Fast Fourier Transform for Feature Extraction And Neural Network for Classification of Electrocardiogram Signals

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***Abstract*—This paper presents a novel approach to complex classification of heart abnormalities registered by electrocardiogram signals. It uses a combined approach of a Fast Fourier Technique for signal filtering and R-peaks detection and heart rate extraction, followed by signal modelling and classification by neural network based on recording of ECG. Obtained information is processed together for a complex evaluation of the signal in time.**

***Keywords*— Fast Fourier Transform, Data Filtering, R-Peak Detection, Electrocardiogram Signal, Neural Network**

I. INTRODUCTION

The human heart is a pump that moves blood via whole organism performing an essential function for a human being. Today's fast changing, dynamic world brings impact on the quality of environment and high load on a human body causing serious health problems. Cardiovascular diseases form a main cause of death worldwide [1] and efforts to prevent, solve and improve cardiac problems create a significant portion in technological and medical research.

Electrocardiogram signals (ECG) are commonly used for analysis and examination in medical environment. Such method is non-invasive, comprehensively fast and efficient and by medical experts often used. Evaluation of complete ECG recording requires knowledge and experience and overall state of the patient and his medication must be also considered. Easily detected are any abnormalities in the heart cycle that can be observed in QRS complex. But also duration of each heart stroke and interval between individual strokes are important factors in definition of cardiac diseases.

The heart cycle rate is normal (between 60 and 100 beats per minute in average adult), or it projects bradycardia (rates slower than 60 beats per minute) or tachycardia (rate is faster than 100 beats per minute). Generally, any irregular heart rates are termed arrhythmias and are mostly caused by underlying heart diseases. However, in some cases, arrhythmias are not necessarily associated with any significant disease. They can occur randomly or are transient in nature.

Different types of arrhythmias can be defined by several categories - benign, bradyarrhythmias and heart blocks and tachyarrhythmias. For the first group of benign arrhythmias, atrial premature contractions (APCs) can occur several times per minute without any serious effect, but more frequent occurrence can discover more serious conditions leading to tachyarrhythmia. Very similarly, ventricular premature contractions (PVCs) can occur normally with healthy adult, however, more than six PVC per minute are abnormal. PVCs can occur in isolation, in pairs or triplets, alternating with regular beats (bigeminy, trigeminy) or in other regular sequences with normal beats. The ECG representation is a wide QRS complex of greater than 0.12 seconds. Set of more than three consecutive PVC complexes is termed as ventricular tachycardia, serious and potentially life threatening condition. More frequent or polymorphic PVCs represent more significant heart conditions.

Bradyarrhythmia, represented as the second group of heart disorders, usually arises from a failure in conducting signals in the normal sequence or through normal pathways and are defined as heart blocks.

The third group of arrhythmias can be represented by atrial fibrillation and very serious ventricular tachycardia (VT) or fibrillation (VF). Atrial fibrillation is described as a quiver of atria that sends irregular and frequent signals to the ventricles to contract. Resultant ventricular rate is very rapid and blood flow to the body is reduced due to the incomplete blood filling of the left ventricle. Atrial fibrillation is represented in the ECG with the absence of a distinct P wave and random and fast QRS complexes. Very similarly, ventricular arrhythmias represent the random heart beating resulting in an inefficient blood flow. Ventricular arrhythmias may have life threatening implications. Ventricular tachycardia (VT) occurs as a rapid heart beating at rates greater than 100 beats per minute with wide QRS complex (greater than 0.12 seconds) and often inverted from

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the standard pattern. Short bursts of VT with several seconds duration, are frequently represented as strings of consecutive PVCs that may spontaneously revert to normal sine rhythm (NSR). However, VT may degenerate into ventricular fibrillation (VF), a rapidly fatal condition with loss of consciousness and death.

Many electronic computer based devices evaluate important features in the measured ECG signal. According to rules, these features are being evaluated and device states abnormalities found with classification into possible disorder group. However, these devices cannot recognize and consider all factors connected with a patient state and can give out false results. Target is to bring more accurate results by such devices. Aim of this paper is to find a possible approach to this problem by combination of several methods nowadays used in ECG evaluation by computer based devices.

II. METHODS

In order to consider all factors in human body correctly, it is necessary to evaluate individual features of the ECG separately. Irregularities in the heart rate and periodicity of the ECG waves must be evaluated over the whole recording of the ECG or on a selected section of the signal. Usually, window wavelet methods are the best tools in such evaluation, because they scan the whole length of the signal and evaluate only the part of the signal inside the scanning window. Results from this method can be extracted and considered for the evaluation further on, i.e. position of R-peaks in the QRS interval, distances between peaks for evaluation of heart frequency disorders, heart rate on particular intervals of the signal and average heart rate of the recorded ECG.

Any abnormalities in the signal that are dependent on the heart stroke itself can be observed in QRS complex. Differences in the QRS complex from the normal heart beat can project any heart disorders related to atria, ventricles and generated voltage during the heart stroke. Very good tools for differentiation and modelling of such signals are neural networks and are widely used for classification tasks. In this particular case, several shapes of QRS wave will be differentiated by the neural network and tested on the complete signal for its classification strength.

Finally, any other factors, as medication, cordial breakdowns, heart attack and patient state can also influence classification of heart disorders. Such information can be added further on to improve the evaluation process and deliver better results.

A. Detection of the R-Peak

As the heart undergoes depolarization and repolarization, the electrical currents that are generated spread not only within the heart, but also throughout the body. This electrical activity generated by the heart can be measured by an array of electrodes placed on the body surface. The recorded tracing is called an electrocardiogram (ECG). The different waves that comprise the ECG represent the sequence of depolarization and repolarization of the atria and ventricles. The heart rate can be calculated from the intervals between different waves [2].

Fast Fourier Transform (FFT) represents an efficient algorithm for calculation of discrete Fourier transform and can be used in various applications from data filtering, digital signal processing and solving of partial differential equations.

A piecewise continuous function *f(t)* defined on interval $t \in \langle 0, \alpha \rangle$ can be defined by a periodic extension with period α:

$$f(t) = \sum_{k=-\infty}^{\infty} c_k e^{i 2\pi k \frac{t}{a}} \tag{1}$$

Function *f(t)* can be sampled at discrete time $t_j = j\frac{a}{N}, \quad j = 0, \ldots, N$:

$$f_j = f(t_j) = \sum_{k=-\frac{N}{2}}^{\frac{N}{2}} c_k e^{i 2\pi k j \frac{1}{N}}, \quad j = 0, \ldots, N \tag{2}$$

This extension has *N+1* values f_j and therefore *N+1* coefficients c_k can be calculated [3], [4], [5].

B. Neural Network Modelling

Artificial Neural Networks (ANNs) are very interesting modelling tools nowadays. Though they do not allow us (in most cases) to describe modelled system in a classical form (e.g., in differential equations) they enable us to develop a „black box“ model that approximates behavior of the modelled system with needed precision.

There are many types of ANNs nowadays. In this paper are published results of application of simplest ANNs with linear neurons (MLP networks). (The more complicated ANNs, e.g., networks with quadratic neurons were also explored – however with significantly better results.)[6].

In model of artificial neural network is neuron described by transform function:

$$y = S\left(\sum_{i=1}^{N} (w_i x_i) - \theta \right) \tag{3}$$

In equation (3) are:

x_i ..... inputs of the neuron,
w_i ..... weights emulating synaptic connections
θ ..... neural bias
S(x) ..... activation function
y ..... output of the neuron

Bias is the reference level for input signals. Weights are associated with particular input variable x_i and their quantities are computed by a specific learning algorithm. In the learning process weights are tuned by a backpropagation algorithm.

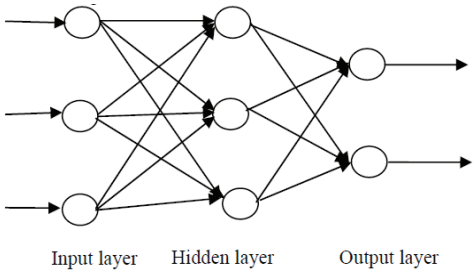

Fig. 1: Sketch of multi-layer neural network [9]

Feedforward neural network or multilayer perceptron (MLP) is one of the most common neural classifier (Fig. 1). Backpropagation is normally used as its learning rule. The input-output relation of a MLP is given by $y = f(w, x)$, where x, y, and f are the input vector, output vector and function defined by the interlayer weights w of the network, respectively. If the vector x is provided, the network calculates the output vector y [7]. MLP presents strong tool in classification tasks, but with growing amount of data, computation time grows rapidly.

III. Results

Applied methods were evaluated using the physiological signal data of ECG from the MIT-BIH Arrhythmia database that contains data recorded by Beth Israel Hospital Arrhythmia Laboratory between years 1975 and 1979. Database contains ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) of the hospital. Database has a total of 48 records, each one of length of 30 minutes and 5.556 seconds obtained from 47 subjects. Remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample [8].

Each record contains data from two channels that are sampled at 360 Hz with 11-bit resolution over a 10 mV range [8]. The first channel is the use of calibration limb leads II, the second channel used correction V1 (occasionally records contain V2, V5 and V4 leads) [9].

A. R-peak detection

For the evaluation of the method, eight different records from MIT-BIH Arrhythmia Database were selected and tested. Records contain regular and irregular beats, high and low amplitudes, shifted baseline, premature ventricular contractions and atrial premature beats with detected supraventricular tachyarrhythmia. Complete record length was evaluated and peaks denoted as follows. All properly detected heartbeats were assigned as true positives. Heartbeats that were not detected by proposed methods were denoted as false negatives and beats that were detected but are false findings were listed as false positives.

Following Fig. 2, Fig. 3 and Fig. 4 display selected part of the signal from records 100, 200 and 201 from MIT-BIH Arrhythmia Database [8]. Detected peaks are marked with a circle and each peak position can be read [10]. Method uses FFT with a sliding window with a fixed size and with fixed

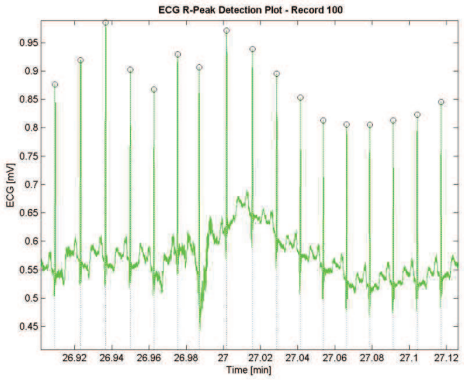

Fig. 2: Detection of R-peaks in ECG signal with regular heart rhythm and no arrhythmias or cordial disorders (record 100, MIT-BIH Arrhythmia Database [8])

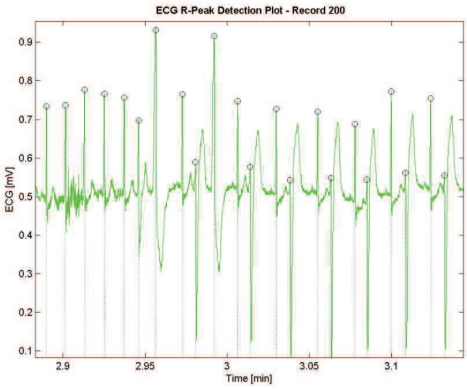

Fig. 3: Detection of R-peaks in ECG signal with regular heart rhythm with a noise and premature ventricular contractions (record 200, MIT-BIH Arrhythmia Database [8])

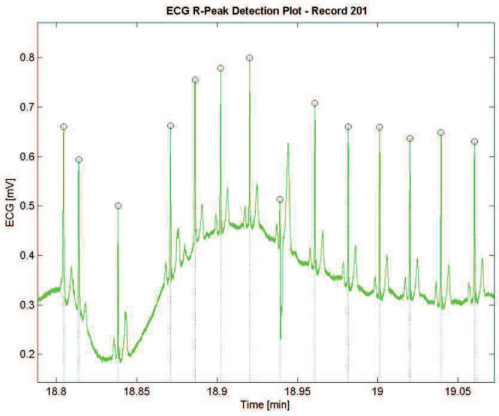

Fig. 4: Detection of R-peaks in ECG signal with irregular heart rhythm, with normal beats and premature ventricular contractions and with fluctuation around the baseline (record 201, MIT-BIH Arrhythmia Database [8])

thresholds that need to be tuned up for the ECG record. More variable records are, more difficult the setup is and the influence on results is significant.

Used method returns positions of individual R-peaks in the ECG signal. Such positions in time create an important role in the ECG signal evaluation. First, it gives us information about the heart rate frequency in selected intervals and average heart rate of the record. From this information, it is possible to estimate the heart rate.

Evaluation method for results was used according to authors [11]. Classification functions sensitivity (true positive rate) and specificity (true negative rate) is a statistical measure of performance of a binary classification test. True positive (TP) is number of hits, or correctly identified peaks, false positive (FP) is number of incorrectly identified peaks or false alarms. True negative (TN) would be all correctly rejected peaks (here not considered) and false negative (FN) represents incorrectly rejected or missed peaks. Results are summarized in Table 1. It shows that the method has 99.93 % successful detection of heartbeats with false positives and 96.59 % successful detection of heartbeats with false negatives.

$$S_{FN} = \frac{TP}{TP + FN} \cdot 100\,[\%] \tag{4}$$

$$S_{FP} = \frac{TP}{TP + FP} \cdot 100\,[\%] \tag{5}$$

Compared to other authors who use adaptive thresholds [1], used method is more sensitive to settings of thresholds (which peak will be selected as correct one and which will be filtered out) and window sizes. Without modification of thresholds and window size, it will be necessary to adjust these values for every patient separately and this would limit this method. Further improvement of this method will be performed in order to receive more accurate results.

TABLE I. R-PEAKS DETECTION

R-Peaks Detection	**Number of Detected Peaks in Individual Signals**					
Record	***Beats***	***TP***	***FN***	***FP***	S_{FN}	S_{FP}
100	2273	2273	0	0	100.00	100.00
102	2187	2148	39	0	98.22	100.00
103	2084	2084	0	0	100.00	100.00
108	1774	1218	552	2	68.81	99.84
112	2539	2539	0	0	100.00	100.00
116	2412	2395	17	1	99.30	99.96
200	2601	2603	2	4	99.92	99.85
201	2000	2000	0	5	100.00	99.75
TOTAL	**6874**	**6721**	**610**	**12**	**96.59**	**99.93**

B. MLP modelling

In order to model each shape of the heart beat by means of QRS complex, it is necessary to localize where the heart beat is located within the whole record. Detection of R-peaks explained in the previous section allows us to use position of the R-peak and consider 124 samples before the peak and 124 samples after the peak. This would be our evaluation interval for the neural network.

Used neural network has an input layer, one hidden layer and an output layer. Input matrix X consists of set of training patterns, each set representing one ECG beat type – normal beat (7 samples), premature ventricular contraction (3 samples) and aberrated atrial premature beat (2 samples). Neural network is trained on these patterns in 1 000 000 iterations and is tested on six records from MIT-BIH Arrhythmia Database, in total of 12 944 samples. Fig. 5 shows the mean square error (MSE) during the learning process. Testing samples were taken from records 100, 113, 116, 121, 200, 201 and the performance of the network is calculated using sensitivity rate:

$$S = \frac{TP}{TP + FN + FP} \cdot 100\,[\%] \tag{6}$$

TABLE II. PERFORMANCE OF MLP CLASSIFICATION

Performance of MLP Classification		**Number of Detected Patterns in Records**					
		R 100	***R 113***	***R 116***	***R 121***	***R 200***	***R 201***
MIT-BIH Database	***Total***	2273	1795	2412	1863	2601	2000
	Normal	2272	1789	2303	1862	1773	1655
	PVC	1	0	109	1	826	198
	Other	0	6	0	0	2	147
Overall	***Total***	2271	1817	2394	1836	2744	2003
	Normal	2270	1800	2286	1833	1668	1630
	PVC	1	11	95	0	872	264
	Other	0	6	13	3	204	109
N	***TP***	2270	1789	2286	1833	1668	1630
	FN	2	0	17	29	105	25
	FP	0	11	0	0	0	0
	S [%]	**99.91**	**99.39**	**99.26**	**98.44**	**94.08**	**98.49**
PVC	***TP***	1	11	95	100	826	198
	FN	0	0	14	0	0	0
	FP	0	11	0	0	46	66
	S [%]	**100.00**	**50.00**	**87.16**	**100.00**	**94.72**	**75.00**
Other	***TP***	0	6	0	0	2	109
	FN	0	0	0	0	0	38
	FP	0	0	13	3	204	0
	S [%]	**100.00**	**100.00**	**0.00**	**0.00**	**0.97**	**74.15**

Overall sensitivity of used method gives satisfying results for correct detection of normal beats (N) of 98.26 %. In detection of PVC, only three samples were selected for training. However, results show that sensitivity rate is moderate 84.48 % and a lot of peaks were defined as false positives. Section other beats includes all beats that were not classified into two groups above (i.e. fusion PVC, aberrated APC, blocked APC, junctional escape, junction premature, etc.) and also all peaks that were found as false positives in FFT method and did not represent QRS complex.

All results are summarized in Table 2 in the following order. There are six columns named "Number of Detected Patterns in Records". Each column represents one record from MIT-BIH Arrhythmia Database (record 100, 113, 116, 121, 200 and 201). Table is horizontally separated into five sections. First section named "MIT-BIH Database" gives number of detected beats in each record separated into three groups – normal beats (N), PVC beats and Other beats. Similar segmentation is done for section named "Overall". This section summarizes number of peaks detected by proposed method. Remaining three horizontal sections named "N", "PVC" and "Other" displays number of beats detected by the method and their classification as TP, FN or FP. Sensitivity is given by formula (6) and is calculated for each beat type.

Beats described in records above as aberrated APC are same as normal beats, but occur right after normal beat. Thus they can be found based on R-peak detection method by comparison of peak to peak distance (so called R-R interval). QRS that is defined as a normal beat but occurs after normal peak would be defined as aberrated. Very similar methodology must be applied to arrhythmias – i.e. atrial fibrillation is defined as random and fast beats compared to normal heart rhythm. Bigeminy or trigeminy is defined as alternation of normal and PVC beat. To define this arrhythmia, it is necessary to compare occurrence of such beats in the record one by one [12]. Other beats, i.e. junctional escape and junction premature, can be also classified and this widening will be performed in further work, tested on more records where they occur.

If testing samples are selected from the same record, as are training patterns, then the network is able to achieve high accuracy. However, if the testing sample is selected from other record, it is more likely defined as a different pattern. Thus, it is necessary to select more patterns for training in order to reach better performance of the network, as authors show in their work [13].

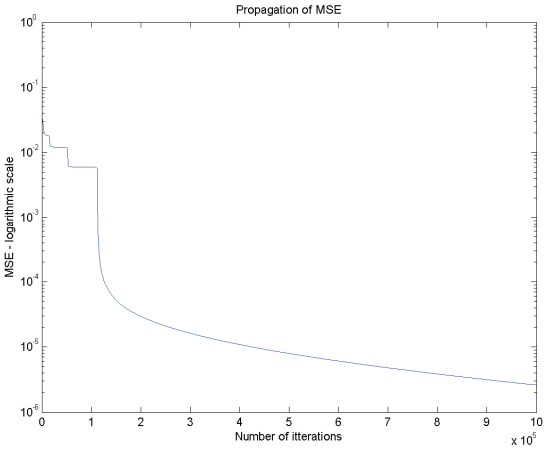

Fig. 5: MSE during learning process

IV. Conclusion

Performance of the R-peak detection is reliable on more constant ECG recording with low noise. In case that the record with noise and significant baseline drift is evaluated, method displays limitations and requires the use of more variable methods of window size and especially threshold setup. Such adjustments can be implemented and improve overall performance of the method. Especially, biggest issue is the detection of false negatives – all missed QRS complexes. This can have a significant influence on the performance of the neural network and further evaluation of the complete ECG recording.

MLP proved that the classification performance is good on the test samples that come from the same record as training patterns. Overall performance can be improved by applying more training sets to the neural network. More testing then will be performed also with more testing samples in the further work.

Further work will combine results achieved by R-peak detection method and outputs from MPL. With both inputs, overall signal can be classified for the occurrence of arrhythmia in the record. Additionally, other data must be also considered for a complete evaluation of ECG recording (i.e. age of the patient, medications, heart state, etc.).

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