Application of Clustering for Increasing the Evaluation Objectivity of Electroencephalographic Recordings

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Abstract. Visual analysis is still a widespread method for analysis of electroencephalographic recordings. Hence, the problem of evaluation objectivity remains. In this paper we present study undertaken to identify possible method improving objectivity in evaluation of this kind of recordings and visualization of obtained results. Two datasets were used in order to illustrate designed processing methodology and obtained results. Analysis was performed on both non-clinical and clinical data. Experiments have shown that expert's evaluation does not always correspond completely with measured data and that automatic algorithm based on clustering can provide additional information for final classification. This automatic algorithm is not meant to be used instead of an expert but as a decision support tool.

1 Introduction

Electroencephalography (EEG) has many important applications in medicine and cognitive science. Still a widespread method for analysis of this kind of data is visual analysis, so the problem of evaluation objectivity remains. Aims of computer assisted processing of EEG and polysomnographic (PSG) recordings are to simplify tedious and time consuming work of neurologists, make the evaluation more objective, and visualize obtained results and represent them in a convenient form. This kind of processing also permits computation and analyses of features which were not possible only by visual analysis.

The main objective of our long-term research has been the design and implementation of appropriate algorithms for classification of EEG and PSG recordings. In this particular work we focused our attention on methods improving objectivity in evaluation of this kind of recordings and visualization of obtained results. We would like to illustrate the improvement in distinction between artifact-free segments and segments containing artifacts, thus improving accuracy and objectivity in evaluation of EEG recordings. Signals naturally contain various artifacts that may occur at many points during the recording process [1]. They increase the difficulty of analysing EEG in that way that recording can be unreadable or artifacts can be misinterpreted as pathological activity. Also, we present how the clustering analysis results may point out to important changes in signals in long-term recordings.

The rest of the paper is organized as follows. Section 2 encompasses description of used datasets and methods applied in particular signal processing steps. The results are presented in Section 3. Some concluding remarks are given in Section 4.

2 Methods

2.1 Data

Two datasets were used in this study in order to illustrate designed methods and obtained results.

The first dataset was created from data measured in non-clinical environment, namely in faculty EEG laboratory at the Department of Cybernetics, Faculty of Electrical Engineering. The EEG activity was recorded by EEG system EADS 220 Brainscope, electrodes were positioned according to the standard defined by the international 10-20 system [2], sampling frequency was 250 Hz. Other polysomnographic signals were not recorded. Data were manually classified into one of three following classes: normal activity, muscle artifact, eye-blinking artifact.

The second dataset consisted of polysomnographic comatose recordings. Coma is a state of brain function. It can be very roughly compared to sleep. However, an individual cannot awaken purposefully from coma, using either internal or external stimulus [3]. There has been great effort devoted to scaling comatose states into different levels according to seriousness, depth, and to prediction of probable development of patient state.

The comatose data were obtained from a cooperating medical institution – The University Hospital Na Bulovce. The EEG activity was recorded from nine referential derivations, namely F7T3, T3T5, T5O1, F8T4, T4T6, T6O2, FzCz, T3Cz, CzT4, positioned under the international 10-20 system, sampling frequency was 250 Hz. Other measured polysomnographic signals were: electrooculogram (EOG), electromyogram (EMG), electrocardiogram (ECG) and respiration (Nslt). Individual systems of coma classification differ in number of levels, way of examination, precision, etc [4], [5]. The data were scored by an experienced neurologist. Classification was made to ten comatose stages (C1 to C10).

2.2 System description

Processing of EEG recordings represent a multilevel procedure composed of several methods [6]. A diagram in Fig 1. represents typical steps in processing of this kind of complex signals. In this work we focused our attention on classification and visualization. For better understanding of the used approach segmentation and feature extraction steps will be also explained. All data were resampled to 128 Hz.

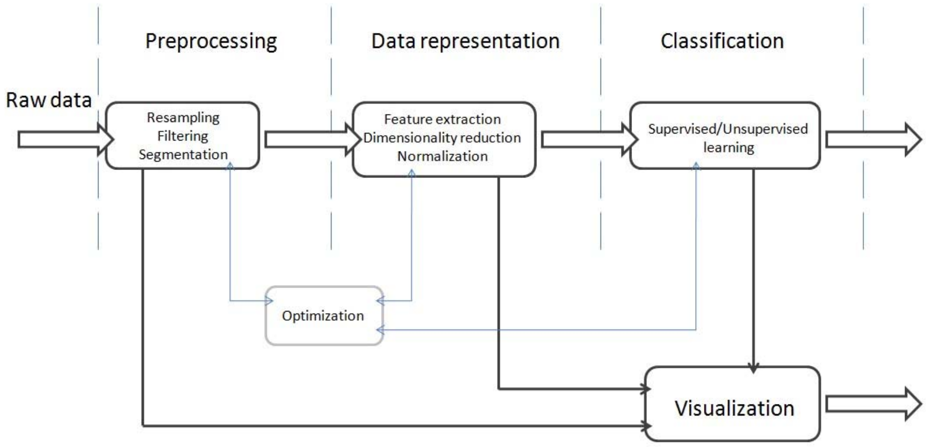

Fig 1.Diagram of typical steps in EEG/PSG signal processing.

Instead of typically used constant segmentation, adaptive segmentation was applied to each EEG channel. In this way signals were divided into quasi-stationary segments of variable length [7], [8]. The applied algorithm of adaptive segmentation is based on the principle of two connected windows of the same length, sliding along a signal, and a calculation of the differences of the predefined signal parameters comprised in windows (e.g. combined amplitude and frequency difference measure). When this calculated measure of the difference exceeds predefined threshold, the point is marked as a segment border. The reason for introducing such algorithm is that the subsequent feature extraction from relatively homogenous segments would be substantially more effective than feature extraction from segments of constant length.

Each segment derived from the segmentation process was further represented with a set of features. The set of commonly used features in EEG analysis, e.g. statistical features and power spectra in typical EEG bands, was extended with features obtained by analysis in the time domain and wavelet transform. The complete set of extracted features can be divided into three groups:

- Group 1 - features derived form signal, without the application of any signal transform,
- Group 2 - features derived after the application of Fourier transform,
- Group 3 - features derived after the application of wavelet transform.

Group 1 features were: minimum, maximum, mean, standard deviation, kurtosis and skewness values, zero crossing rate, maximum and mean absolute values of the first and second derivatives, line length, nonlinear energy, root mean squared value, second and third Hjorth parameters (mobility and complexity, respectively) [9], [10]. After the application of Fourier transform, we extracted features from the frequency domain, namely absolute and relative powers for typical EEG frequency bands (delta, theta, alpha, beta and gamma), and they constitute Group 2. Features comprised in Group 3 were derived from wavelet coefficients. Minimum, maximum, mean, standard deviation, kurtosis and skewness values, maximum and mean absolute values of the first and second derivatives and zero crossing rates were calculated as well as wavelet energy and energy percent for typical EEG frequency bands. Daubechies 4 wavelet [11] and decomposition to 4 levels of decomposition were used.

Further on, k-means algorithm and hierarchical clustering were applied as representatives of unsupervised classification methods [12], [13]. The clustering was applied to segments acquired by adaptive segmentation for which appropriate features were computed. We used the Ward's method as the specific procedure for hierarchical clustering analysis. Hierarchical clustering allows direct estimation of the optimal number of clusters and Ward's linkage is suitable for the decreasing of total within-cluster sum of square error.

The one of the most essential issues in cluster analysis is the estimation of the optimal number of clusters. Our approach is based on distance criterion for forming clusters. We use distance between two sub-nodes in dendrogram merged at a node to measure node height. All leaves in dendrogram at or below a node with height less than predefined constant are grouped into a cluster. This constant was set experimentally by visual inspection of the clustering results. In our case, optimal number of clusters was 5 for the first dataset and 8 for comatose data. In this study, clustering was performed only with EEG data. Other PSG signals were not considered.

Visualization is important because it allows doctors to have a clear overview of processing steps and their intermediate results, without the need of understanding underlying mathematical tools [14]. In this work final results and classification were presented in appropriate form in order to enhance visual differentiation between important states.

3 Results

3.1 Recognition of artifacts

As already mentioned, data from the first dataset were manually classified to three stages: normal activity, muscle artifact and eye-blinking artifact. This classification was used for the visual comparison with the results obtained by application of our algorithm. The clustering was done to five clusters. As a result, EEG activity was grouped in two clusters, one cluster represented eye-blinking artifacts and last two clusters obtained segments with muscle artifacts. The lower and higher number of clusters were also tested. With a lower number of clusters it was not possible to reliably distinguish between these two types of artifacts. On the other hand, as the number of clusters was increasing the further subdivision of artifacts to clusters was obtained, e.g. segments of the same eye-blinking artifact from frontal-polar electrodes and all other electrodes were clustered to different clusters due to the positive or negative amplitude of the signal waves.

The example of obtained results is shown in Fig 2. Even though artifacts are visible in the recording, in the evaluation of an expert a correct classification is missing in the last part of the shown signal (bottom part of the figure). This artifact is recognized by the system and it is clearly visible on the middle part of the figure, on the position marked with T2. Another advantage of this kind of approach can be seen on the position marked with T1, where it can be seen on which electrodes artifacts are present.

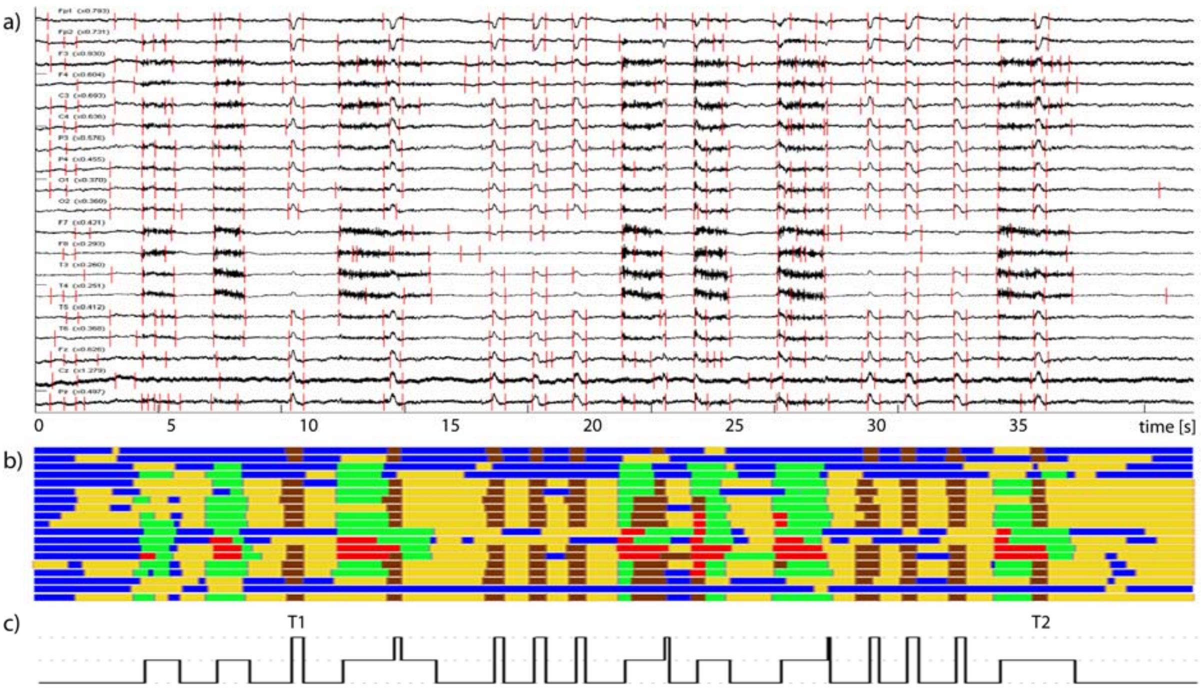

Fig 2. a) Part of EEG recording (19 electrodes) with marked signal borders, b) results of Ward's clustering (obtained clusters are represented in different colors), c) classification made by an expert.

3.2 Comatose data

The algorithm described in Section 2.2 was also applied to available comatose data. The example of this kind of recording is given in Fig 3. The upper part of Fig 4. illustrates the classification of a whole long-term comatose recording provided by an expert (in this particular recording, stages C8 - C10 did not occur in the expert's classification and therefore they are not illustrated). In the same figure, clustering results of our automatic analysis are visualized. For this dataset, number of clusters was experimentally set to 8. From the Fig 4. some resulting remarks can be made. In the first third of the expert's classification there are transitions between stages, and presence of different clusters on the figure bellow corresponds to the presence of changes. On the other side, on the last third of the expert's classification there are no changes in the stages, but according to the automatic analysis and representation with clusters data would be classified to more stages. With the inspection of the bottom figure it can be also revealed that parts of a recording with same characteristics were classified differently. This can be a sign to the neurologist to inspect again this part of a recording. Also, attention should be given to the parts of the recordings which are grouped in the same cluster but manually classified to different stages.

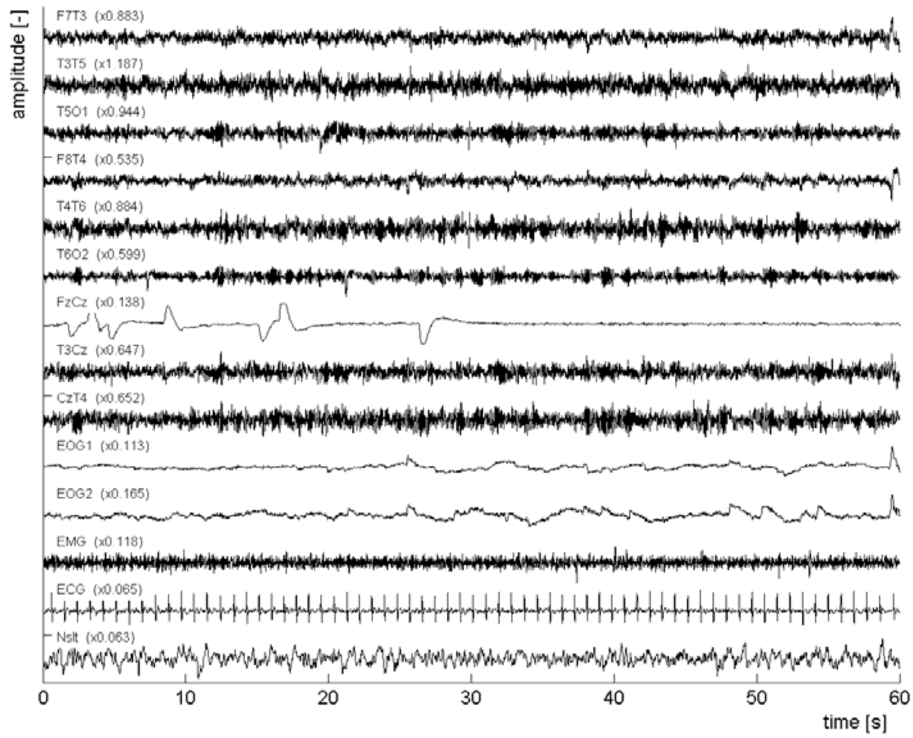

Fig 3.One minute of comatose PSG recording. It constists of nine EEG channels, two electrooculographic (EOG) channels, electromyogram (EMG), electrocardiogram (ECG) and respiration signal.

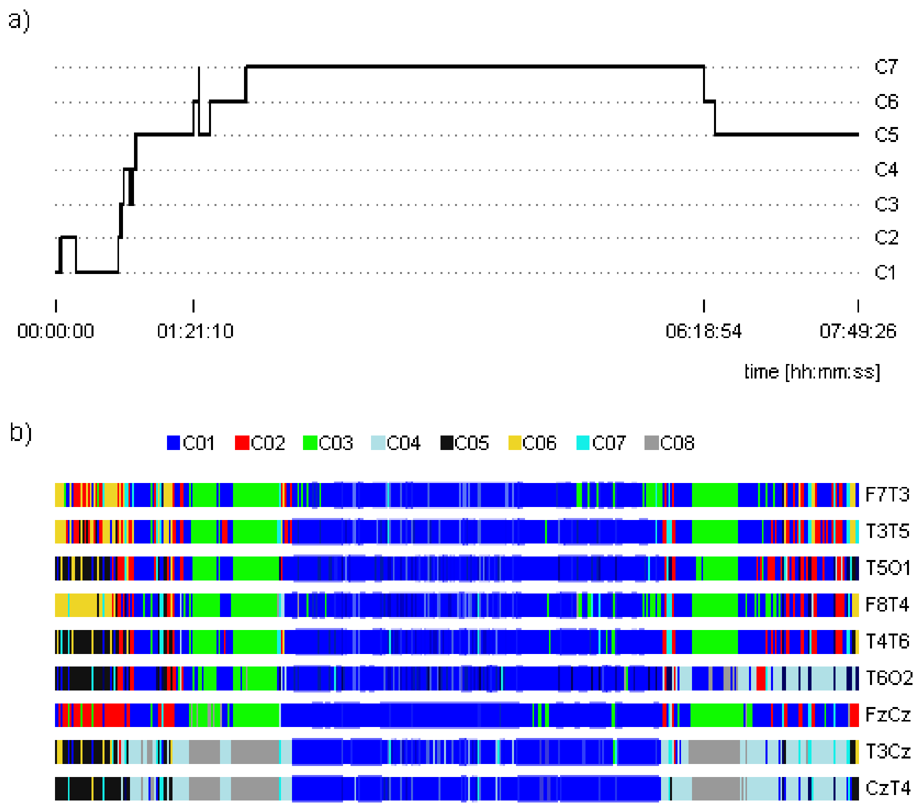

Fig 4.a) Expert's evaluation of a comatose recording, b) clustering results for appropriate EEG channels. Time line in both figures is the same.

The used clustering approach is also compared with k-means algorithm [7]. Both approaches have their innate disadvantages. Hierarchical clustering requires a great amount of memory and also it cannot represent distinct clusters with similar expression patterns. K-means clustering requires a specified number of clusters in advance and it is sensitive to noise and outliers. Results obtained with k-means algorithm and Ward's clustering method were very similar for both datasets (statistically comparable). The k-means runs were repeated 10 times in order to find an optimal solution.

4 Conclusions

The traditional way of EEG analysis is visual inspection of signals. This kind of evaluation is tedious and time consuming. It should be also mentioned that the scoring accuracy between two or more neurologists is about 70-80%. Thus some of the reasons for introducing computer assisted processing were to simplify the work of medical doctors and to make the evaluation more objective. For the classification based on supervised learning algorithms it is necessary to have data completely evaluated by an expert. But visual evaluation is prone to mistakes due to the subjective point of view of neurologists, as they are making this evaluation according to their experience obtained in clinical practice. So, the developed algorithm presented in this study encompasses clustering, as a representative of unsupervised learning methods.

The designed approach has been tested on two different datasets. In most cases, the agreement of an automatic method with visual analysis is a basic criterion for its acceptance. But, according to obtained results, it can be noticed that expert's evaluation does not correspond completely with measured data. It should be also stressed out that this automatic algorithm is not meant to be used instead of an expert but as a decision support tool. Clustering results can be used as additional information for final classification, as well as for the control of already conducted classification (e.g. some transitions may be overlooked). This kind of analysis can also alert medical doctors to the appearance or repetition of a certain specific wave, graphoelements, important parts of a recording, changes and trends that must not be observable by manual analysis. Thus with suggested method based on clustering final classification may be improved and the objectivity may be increased.

The differentiation between classes can be also improved by including information from other polysomnographic channels, if they are available. The analogical procedure used for EEG channels can be applied to these data.

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