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Heart-Rate Resistance Electrocardiogram Identification Based on Slope-Oriented Neural Networks

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***Abstract*—**For electrocardiogram (ECG) biometrics system, it is a tedious process to pre-install user's high-intensity heart rate (HR) templates in ECG biometric systems. Based on only resting enrollment templates, it is a challenge to identify human by using ECG with the high-intensity HR caused from exercises and stress. This research provides a heartbeat segment method with slope-oriented neural networks against the ECG morphology changes due to high intensity HRs. The method has overall system accuracy at 97.73% which includes six levels of HR intensities. A cumulative match characteristic curve is also used to compare with other traditional ECG biometric methods.

***Keywords*—**High-intensity heart rate, heart rate resistant, ECG human identification, decision based artificial neural network.

I. Introduction

BIOMETRIC techniques, which use anatomical, physiological or behavioral traits to prevent losses, provide an alternative strategy for identity verification over traditional ID/password based systems. The technologies are deployed in broad range of applications from security protections to criminal investigations. Several biometric systems that have been used commercially for human identity verification are facial geometry, iris, keystrokes, fingerprints, and voice analysis [5]. Moreover, ECG is also recently verified as a new biometric for human identification because of its uniqueness modality [1]-[3].

The ECG has exceptional advantages to compare with other biometrics, including (1) proper for all disability population, (2) invisible by ordinary human eyes, (3) easy to fuse in user perceived interface of a multi-modal biometric system [4], (4) applicable on ECG-embedded healthcare systems without extra costs, and (4) difficult to artificially mimic if it is considered with other heart-rhythm related variants (such as HR variability).

A. Significance and Background for ECG Human Identification

ECG records electrical potentials generated by the heart and is utilized for medical diagnosis proposes over a hundred year. Because ECG is a vital sign for life which is essential for live, it is often built in medical-related applications.

Some pioneer studies showed to identify people with a one-lead ECG signal on a small population (<30). Biel et al. [6] and Israel et al. [7] used principle components analysis (PCA) method and Shen at al. [1] applied template matching plus LDA distance classification to identified 168 persons with 95.3% accuracy on testing dataset. Khalil et al. [8] found the most unique signature bearing parts on QRS Complex of ECG for human identification by applying the high-order Legendre Polynomials. Wang et al. [9] proposed a combined model on autocorrelation (AC) in conjunction with discrete cosine transform (DCT). Also, the discrete wavelet transform was applied for extracting ECG features from wavelet coefficients. Their experimental results demonstrated that the proposed approach worked well for normal 35 subjects, but the accuracy is reduced on 10 arrhythmia patients [10]. It is challenge to apply ECG identification on arrhythmia patients. The previous work by Agrafioti and Hatzinakos [11] shows that abnormal ECG or ECG with arrhythmia may affect morphological changes of the signal, so their proposed method discards PVC windows to increase the robustness. This may alter the classification decision and performance especially when the system had never been trained with such data. Chen et al. [12] introduced complexity-based approach to deal with abnormal ECG for biometric identification purpose. Some of the pervious researches [13], [14] work on low-intensity HR which is about 20 increasing beats comparing with resting HRs. However, the high-intensity HR is still an open issue today.

B. Challenge on ECG with High-Intensity HR

The directional nature of ECG makes it highly variable with respect to the position, size, and anatomy of the heart even among normal people. In addition, age, sex, relative body weight, chest configuration, and various other factors create ECG variants among people with the same cardiac conditions [15]. Our experiment showed our ECG features had a low correlation or were non-correlated with age, weight, height, and body mass indexes [16]. That is, ECG variants make better distinguish one person from another; on the other side, the some variants can create disturbances on the stability of ECG biometrics. Those variants include body positions, high-intensity HRs, as well as ECG morphology changes due to cardiac diseases, aging affect, and sensor locations. For general population applications, to stabilize ECG biometric

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systems due to high-intensity HRs caused from exercises and emotion is one of most important issues to be considered. In this research, a high-intensity HRs resistant method is presented to make ECG biometric systems functional when person's high-intensity ECG morphology is unknown when the system was developed.

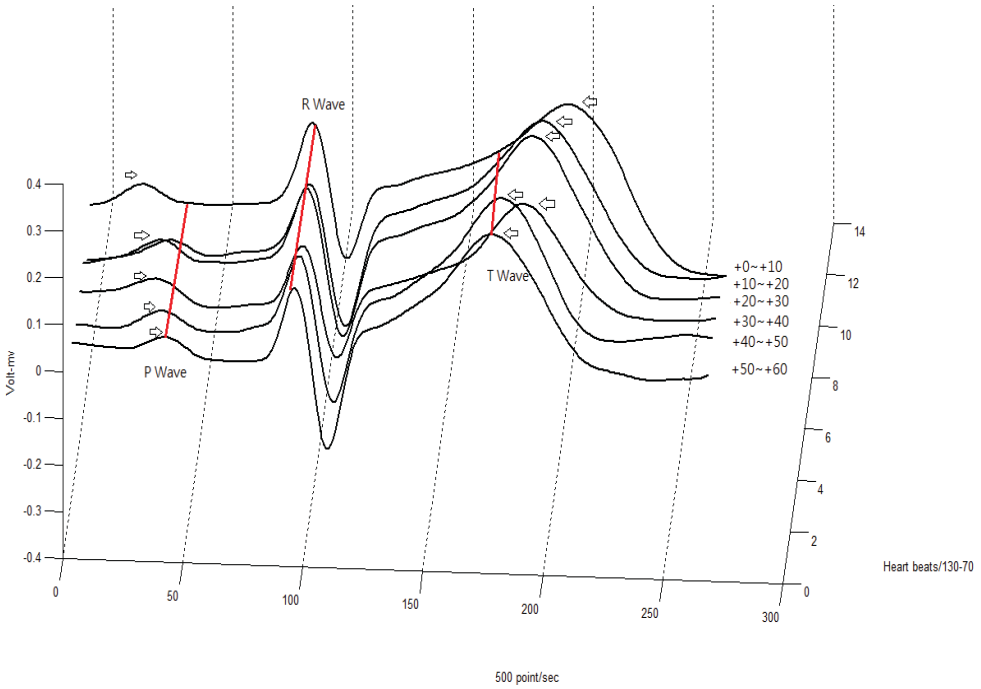


Fig. 1 Example of placing a figure with experimental results

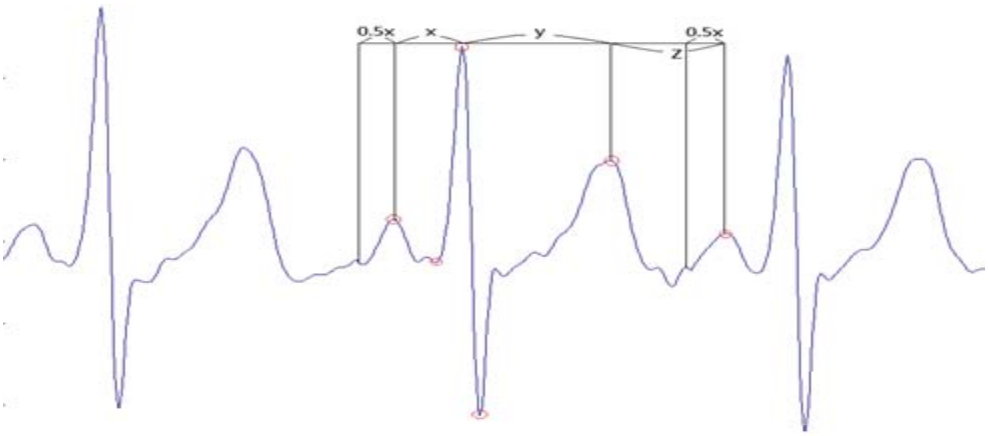


Fig. 2 Definitions of beginning and ending points for each heart beat

II. Materials and Method

Unlike the most of MIT/BIH database [17] of ECG signals from cardiology patients, this research focuses on normal, healthy people. 25 randomly selected subjects (including sixteen males and nine females) at ages between 18 and 24 with no previous known heart disease were involved in this study. Our experiment protocol is to ask those volunteers resting for two minutes and stepping on exercise bikes for about 3 minutes until subjects reach at least 50 beats above their resting rhythm. Once the target HR achieved, the subjects remain at situation for at least 10 minutes to make sure their HRs stabilized at resting rhythm. Therefore, the database templates, so-called the gallery set, are randomly selected from resting heat beats among 25 subjects. The probe set contains six subsets which contains six levels of heart rhythms, including resting heart rate (rHR) level, 10-beat per minute more than rHR (rHR+10) set, for 20-beat per minute more than rHR (rHR+20) set and so on until the rHR (rHR+60) set. Overall, the total of probe heart beats is 150 heartbeats. There are no overlapping heart beats between gallery set and the probe set. The entire lead-I ECG signals were monitored by MP35 (BioPack, Inc.) at 500 sps.

A. Preprocessing and Heart Beat Segmentation

In preprocessing, the ECG is low-passed by filters at 50 Hz cut-off frequency and the baseline wander is removed by a median filter. Then, the traditional ECG fiducial points, PQRST, are detected for temporal feature extraction and template generation by using several digital signal processing technologies, including Pan and Tompkins method [18], first derivative ECG method (that is, dECG) [19], and the zero-crossing method. The beginning point of each beat was defined as 0.5*dist(x), where the dist(x) is the distance between P and R points; the ending point of each beat was defined as dist(z)-0.5*dist(x), where the dist(z) is the distance between T and next P points. The detail segmentation is plotted in Fig. 2. In addition, seven new reference points (S1~ S7) are added for further to use. The time markers of those points are listed as,

$$S1_t = P_t - 0.5 * \overline{PQ}_t \quad (1);$$

$$S2_t = P_t + 0.5 * \overline{PQ}_t \quad (2);$$

$$S3_t = S_t + 0.5 * \overline{RS}_t \quad (3);$$

$$S4_t = S3_t + 0.5 * \overline{S3\_T}_t \quad (4);$$

$$S5_t = T_t + 0.5 * \overline{S3\_T}_t \quad (5);$$

$$S6_t = S4_t + 0.5 * \overline{S4\_T}_t \quad (6);$$

$$S7_t = T_t + 0.5 * \overline{T\_S5}_t \quad (7)$$

where, in Fig. 3., $S1_t$, $S2_t$, …, and $S7_t$ are the time markers (by number of points) for each fiducial point from S1 to S7. All of those fiducial points segment one beat into 11 pieces which represents significant sessions of ECG signals.

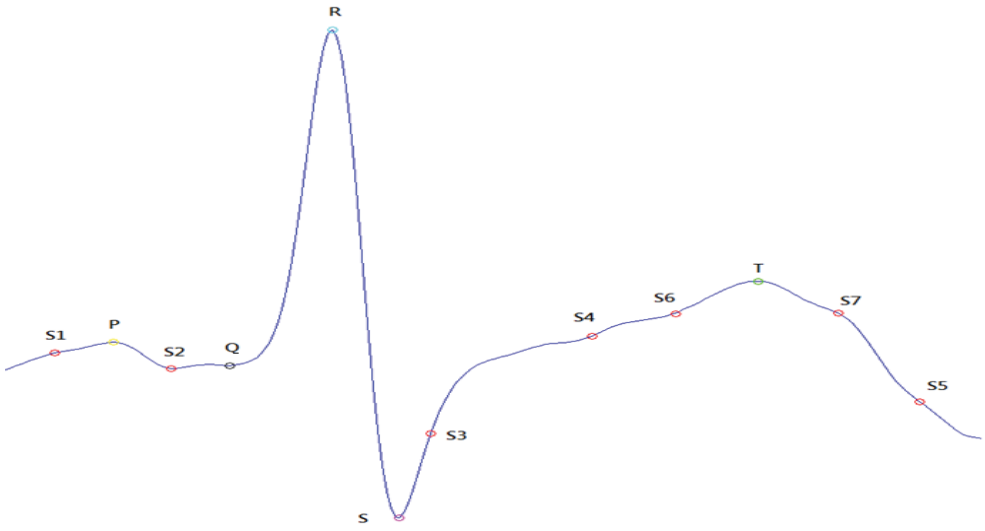


Fig. 3 Definitions of seven reference points for each heartbeat

B. HR Resistant Feature Extraction

In clinical diagnosis, the Bazett's and Framingham formula is often to normalize R-R interval. Previous research [1] showed that the Bazett formula fits better with resting ECG identification than the Framingham linear regression equation. Even Framingham formula is more accurate to normalize R-R intervals with fast HRs [20]; however, the entire ECG segment modeling is more complex issue because of individual variants. There is a need for more robust features on situation of high-intensity HR. As we known, when the HR increases, it has to be noticed that the ST segments (S_nT_n, where n is the nth heart beat) and the TP segments (T_nP_n+1) are significantly decreased. Many data reduction techniques provide high compression ratio at ECG plateau sessions (such as $\overline{S2\_Q}$ and $\overline{S3\_S4}$), but those plateau sessions in time scale point of view change significantly when the high-intensity HR is achieved. Hence, Fig. 4 shows that the same person has a resting beat and a high-intensity beat. Each slope of segmentations of PQRST and seven reference points are HR resistant. The slope is computed as

$$slope_N = \frac{po\,\mathrm{int}_k(i) - po\,\mathrm{int}_{k+1}(i)}{T} \quad (8)$$

where N is the number of features, k is the number of fiducial points (k<11), and T is number of samples between two points in time.

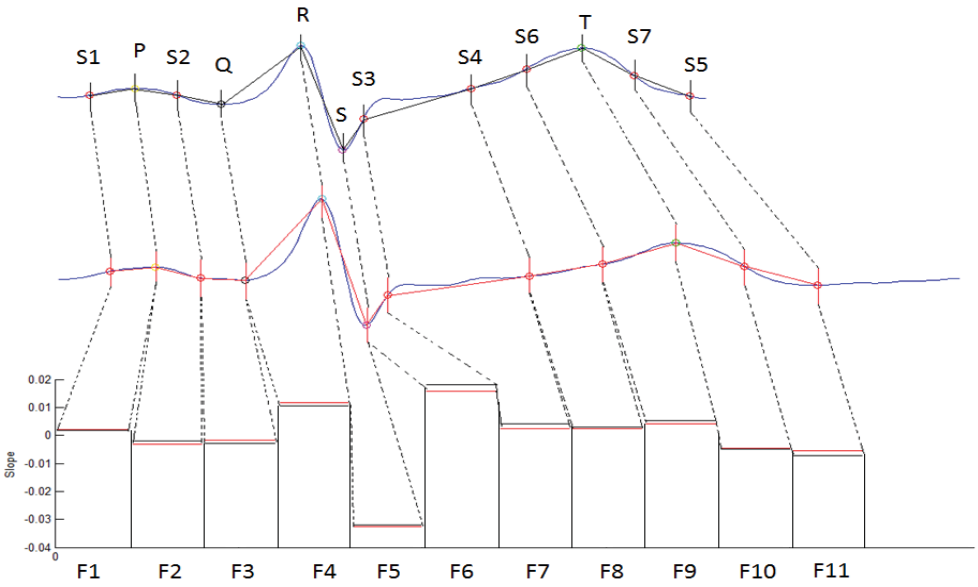


Fig. 4 Example of stability of session slopes (mV/points) for a person whose resting and high-intensity heart beats

C. Decision Based Artificial Neural Network Classifier for ECG Identification

A biometric system declared match between the input pattern and a matching pattern in the database is so-called identification or claimed the pattern associated with the correctly identity is so-called verification. In this proposed artificial neural network method, a decision-based neural network (DBNN) is applied for human identification, which adapts the weight vector either in the direction of the gradient of the discriminant function or in the opposite direction. The algorithm of the decision-based learning rule is as follows: The system input is a feature vector $\mathbf{x}=(x_1,x_2,x_3,...,x_N)$ that represents above N ECG features. Suppose that $S=\{\mathbf{x}^{(1)},...,\mathbf{x}^{(L)}\}$ is a set of given training input vectors, where L the number of training vectors is. Each of the training vectors corresponds to one of the M classes $\{\Omega_i, i=1,...,M\}$. The M (equal to 25) neurons correspond to M different persons that are to be identified. Each neuron i implements a discriminant function $\phi(\mathbf{x},\mathbf{w}_i)$, where $\mathbf{x}$ and $\mathbf{w}_i$ are the input and weight vectors, respectively, for the neuron i. The outputs of these neurons are fed to a MAXNET which determines the winner and the class corresponding to the winning neuron. The output of each class is modelled as a subnet with discriminant functions $\phi(\mathbf{x},\mathbf{w}_i)$, $i=1,...,M$. Suppose that the l th $(1\le l\le L)$ training vector $\mathbf{x}^{(l)}$ is known to belong to class Ω_i and the subnet outputs $\phi(\mathbf{x}^{(l)},\mathbf{w}_j)>\phi(\mathbf{x}^{(l)},\mathbf{w}_m)$, $\forall j\neq m$, where the winning class is the j th class, an arbitrary class is the m th class, and the correct class is the i th class.

If $j=i$, then the feature vector $\mathbf{x}^{(l)}$ is correctly classed and nothing needs to be updated.

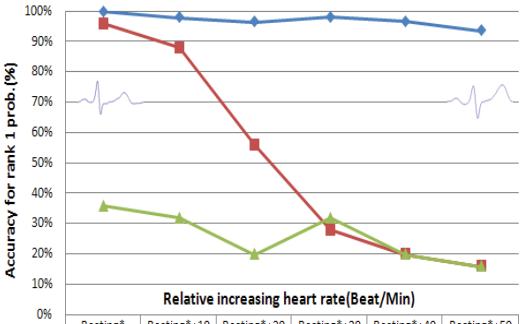
If $j\neq i$, it means $\mathbf{x}^{(l)}$ is misclassified. Hence, the weight taps need to be updated in order to get the correct classification, and then the following update is performed as

$$\mathbf{w}_i^{(l+1)}=\mathbf{w}_i^{(l)}\pm\Delta\mathbf{w} \tag{9}$$

where $\Delta\mathbf{w}=\eta\nabla\phi(\mathbf{x}^{(l)},\mathbf{w})$ is the step size for the weight changes. $\nabla\phi(\mathbf{x}^{(l)},\mathbf{w})$ is the gradient of the discriminant function and η is a convergence constant which represents a positive learning rate, where ϕ is set as radial basis function in this investigation.

III. Results

We assure the proposed system which only stores resting templates as gallery set, and all information of high-intensity HR beats is unknown. That makes identification became harder. If six subsets ($p_0, p_1, p_2, p_3, p_4,$ and p_5), have been considered separately, the performance of traditional temporal ECG identification methods (such as correlation only and LDA feature classifier only) drops dramatically at subset $p_2, p_3, p_4,$ and p_5. However, even in the toughest condition p_5, the presented method successfully identifies people at 93.73% accuracy which is averaged from repeated 30 times on system performance on subset p_5. The overall biometric system accuracy is 97.73% for 30 repeat runs. The false match rate (FMR) is 2.27% over 150 probes with six levels of HRs.



	Resting*	Resting*+10	Resting*+20	Resting*+30	Resting*+40	Resting*+50
Prescreening+DBNN	100%	97.96%	96.53%	98.13%	96.66%	93.73%
Template Matching	96%	88%	56%	28%	20%	16%
LDA	36%	32%	20%	32%	20%	16%

Fig. 5 The proposed method provided over 93.73% accuracy on each subset, even the HR has 50 bps increased from resting

IV. Discussion

For analyzing the performance of a biometric system, especially when it is operated in the identification mode, a cumulative match characteristic (CMC) curve depicts the increase in the identification rate of the system with increase in the rank before which a correct match is obtained [21]. To compare with other methods, the DBNN methods reached 100% on cumulative match score after the list of rank 2 recognition is involved. That is, even the system has 97.73% rank one accuracy, the exact candidates are all in the top 1& 2 ranks.

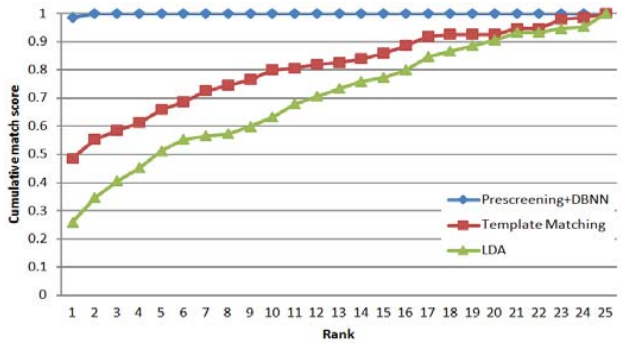


Fig. 6 CMC curves of three methods. The presented method offered 100% score after rank 2 involved

V. Conclusion

We presented a slope-oriented method with a DBNN structure to enhance current ECG biometric systems to against identification difficultness of high-intensity HR ECGs. For most of people, the method can push the ECG biometric technologies to work at target HRs about 130 bpm and above. The method successfully increases the accuracy to compare with other traditional ECG morphology methods. Then, the method demonstrates a possibility to apply ECG biometrics on exercise, daily activity monitoring, u-healthcare system, improvement of ECG compassion, and emotion driven applications in the future.

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