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Biometric Sample Extraction using Mahalanobis Distance in Cardioid Based Graph using Electrocardiogram Signals

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Abstract— **In this paper, a person identification mechanism implemented with Cardioid based graph using electrocardiogram (ECG) is presented. Cardioid based graph has given a reasonably good classification accuracy in terms of differentiating between individuals. However, the current feature extraction method using Euclidean distance could be further improved by using Mahalanobis distance measurement producing extracted coefficients which takes into account the correlations of the data set. Identification is then done by applying these extracted features to Radial Basis Function Network. A total of 30 ECG data from MITBIH Normal Sinus Rhythm database (NSRDB) and MITBIH Arrhythmia database (MITDB) were used for development and evaluation purposes. Our experimentation results suggest that the proposed feature extraction method has significantly increased the classification performance of subjects in both databases with accuracy from 97.50% to 99.80% in NSRDB and 96.50% to 99.40% in MITDB. High sensitivity, specificity and positive predictive value of 99.17%, 99.91% and 99.23% for NSRDB and 99.30%, 99.90% and 99.40% for MITDB also validates the proposed method. This result also indicates that the right feature extraction technique plays a vital role in determining the persistency of the classification accuracy for Cardioid based person identification mechanism.**

I. INTRODUCTION

ECG biometric has become an active field of research for human recognition since a decade ago. The fact that the geometrical and physiological deviations of the heart in different individuals portray certain uniqueness, distinctiveness and stability of the ECG signal [1], [2] validates its claim as a biometric modality to possibly use it as a security and privacy tool for highly protected resources.

The advancement in medical equipments, information and communication technology has the tendency to change and improve remote healthcare system. This critical development has made it easier for the aged society to monitor and maintain their own well beings especially in home healthcare systems. It is crucial to recognize the identity of a person in assisting general practitioners and medical officers to obtain records of patients in a remote healthcare facility in split seconds. ECG biometric using Cardioid based graph which was introduced by Sufi et. al. in [3] represents an alternative method of identification in a faster and feasible way as compared to using ECG recordings based on the lengthy Holter readings for remote healthcare systems. Not only limited to person identification method, Cardioid based graph is capable of detecting irregularities in the heart beats which may be caused by cardiac abnormalities and other forms of dementia as in [4]. The current approach of extracting features to obtain the Cardioid based graph using Euclidean distance produces reasonably good classification accuracy to differentiate between individuals. However, the classification rate could be further improved by using features extracted using Mahalanobis distance instead of Euclidean distance. The difference between the two distance measurements is that Mahalanobis distance takes into consideration the correlation of the data set itself. The higher the correlation factor, the more related the data set to each other.

Based on the results of our experimentations, the classification rate of Cardioid based graph using Mahalanobis distance as compared to using Euclidean distance was further enhanced from 97.15% to 99.8% for NSRDB and 96.5% to 99.4% for MITDB . High values of sensitivity, specificity and positive predictive values support the proposed method. This gives an indication that feature extraction plays a significant role in determining the persistency of a biometric system.

The remaining of the paper is organized as follows; the next section elaborates the method of the study which includes signal acquisition, preprocessing stage, domain transformation, biometric sample extraction method using Mahalanobis distance and Radial Basis Function network as the classification mechanism. Later, Section III discusses about the performance of the proposed feature extraction method as compared to the current technique. Finally, in Section IV, we conclude the study based on the experimentation and results in the previous section.

II. METHODOLOGY

In remote healthcare infrastructure, for example in nursing homes, several patients are connected to the medical monitoring equipments at once. Medical officers in hospitals will be flooded with ECG data coming from remote healthcare centres. This may create redundant and irrelevant data that could increase resource allocated and computational complexity in the hospital's server which would hinder the overall performance of the system. Cardioid based graph was proposed as a solution to this matter where once the identity of a patient has been validated, medical officers can take appropriate measures regarding the patient's heart condition [3]. However, in order to avoid data that are transmitted as being redundant or irrelevant, we propose to verify the correlation between the dataset using Mahalanobis distance measurement so that the performance of the healthcare system could be further improved. ECG signal acquisition from subject in NSRDB and MITDB is the first main step for this system, followed by QRS complex segregation in

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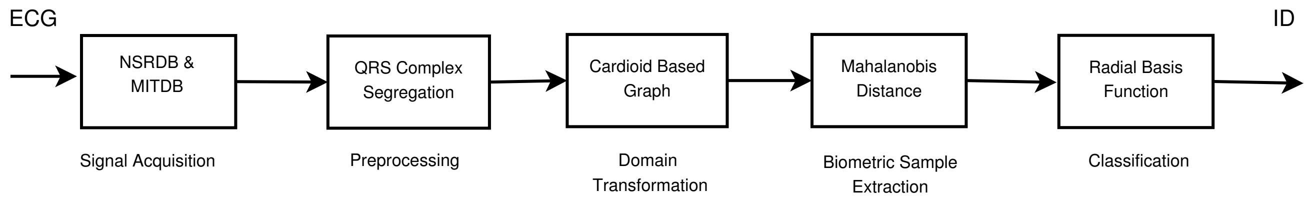

Fig. 1. The Proposed Method For Cardioid Graph Based ECG Biometric

the preprocessing stage, then domain transformation from time domain to a Cardioid based graph, biometric sample extraction for features extraction on the ECG data and finally substituting these extracted features in Radial Basis Function network for classification purpose. The proposed method is depicted as in Fig. 1.

A. Signal Acquisition

A total of 30 ECG datasets consisting subjects from two different databases used in this work were taken from PhysioNet, a publicly available physiological signal archive [5]; 18 subjects from MITBIH Normal Sinus Rhythm database (NSRDB) and 12 subjects from MITBIH Arrhythmia database (MITDB) each with sampling frequency of 128 Hz and 360 Hz respectively. The reasons that we used these two databases were mainly because i) these databases cover both categories of people in the daily world which are healthy and unhealthy people and ii) these are the most commonly used and well established databases in ECG research for decades.

B. Preprocessing

Once ECG data collection has been done, an analytical method is used to segregate the QRS complex, starting from the R wave since it corresponds to the most highest and prevalent peak in an ECG morphology due to the ventricular activity. This wave portion then becomes the reference point where we select equal points from both directions; the right and left of the identified R wave and we iterate the procedure 12 times for each subject where it would cover the whole QRS segment. First Derivative based technique was used to automate this process [6]. The reason QRS complex was chosen in this analysis instead of P or T wave or even the whole ECG morphology were mainly because it is less effected by cardiac abnormalities, noise and artifacts as shown in previous works as in [7], [8], [9], [10]. Then, using these QRS complexes, Cardioid based graph was applied to obtain uniquely extracted features as demonstrated in [3], [4].

C. Cardioid Based Graph

This next step is very crucial as it determines the persistency of the classification accuracy for Cardioid based person identification mechanism. Lets assume that ECG signal can be represented by **x**(t) as in Eq. 1.

$$\mathbf{x}(t) = \{x(1), x(2), x(3), \ldots, x(N)\} \quad (1)$$

where **x**(t) are ECG signals consisting of QRS complexes and N is the total number of QRS complexes for a given time. In order to create the Cardioid, the QRS complexes are differentiated as in Eq. 2.

$$\mathbf{y}(t) = \mathbf{x}(n) - \mathbf{x}(n-1) \quad (2)$$

where $t = 1, 2, 3, \ldots, (N-1)$ and $\mathbf{y}(t)$ is the differentiated ECG dataset.

A closed loop graph is generated based on a scattered XY graph called the Cardioid after obtaining vectors **x** and **y**. The ECG amplitudes of the QRS complexes are the x-axis and the differentiated ECG values of x are the y-axis. After this process is done, the time series of the ECG signals lost and is converted to a two dimensional loop. From this closed loop graph, the centre coordinate called centroid and the distance of the centroid to a given point on the Cardioid called extrema points are extracted coefficients as illustrated in Fig. 2.

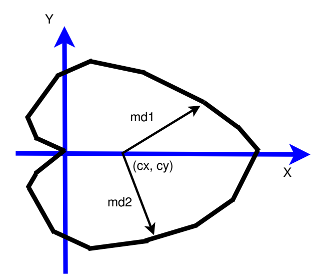

Fig. 2. A Cardioid Based Graph

Centroid is obtained by Eq. 3 as

$$(cx, cy) = \left[\frac{\sum_{i=1}^{N}\mathbf{x}(i)}{N}, \frac{\sum_{i=1}^{N}\mathbf{y}(i)}{N}\right] \quad (3)$$

where cx and cy are the coordinate position of the centroid in the Cardioid based graph. Making the centroid as the reference point in Cardioid, the Mahalanobis distances are then computed as the extrema points.

D. Biometric Sample Extraction

Biometric samples are extracted using Mahalanobis distance as compared to Euclidean distance as in [4]. Mahalanobis distance is a measure of dissimilarity between two unknown sample set with the same distribution, in our case, it is between the enrolment and recognition ECG vector data set and can be represented as in Eq. 4.

$$md(i) = \sqrt{(\mathbf{x}(i) - cx)C^{-1}(\mathbf{y}(i) - cy)} \quad (4)$$

where $\mathbf{x}$, $\mathbf{y}$, cx, cy and C are the enrolment ECG vector, recognition ECG vector, centroid of x, centroid of y and covariance values respectively.

The advantage of using Mahalanobis distance as compared to Euclidean distance is that Mahanlanobis distance takes into consideration the correlations, C, between the variables by which different patterns can be identified and analyzed with respect to a based or reference point [11]. After obtaining the Mahalanobis distances, these extracted features will then be compared with Euclidean distance as suggested in [3].

E. Classification

Radial Basis Function (RBF) network classifier has an input layer, $\mathbf{x}$), a hidden layer with activation functions and an output layer as depicted in Fig. 3.

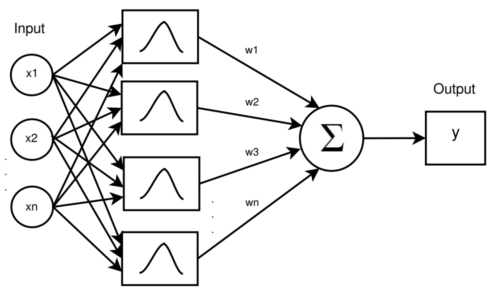

Fig. 3. Radial Basis Function

Output of the Gaussian transfer functions which are inversely proportional to the distance from the centre of the neuron are located in the hidden layer. The RBF network places one or more of these neurons in the space described by the predictor coefficients. The dimension of the space is equivalent to the number of predictor coefficients. The distance is calculated from the point being evaluated to the centre of each neuron, c_i and an RBF is then applied to the distance to evaluate the weight (which is also known as influence), w_i for each neuron. The closer a neuron is from the point being evaluated, the more influence it has and vice versa. Adding up the output values of the RBF functions multiplied by weights calculated for each neuron is the best predicted value for new point which computes the classification accuracy of the ECG signal as shown in Eq. 5.

$$\mathbf{y}_n = \sum_{i=1}^{N} w_i \phi(\|\mathbf{x} - c_i\|) \quad (5)$$

III. EXPERIMENTATION AND RESULTS

A total of 12 QRS complexes from each subject were taken from both databases where 12 different time instances were used for this purpose. This gives a total of 216 instances for all the subjects in NSRDB and 144 instances for all the subjects in MITDB which gives a grand total of 360 instances. To perform classification, half of the QRS complexes for each subject were used as enrolment ECG data and the remaining as the recognition ECG data. Figures 4 and 5 shows the Cardioid based graph of 3 subjects from each database. With reference to these figures, self-similarities shown in the Cardioid based graph further verifies the possibility of using ECG for subject recognition. Figures 4 and 5 also suggest that when these Cardioid based graph are overlapped with each other, it tends to be similar but distinct with other subjects.

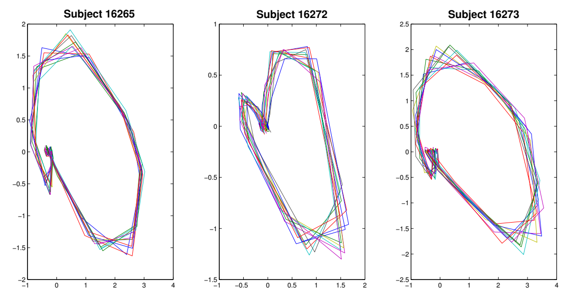

Fig. 4. Cardioid Based Graph for subjects 16265, 16272 and 16273 from NSRDB

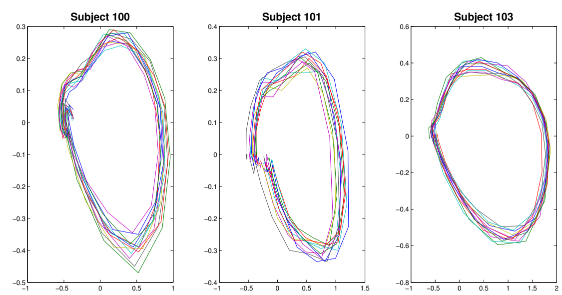

Fig. 5. Cardioid Based Graph for subjects 100, 101 and 103 from MITDB

A. Performance Evaluation

For the overall performance evaluation of the proposed method towards the two databases, standard performance metrics are used which is not limited only to classification accuracy as it is often a poor metric as the class distribution and misclassification cost are imprecise [12], [13]. Other performance metrics which are used to validate the proposed method includes sensitivity (SS), specificity (SP), and positive predictive value (PPV).

$$SS = TP/(TP + FN) \quad (6)$$

$$SP = TN/(TN + FP) \quad (7)$$

$$PPV = TP/(TP + FP) \quad (8)$$

where TP, TN, FP and FN refers to true positive, true negative, false positive and false negative respectively.

SS is the measure of the proportion of actual positives which are correctly identified. While, SP is the measure of

TABLE I

A COMPARISON OF THE CLASSIFICATION ACCURACY BETWEEN EUCLIDEAN DISTANCE AND MAHALANOBIS DISTANCE

Classification Accuracy	Feature Extraction Using Euclidean Distance	Feature Extraction Using Mahalanobis Distance
NSRDB	97.50%	99.80%
MITDB	96.50%	99.40%

TABLE II

AVERAGE CLASSIFICATION PERFORMANCE OF SUBJECTS FROM NSRDB AND MITDB

Database	Sensitivity (%)	Specificity (%)	Positive Predictive Value (%)
NSRDB	99.17	99.91	99.23
MITDB	99.30	99.90	99.40

the proportion of actual negatives which are correctly identified and PPV is the degree to which repeated measurements under the same conditions gives the same output.

For a good subject recognition system, high SS, SP and PPV will be compulsory for a reliable and secure identification mechanism. Results of the classification performance of subjects from the two databases using RBF to classify the subjects are shown in tables I and II. Referring to Table I, applying Mahalanobis distance as compared to Euclidean distance to Cardioid based graph further increases the accuracy from 97.50% to 9.80% for NSRDB and from 96.50% to 99.40% for MITDB. While, Table II shows that high values of SS, SP and PPV are obtained from the two databases. High values of SS and SP confirms the capability of the classifier to identify positive and negative results correctly. While, high PPV has a twofold meaning; i) ECG data set used in the study are precise and remains consistent in different time frames and ii) selecting only the QRS segment is able to successfully identify subject for recognition.

Thus, the results of the experimentation using the proposed method validates our main objectives for this study which are i) to increase the classification performance of identify individuals using Mahalanobis distance in Cardioid based graph and ii) to verify that QRS alone can act as biometric modality for ECG without using the whole PQRST morphology.

IV. CONCLUSIONS

This paper demonstrates the idea of person identification by using Mahalanobis distance as the biometric sample extractor as compared to using Euclidean distance as in [3] implemented for two different public ECG databases consisting of subjects with abnormal heart conditions. The objective of the study is twofold; i) to recognize and identify individuals more accurately and i) to use the advantage of the covariance as the correlation factor that links different variables. Our experimentation results suggest that applying Mahalanobis distance achieves better classification performance of subjects in both databases with accuracy from 97.50% to 99.80% in NSRDB and 96.50% to 99.40% in MITDB. High sensitivity, specificity and positive predictive value of 99.17%, 99.91% and 99.23% for NSRDB and 99.30%, 99.90% and 99.40% for MITDB validates the proposed method. This result also indicates that the right biometric sample extraction technique plays a vital role in determining the persistency of the classification accuracy for Cardioid based person identification mechanism.

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