



New ways in non-stationary, nonlinear EEG signal processing

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Abstract: In studying neurobiological signals, it has always been a challenge how to gain information from them. It is important to find what is happening in the supposed frequency and time related components of those signals. The results of combined time-frequency domain analysis are very challenging. There are procedures which can give us only time information and those which give only frequency information, but the best methods for non-stationary signals are time-frequency procedures. These can be the most useful procedures for analyzing EEG signals. As we know, the EEG signals are usually nonlinear and non-stationary signals. To analyze them, we need more complicated (or the way to an acceptable solution is complicated) methods than methods based on Fourier transform. The combined procedures of classical methods (up to second order statistical methods, Fourier transform based procedures, correlations, coherence based analysis) and new approaches (DTW- Dynamical Time Warping, HOSA - Higher Order Statistics, CWT-Continuous Wavelet Transform) are giving us more opportunity for a better understanding of brain events and we can create a control signal output vector to be usable for external systems commands.

This paper is focused on developing tools for new signal processing approaching. EEG signals are recorded variations of electrical potential between to different point on the scalp. We need proper methods to analyze the type of information carried by these signals. The used procedures must not modify the basic characteristics of EEG signals. Here is about phase and frequency structures of signals. EEG signals should have variation of milliseconds at μV amplitude scale. For a correct interpretation, we must keep the internal relationship, harmony of the signal components. Some aspect of the accuracy and information classification in time-frequency domain analysis are shown.

Keywords: time-frequency analysis, wavelet transform, independent components.

1. Introduction

In recent years, the effective clinical and healthcare services have made steps toward a more efficient human treatment system. For this reason, new techniques and equipment have been developed to help in the monitoring, diagnosis, and treatment of diseases of the human body. Biomedical signals (bio-signals) in their diverse forms are rich in information. Appropriately processed signals have the potential to facilitate scientific advancements. Digital signal processing concepts are almost compulsory in biomedical engineering. Advancements in bio-electronics and signal processing and classification technologies are in most of the cases based on digital signal technologies. The Central Nervous System (CNS) consists of nerve cells and glia cells (which are located between neurons). The synchronized activity of a group of principal cells from cortical regions of the brain can be recorded. These are the electroencephalogram (EEG) type bio-signals. Different cortical areas on both brain hemispheres can be covered with sensitive, non invasive network of electrodes. There are different standards to cover cortical areas with electrodes. The most used standard is the international 10-20 standard (The International Federation of Societies for Electroencephalography and Clinical Neurophysiology). In the category of bio-signals are included the electrocorticograms (ECoG), electrocardiograms (ECG), electromyograms (EMG) and other signal types. The main characteristics of these signals are their very low amplitude (from mV down to μ V level) and their contamination with internal (physiological) or external noises (atmospheric electromagnetism or the 50Hz components of the AC power supply). Considering these facts, we must have knowledge about the signal recording details, about the chain how to achieve the signal conditioning and amplification, about the methods to improve the SNR (signal to noise ratio), increasing it as much as possible.

The basic idea of this paper is to present some development in the bio-signal processing area and find a vector space based classification. It is important to consider improved concepts of processing because of our research engagement in EEG signal recordings and in their use in special purposes. There are well known the domains and efficacy of classical methods as Fourier transform. It is also well known that bio-signals can be included into a special class of signals, the nonlinear and non-stationary signal class. The classical processing methods are not proper for this class, if we want to have a very accurate processing for special external events control. Also, we are providing suitable graphs and images and simulations to assess the efficacy of the developed methods. From here, it is obvious that BCI linked signal processing is a multidisciplinary domain [1].

The EEG signal is measured on the surface of scalp and can be considered the effect of extremely fast polarization and re-polarization of a group of synchronized cortical, principal cells of those having their longitudinal axis perpendicular to the contact surface of the recording electrodes. In this sentence, there are too many, necessary conditions for an optimal recording process. Not only these conditions, but the entire neural system is generating nonlinear and non-stationary type of signals. If we consider that the human head includes different structures as scalp, skull and brain, each with different electrical parameters, we can realize that the recorded signal should have components not depending only on the basic activities of the central nervous system. The skull, because of its impedance, attenuates the electromagnetic signals, approximately one hundred times more than the soft tissue.

The EEG signals are later amplified generally for analysis and display purposes. It is to be considered, not to amplify noise in a same way as the not noise type components of the recordings [2][3].

In healthy adults, the amplitudes and frequencies of such signals change from one brain state to another. The EEG signals can help in diagnosis of many neurological disorders and abnormalities. A normal brain is generating bio-signals usually in five major brain waves category, distinguished by their different frequency ranges (respectively delta (δ), theta (θ), alpha (α), beta (β) and gamma (γ) ranges).

For EEG based information classifications, we have created a pattern vector. The classification methods are based on these pattern vectors, but classification methods are not significantly considered in this paper. It is well known, that each recording procedure has its specificity. At this step, we don't consider clinical type of analysis. We must test procedures suitable for engineering tasks working in real time on-line recording process.

2. EEG-signals

Figure 1 is representing a 14 electrode multichannel recording result (the recording is Petra 2-08.03.2012, left and right hemisphere recordings, 60s long, sampling rate of 256Hz). The odd numbered electrodes on the figures are on the left and the even ones on the right lobe of the cortex. For each figures, we have used only our EEG recordings.

To avoid the use of procedures proper only for linear and stationary signals, from the beginning we have considered the methods usable in case of each four category of bio-signals (linear and stationary, nonlinear and stationary, linear and non-stationary and nonlinear - non-stationary). The theory of the nonlinear and non-stationary signals category are considered in recent years. The time-

frequency transforms are included into this category. We have developed algorithms only for EEG type signal processing.

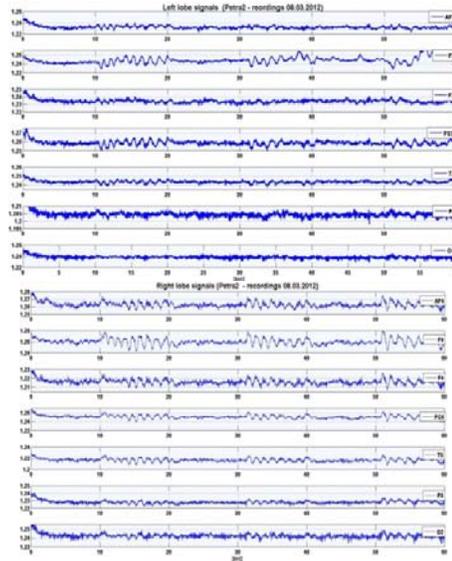


Figure 1: Multichannel EEG recording. Left panel: seven channel recordings from left hemisphere (AF3, F7, F3, FC5, T7, P7, O1). Right panel: seven channel recordings from right hemisphere (AF4, F8, F4, FC6, T8, P8, O2). Our recording, Petra2 file of 60s recording (from 08.03.2012) with sampling frequency of 256Hz. (repeated eyelashes flutter with a period of 10s of flutter and non-flutter)

3. Parameters for a pattern vector

It is a difficult task to compare two time series (TS), two EEG recordings. Not only because they are stochastic signals but because from many points of view, the EEG signals reflect a chaotic dynamical system activity. A straightforward parameter for a chaotic behavior is its attractor dimension. There are methods from chaos theory and analysis of the dynamics of time series such as dissimilarity, attractor dimension, and largest Lyapunov exponents (LLE). These parameters can characterize the nonlinear behavior of EEG signals. Strogatz [7] provides a working definition of chaotic events as 'aperiodic long-term behavior in a deterministic system that exhibits sensitive dependence on initial conditions'. In some cases, it is important to know the largest Lyapunov exponent (LLE). If the largest value LLE is positive, it means that the system is chaotic. The LLE equal to zero indicates periodic or quasi-

periodic dynamics. If all Lyapunov exponents are negative then the stable critical point is an attractor. So, it is of considerable interest to estimate the largest Lyapunov exponent (LLE) for a given time series because it can provide a clue to compare EEG TS signals. The SNR value has a great influence upon the LLE estimated value [4][5]. In our experiments the recorded EEG signals showed close to zero LLE. The LLE value is proper to be a component of the pattern vector.

The non-stationary of the EEG signals can be checked by measuring or estimating some higher-order statistical moments such as skewness, kurtosis (see Figure 4), and Kulback–Laibler (KL) distance of distributions [6]. This KL distance is useful also in case when we want to compare two histograms (distributions) of two TS. We have tested the method based on KL measure, giving an average, usable measure of difference of the considered histogram distribution and a uniform distribution in the same event domain. The KL measure is proper to be an other component of pattern vector.

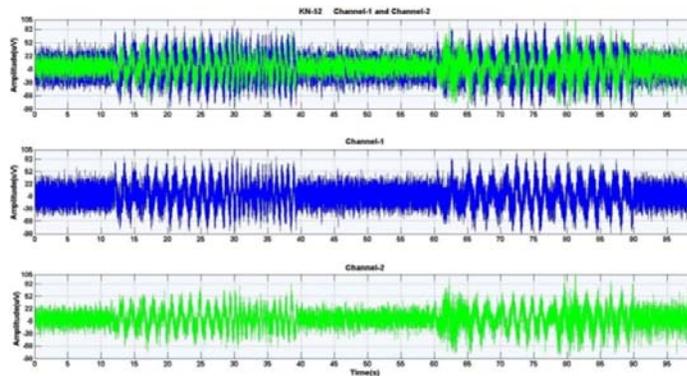


Figure 2: Signals recorded by T7, T8 electrodes (EEG_KN-52 recording, with 256Hz sampling period, 10s period eyeball moving (17.12.2010)).

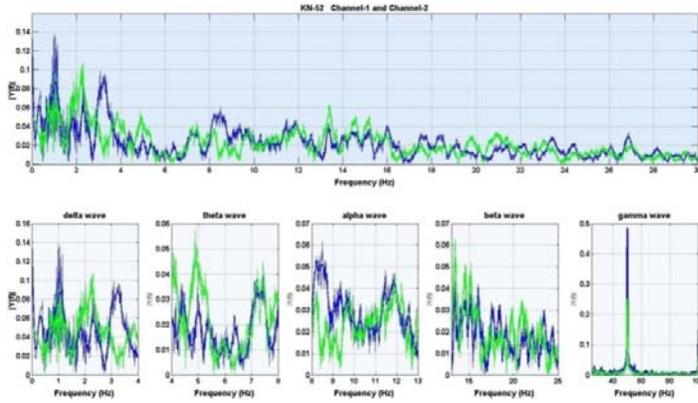


Figure 3: The power spectrum of the two signals (see also Figure 2). In the bottom row we have the power spectrum of the biologically significant frequency bands (delta (δ 0-4Hz), theta (θ 4-8Hz), alpha (α 8-13Hz), beta (β 13-25Hz) and gamma (γ >25Hz)). In the gamma band it is visible the noise of 50Hz power supply network effect.

The high order statistical elements (HOSA) of these signals have been tested for EEG signals. For the channel 1 and channel 2 of EEG_KN-52 recordings, in the title domain of the figures, the skewness and kurtosis values are presented. These values are usable parameters for the signal classification vector's

structure (pattern vector). The power spectrum (PS) of a signal is a frequency domain representation of a signal. Figure 3 represent the PS of two EEG signals. It is important that we are considering the biologically usable frequency bands in PS diagrams. The correlation of these two PS are usable parameters in the TS comparison methodology. The correlation factor of PS also can be used as a component of pattern vector for TS comparison methods.

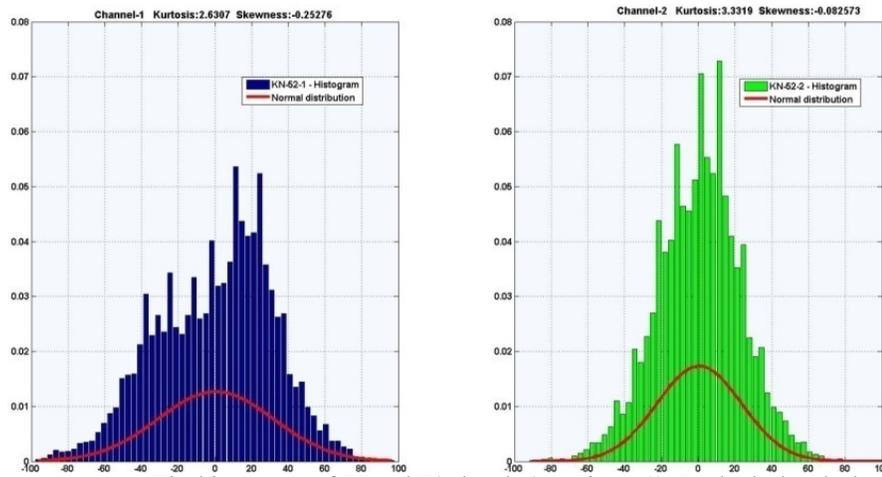


Figure 4: The histograms of T7 and T8 signals (see Figure 2). For both signals the skewness value is negative (very small values), it means an almost insignificant skew to left relative to the best fitting (to the histogram) normal distribution (red line). Relative to the same normal distribution the kurtosis values are T7 - 2.6307 and T8 - 3.3319.

Conclusion: the two signals are information carriers included in pattern vector.

The objective of classification is to draw a boundary between two or more classes of TS and to label them based on their considered features included in pattern vector, as we have considered before.

4. Classification ideas and signal transforms

There are several clustering and classification techniques developed. We have tested artificial neural networks (ANN), linear discriminant analysis (LDA), k-means clustering, fuzzy logic, and self-organizing methods (SOM). Dynamic time warping (DTW) is an effective tool to characterize the similarity of two TS.

We have developed independent the component analysis (ICA) and principal components analysis (PCA) for our EEG signals. These components can be used to provide the previously described classification pattern vector components [8]. A result of the algorithm to find independent components can be seen on Figure 5. An important application of ICA is in blind source separation (BSS). BSS is an approach to estimate and recover the independent source signals using only the information of their mixtures observed at the recording channels [9][10].

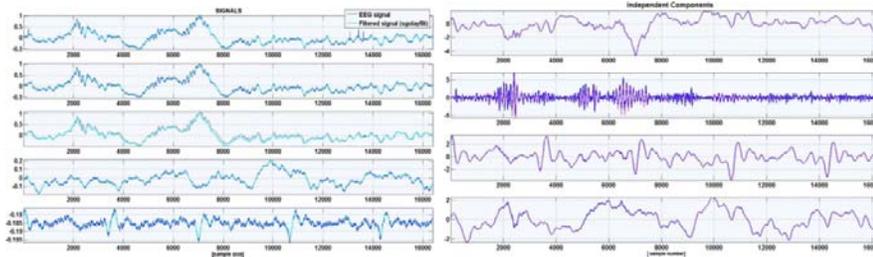


Figure 5: The five signal segments (blue-signal, cyan-average signal values) on the left panel. The obtained four ICA components on the right panel (blue - the ICA components, magenta- average ICA component values).

As a method, the cross-correlation is a measuring the strength of similarity of two time series. The cross-correlation is a function whose independent variable is the time-lag. It can be used to find the occurrence of a signal component (feature) within an other signal. Pattern recognition is basic for BCI systems. In signal processing the cross-correlation between two TS describes the normalized cross-covariance function. It is also a good tool to characterize the time-delay between two TS. The auto-correlation is the cross-correlation of a signal with itself. We have tested these transforms to have the possibility of their use in signal classification feature extraction.

We have used these methods for two EEG recordings (T7,T8 from EEG_KN-52, represented on Figure 2).

The result of the auto-correlation and cross-correlation is on Figure 6.

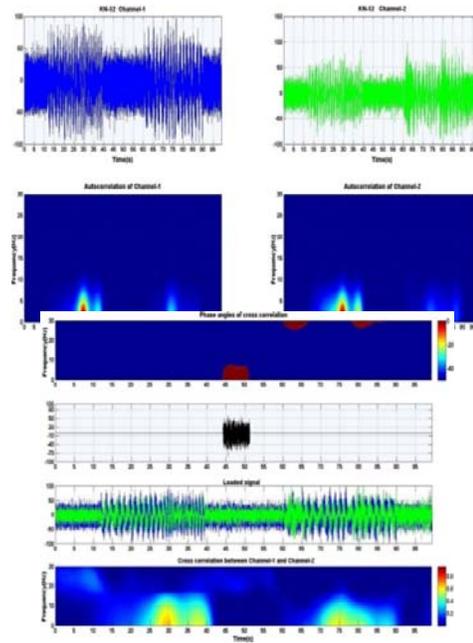


Figure 6: Left panel: The auto-correlation of the two signals (T7, T8). The time-frequency representation (bottom row) is showing the strength of the coupling (red-high value, blue-low value for the coupling strength). Right panel: The cross correlation between the two signals (bottom). The cross-correlation function is a complex function. The phase angles are also calculated and the zero phase time sequence are represented on the top two sub-panels. The zero phase it means a very strong correlation of T7, T8 recordings.

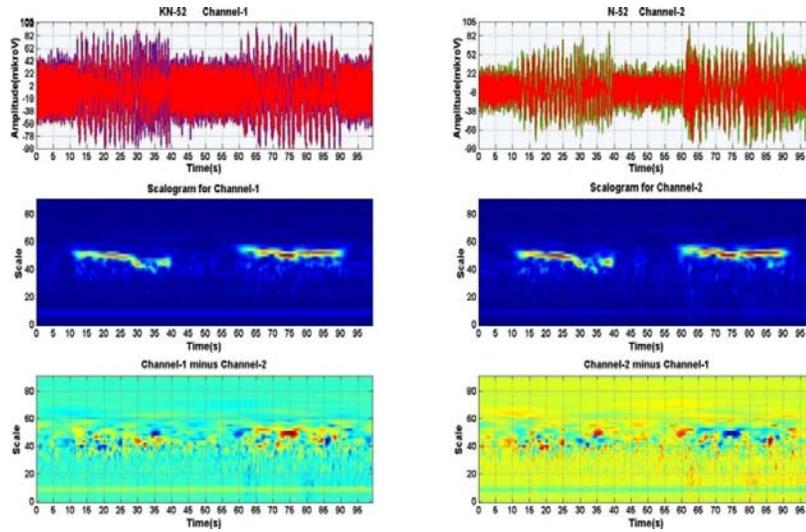


Figure 7: The CWT of the two signals from EEG_KN-52 recording (T7, T8). The time-frequency representation is on the middle row of the figure. In left side is the T7 signal (top left) superimposed with a component after noise removal. In the middle row is the time-frequency domain representation of T7. In the right column are the same representation for T8 signal. In the bottom row we have the the difference of the two signals. In the left is T7-T8 on the right side there is the T8-T7 difference.

It is useful to understand the logic of continuous wavelet transform (CWT). This is a good tool to analyze non-stationary signals. This transform is using a orthonormal wavelet function, example, the Morlet function. This transform is providing the frequency of a signal and the time moment associated to that frequency. We can say that CWT is dividing a continuous time function into a 2D representation of it (on a time frequency domain). It offer a good time and frequency localization of the events in the recorded signals [6]. This transform is using the so called scaling function, but it is important to understand that if we want to increase the spectrum coverage in time domain then we must decrease the the bandwidth in the frequency domain ($dtd\omega \geq 1/2$). The transform is resistant to the noise in the signal. We are exemplifying the method's results on Figure 7.

On Figure 7 it is also visible that the final result of the transform is an image. Image processing methods are available for feature extractions. Features classified are part of pattern recognition procedures. Recognized pattern after classification generate control signals in a BCI system.

5. Conclusions

This paper has focused to test our recordings (multichannel EEG signals) in case of different methods to extract parameters for a pattern vector of each recording. These pattern vectors are usable for EEG signals classifications (LDA, ANN, SOM). We have tested the opportunity to use largest Lyapunov Exponent, Kulbach-Laibler distance, skewness, kurtosis, power spectral correlates as the components of a pattern vector. The methods have been test considering the EEG-signal set but also different transforms of the recorded signals. We have tested the pattern vector in case of ICA-PCA components, on correlation pattern and CWT transform 2D images. Each of the parameters have their contribution to the pattern recognition idea so important for engineering type of applications based on real time EEG recordings and processing. The problem relative to this methods is about their high demand of computer time. The next step must be the improvement of the tested algorithms and to find hardware implementation (with capability of parallel processing) of them.

Also, for BCI applications there are necessary to try other, different new methods to improve pattern classification accuracy. This paper is about signal processing approaches and not on pattern recognition or pattern classification algorithms. It is obvious that methods based on statistical approaches (HOSA, Correlations) and wavelet transform can provide more accurate results. In BCI systems the on-line processing is almost all the execution time is a vital consideration.

Acknowledgements

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