Feature Extraction from Biological Signals: A Case Study

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Abstract – **This paper presents two case studies illustrating the problem of data preprocessing as the first step in computer-aided analysis of biological signals used in clinical decision support. Methods for data extraction from ECG and EEG signals are described. We show the differences between these two signal types and the reasons why different approaches are used for their preprocessing. Analysis of ECG records is performed by the wavelet transform, and analysis of EEG records is performed using adaptive segmentation and the Fourier transform. The wavelet transform allows good localisation of QRS complexes, P and T waves in time and amplitude. The average accuracy of detection of all events is above 87 per cent. Adaptive segmentation abstracts the EEG signal data into stationary segments and the Fourier transform calculates their basic characteristics. In both cases extracted data are used as inputs for machine learning methods.**

I. INTRODUCTION

The medical domain is one of the areas in which Artificial Inteligence (AI) and machine learning methods are most frequently applied. This is quite natural because modern medicine generates huge amounts of data, but at the same time there is often a lack of explicit relations among this data and a lack of data understanding. In particular, data mining and knowledge discovery [1] are tools than can help in dealing with this problem. In the medical domain, data exists in various forms – single numerical values, non-numerical expressions, measured signals (e.g. ECG, EEG, EMG). Therefore it is necessary to pre-process and transform the data into the most suitable form to serve as an input for a decision support system. These tasks re-appear frequently in the process of data-mining, and are not specific to the medical domain only. For this reason it seems useful to develop a general tool supporting data pre-processing and transformation tasks for Data Mining and DataWarehousing. SumatraTT (Transformation Tool) has been designed [2] for this purpose. It is an interpreter of a transformation-oriented scripting Java-like language called SumatraScript complemented by a GUI interface.

The paper considers the use of signal processing approaches for data extraction from biological signals. The framework is applied to detecting ECG and EEG events. In order to achieve this goal we use two methods: the wavelet transform [3] for ECG feature extraction and the Fourier transform for EEG feature extraction. This paper is organised as follows. Section 2 presents a brief description of ECG and EEG signal analysis. Section 3 reviews some related work. Section 4 describes the wavelet transform and analyses the results obtained with the wavelet transform applied to the ECG signal. Section 5 describes the Fourier transform and analyses the results obtained with the Fourier transform applied to the EEG signal. Finally, section 6 summarises the conclusions.

II. ECG AND EEG SIGNAL ANALYSIS

A. ECG signal analysis

An electrocardiogram (ECG) is a recording of the electrical activity of the heart in dependence on time. The mechanical activity of the heart is linked with its electrical activity. An ECG is therefore an important diagnostic tool for assessing heart function. An ECG signal can provide us with a great deal of information on the normal and pathological physiology of heart activity. An ECG as an electrical manifestation of a human activity is composed of heartbeats that repeat periodically. In each heart beat several waves and interwave sections can be recognised. The shape and length of these waves and interwave sections characterise cardiovascular diseases, arrhythmia, ischemia and further heart diseases. Basic waves in ECG are denoted by P, Q, R, S, T, U. From these, the denotation (and length) of the intervals and segments is derived. The time axis uses the order of milliseconds, while the potential axis uses the order of mV. There exist classification systems that are able to localise pathological changes in ECG records, detect the QRS complex [4], the ST segment [5, 6], find the RR interval [7], the appearance of individual waves [8, 9], and many other values. On basis of these and with the support of such a classification system, the doctor can determine the diagnosis.

ECG temporal analysis. In medical practice ECG analysis is performed nearly exclusively as a temporal analysis. When interpreting an ECG, physicians first locate the P waves, QRS complexes, T complexes and U waves. Then they interpret the shapes (morphology) of these waves and complexes; in addition they calculate the heights and the interval of each wave, such as the RR interval, PP interval, PR interval, QT interval, and ST segment. From the technical point of view, the assumption for ECG analysis is the existence of perfect ECG signals (i.e. signals with sufficient dynamics and a minimum of artefacts).

B. EEG signal analysis

EEG is spontaneous cortical electrical activity recorded at the scalp. Typical values might be 20-100 microVolts for EEG with lesser values being recorded in averaged evoked potentials: perhaps 10 microVolts. Larger values are recorded in epilepsy and other disorders which can be diagnosed using EEG. These potentials are easily recorded. The EEG signal is small compared to the amplitude of common artefacts (muscle, mains power frequency radiation). Clean signals are dependent on low scalp/electrode impedance, differential amplifiers, and filtering. EEG is most often recorded from many electrodes arranged in a particular pattern. A common standard for describing these position is the International 10/20 System.

Electroencephalography waveforms generally are classified according to their frequency, amplitude, and shape, as well as the sites on the scalp at which they are recorded. The most familiar classification uses EEG waveform frequency (e.g. alpha, beta, theta). Information about waveform frequency and shape is combined with the age of the patient, state of alertness or sleep, and head site to determine significance. As a result we can divide EEG signal into two groups: according to its frequency context and morphology characteristics [10].

Most waves range from 0.5-500 Hz, but most clinical EEGs were performed on paper-writing machines with upper ranges of 20-40 Hz. The basic wave frequencies are denoted: alpha (8-13 Hz), beta (greater than 13 Hz), theta (3.5-7.5 Hz), delta (3 Hz or less). The morphology identifies waves by their shape and form and by their frequency. They include waves that may be normal in some settings and abnormal in others. Let us briefly list the shapes: spike and wave, polyspike and wave, lambda and POSTS (positive occipital transients of sleep), K complexes, V waves, Mu activity, psychomotor variant, fourteen and six rhythm, periodic lateralized epileptiform discharges (PLEDS), triphasic waves, burst suppresion, artefacts (sweat artefacts, ECG and pulse artefacts, electrode and other movement artefacts, intravenous artefact, 50 Hz artefacts).

The term epilepsy refers to a group of neurologic disorders characterized by the recurrence of sudden reactions of brain functions caused by abnormalities in its electrical activity, which is clinically manifested as epileptic seizures. Manifestations of epileptic seizures vary greatly, ranging from a brief lapse of attention to a prolonged loss of consciousness; this loss is accompanied by abnormal motor activity affecting the entire body or one or more extremities.

III. Related Work

There are a number of approaches to ECG and EEG analysis and classification, including filtering algorithms, transforms, and machine learning methods. In some cases, combinations of two or more methods are used.

The most frequently used (or cited) ECG classification method is neural network classification [11, 12]. It is followed by expert systems [13, 14], machine learning methods [15], fuzzy systems [16] and, more recently, the wavelet transform [17, 18] and genetic algorithms [19]. Morlet et al. [20] use the wavelet transform to acquire contour maps that allow the localisation of short, low energy transient signals, even within the QRS complex. In several applications, digital filtering is used for detecting certain significant shapes in an ECG [21].

In EEG analysis and classification, attention is focused mostly on pathologies, one of them being epilepsy. Several attempts to detect epileptic seizures have already been made. They use formalisms such as conventional temporal and frequency analyses [22], [23], [24], quantitative characterization of underlying non-linear dynamical systems [25], local texture features in conjunction with wavelet transform [26], neural networks [27].

IV. Wavelet Transform and Its Application to ECG Feature Extraction

A. Wavelet Transform

The wavelet transform (WT) is a modern and promising method for time and frequency signal analysis. A signal is decomposed into building blocks that are well represented in time and frequency. In the search for significant features of the ECG signal we used filtering of the signal using wavelet filtering based on the wavelet transform. The set of decomposition functions of the wavelet transform is wider and different sets of decomposition functions are used. This property of the wavelet transform allows us to select the most suitable set of decomposition functions according to the specific signal and its properties, and to achieve optimal results for specific types of signals. The wavelet transform can be characterised in general as follows: (i) Decomposition functions are building blocks to construct or represent a signal or function. (ii) Decomposition by the wavelet transform gives time-frequency localisation of the signal. (iii) The coefficients can be calculated efficiently. The transformation can be calculated in $O(N \log(N))$ steps in general, the same as the fast Fourier transform. Many wavelet transforms can be calculated in $O(n)$ steps.

B. Input Data

We used the physionet database of biological signals as a source of ECG records, namely the MIT-BIH ECG Database. This database is freely accessible on the internet on http://www.physionet.org/. An excellent advantage of this data source is that it is widely used in experimental works on classification of ECG signals and biological signals in general. The data files were recorded with different sampling frequencies, so we needed to resample the records to a unified frequency. As the unified frequency we used the lowest frequency among the records f_s=125 Hz. Each data file consists of time stamps and values recorded from two electrodes; the length of each record is 60 seconds. We worked with five classes – Atrial Fibrilation, Malignant Ventricular Ectopy, Supraventricular Arrhythmia, Arrhythmia, and Normal Sinus Rhythm.

C. ECG Signal Analysis Using the Wavelet Transform

A signal is decomposed into building blocks that are well represented in time and frequency. According to [3] dyadic WT is used for extracting ECG characteristic points. Our approach is based on the work of Mallat [28] and Li et al. [17]. The basic idea stems from the properties of the function derivatives that represent useful information about the analyzed signal in the time domain, i.e. the morphology of the signal. We can think of an ECG signal as of a composition of basic elements. We detect significant points of a signal by using zero-crossing points of the first derivatives of the signal smoothed with the smoothing function Θ.

For numerical application we cannot compute the wavelet transform at infinitely fine scale. Parameters of the smoothing function determinate parameters of finite impulse response (FIR) filter, that we use to obtain all details we use for ECG signal analysis. In this work we use the cubic spline smoothing function and the quadratic spline wavelet function with compact support, for details see [28].

D. Detection and Extraction of Significant Points on an ECG Signal

Detection of the QRS complex is performed using all four details of the processed signal acquired by filtering with equivalent FIR filters of the wavelet transform according to [17].

In the first step we find all extremes on the fourth detail bigger than an empirically selected threshold value ε_4= 0,1. As a result we get a set of extreme positions $\{n_k^4 | k = 1,\dots,N\}$, where N is the number of extremes found. In the next step we find extremes on the third detail bigger than an empirically selected threshold value ε_3= 0,5. Among the found extremes we look for extremes in the neighbourhood of extremes n_k^4. If there is no extreme in the neighbourhood we set the values n_k^3, n_k^2 and n_k^1 to zero. As a result we get the set of extreme positions on the third detail $\{n_k^3 | k = 1,\dots,N\}$. In an analogical way we acquire sets of extreme positions for the second and first details $\{n_k^2 | k = 1,\dots,N\}$ and $\{n_k^1 | k = 1,\dots,N\}$, while the threshold values ε_2 a ε_1 are set to ε_2= 0,5 [-] and ε_1= 0,25 [-]. Now we have a set of positions of extremes on each of the details. We set the position of the R wave as a cross-point of the two near extremes on the first detail of the ECG signal.

In the next step we find the on-set and position of the Q wave on the first detail. We use the first detail because the base-line drift is removed in it. The search is performed in the time window before the wave. The width of this window is set to the value δ_Q = 5 samples for sampling frequency f_s=125 Hz. As the Q wave position we select the first local extreme of the opposite sign to the detected R wave. This extreme must be greater than an empirically set threshold ε_Q= 0,05 [-]. As the onset of the Q wave we select the first zero cross-point before the extreme found on the first detail. If the Q wave cannot be found, we try to find the QRS complex onset. We do this by selecting the first zero cross-point before the R wave. Analogically, we find the S wave and its offset in a time window after the detected R wave. The width of this time window is set to be the same as in the case of the Q wave, because of the similar character of the two waves. As the S wave position we select the first local extreme of the opposite sign to the detected R wave. If no S wave is detected we try to find the offset of the QRS complex. Its position is set to the first zero cross-point in the selected time window.

Detection of P and T waves. When the parameters of the QRS complex are selected, we proceed with a search for the P and T waves. Both of these waves are detected on the fourth detail of the ECG signal, using the same method with slight differences in its parameters. This is possible because of the similarity of the two waves. The search for the P wave is performed in the time window before the R wave. The width of this window is set to the value δ_P = 40 samples for sampling frequency f_s=125 Hz. If the width of the time window exceeds half of the time span between two neighbouring R waves, we change the width of the time window to half of the time span of the R-R waves. In the time window we search for a pair of extremes with opposite signs that exceed the threshold value ε_P= 0,0025 [-] and that is the closest pair to the detected QRS complex. The pair signs have to be ordered [+ -] when the detected R wave is oriented to $+\infty$, and [- +] otherwise. The onset of the P wave is detected as the zero cross-point position or the first minimum that precedes the first extreme. The position of the P wave is selected as a zero cross-point between the two selected extremes. We select the offset of the P wave as a zero cross-point or the first local minimum after the second selected extreme. While the FIR filtering moves the details forward on the time axis we have to subtract the constants for sharp P localisation. These values are empirically set to Δ_{P1}=7, Δ_{P2}=10 and Δ_{P3}=11 for the onset, position and offset of the P wave, respectively.

The search for the T wave is performed in the time window after the detected R wave. The width of this window is set to the value δ_T = 65 samples for sampling frequency f_s=125 Hz. If the width of the time window exceeds two thirds of the time span between two neighbouring R waves, we change the width of the time window to two thirds of the time span of the R-R waves. In the time window we search for a pair of extremes with opposite signs that exceed the threshold value ε_P= 0,0025 [-] and is the closest pair to the detected QRS complex. The pair signs have to be ordered [+ -] when the detected R wave is oriented to $+\infty$, and [- +] otherwise. The onset of the T wave is detected as the zero cross-point position or the first minimum that precedes the first extreme. The position of the T wave is selected as a zero cross-point between the two selected extremes. We select the offset of the T wave as a zero cross-point or the first local minimum after the second selected extreme. While FIR filtering moves the details forward on the time axis we have to subtract constants for sharp T localisation. These values are empirically set to Δ_{T1}=7, Δ_{T2}=16 and Δ_{T3}=17 for onset, position and offset of the T wave, respectively.

For the task of learning and classification it is important to select a set of significant parameters of the ECG signal that allows us to successfully learn and classify the data. Initial selection of the attributes was based on consultations with medical doctors, and in accordance with [18]. We used the following attributes – P wave amplitude, P wave duration, P-R interval duration, QRS complex duration, S wave duration, R wave amplitude, Q-T interval duration, T wave duration, S-T interval, Q-T interval area.

V. Fourier Transform and Its Application to EEG Feature Extraction

A. Input Data

In our experiments, we analyzed the EEG signal of epileptic patients. The signals were recorded at the Neurological Clinic of the Bulovka University Hospital in Prague. System 10-20 (Montreal convention) was used for EEG recording, i.e. signals from 21 channels were acquired. The input file has standard text format. For testing the implemented program we used two records of one epileptic patient. The signal contains epileptic graphelements of type spike-wave complex of frequency 3 Hz. In both records there are two epileptic seizures.

B. Mathematical Apparatus for EEG Signal Analysis

In general, signals can be analysed both in temporal and frequency domains. The basic characteristics in temporal domain are the mean (the average value of a signal) and signal variance (square of standard deviation). Signal variance is the measure of diversity of samples and their mutual distance. If the values are concentrated around its mean value the variance is low. The greater the distance of the signal samples is from their mean values the greater their variance is. Another important parameter is signal-to-noise ratio, which is equal to the mean divided by the standard deviation. In frequency domain, one of the basic transforms used for signal description is the Fourier transform. It may be applied both to continuous and discrete signals. Discrete signals are processed by Discrete Fourier transform. Its efficient software implementation is called Fast Fourier Transform (FFT). Its advantage in comparison to analysis using digital filters is that we acquire as results not only amplitude spectrum but also phase spectrum. Then it is possible to calculate further signal characteristics, for example correlation function and power spectra. Correlation contains information on relation of signal value $x(t)$ for time $t = t_0$ and value of this signal $x(t)$ (or another signal $y(t)$) for time $t_1 = t_0 + \tau$. Correlation represents optimal way to detect a known waveform in a signal. Autocorrelation is used for a signal correlated with itself. This function is very useful and frequently used because its Fourier transform is the power spectrum of the original signal. It is used, for example for detection of signal periodicity. However we must consider the fact that the Fourier transform **is not suitable** if the signal has time varying frequency, i.e., the signal is **non-stationary**. In such a case the signal must be divided to stationary segments.

C. Adaptive Segmentation

In automatic signal analysis, extraction of informative attributes with the greatest possible discriminative ability belongs to important tasks. If we use signal divided to intervals of constant length for acquisition of informative attributes, non-stationariness of the signal may cause distortion of characteristics estimation. Segments defined in this way may contain mixture of waves of different frequencies and shapes. It is preferable to divide signal to segments of different interval length that are stationary. Then a new segment starts at the exact instant when the signal changes its characteristics. There exist several approaches to adaptive segmentation [29], [30] which divide signals to stationary segments. In principle, these methods are based on autocorrelation function (ACF) [29], spectral error measure [29], and generalized likelihood ratio (GLR) [31]. Appel and v. Brandt [32] performed a comparative analysis of the performance of the ACF, SEM, and GLR methods of adaptive segmentation. The results showed that the GLR method is the most accurate in the exact location of segment boundaries. However, it is at the price of high computational load.

Adaptive Segmentation Based on Autocorrelation Function[29]. Let us have two windows, one of them is reference window and is fixed to the beginning of the segment. The second window is sliding (testing) and slides along the signal. Signal characteristics are calculated in the fixed reference window. The same characteristics are calculated in the sliding window. From the differences of signal characteristics in both windows measure of difference (deviation from stationariness) is determined. This measure corresponds to difference of signals in both windows. If the measure of difference exceeds defined threshold, the point is marked as segment boundary. The reference window is fixed to the beginning of a new segment and the procedure is repeated. Measure of difference is calculated from the difference of autocorrelations of reference and testing windows. The disadvantage of this method is delay of indication of segment boundary time stamp behind the real boundary. This delay must be estimated from further signal course.

Adaptive Segmentation Based on Two Joint Windows. The idea of sliding two joint windows follows the method proposed in [33]. It is based on calculation of differences of two windows. The difference is calculated from spectra of both windows, using FFT. The method is very slow because the difference is calculated using FFT for each window shift. In addition, the method indicates boundaries even around real segment boundaries. Therefore in our approach the autocorrelation is used for calculating measure of difference, similarly to [29]. Advantage of this new method is indication of segment boundaries without delay and possibility of multichannel segmentation. Following procedure enables to indicate segment boundaries: Two joint windows slide along the signal. For each window the same signal characteristics are calculated. Measure of difference is determined from the differences of signal characteristics in both windows. This measure corresponds to difference of signals in both windows. If the measure of difference exceeds defined threshold, the point is marked as segment border.

D. Selection and Calculation of Attributes

After segmentation, attributes that will be used for classification must be selected. For more comprehensive description of the EEG signal, set of attributes including not only attributes from frequency domain, but also attributes characterising signal shape were selected. The following attributes describing signal are used: average AC amplitude in the segment, variance of AC amplitude in the segment, maximum positive and minimum negative values of amplitude in the segment, maximum value of the first derivation of the signal in the segment, maximum value of the second derivation of the signal in the segment, average value of frequency in the segment, amplitude values in defined frequency bands (e.g. for EEG in alpha, beta, theta, and delta bands). All attribute values are standardized. These values serve as input data for cluster analysis module.

VI. Conclusion

One of the aims when developing an ECG or EEG classification system is to ease the work of medical doctors. These systems are to help the doctor interpret ECG or EEG records correctly, and then to propose the most appropriate treatment. Further applications of these systems can be in educating new doctors, in evaluating long-time ECG and EEG records, in ECG monitoring in intensive care units, or in EEG monitoring at neurological clinics. There are a number of algorithms that may be employed to classify unknown ECG or EEG signals. Basically, they can be divided into two groups.

The first group is based on rules defined by human experts. Since there is no exact algorithm or gold standard specifying ECG signals of healthy persons and patients with different diagnoses, the rules are biased towards human expertise. The same situation arises when a single ECG recording is evaluated by several human experts [34]. In case of EEG signals the situation is even worse because the nature of EEG signal completely differs from the nature of ECG signal. ECG is periodic with relatively easily detectable parts. Even the pathological changes are nowadays more or less exactly described. EEG is not periodic and is non-stationary. Its shape depends on many factors such as mental or motoric activities, pathologies (e.g. epilepsy), vigilance, or sleep, etc. Therefore more steps in pre-processing are required before we get description in the form of attribute values.

The second group utilises various forms of learning, thus avoiding human biasing. Both groups of algorithms have their advantages and drawbacks. Attempts have been made to combine rules defined by human experts with rules generated by the See5 program [35]. The experiments showed that a knowledge base originally created from expert rules refined with generated rules gives better results than the original knowledge base and decision tree as separate systems.

Proper selection of attributes plays a very important role in classification systems. It may significantly influence the success rate of classification. Use of irrelevant and weakly relevant attributes can decrease the accuracy. The attributes can be selected either automatically or manually. Automatic selection can be viewed as a state space search where each state represents a single combination of attributes. The goal of the search is to find the state with the highest value of the evaluation function that characterises the success rate of classification with the corresponding attributes. It is obvious that such an evaluation function is only an estimation of the success rate of the classification, because the training set is limited. The transition operator is attribute adding or deleting. The average accuracy of cross-validation is usually used as an evaluation function. Manual selection, on the other hand, is a more or less intuitive process based on experience.

One of the most important aspects of the ECG and EEG classification systems is reliable analysis of ECG and EEG records respectively, which enables significant values to be identified on the measured signal. This analysis is a necessary condition for correct classification.

The wavelet transform has proven to be a good tool for ECG signal analysis. The detection of attribute values achieves a sufficiently high level of reliability – about 80 per cent, which is higher than manual reading from the signal. It enables to detect required values of selected attributes in few steps which is important from the point of view of time required for processing. The extracted values are then used as input values for a classification system. In our case study we used decision tree induction and successive classification with the See5 program (http://www.rulequest.com).

As mentioned above, the EEG signal is more complex, and thus it requires more steps of pre-processing. The first step is the adaptive segmentation that divides the EEG signal into stationary segments. The adaptive segmentation based on two joint windows enables on-line processing of multi-channel signals and the segmentation proceeds in each channel independently on the other channels. When the signals are segmented, all attributes are calculated, some of them in time domain, some of them in frequency domain. The extracted values are used as input values of a classification system. In our case study we used cluster analysis and neural network [36].

It is necessary to stress that the selection of a pre-processing method is a very important step in data mining process, especially when working with continuous signals. Application of a certain method is usually very closely linked with the choice of attributes and thus requirements laid on extraction and calculation of values from the signal.

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VIII. REFERENCES

[1] K.J. Cios, ed., *Medical Data Mining and Knowledge Discovery* (Physica-Verlag, Heidelberg, 2001)

[2] P. Aubrecht, F. Zelezny, P. Miksovsky, O. Stepankova, SumatraTT: towards a universal data preprocessor, in: *Cybernetics and Systems 2002, Proceedings of 16th European Meeting on Cybernetics and Systems Research* (2002) 818-824

[3] C.S. Burrus, R.A. Gopinath, H. Guo, *Introduction to wavelets and wavelet transforms* (Prentice Hall, 1997)

[4] Y. Sun, K.L. Chan, S.M. Krishnan, A new approach for electrocardiogram analysis using wavelet-based nonlinear dynamic, *Medical & Biological Eng. Comp.* 37, Suppl. 2 (1999) 390-391

[5] C. Papaloukas, D.I. Fotiadis, A. Likas, L.K. Michalis, A rule based technique for the automated detection of ischemic episodes from long duration ECGs, *Medical & Biological Eng.Comp.*37, Suppl. 2 (1999) 728-729

[6] F Jager, R.G. Mark, G.B. Moody, S. Divjak, Analysis of transient ST segment changes during ambulatory monitoring using the Karhunen-Loeve transform, *IEEE Computing Cardiology* (1992) 691-694

[7] F. Azuaje et al, Knowledge discovery in electrocardiographic data based on neural clustering algorithms, in: *Proceedings Medicon '98 of the IFMBE* (1998)

[8] Ü. Olli et al, Analysis of T-wave morphology for discrimination of life threatening arrhytmias – preliminary study, in: *Proceedings Medicon 2001 of the IFMBE* (2001)

[9] M. Jeras, R. Magjarević, E. Paćelat, Real time P-wave detection in surface ECG, in: *Proceedings Medicon 2001 of the IFMBE* (2001)

[10] S. Louis, Department of Neurology, Brown University School of Medicine, http://www.emedicine.com/neuro/topic275.htm

[11] C. Papaloukas et al, An ischemia detection method based on artificial neural networks, *Artificial Intelligence in Medicine* 24 (2) (2002) 167-178

[12] N. Izeboudjen, A. Farah, A new neural network system for arrhythmias classification, in: *Proc. Medicon '98 of the IFMBE* (1998)

[13] L. Gargasas, R. Ruseckas, R. Jurkoniene, An expert system for diagnosis of coronary heart disease (CHD) with analysis of multicardiosignals, *Medical & Biological Engineering Computing* 37, Supplement 2 (1999) 734-735

[14] W. Mautgreve et al, HES EKG expert - an expert system for comprehensive ECG analysis and teaching, in:*Proc.Computers in Cardiology* (IEEE Computer Society Press, 1990) 77-80

[15] M. Kukar et al, Analysing and improving the diagnosis of ischaemic heart disease with machine learning, *Artificial Intelligence in Medicine* 16 (1) (1999) 25-50

[16] M. Kundu, M. Nasipuri, D.K. Basu, A knowledge based approach to ECG interpretation using fuzzy logic, *IEEE Trans. System, Man and Cybernetics* 28 (2) (1998) 237-243

[17] C. Li, Ch. Zheng, Ch. Tai, Detection of ECG characteristic points using wavelet transforms, *IEEE Trans.on Biomedical Engineering* 42 (1) (1995) 21-29

[18] M. Yang; W. Hu; L. Shyu, ECG events detection and classification using wavelet and neural networks, in *Proceedings – 19th International Conference – IEEE/EMBS* (Chicago, IL. USA, 1997)

[19] R. Poli, S. Cagnoni, G. Valli, A genetic algorithm approach to the design of optimum QRS detectors, *University of Florence Technical Report No. 940201*, Florence, Italy, 1994

[20] D. Morlet, et al, Time-scale analysis of high-resolution signal-averaged surface ECG using wavelet transformation, in *Proc. Computers in Cardiology* (IEEE Computer Soc. Press, 1991) 393-396

[21] D.F. Sittig, et al, A parallel implementation of a multi-state Kalman filtering algorithm to detect ECG arrhythmias, *Int. Jour. of Clinical Monitoring and Computing* 9(1) (1992) 13-22

[22] B.L.K. Davey et al., Expert system approach to detection of epileptiform activity in the EEG, *Med. Biol. Eng. Comput.* 27(4), (1989) 365-370

[23] J. Gotman, Automatic recognition of epileptic seizure in the EEG, *Electroencephalogr. Clin. Neurophysiol.* 83 (1982) 271-280

[24] H. Qu, J. Gotman, Improvement in seizure detection performance by automatic adaptation to the EEG of each patient, *Electroencephalogr. Clin. Neurophysiol.* 86 (1993) 79-87

[25] G. Mayer-Kress, Localized measures for nonstationary time-series of physiological data, *Integrative Physiological Behav. Sci.* 29 (3) (1994) 205-210

[26] A. Petrosian, R.W. Homan, S. Pemmaraju, S. Mitra, Wavelet-based texture analysis of EEG signal for prediction of epileptic seizure, *SPIE Proceedings on Wavelet Applications in Signal and Image Processing*, Vol. 2569, San Diego, CA, (1995) 189-194

[27] W. Weng, K. Khorasani, An adaptive structure neural networks with application to EEG automatic seizure detection, *Neural Networks* 9(7) (1996) 1223-1240

[28] S. Mallat, S. Zhong, Characterization of signals from multiscale edges, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 14(7) (1992) 710–732

[29] G. Bodenstein, H.M. Praetorius, Feature extraction from the electroencephalogram by adaptive segmentation, *Proc. IEEE*, 65 (1977) 642-652

[30] V. Krajca, S. Petranek, V. Ondruska, J. Doruzkova, D. Pecharova, Multichannel adaptive segmentation – basis for EEG record pre-processing, *Lekar a technika*, 23(2) (1992) 28-34

[31] U. Appel, A. v. Brandt, Adaptive sequential segmentation of piecewise stationary time series. *Information Science* 29 (1983) 27-56

[32] U. Appel, A. v. Brandt, A comparative analysis of three sequential time series segmentation algorithms, *Signal Processing* 6 (1984) 45-60

[33] D.Z.A Silin, K.M. Skrzlev, Avtomaticeskaja segmentacija EEG, *Zurnal vyssej nervovej dejatelnosti*, 36 (1997) 1152-1155

[34] J. Willems, et al, Comparison of diagnostic results of ECG computer programs and cardiologists, in *Proceedings of the Computers in Cardiology Conference* (Durham, North Carolina, 1992) 93-96

[35] M. Sorf, L. Lhotska, L. Janku, V. Eck, Application of AI approaches to personality type classification, in: *Proceedings of the IASTED International Conference Modelling, Identification and Control* (IASTED, Calgary, 2001) 403-408

[36] L. Lhotská, M. Zvolánek, Adaptive Segmentation and Classification of Non-Stationary and Time-Varying Signals. In: *Intelligent E-Health Applications in Medicine and Other Medical Applications of Adaptive/Hybrid Intelligent Systems*. Aegean: University of the Aegean, 2002, vol. 1, 167-172