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Estimation of cardiac abnormalities based on ECG waveform using Multivariate Quadratic Surface Modeling

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Abstract— Biomedical signal analysis and processing is important for estimating the health state of an individual. Biomedical signals are a collection of electrical signals acquired from an organ of interest using physiological instruments. These signals are normally a function of time and are described in terms of its amplitude, frequency, and phase. The analysis of these signals is important both for research and for medical diagnosis and treatment. Biomedical signal processing involves analyzing these signals to provide important information that aid in decision making. The decision making had been subjective for a long time and depended on the skills of the decision maker. However there is a growing need for automating the process of disease diagnosis and decision making. Hence researchers are discovering new ways to process these signals using a variety of mathematical formulae and algorithms in order to provide greater insights to aid in clinical assessments. This research paper deals with Electrocardiogram (ECG) signals and classifies them into three kinds of heart disease classes. The research is performed in four phases: data collection, feature extraction of ECG signal, estimating a mapping function between the training signals and corresponding class labels, prediction of class label of testing signals.

Keywords— Classification; ECG; MFCC; Multivariate quadratic surface modeling

I. INTRODUCTION

The electrocardiogram (ECG) assesses the electrical and muscular functions of the heart. It represents the electrical manifestation of the heart activity. It is recorded over a period of time using electrodes placed on the skin [1]. The human heart has four chambers – two auricles and two ventricles. The right atrium is the first structure to be depolarized during a normal cardiac rhythm. It is closely followed by the left atrium. The first wave that originates in an ECG signal is the P wave and represents the depolarization of the atria. The P wave is followed by a short period of no electrical activity called as the PR interval which represents the short delay before the depolarization of the ventricles [2]. The PR interval is represented by a straight line. Depolarization of the ventricles is represented by the QRS complex. The Q wave is the 'negative' deflection followed by the R wave which is the next upward deflection which is followed by the next negative deflection below the isoelectric line called the S wave. The repolarization of the ventricles is represented by the ST segment and the T wave. The ST segment is a straight line while the T wave is a positive deflection above the isoelectric line [3]. A typical ECG signal is shown in the fig 1. The ECG signals can be used to detect and diagnose heart diseases and abnormalities like arrhythmia, congestive heart failure etc. The identification of cardiac abnormalities through traditional techniques by physicians is a subjective decision based on their skills and precision. This leads to the need to automate the decision making process. This paper presents a model that learns the features of training data that are labeled with a heart condition. Later the model is used to predict the heart conditions of unlabelled testing data. The paper discusses in detail the algorithms used to develop the model. The feature extraction algorithm used to extract the important characteristics of the ECG signal is the Mel-frequency cepstral coefficients. The learning of the important features and testing of the unlabelled ECG signals is performed using multivariate polynomial surface modeling.

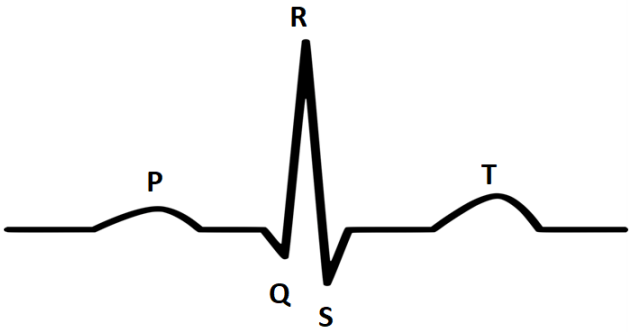

Fig. 1. The major waves of a single normal ECG pattern

II. MEL-FREQUENCY CEPSTRAL COEFFICIENTS

The Mel-frequency cepstral coefficient (MFCC) is a linear representation of the cosine transforms of a short duration of logarithmic power spectrum of the speech signal on a nonlinear Mel scale of frequency [4].

The Mel filtering is realized by a filter bank composed of triangular filters uniformly spaced in the Mel scale [5], [6]. The Mel scale is given by

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$$f_{mel} = 2595 \log_{10}\left(1 + \frac{f}{700}\right)$$

where f is the frequency in Hz. The Mel filter bank is given in fig 2.

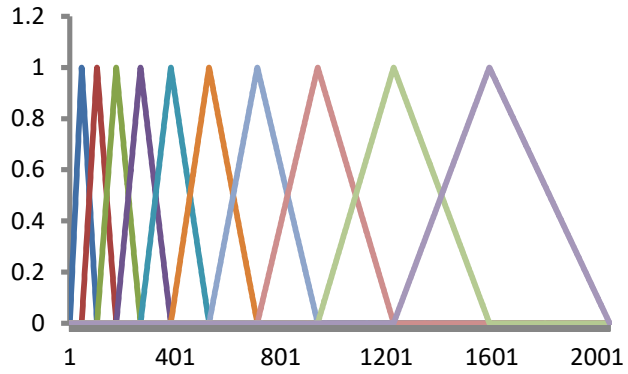

Fig. 2. Mel filter bank

Mel-frequency cepstral coefficients together make up an MFC. This feature extraction process transforms the raw signals into feature vectors in which specific properties are emphasized and statistical redundancies are suppressed [7], [8]. MFCC is based on the variation of the human ear's critical bandwidth with frequency [9]. The MFCC extraction results in the features of the signal to be concentrated in the first few coefficients [10]. The overall process of MFCC calculation is given in the fig 3.

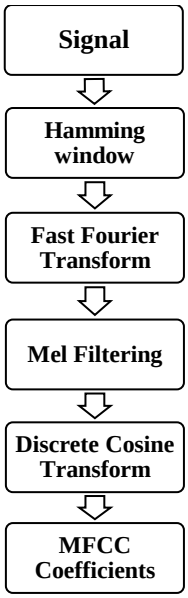

Fig. 3. Overall process of MFCC Calculation [11]

III. Multivariate Polynomial Surface Modelling

According to multivariate polynomial surface modeling, a multivariate polynomial surface f can be constructed from an m-dimensional function g known at q points with some error at each point as per the equation given below as [12]

$$g({}^{n}_{1}w, {}^{n}_{2}w, \ldots\ldots, {}^{n}_{m}w) = f({}^{n}_{1}w, {}^{n}_{2}w, \ldots\ldots, {}^{n}_{m}w) + \epsilon_n \quad (1)$$

where n= 0,1,……,q-1. The multivariate function is written as

$$f(w_1, w_2, \ldots\ldots, w_m) = \sum_{k=0}^{p-1} c_k \emptyset_k(w_1, w_2, \ldots\ldots\ldots, w_m) \quad (2)$$

where p is the number of terms in the polynomial of m variables. By combining equations (1) and (2), we get a matrix equation [12]

$$b = Az + \epsilon \quad (3)$$

where b, z and ∈ are given by

$$b^T = [g_0\ g_1 \quad \ldots \quad g_{q-1}]$$
$$z^T = [c_0\ c_1 \quad \ldots \quad c_{p-1}]$$
$$\epsilon^T = [\epsilon_0 \epsilon_1 \quad \ldots \quad \epsilon_{q-1}]$$

And matrix A is a q x p matrix, with elements given as [12]

$$a(n,k) = \emptyset_k({}^{n}_{1}w, {}^{n}_{2}w, \ldots\ldots, {}^{n}_{m}w), 0 \le n \le q, 0 \le k \le p-1$$

The solution is obtained as

$$z = (A^T A)^{-1} A^T b \quad (4)$$

where $(A^T A)^{-1} A^T$ is called the pseudo-inverse of A.
A mapping function is generated using this method to obtain a correlation between the features of the training input signals and their respective class in order to interpolate the class of the testing signals. The total number of terms in a quadratic expression with m variables is
$p = 1 + 2m + {}^{m}_{2}C$ [12], [13].

IV. METHODOLOGY

The research work is performed in four phases: data collection, feature extraction [14], [15] of ECG signals, establishing a mapping function between the features of the class labeled signals i.e. training signals and the class label values, predicting the class labels of unlabelled signals i.e. testing signals by applying the transformation or mapping function.

A. Data Collection

The ECG signals are obtained from an online database available at physionet.org. The signals of three heart

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conditions are acquired namely arrhythmia disease, congestive heart failure and normal sinus rhythm. The ECG signals are labelled with their corresponding class labels. A total of 162 signals with a sampling frequency of 128 Hz are used of which 96 signals belonged to the class arrhythmia disease (ARR), 30 signals belonged to the class congestive heart failure (CHF) and 36 signals belonged to the class normal sinus rhythm (NSR). The complete dataset is divided into 129 training signals and 33 testing signals. The ECG waveforms belonging to the three classes ARR, CHF and NSR are represented in fig 4.

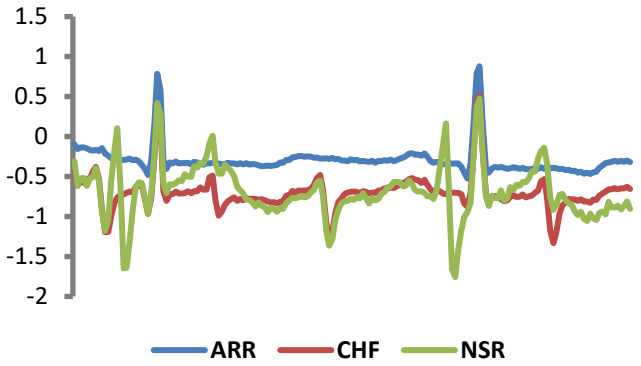

Fig. 4. ECG waveforms

B. *Feature Extraction*

The labeled signals obtained in the first section are analyzed using Mel-frequency cepstral coefficients (MFCC) for obtaining the important features of the signals. The MFCCs (order=21) are estimated from the magnitude spectrum according to the following formula

$$C_m = A\sum_{m=0}^{M-1} cos\, j\frac{\pi}{M}(m+0.5))\, log_{10}\, E_m \quad (5)$$

where A is taken as 100 [16] and E_m is the energy in each critical band in the spectrum.
The frame by frame alignment of the parameters for the ECG signal frames is performed using Dynamic Time Warping [17].

C. *Estimation of mapping function*

The transformation is estimated using multivariate quadratic modeling (MQM). In this each class label value in the vector **y** is modeled as a multivariate quadratic function of all the components in the source vector **x,**

$$y_i = f(x_1, x_2, \dots\dots\dots, x_{M-1}) \quad (6)$$

where $0 \le i \le M-1$ and M=20 for MFCCs. Coefficient for the function, for mapping between the source frame vector to the class label vector is obtained using (4).

D. *Prediction of class labels*

This mapping function obtained using MQM is used on the unlabelled signals after obtaining the source frame vector in order to predict the class label of the signals by estimating the class label value.

V. RESULTS

The confusion matrix for the classification of ECG signal into three classes: arrhythmia disease (ARR), congestive heart (CHF) and normal sinus rhythm (NSR) using multivariate quadratic modeling (MQM) is given in TABLE I.

TABLE I. Classification results using MQM.

Actual Class	Predicted Class		
	ARR	CHF	NSR
ARR	95%	5%	0
CHF	50%	33%	17%
NSR	0	0	100%

The accuracy of the above classifications is obtained by dividing the correct classifications by the total classifications. The accuracy of classification using MQM comes out to be 84.85%.

VI. CONCLUSION

The research work involved analyzing the ECG signals for detection of cardiac abnormalities. A total of 162 ECG signals obtained from an online database were analyzed. A model has been developed that learns the features of ECG signals that were labeled with a class of cardiac disease. Based on the correlation established between the signal features and the class label values, a mapping or transformation function was developed. This transformation function was later applied to the unlabelled signals to predict their class labels i.e. their corresponding cardiac disease.

REFERENCES

[1] Josef Goette, "Review of various Biomedical signals," *Biomedical Signal Processing and Analysis*, February 2014.

[2] Z. Mizwan and H. kasturiwale, "Study and Review of the Biomedical Signals With Respect To Different Methodologies," *International Journal of Computer Science and Information Technologies* (IJCSIT), vol. 5, no. 2 , pp.1307-1309, 2014

[3] M. Rizzi and M. D. Aloiaastagnolo, "Fast Parallelized Algorithm for ECG Analysis," *WSEAS Transaction on Biology and Medicine*, Issue 8, vol.5, August 2008.

[4] S. Lalitha, D. Geyasruti, R. Narayanan and M. Shravani, "Emotion Detection Using MFCC and Cepstrum Features," *Procedia Computer Science*, vol. 70, pp. 29-35, 2015.

[5] Z. Wanli and L. Guoxin, "The Research of Feature Extraction based on MFCC for Speaker Recognition," in *Proc. 2013 3rd International Conference on Computer Science and Network Technology* , China, Oct 2013.

Parul Sahi, Pawanesh Abrol and Parveen Kumar Lehana, "Estimation of cardiac abnormalities based on ECG waveform using Multivariate Quadratic Surface Modeling," *International Journal of Scientific and Technical Advancements*, Volume 4, Issue 3, pp. 23-26, 2018.

[6] H. Seddik, A. Rahmouni and M. Sayadi, "Text Independent Speaker Recognition using the Mel Frequency Cepstral Coefficients and a Neural Network Classifier," in Proc. *Ecole Nationale Des Sciences Informatiques*, Manouba, Tunisia, 2010.

[7] S. Sahay, A. K. Wadhwani and S. Wadhwani, "A Survey Approach on ECG Feature Extraction Techniques," *International Journal of Computer Applications*, vol. 120, no.11, June 2015.

[8] M. V. G. Miranda, I. P. V. Espinosa and M.J.F. Calero, "ECG signal feature extraction," in *Proc. 2016 IEEE Ecuador technical Chapters Meeting*, 2016.

[9] S. Gupta, J. Jaafar, W. F. W. Ahmad and A. Bansal, "Feature Extraction using MFCC," *Signal & Image Processing: An International Journal* (SIPIJ), vol.4, no.4, August 2013.

[10] K.V. Krishna Kishore and P. Krishna Satish, "Emotion Recognition in Speech using MFCC and Wavelet Features," *in Proc. 3rd IEEE International Advance Computing Conference*, Ghaziabad, India, May 2013.

[11] M. Boussaa, I. Atouf, M. Atibi and A. Bennis, "ECG signals classification using MFCC coefficients and ANN classifier", in *Proc. IEEE International Conference on Electrical and Information Technologies*, May 2016, pp. 480-484.

[12] P. K. Lehana and P. C. Pandey, "Transformation of short-term spectral envelope of speech signal using multivariate polynomial modeling," in *Proc. National Conference on Communications*, Jan. 2011, pp. 1 -5.

[13] R. L. Branham, "Scientific Data Analysis: An Introduction to Overdetermined Systems," *London: Springer-Verlag*, 1990.

[14] A. Sharma and P. Abrol, "Eye Gaze Techniques for Human Computer Interaction: A Research Survey," *International Journal of Computer*, vol. 71, no.9, May 2013.

[15] A. Sharma and P. Abrol, "Direction Estimation Model for Gaze Controlled Systems," *Journal of Eye Movement Research*, vol. 9, no. 6, pp.1-12, 2016.

[16] O. Cappe, J. Laroche and E. Moulines, "Regularized estimation of cepstrum envelope from discrete frequency points," in *Proc. EuroSpeech Madrid, Spain*, 1995, pp. 451-454.

[17] C. S. Myers and L. R. Rabiner, "A comparative study of several dynamic time-warping algorithms for connected word recognition," *The Bell System Technical Journal*, vol. 60, no. 7, pp. 1389-1409, 1981.

Parul Sahi, Pawanesh Abrol and Parveen Kumar Lehana, "Estimation of cardiac abnormalities based on ECG waveform using Multivariate Quadratic Surface Modeling," *International Journal of Scientific and Technical Advancements*, Volume 4, Issue 3, pp. 23-26, 2018.