4* *(Q=99)*
DFT	0.31	0.61	0.53	0.55
DWT/db4	0.32	0.37	0.35	0.47
DWT/harmonic	0.21	0.22	0.25	0.23

6 CONCLUSION

The paper presents selected aspects of multi-channel signal processing including the application of principal component analysis to define time-series used for signal change-points detection. Mathematical methods used in this connection include discrete wavelet transform as a tool for signal de-noising and signal segments feature extraction to define the pattern matrix for feature vectors classification. Dual-tree complex wavelet transform is mentioned as well as a tool for shift-invariant features estimation.

Methods proposed are applied to EEG signal de-noising, their segmentation using principal component analysis and classification of feature vectors. Signal classification proposed assumes the knowledge of the number of classes while self-creating neural network structures used for classification [5] are able to find the optimal value of classes and to exclude the possibility of dead neurons.

The paper studies the influence of signal features definition to the compactness of resulting clusters using wavelet transform as a tool for signal segments analysis in the time-scale domain. Proposed methods of multi-channel signal analysis including their filtering, principal component analysis and signal features classification are designed as graphical user interfaces in the MATLAB environment to allow simple signal analysis and processing. The compactness of resulting clusters is numerically studied through distances of class individuals and their center.

Further research will be devoted to the more detail analysis of signal segments features to find clusters with their individuals as close to cluster centers as possible. Further studies will be devoted to extensive application of methods proposed including the study of correlation between EEG observations and MR image analysis.

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