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Human Identification Using ECG Feature Extracted From Fiducial and Non-Fiducial Approach

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***Abstract*—Electrocardiogram (ECG) will be employed in clinical identification for cardiac perform. Also, because people have completely different electrocardiogram traces, therefore, they can be non-inheritable as promising biometric options for human identification. According to the utilized options, the existing ECG based mostly biometric systems is classified to fiducial and non-fiducial systems. The identification of fiducial features needs the correct detection of fiducial points that is a terribly difficult task. On the other hand, non-fiducial approaches relax the detection process however typically result in high dimension feature area. This paper presents a combined approach of these two strategies for electrocardiogram primarily based individual identification. A fiducial based approach that utilizes a feature set chosen by local features of heart beats for biometric template style. Furthermore, a non-fiducial wavelet based mostly approach is projected. To avoid the high dimensionality of the resultant wavelet coefficient structure, the structure has been investigated and reduced using principal component analysis. The proposed feature sets were examined and compared using SVM classifier. To the effectiveness of this approach, records from the ECG-ID database using single lead are used to check subject identification, yielding high accuracy in identification.**

***Keywords*— Human Identification, ECG, PCA, Discrete Wavelet Transform**

I. INTRODUCTION

A branch of biometrics which has been picking up energy over the previous decade is the sending of electrocardiogram (ECG) as a biometric attribute. ECG has been utilized for quite a long time as a dependable diagnostic device. As of late, the likelihood of utilizing ECG as a biometric attribute has been proposed. Its legitimacy is upheld by the way that the physiological and geometrical contrasts of the heart in various subjects uncover certain uniqueness in their ECG signals [1, 2]. Contrasted with other physiological attributes (ex: iris, unique mark, face… and so on.) and behavioural characteristics (ex: signature, stride… and so forth.), the potential advantage of sending ECG in the field of biometrics is its trouble to be satirize or distorted. Besides, ECG as a natural sign is an existence pointer. Along these lines, it can be utilized as an apparatus forever identification [1,2].

The existing ECG based biometric systems can be generally categorized according to the nature of the utilized features as fiducial or non-fiducial based systems [2, 3 and4]. The fiducial based approach requires the detection of fiducial points from the three complex waves labelled: P,QRS and T displayed for each normal heartbeat in an ECG trace and occurred in this temporal order. On the other hand, non-fiducial based approaches capture the holistic patterns in ECG data by usually investigating their frequency content.

The proposed approach utilizes fiducial features and also discrete wavelet coefficients as features. In order to avoid high dimension limitations, a principal component analysis (PCA) is proposed to preserve only the significant wavelet coefficients. The proposed methods were examined and compared using SVM classifier. Moreover, Physionet databases were utilized for training and testing purposes and Critical issues such as: stability over time and rejection of impostors were addressed.

II. PROPOSED SYSTEM

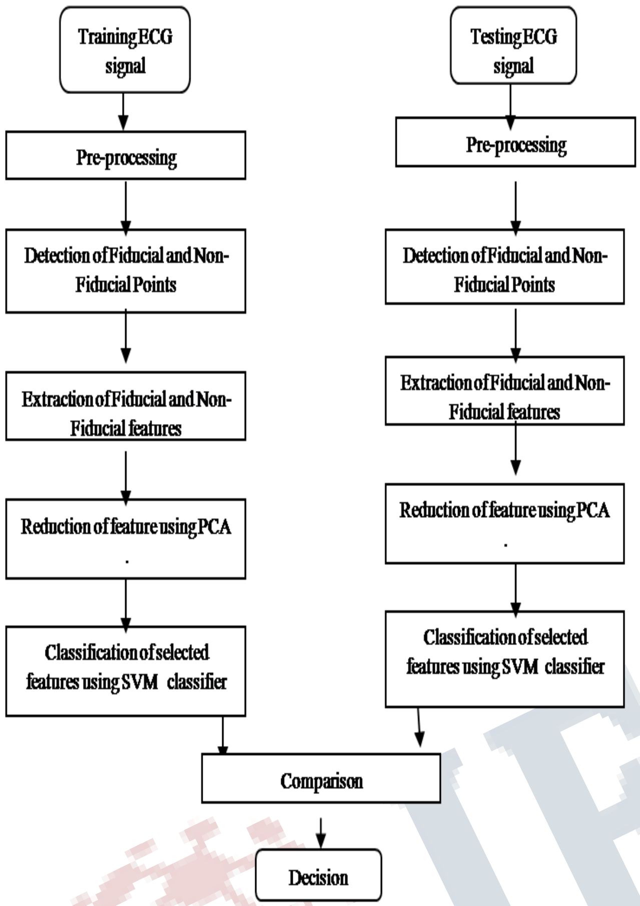

Fig1: flow chart of proposed method

A. Notch Filter:

In numerous Signal handling applications it is coveted to evacuate the noise leaving the original signal unaltered. Applications like correspondences, biomedical designing and so forth are real territories of utilizing the Notch channels. Reaction of the computerized step channel fulfils the accompanying requirements. The recurrence second request

IIR step channel is utilized for expelling the electrical cable impedance in the ECG signal the given signal is contaminated with noise at 50 Hz and also with the baseline wander. The notch filter is designed to remove the 50 Hz power line interference and the low pass filter is used to remove the baseline wander.

B. Discrete Wavelet Transformation

The wavelet change portrays a multi-determination deterioration process as far as extension of a sign onto an arrangement of wavelet premise capacities. Discrete Wavelet Transformation has its own particular great space recurrence restriction property. Use of DWT in 1D signal relates to 1D channel in every measurement. The information Daubechies Wavelet as mother wavelet is isolated into 8 non-covering multi-determination sub-groups by the channels, specifically db1, db2, db3up to db8, where db is acronym for Daubechies. The sub-band is prepared further to get the following coarser size of wavelet coefficients, until some last scale "N" is come to. At the point when a sign is disintegrated into 8 levels, the db6 sub-band flag best mirrors the first flag, subsequent to as per the wavelet hypothesis, the estimate signal at level n is the accumulation of the guess at level n-1 or more the subtle element at level n-1

C. Dimensionality Reduction

To lessen model unpredictability, PCA was utilized to decrease the list of dimension size by selecting the variables with maximal difference. Quickly, PCA rearranges the list of capabilities through straight blend of elements to create another arrangement of variables, termed foremost segments. These orthogonal primary parts, successfully decreasing our components, frame an orthogonal premise for the changed list of capabilities while catching 99% of the information fluctuation. By decreasing excess data, central parts in this manner lessen the dimensionality of our demonstrating without relinquishing autonomous data contained in the bigger list of capabilities

D. Classification

Other biometric ECG applications have used SVM in ECG classification [16], and we build on these approaches by using our wavelet transformed feature set (with features extracted across different scales) in addition to dimensionality reduction through PCA. SVM then provides biometric ECG signal classification by optimizing a decision boundary to separate data classes [17]. The optimization problem to maximize this decision boundary margin between data classes is given by:

$$\min_{\gamma,w,b} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}\xi_i$$

$$\text{s.t.} \quad \gamma^i = y^{(i)}\left(w^T x^{(i)} + b\right) \quad \text{and} \quad \gamma^i \geq 1 - \xi_i$$

Where training sets are given by a vector

$$\{(x_1, y_1) \ldots (x_i, y_i)\}$$

and w represents the normal vector separating data from the decision boundary, or hyper plane, and b represents an offset. Optimizing the normal vector w in conjunction with a penalty cost C for misclassifications ξ allows for optimal discrimination in non-separable cases. To classify non-linearly separable data, a kernel transformation is used to remap features to a domain where they are linearly separable. Here we use the radial basis function in feature (xi) remapping:

$$e^{\left(-\gamma\|x_i - x_j\|^2\right)} \qquad \gamma > 0$$

Feature remapping and cost penalties are critical to classifier optimization. As such, cross validation was performed across kernel shape γ and penalty coefficient C to maximize positive and negative predictive values (PPV, NPV) as statistical metrics for performance. To expand SVM from binary classification to that of multiple individuals, we used a one-versus-all approach. By this method, a separate SVM classifier was trained for each individual in which the respective individual's sample was classified as positive and all other samples classified as negative. Cross validation was performed across all subjects' models, and the optimal values were averaged into a singular set of parameters used uniformly across all subjects' SVMs for testing.

III. EXPERIMENTAL RESULTS

In the training stage the database of the ECG signal are calculated by performing the steps from noise removal to classification, then query signal is selected from the trained signal and applied as a query. The system has to perform feature extraction, feature reduction and the classifier has to identify its class and has to indentify the similar signal from the database by comparing the features of the query and database features

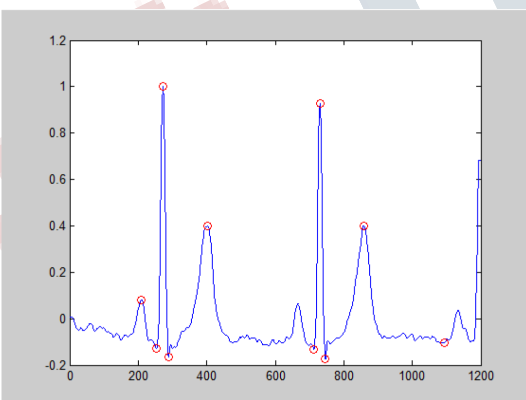

Fig. 3: Visualization of fiducial markings on P,Q,R,S and T waves on ECG recording during feature extraction.

IV. CONCLUSION

To conclude, the combination of two approaches for feature extraction is introduced for an ECG based biometric recognition. First, a fiducial based approach is proposed, and then a non-fiducial method is done using Daubechies Wavelet transform. Features across the ECG signal extracted using fiducial and non-fiducial approaches provide sufficient information for discriminating subjects. Dimensionality reduction further reduces model complexity and improves computational performance. Verification of ECG signals for biometric identification is done for 12 subjects accurately. The high accuracy of this proposed method had become potential for ECG as an accurate biometric that is robust to signal falsification.

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