AR-based Method for ECG Classification and Patient Recognition

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Abstract

The electrocardiogram (ECG) is the recording of heart activity obtained by measuring the signals from electrical contacts placed on the skin of the patient. By analyzing ECG, it is possible to detect the rate and consistency of heartbeats and identify possible irregularities in heart operation. This paper describes a set of techniques employed to pre-process the ECG signals and extract a set of features – autoregressive (AR) signal parameters used to characterise ECG signal. Extracted parameters are in this work used to accomplish two tasks. Firstly, AR features belonging to each ECG signal are classified in groups corresponding to three different heart conditions – normal, arrhythmia and ventricular arrhythmia. Obtained classification results indicate accurate, zero-error classification of patients according to their heart condition using the proposed method. Sets of extracted AR coefficients are then extended by adding an additional parameter – power of AR modelling error and a suitability of developed technique for individual patient identification is investigated. Individual feature sets for each group of detected QRS sections are classified in p clusters where p represents the number of patients in each group. Developed system has been tested using ECG signals available in MIT/BIH and Politecnico of Milano VCG/ECG database. Achieved recognition rates indicate that patient identification using ECG signals could be considered as a possible approach in some applications using the system developed in this work. Pre-processing stages, applied parameter extraction techniques and some intermediate and final classification results are described and presented in this paper.

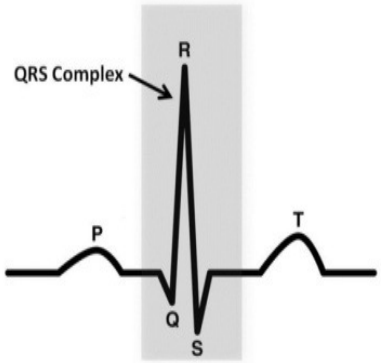
Keywords: Electrocardiogram Classification, Individual Patient Recognition, AR Model, MIT/BIH Database.

1. INTRODUCTION

The electrocardiogram (ECG) represents a measure of the electrical activity of the heart. To measure this activity electrodes are placed on the skin in order to detect the bioelectric potentials given off by the heart that reach the skins surface. Studying the ECG signal can, in many cases, provide an insight into understanding life-threatening cardiac conditions [1]. These studies are usually concerned with detecting and classifying various types of arrhythmias, which can be defined as an irregular heartbeat rate or a disturbance in the regular heartbeat rate. Irregularities in the rhythm of the heart can indicate various causes including disease (e.g., coronary artery disease, diabetes, and cardiomyopathy), medications, an aging heart or metabolic problems.

Arrhythmia usually causes the heart to pump blood less effectively. While most of cardiac arrhythmias are temporary and benign, some arrhythmias may be life-threatening and require medical treatment. One of the most serious arrhythmias is sustained ventricular arrhythmia, usually caused by the damaged heart muscle [1]. This condition is dangerous because it may

degenerate into a totally disorganized electrical activity known as ventricular fibrillation, when the heart's action is so disorganized that it quivers and does not contract, thus failing to pump blood. It is therefore crucial for the patient to receive urgent medical attention when this type of arrhythmia occurs. Detection of ventricular arrhythmia can be done from the electrocardiogram (ECG) signal. It should however be mentioned that a normal ECG does not rule out serious heart disease and that some heart attacks cannot be detected by ECG. The same potential difference on the body surface for example can be due to different configurations of sources; hence, abnormal activity may be masked. Continuous observation and detection of abnormal ECG signals can be difficult due to a large number of patients in intensive care units. In addition to a simple ECG test, a longer recording using a portable Holter monitor worn by the subject during a 24 to 48 hour period can be made [2]. The Holter monitor results are passed to a cardiologist who needs to examine the recordings and determine a diagnosis. Examination of these recordings is a time-consuming process and an automated processing of the ECG that assists the cardiologist in determining a diagnosis would be of assistance. A number of different methods for automated arrhythmia detection have been developed in the past few decades in attempt to assist with the ECG monitoring task. Most of the methods report recognition of heart condition with a certain level of accuracy. This paper proposes an improved method that can achieve high classification accuracy on the test signals available from the web-based ECG database (MIT/BIH) and Milano VCG/ECG database. Most common arrhythmia detection methods rely on QRS detection [3][4] and beat classification using a number of classification techniques. A QRS complex, including other most important features of the ECG signal, is shown in FIGURE 1 using an idealised plot of a single heart beat with indicated main intervals and segments during the heart activity.



P wave	Depolarization of the atria.
Q wave	Activation of the anterioseptal region of the ventricular myocardium
R wave	Depolarization of the ventricular myocardium.
S wave	Activation of the posteriobasal portion of the ventricles.
T wave	Rapid ventricular repolarization.

FIGURE 1: Ideal ECG Signal with Indicated Key Features.

QRS or beat detection is the crucial part of almost any ECG processing algorithm. QRS is a major feature of ECG signal, caused by ventricular depolarization of the human heart. Once the positions of the QRS complexes are found, the locations of other components of ECG can be found relative to those positions and cardiac period established. In many cases simple pre-processing and thresholding of the heart rate can be sufficient for correctly identifying many arrhythmias. However, the QRS pattern recognition techniques can also be severely affected by noise due to unfavourable signal acquisition conditions so other, more advanced, approaches have been developed.

The ECG features can be extracted in time domain [4] or in frequency domain [5] using more advanced feature extraction methods. Wigner-Ville analysis in a two-dimensional frequency domain has also been proposed to address the lack of spectral features and non-stationary behaviour of ECG signals [6]. Some other recently implemented methods include Discrete Wavelet Transform [7][8], Karhunen-Loeve Transform [9], Hermitian Basis [10] and other techniques [11]. Paper [8] uses wavelet transform to decompose the ECG signal into elementary

building blocks well localised in time to detect QRS complex. Detection accuracy reported in [8] is 99.8% despite noise, baseline drift and other artefacts present in majority of ECG signals. In [11] the QRS beats were obtained as 29 point templates. 14 points on either side of the main peak were used to form this template in the first stage of the process but those dimensions were then reduced using principal-component analysis (PCA) also known as Karhunen-Loeve Transform. Reduced number of "effective" features was obtained by discarding the linear combinations with small variance and retaining terms with large variance to represent a template used for QRS complex detection. In [12] a method to detect QRS complex using a delineation function defined via an envelope of the ECG signal was reported. This method yields a single positive pulse for each complex and uses a delineation function to define the onset and end of the QRS with a high accuracy. Hermitian Basis representation of the QRS complexes was later proposed in [10] resulting in a set of parameters that can be used to accurately represent the QRS complex detected in this way. Parameters extracted using this approach can be used in various other applications including data compression. The Hermite Basis approach also provides a width parameter to describe the QRS complex and can therefore describe beats with large differences in QRS duration while the Karhunen-Loeve transform approach encounters problems in those cases. This approach is further developed in [13] to include the multiple-input adaptive linear combiner, using as inputs the succession of the QRS complexes to estimate parameters of Hermitian Basis including the estimation of the width related parameter.

Various machine learning algorithms can then be applied to classify the ECG signals according to the features and information extracted. Machine learning algorithms used for ECG classification include Bayesian [14] and heuristic approaches [15], expert systems [9], Markov models [16], self-organizing map [10], and Artificial Neural Networks [17][18][19][20]. Naïve Bayes is one of the simplest probabilistic classifiers. The model constructed by this algorithm is a set of probabilities where each member of this set corresponds to the probability that a specific feature f_i appears in the instances of class c, i.e., $P(f_i|c)$. The Naive Bayes classifier is known to be optimal when all features describing the class c are independent of each other although several studies have shown Naive Bayes to be competitive with more sophisticated classifiers [21] even when the clear dependence amongst the variables in the class does exist. Artificial neural networks are mathematical models for information processing based on the biological neural complexes. Both Back Propagation (BP) and Radial Basic Function (RBF) networks are well-known variants of neural networks and have been used in various tasks of classification of biomedical signals. Performance of BP and RBF networks in classification tasks using ECG and blood pressure data has been investigated [22]. RBF network using K-nn means clustering algorithm as a basis function was proven to result in slightly higher classification accuracy for cardiac diagnosis compared to BP networks. In [23] AR modeling was performed on ECG data from normal ECGs as well as various arrhythmias. The AR coefficients were computed using Burg's algorithm and classified using a generalized linear model (GLM) based algorithm. AR modeling results showed that an order of four was sufficient to accurately model majority of ECG signals. The accuracy of detecting and classifying heart conditions was 93.2% using the GLM based classification algorithm. The research reported in [24] demonstrates that the all pole, low order AR model can be used to construct a feature space for accurate classification of underwater passive sources, combining it with the simple K-nn classifier. ECG features can also be extracted using this approach and combined with different classification algorithms to achieve high classification rate. Quadratic Discriminant Function (QDF) based algorithm has recently been used to classify certain cardiac arrhythmias with 97% classification accuracy [25] indicating significant improvement compared to most of the previously reported results.

In general, the ECG classification results are strongly determined by two main factors – derived set of heartbeat features and selection of techniques employed to recognise and classify those features. The approach and techniques adopted in this work are described and discussed in the rest of the paper. Section 2 lists the main stages in the system and discusses techniques and function of each system block, while the Section 3 presents the intermediate and final classification results achieved with the system. Results and some further work and ideas are summarized and outlined in the concluding section.

2. METHOD

The method developed in this work consisting of four major stages proposed to classify the patients according to recorded ECG signals. Those stages are: pre-processing of the raw ECG signals to reduce noise and various other artefacts present in the signal, QRS detection, AR parameter extraction and classification of extracted parameters and corresponding signals.

2.1 Pre-processing

Real ECG signals are usually non-stationary, containing slow linear drifts or more complex trends. Causes of those trends are explained in details in [26] but the two most important factors can be considered to be respiratory modulation and the baseline drift. The baseline drift of the ECG signal is mostly generated due to the variation of interaction between the sensor and the body. To enable further analysis of the ECG signals various methods to remove those trends have been used in the past. Those have mainly concentrated on removing slow, nonstationary trends from the ECG signals. Various methods to remove those trends have been developed [26]. In this work a recently reported method based on smoothness priors approach [27] has been used. Using this approach the trend component z_{trend} of the ECG signal is modelled using linear observation model. The RR interval series of ECG signal can be represented as:

$$z = (R_2 - R_1, R_3 - R_2, \dots, R_N - R_{N-1})^T \quad \in \mathbf{R}^{N-1} \tag{1}$$

where N is the number of R peaks detected. The RR series can be considered to consist of two components:

$$z = z_{stat} + z_{trend} \tag{2}$$

where z_{stat} is the nearly stationary RR series of interest and z_{trend} is the low frequency aperiodic trend component. The trend component can be modeled with a linear observation:

$$z_{trend} = H\theta + v \tag{3}$$

Where $H \in \mathbf{R}^{(N-1)\times M}$ represents the observation matrix, $\theta \in \mathbf{R}^{M}$ contains the regression parameters and v is the observation error. To obtain the estimate of the regression parameters $\hat{\theta}$, the regularised least square approach is used:

$$\hat{\theta}_\lambda = \arg\min \{\|H\theta - z\|^2 + \lambda^2 \|D_d(H\theta)\|^2\} \tag{4}$$

resulting in:

$$\hat{\theta}_\lambda = \left(H^T H + \lambda^2 H^T H_d^T D_d H\right)^{-1} H^T z \tag{5}$$

where λ is the regularization parameter and D_d indicates the discrete approximation of the d'th derivative operator. It has been shown [27] that this method operates as a time-varying FIR high-pass filter where the cut-off frequency of the filter decreases when λ increases.
The detrended ECG signal, z_{trend} can now be obtained as:

$$z_{trend} = z - z_{stat} = H\hat{\theta}_\lambda = z(I - (I + \lambda^2 D_2^T D_2)^{-1}) \tag{6}$$

This signal is further filtered through the band-pass filter before the detection of QRS complex is attempted.

2.2 QRS Detection

The single most important feature of ECG signal is the QRS complex. As indicated in FIGURE 1. all other features, the P and T waves as well as the onset and offset of the QRS complex are defined relative to the QRS complex. The P and the T wave occur before and after the QRS

complex respectively. Without the accurate knowledge of the QRS location, P and T waves are hard to detect and distinguish from each other. Most of the QRS detection methods depend heavily on filtering stage followed by averaging according to a threshold value. This threshold value is used to distinguish between noise signal and the QRS complex, It can be chosen based on the peak height or peak location of the ECG signal [28]. There are other methods depending on the machine learning algorithms [28] like the P-spectrum method [29] which is a robust method for periodicity detection based on the data singularity.

In order to accurately detect the positions of QRS complex in the recorded ECG signals, filter bank analysis method [30] was used. This approach employs a bank of linear phase filters to decompose the ECG signal into subbands with uniform frequency bandwidths in order to account for the ECG signal energy distribution in the frequency domain. A number of features related to QRS complex are extracted from individual subbands and combined to indicate the position of the QRS complex in the analysed signal. The filterbank used to analyse ECG signals contains M analysis and M synthesis filters, each of length L and is used to produce the subband signals $U_l(z)$ by filtering the input signal $X(z)$:

$$U_l(z) = H_l(z)X(z) \qquad l = 0,1,\dots,M-1 \tag{7}$$

where $H_l(z)$ represents the transfer function of each bandpass filter. After down sampling, each (down sampled) signal can be expressed as:

$$W_l(z) = \frac{1}{M}\sum_{k=0}^{M-1} U_l\left(Z^{\frac{1}{M}} W^k\right) = \frac{1}{M}\sum_{k=0}^{M-1} H_l\left(Z^{\frac{1}{M}} W^k\right) X_l\left(Z^{\frac{1}{M}} W^k\right) \tag{8}$$

where $l = 0,1,\dots,M-1,\ W = e^{-j\left(\frac{2\pi}{M}\right)}$. A variety of features, indicative of the QRS complex have been extracted from the signal by combining the subbands of interest. For example, feature P_1 corresponding to the energy in those subbands 1, 2 and 3, can be computed as:

$$P_1 = \sum_{l=1}^{3} |W_l(z)| \tag{9}$$

Similarly, features P_2 and P_3, computed for the subbands {1, 2, 3, 4} and {2, 3, 4}, are proportional to the energies in the corresponding bands. A sum-of-squares feature P_4 is computed using the following equation:

$$P_4 = \sum_{l=1}^{3} (W_l(z))^2 \tag{10}$$

Heuristic beat detection logic uses these features to identify positions of QRS complexes in the ECG signal. Detection system consists of a number of sequential levels of logic designed to maximise the number of true positives (TPs). For this purpose multiple detectors are operated simultaneously and the results of each detector are fused together to arrive at the final decision about the beat positions in the signal.

First level serves as an “event detector” and uses a moving window integrator (MWI) which averages two samples of a particular feature (P_1 for example) at the downsample rate. Inflexion points in the output of this MWI are then used to identify possible beat candidates for the beats as peaks in the MWI output. These candidates then go through the further logic in level 2 designed to eliminate large number of false positives (FPs), events inaccurately identified as beats by level 1, mostly introduced by the presence of noise in the signal. This level operates two one-channel beat detection blocks which have complementary FN and FP detection rates with outputs finally

combined in level 3 of the detector by incorporating a set of if-then-else rules. If channels 2 in level 2 indicates the beat than the output of level 3 classifies the current event as a beat. If channel 1 indicates a beat and channel 2 indicates not-a-beat detection strengths of each channel are compared and the final decision is made based on this comparison. Level 4 is used as one more check before the final decision about the presence of the beat in the ECG signal is made. This level uses P_3 as the input to MWI to confirm decision made at level 3 and reduce the rate of FNs introduced at previous levels. After beat occurs there is a physiological refractory period of about 200 ms before another can occur. Level 5 uses timing information of the ECG signal to eliminate possible FPs during the refractory period which further improves the accuracy of the beat detection in this system through the partial blanking of the refractory period.

Approach to detect individual beats in the recorded ECG signal is implemented in Matlab function "`nqrsdetect`" published and available on the web. Function can be applied using syntax: "`QRSs=nqrsdetect(ECGsignal,Fs);`" where `Fs` represents the sampling frequency of the analysed ECG signal ("`ECGsignal`"). Upon the execution of this function, vector "`QRSs`" contains the positions of detected R peaks in the signal.

2.3 Parameter Extraction

Feature selection and extraction is one of the crucial stages in the classification system.

In this work a simple approach of modelling two or more successive ECG beats, using a discrete form of an autoregressive (AR) signal model of order p, $AR(p)$, has been applied. ECG beats are detected using filterbank method briefly explained in the previous section. Coefficients of the estimated AR model are then used as features suitable for signal classification in the final stage of the system.

Using an AR model, a signal sequence $y(t)$, extracted group of ECG beats in this case, can be represented by the relationship:

$$y(n) = a_1 y(n-1) + a_2 y(n-2) + \cdots + a_p y(n-p) + \varepsilon(n) \tag{11}$$

where $a_k = (1,2,\ldots,p)$ are the model coefficients, also known as autoregressive parameters, used in the classification process and the $\varepsilon(n)$ is a white noise series, innovation process with zero mean and variance σ^2. An estimated autoregressive model of the same order p can then be written as:

$$y(n) = \hat{a}_1 y(n-1) + \hat{a}_2\, y(n-2) + \cdots + \hat{a}_p\, y(n-p) + \hat{\varepsilon}(n) \tag{12}$$

where $\hat{a}_k = (k = 1,2,\ldots,p)$ are the estimated parameters of the autoregressive model and $\hat{\varepsilon}(n)$ are the estimated innovations. The estimated autoregressive model can be interpreted as the p-point prediction filter where value of the output $y(n)$ is estimated from the previous $p-1$ output values of the AR process:

$$\hat{y}(n) = \sum_{i=1}^{p} \hat{a}_k y(n-i) \tag{13}$$

As samples $y(n)$ can not be predicted exactly a modelling error is introduced. This error or residue corresponds to difference between the measured and the estimated values and is in fact equal to the value of the estimated innovation:

$$r = y(n) - \hat{y}(n) = \hat{\varepsilon}(n) \tag{14}$$

A number of methods can be used to estimate autoregressive parameters of the AR model. Most often used are the least-squares approach (LS), the Yule-Walker approach (YW) and Burg's

method [31]. Least-squares method minimises the total squared residue over data samples $p+1$ to N, which leads to a system of linear equations:

$$\begin{bmatrix} C_{11} & C_{12} & \dots & C_{1P} \\ C_{21} & C_{22} & \dots & C_{2P} \\ \dots & \dots & & \dots \\ C_{P1} & C_{P2} & \dots & C_{PP} \end{bmatrix} = \begin{bmatrix} \grave{a}_1 \\ \grave{a}_1 \\ \dots \\ \grave{a}_1 \end{bmatrix} = - \begin{bmatrix} C_{01} \\ C_{02} \\ \dots \\ C_{0p} \end{bmatrix} \tag{15}$$

C_{ij} elements of the matrix in the above equation represents an unbiased estimate of the autocovariance function for delay $i-j$:

$$C_{ij} = \frac{1}{N-p} \sum_{n=p+1}^{N} y(n-i)y(n-j) \tag{16}$$

Yule-Walker method includes the first and last p data points which results in matrix equation:

$$\begin{bmatrix} \hat{R}_o & \hat{R}_1 & \dots & \hat{R}_{p-1} \\ \hat{R}_1 & \hat{R}_o & \dots & \hat{R}_{p-2} \\ \dots & \dots & & \dots \\ \hat{R}_{p-1} & \hat{R}_{p-2} & \dots & \hat{R}_p \end{bmatrix} = \begin{bmatrix} \hat{a}_1 \\ \hat{a}_2 \\ \dots \\ \hat{a}_p \end{bmatrix} = - \begin{bmatrix} \hat{R}_1 \\ \hat{R}_2 \\ \dots \\ \hat{R}_p \end{bmatrix} \tag{17}$$

where elements of the matrix in the (18) equation represent the biased estimate of the autocovariance function:

$$\hat{R}_k = \frac{1}{N} \sum_{n=k+1}^{N} y(n)y(n-k) \tag{18}$$

While both LS and YW methods estimate the autoregressive parameters directly, using the autocorrelation matrix of the signal sequence, Burg's method first finds the reflection coefficients of the equivalent lattice structure predictor filter based on the least squares criteria. From these, the AR parameter estimates are determined using the Levinson-Durbin algorithm [32]. The reflection coefficients constitute unbiased estimates of the partial correlation coefficients. Each of the described algorithms above has its own drawbacks and advantages and is used for various applications such as spectral analysis. In most cases, the algorithms result in similar estimated values in most situations. But it has been suggested [33] that Burg's algorithm might be preferable due to poor estimates by YW in some cases and the possible instability of the least squares model.

In the previous discussion, it is assumed that the model order p is known which is not the case in practice. In fact, determination of the model order can be one of the most difficult tasks in time series modeling. In a number of situations, prediction error power for various model orders can be obtained and used as an indicator for the sufficient model order. Another option is to use the Aikike information criterion [34] to determine the order of the AR model. In this work, model order was determined by observing the power of modeling error for various model orders. Orders of p = (2,3,4,5) have been found to yield satisfactory results for the pre-processed ECG signals. Further in the paper a set of results obtained for p=2 and 3 model order is presented. It is also worth pointing that more complex models have been used for time series modeling, prediction and even classification tasks in the past. Autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models [35] are composed of different terms in addition to autoregressive (AR) term. While AR term includes the influence of lagged observed values as already explained, ARMA model combines it with the moving average (MA) term which describes the forecasting errors using the following form:

$$Y(n) = a_1 y(n-1) + a_2 y(n-2) + \cdots + a_p y(n-p) + b_0 \varepsilon(n) + b_1 \varepsilon(n-1) + \cdots + b_r \varepsilon(n-r) \quad (19)$$

where b_k $(k = 1,2,\ldots,r)$ are the MA model coefficients. Autoregressive (AR) part of this model performs well when the signals with the narrowband spectra need to be modeled while the MA model provides a good approximation for those spectra which are characterized by broad peaks and sharp nulls. However, the problem of estimating parameters of MA model is basically a non-linear one, and is significantly more difficult to solve than the AR parameter estimation problem. Since ARMA model combines both AR and MA models, difficulties in MA and ARMA estimation problems are similar and could be avoided if a simpler AR can approximate ECG signal with satisfactory accuracy.

In addition to ARMA model, the ARIMA model also includes an integrating term (I) which can account for the non-stationary of the series. ARIMA model first removes the trends and various cyclic features from the signal that are beyond the capacity of stationary ARMA model which can then be used to model the remaining detrended and depersonalized signal. Use of ARIMA model for ECG beats modeling is currently considered in the continuation of this work, in order to improve the accuracy of patient recognition from short sections of obtained ECG signals. Burg algorithm to estimate the parameters of an AR model is implemented and available in the Matlab System Identification toolbox via "`ar`" function, usually used in combination with the "`iddata`". This function creates an "`iddata`" type object from the given time series in order to analyze it with the "`ar`" function. A short sequence of the Matlab program given in TABLE demonstrates a method used to estimate AR parameters from the part of ECG signal using "`ar`" function.

```
beat =  ECGsignal(QRSs(p):QRSs(p+nb-1));   % extract nb beats from the ECG signal section
data = iddata(beat);                       % convert to "iddata" type object
m = ar(data,mo);                           % calculate AR parameters
ARs = polydata(m);
```

TABLE 1: Estimation of AR Parameters using "ar" Function in Matlab.

2.4 Classification

Various classification algorithms can be used to classify the extracted ECG signal features. In this work, features are represented by multidimensional vectors containing autoregressive coefficients calculated individually for each beat or pair of beats of the measured ECG signal. Effectiveness of classification methods depends on how well the vectors of features can be separated in the feature space. In many cases, where dimensionality of feature vectors is high, various algorithms can be used to reduce the size of the feature vectors. In this work, only a small number of autoregressive coefficients were found to represent a satisfactory model for most ECG signals in the database so no dimensionality reduction scheme was used.

The classifying methods proposed during the last decades include, Fuzzy Logic methods [36], Artificial Neural Network, Hidden Markov Model [16], Genetic Algorithm [37], Support Vector Machines, Self-Organizing Map, Bayesian [38] and other with each approach exhibiting its own advantages and disadvantages [39] Algorithms used for ECG classification can mainly be categorized as either heuristic or statistical classification methods [15]. While heuristic approach tries to emulate the reasoning of the qualified cardiologist and the cardiologist provides the knowledge to construct a classifier, for statistical approach, probability densities of diagnostic features are estimated from a learning set of ECG features and a various multivariate techniques are then used to achieve classification. Main criterion for selection of particular classification method is the classification performance but other aspects should also be considered [15]. Statistical classifiers are considered in this work as they usually require less involvement of skilled operator or cardiologist. Main objective of the statistical approach is the allocation of an ECG to one group of diagnostic categories with minimum probability of misclassification.

Statistical methods used in this work are k-nearest neighbor (k-nn) classifier and linear and quadratic discriminant analysis based classifier [40][41]. Both methods belong to a group of so-called supervised learning methods, where some knowledge about data is available and used to produce an inferred function, classifier.

Because of its simplicity k-nn rule is one of the most often used methods in bioinformatics and other areas but care must be taken in selecting the model order as well as different distance metrics. Another important issue related to the use of k-nn is a complexity issue which can be relatively high if a training set of vectors is large. Linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) methods have been used in a large number of bioinformatics projects. If the data to be classified is not linearly separable, it is than advisable to use QDA method but it should be noticed that the capability of QDA to handle nonlinear data is still limited since it only considers the positive correlation between the variables. If the classification between two classes depends on the negative correlations between the data than noise rather than true information is introduced by QDA in the classification process.

Each of the mentioned methods is implemented in the Matlab Statistics Toolbox via "`classify`" function. LDA and QDA algorithms can be applied by setting the type option to "`linear`" or "`quadratic`" when this function is used. k-nn method is implemented via "`knnclassify`" function.

3. PROCEDURE AND RESULTS

To evaluate the performance of the proposed techniques, ECG data set containing three different types of ECG signals was used. Data set included normal ECG signals (NR) from the Politecnico of Milano VCG/ECG Database on Young Normal Subject [Politecnico Biosignals Archives [42], arrhythmia (AR) from the MIT-BIH Arrhythmia Database and ventricular arrhythmia (VAR) from the MIT-BIH Malignant Ventricular Arrhythmia Database [43]. Each type was represented by 20 half-hour excerpts of two-channel ambulatory ECG recordings, but 10 minutes per patient have been considered in this work. The time series related to the normal subjects were acquired with a sampling frequency Fs = 500Hz, while the time series for arrhythmic patients have Fs = 250Hz. Fs = 360Hz is the sampling frequency for Ventricular Arrhythmia patients (both Ventricular tachycardia and Ventricular fibrillation).

The whole system used for the first project task of ECG arrhythmia detection and classification is summarized in the block diagram given in FIGURE 2. The raw ECG signals are first downsampled to the lowest sampling frequency of the ECG signals from the set (250 Hz in this case). The signals are then processed by smoothness priors method to detrend them and to improve the accuracy of subsequent algorithms implemented in the system. The detrended signal is then passed through the band-pass filter to remove the other types of noise that can still be present in the signal. Suitable cut-off frequencies of this filter have been determined after some experimentation. For the results presented in this section, the 6-th order Butterworth filter with the lower and upper cutt-off frequencies set to 5 and 40 Hz respectively was used. The peak detection algorithm based on the filterbanks is implemented in the next stage. Using detected peak positions, each ECG signal is then split in the groups of 1, 2 or more successive beats and AR parameters are extracted for each obtained group. Finally, classification of extracted features using described classification algorithms is performed.

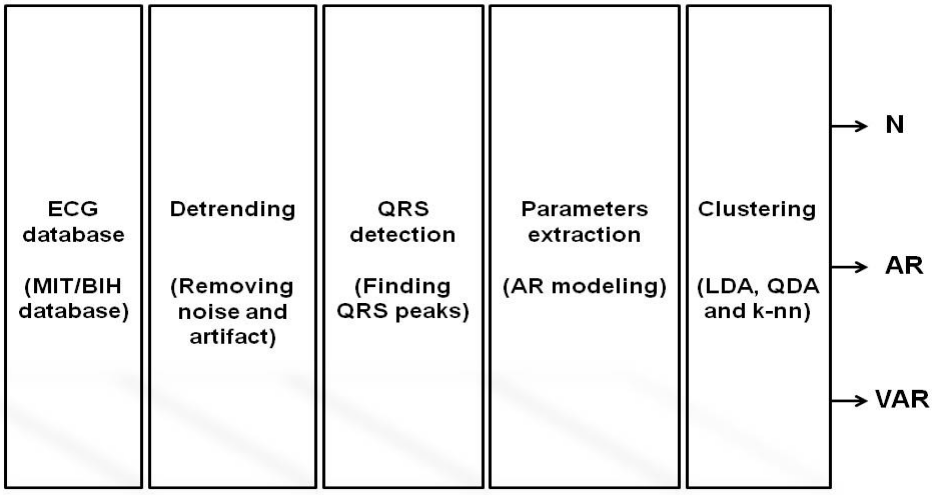
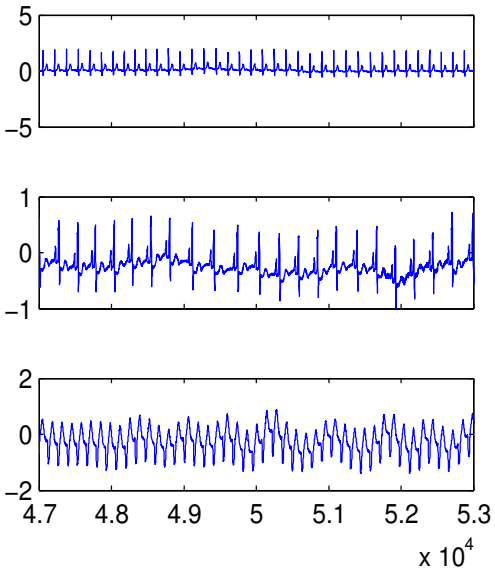
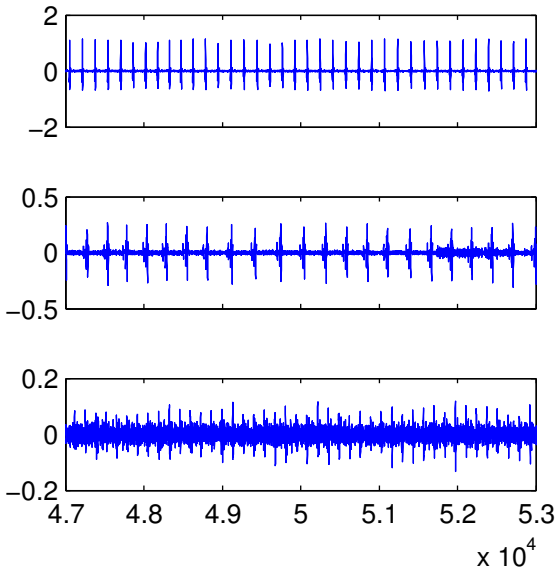


FIGURE 2*:* Stages in the AR based ECG Classification System.

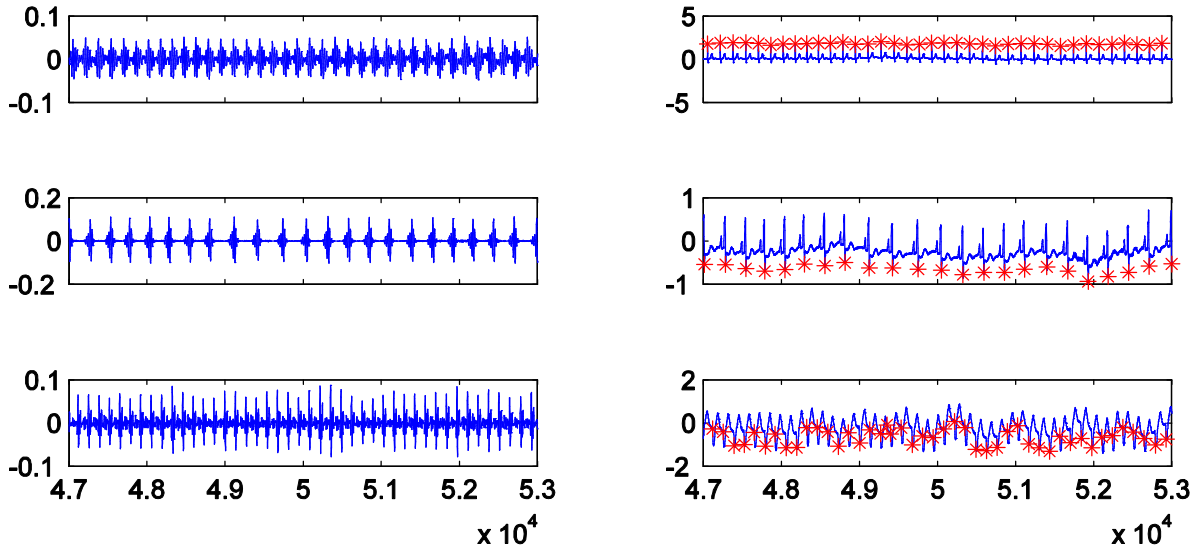
Number of beats in the group as well as the number of AR parameters extracted for each group has a significant effect on the performance of the classification stage of the system, so some experimenting with those parameters has been performed. Good classification rate has been achieved for 1-5 beats in the group and 2-4 AR parameters used to model each section of ECG signal. In this paper, we show results for 2 beats per group and p=2 and 3 AR orders. ECG signals at various pre-processing stages in the system are shown in FIGURE 3. Detected QRS complexes for the section of one ECG signal from each group are indicated in FIGURE 3c.



a) Raw ECG Signals Sections – NR, AR and VAR.



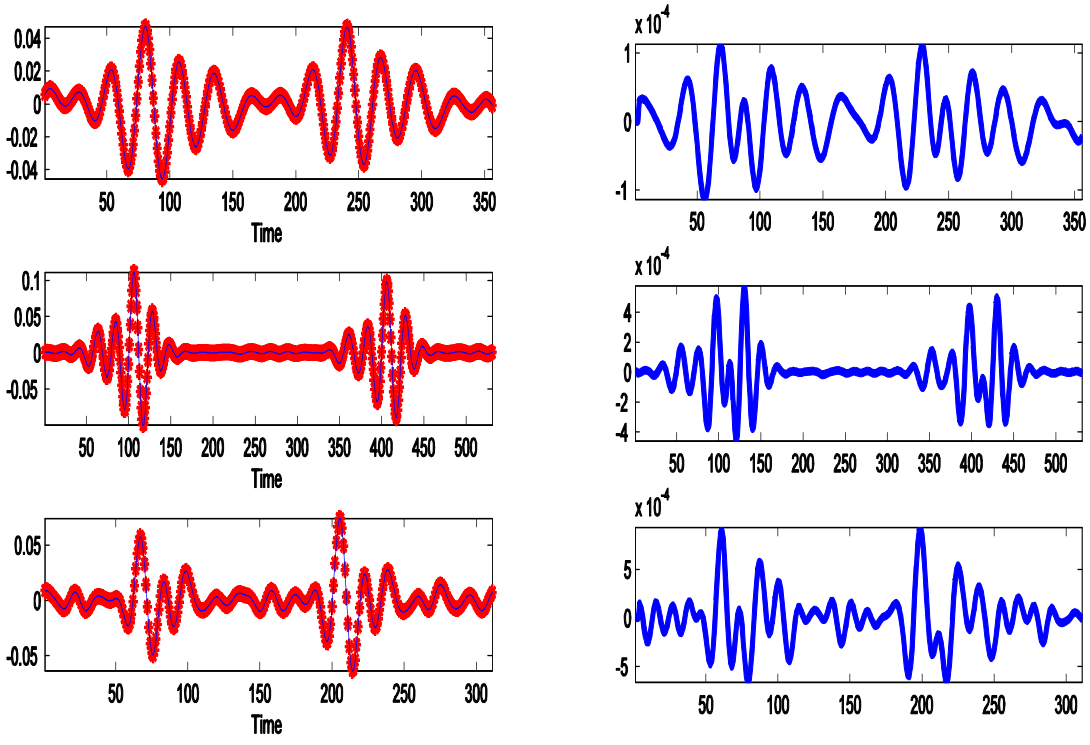
b) Detrended ECG Signals.



c) BP Filtered and Detrended ECG Signals.

d) Raw ECG Signals with Detected QRS Complexes.

FIGURE 3: Sample ECG signals at various stages in the AR based ECG classification system.



a) Model and Original (pre-processed) ECG Signal Section.

b) Modeling Error.

FIGURE 4: Results of a third order AR modeling on signal section consisting of 2 beats for each ECG type.

Individual section containing two beats, extracted from pre-processed EC signal and the corresponding AR(3) model are shown in FIGURE 4. Obtained signal model has been plotted over the original signal section previously detrended and filtered as indicated in FIGURE 2. Accuracy of obtained AR models is high, as indicated by the modeling errors, residuals shown in FIGURE 4 b) for the corresponding sections and obtained models. Following beat detection and signal segmentation stage, AR parameters are extracted for each extracted group of beats. Numbers of beats in the group as well as the number of AR parameters extracted for each group have some influence on the classification algorithm performance. Good classification rate has been achieved for 1-5 beats in the group and 2-4 AR parameters used. In this paper, we show results for 2 beats per group and AR order p of 2 and 3. FIGURE 5 shows the modeling error for different orders of AR model. This figure can generally be used to determine the optimal order of the AR model, which is usually selected at the break point ("knee") of the plot. For comparison purposes, two plots for ECG signals with and without pre-processing are shown. The breakpoint in the plot can easily be determined for processed ECG signal (2 or 3) while it is more difficult to pinpoint the equivalent position in the plot given for raw ECG. It is also worth nothing significantly lower modeling error for the processed signal compared to the modeling error for the same but unprocessed signal section.

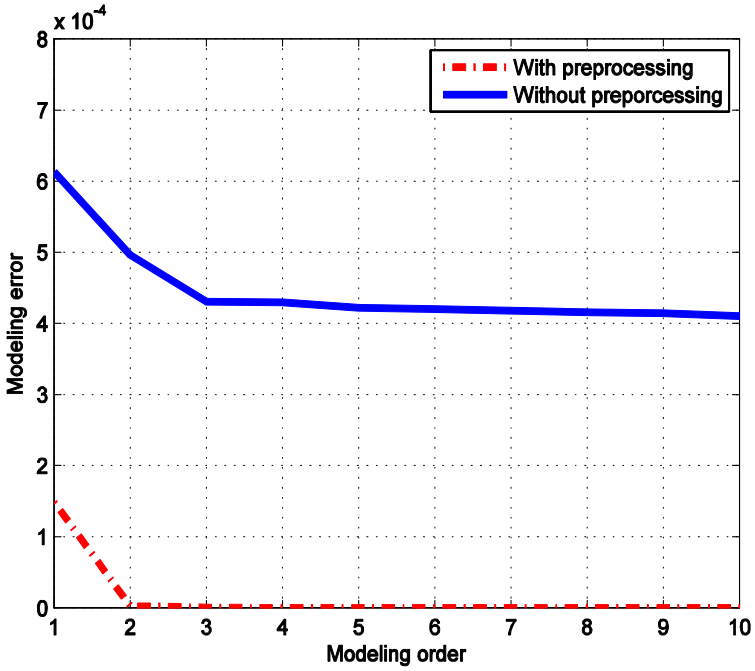
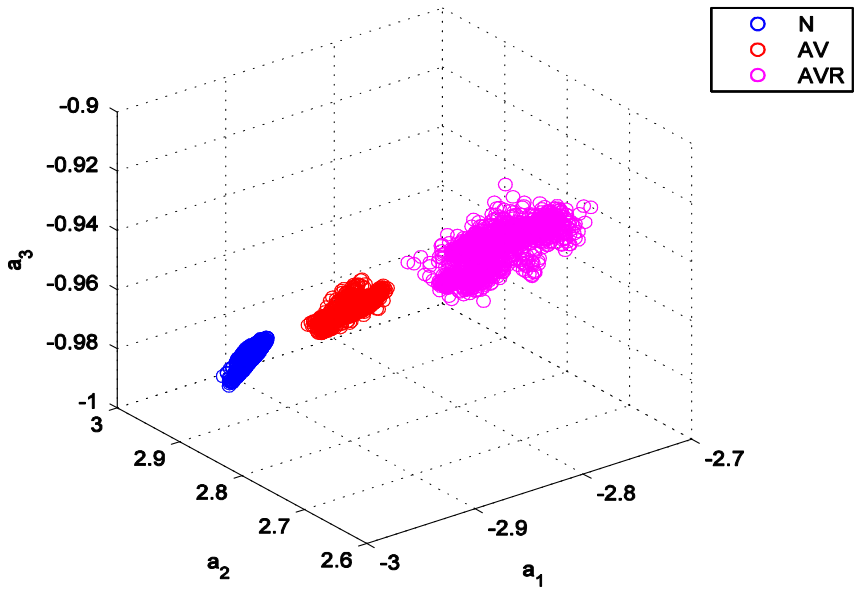


FIGURE 5: Modeling error for different AR model orders with "knee point" usually used for model selection.

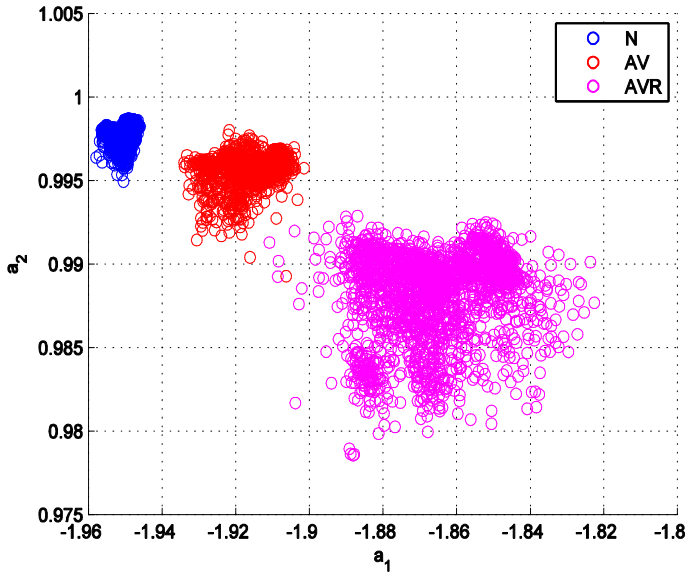
Extracted AR parameters, for each group of 2 QRSs for all signals in the data set are plotted in FIGURE 6 where good separation between 3 data clouds can be observed for both 3D, where AR order = 3 and 2D scatter plots, where AR order = 2, thus enabling accurate classification of each extracted parameter set. A number of described classification algorithms were tested on this set (k-nn, LDA, QDA, Bayes) each resulting in a completely correct, error-free classification of each parameter set. It is also interesting to note tightness of the cluster corresponding to normal ECG signals in contrast to progressively more scattered clouds of parameters related to arrhythmia and ventricular arrhythmia conditions.

Developed algorithm has also been tested on the extension of ECG database, using ECG signals obtained from another 20 patients in each of three classes including normal, atrium fibrillation and

arrhythmia type ECG signals. FIGURE 7 shows the 3D- feature space formed by order 3 AR coefficients extracted from this ECG database.



a) Classification Results for Order 3 AR Coefficients.



b) Classification Results for Order 2 AR Coefficients.

FIGURE 6: Feature space of extracted AR coefficients indicating good separation between three groups of ECG signals a) 3D feature space, b) 2D feature space.

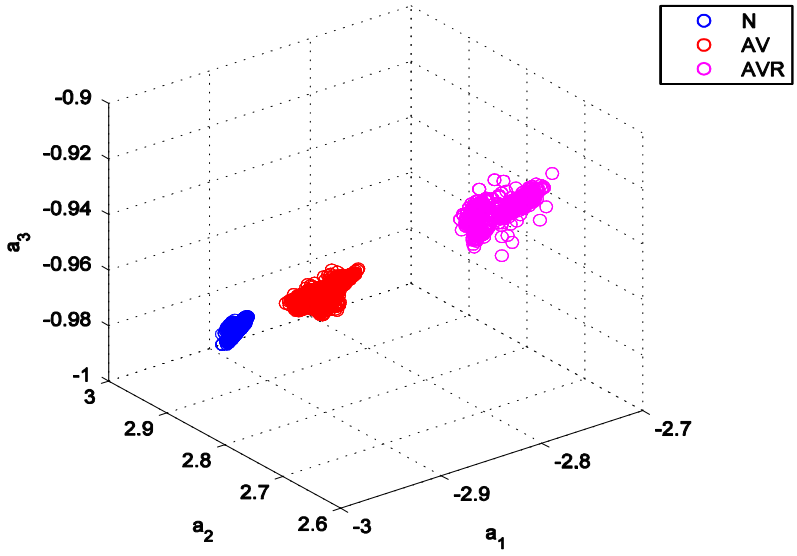


FIGURE 7: 3D-feature space of extracted AR coefficients resulting in completely accurate classification.

To indicate the importance and suitability of the pre-processing methods applied in this work, the rest of this section presents the equivalent set of results, 3D and 2D feature space plots obtained from the raw ECG signals (i.e. no filtering and detrending but including QRS detection). FIGURE 8 shows the results of AR modelling on automatically extracted groups of beats of raw ECG. It can be seen that although relatively good model is achieved it is still not as accurate compared to modelling results achieved with pre-processed ECG signal. More importantly, parameters of the model are poorly separated in 3D and 2D feature space giving no foundation for successful clustering and subsequent recognition of various conditions with any of tested classification methods. FIGURE 9 for example shows the results for p=2 and 3 model order.

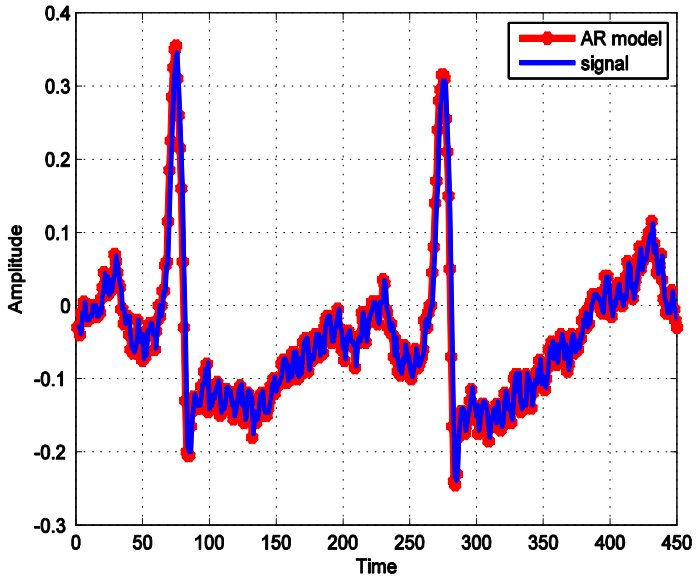
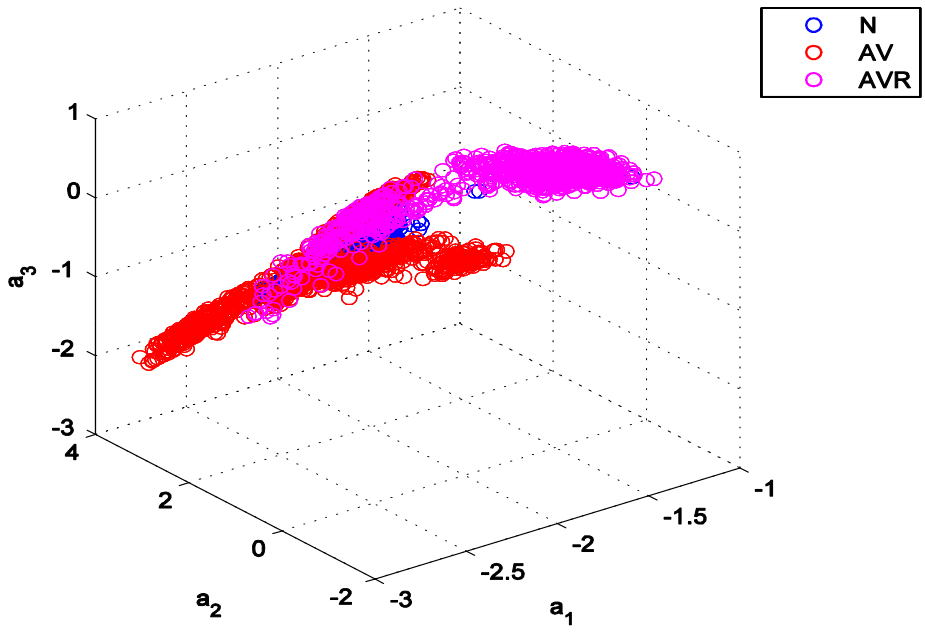
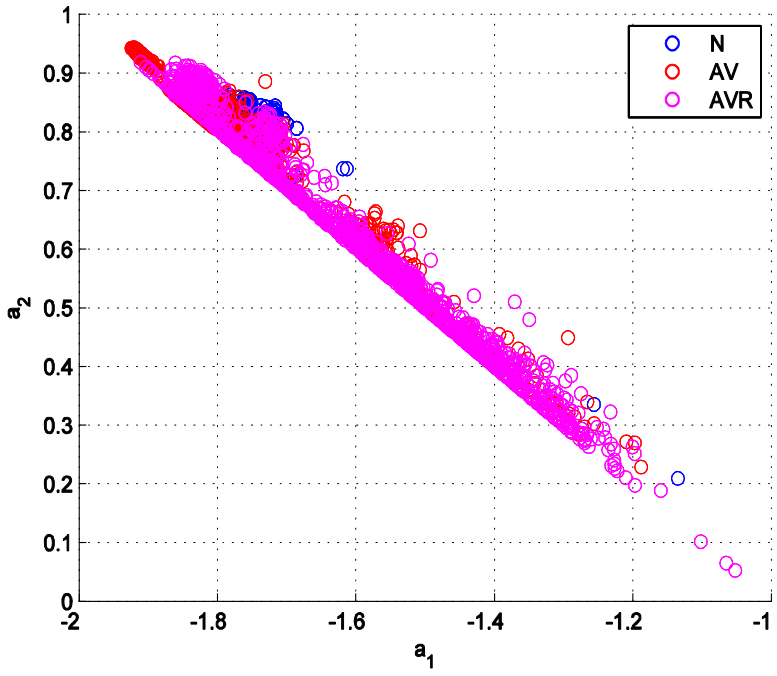


FIGURE 8: Results of AR modeling on automatically extracted groups of beats for raw ECG signal (i.e. no preprocessing stage).



a) Classification Results for Order 3 AR Coefficients.



b) Classification Results for Order 2 AR Coefficients.

FIGURE 9: 3D and 2D-feature space of extracted AR coefficients without any pre-processing steps.

In the reminder of this section, another interesting application of this method – patient identification from recorded ECG signal, is discussed and results summarized in
TABLE 2. Here, each individual section extracted from each ECG signal from the set has been classified into one of q different groups where q corresponds to the number of patients used in the experiment (q = 20 for each condition for the experimental set used in this work). 10-fold cross-validation technique was used to estimate performance of LDA and QDA classification techniques in this task. First part of the table gives the result achieved with the original feature set, i.e. the set containing AR parameters only. Second part of the table contains recognition results achieved with extended feature set, obtained when the power of modeling error, i.e. residual signal is used as an additional classification feature. Improvement in recognition rate is notable and indicates that the modified method using additional dimension in the feature set can be considered in patient identification tasks. It is also worth noting the improvement and higher rate of recognition achieved in the normal (N) and arrhythmia (AR) groups which indicates the possibility of using this approach to complement some biometric identification techniques (voice or face recognition techniques for example). This aspect and possible improvements of developed system are currently being investigated in the continuation of this work.

Technique used	**Feature set = 3 AR coefficients**			**Feature set = 3 AR coefficients + error power**		
	N	A R	VAR	N	A R	VAR
LDA	0.39	0.59	0.37	0.61	0.65	0.47
QDA	0.41	0.62	0.42	0.64	0.71	0.54

TABLE 2: Recognition rate (%) obtained in classification of signal sections corresponding to individual patients.

4. CONCLUSIONS

In this work, a method for automatic classification of ECG signals from three different groups – normal, arrhythmia and ventricular arrhythmia has been proposed. Method first uses smoothness priors approach to pre-process all ECG signals from the database in order to reduce the baseline drifts and other trends in the signals. Filterbank based method to detect peaks in the pre-processed ECG signals is applied in the second stage of the proposed system before the coefficients of an AR signal model are extracted and used to classify each section of ECG signal into one of three possible groups. Decision about the type of each ECG signal from the test set is then made depending on the group into which most of the sections from the same ECG have been clustered. Extracted features, parameter sets are well separated in feature space and accurately classified, indicating that the high classification accuracy can be expected in the practical application of the proposed system. For the standard set of ECG test signals available at MIT/BIH and Politechnico of Milano web sites developed method has managed to achieve 100% accurate classification of three heart conditions.

In addition to this task, as a first step towards possible ECG based patient identification similar approach has been used to decide which of the analysed signal sections belong to the same ECG signal. To enhance the system performance in this application of the system, feature set for this task was extended with one more parameter – power of AR modeling error. Initial results indicate the significant increase in the recognition rate when extended feature set is used and demonstrate the potential of proposed approach for ECG based person recognition task.

Further work to enhance the patient recognition capabilities and accuracy of the system is ongoing and is currently focusing on the use of more complex signal models (ARMA or ARIMA) with the aim of extracting additional signal features needed for more accurate patient recognition. Use of other, advanced classification algorithms will also be considered in the continuation of this study.

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