Fusion of ECG sources for human identification

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***Abstract*—A study about the applicability of electrocardiogram (ECG) signals in human identification systems is presented in this paper. There is strong evidence that ECG signals embed highly discriminative information in a population. In this paper, multiple levels of fusion are described to combine information gained from the standard 12 lead ECG system. Most of the current approaches make use of only one lead electrocardiogram to extract fiducial based features. However, in pattern recognition problems it is believed that the larger the amount of information, the higher the probability of recognizing a subject successfully. The primary goal of the current work is to demonstrate that all ECG leads are suitable for identification and to suggest feature and decision level fusion techniques of combining this data. When the proposed system is tested on a public dataset, considerably high recognition rates are achieved.**

***Index Terms*—biometric, autocorrelation, discriminant analysis, information fusion, classification**

I. INTRODUCTION

As technology for falsification advances, accurate, robust and reliable identification of individuals becomes more and more critical. Conventional strategies for identity authentication depend on entities or passwords that the subject must remember or posses (i.e., ID cards, tokens, PIN numbers). The main disadvantage of such traditional techniques is that these identification entities can be easily stolen or forgotten.

The security gap is nowadays filled by biometric based systems. Biometrics are physiological or behavioral characteristics which are extracted directly from the human body to be used as identification modules. Among the most widely examined and applied biometric traits are the face, the fingerprint, the iris, the voice, the keystroke and the gait. Although high identification rates have been achieved with these characteristics, each one of them suffers from its own weaknesses, which in most cases is their lack of robustness against the application of falsified credentials.

Attention has been drawn lately in the employment of medical biometrics, which are physiological traits traditionally studied for clinical applications. Blood pressure, heart rate variability and the electroencephalogram are some examples of this type of biometric. The idea behind the analysis of medical biometrics, is that they constitute a life indicator for the subject who carries them, decreasing this way illegal penetration into a system considerably.

The employment of electrocardiogram (ECG) signals for biometric purposes is a relatively new area of study. ECG signals reflect the electrical potential of the heart over time, and they have been thoroughly analyzed for medical diagnosis. Their applicability for human identification is supported by the fact that unique patterns are related to numerous physiological characteristics such as the age and gender [1]. In addition, studies have shown that physiological and geometrical variations of the human heart are depicted in the electrocardiogram [2].

Utilizing a powerful biometric increases the challenge of extracting discriminative features for identification. So far, two types of methodologies for feature extraction have been suggested: with fiducial points detection and without it. Fiducial points are instances of interest in single heart beats. Most of the proposed methods take advantage of temporal and amplitude distances of successive fiducial points in the electrocardiogram [3-9]. However, when the interest is confined to a limited number of points, extraction of discriminant characteristics is insufficient. In addition, there is no universally acknowledged rule that can guide the localization of wave boundaries [10].

This problem has been addressed in [11,12], where autocorrelation based features are extracted from ECG windows instead of heart beats. Autocorrelation (AC) has proven to be very effective in creating personalized signatures for different individuals, while the complexity of the system is reduced substantially by avoiding the use of fiducial points detectors.

Most of the works reported are tested on electrocardiogram signals recorded from one lead only. However, the conventional method for ECG recordings offers a variety of 12 different leads. In this paper, we investigate the applicability of using ECG signals from all 12 leads, as they embed highly characteristic features in a population. A non fiducial points detection framework is adopted, which uses autocorrelation in conjunction with the linear discriminant analysis (LDA) for every lead (AC/LDA). Investigating more than one leads at the same time increases the information gained for a subject, which is expected to achieve more accurate recognition. Two kinds of fusion schemes are presented in this paper. A feature based fusion framework is primarily aiming to combine the features extracted from every lead. In addition, a decision based module is examined, to combine different classifiers' decisions on the identity of an inputs.

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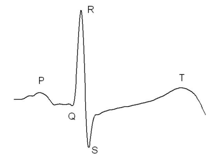

Fig. 1. Components of an ECG heart beat (lead I).

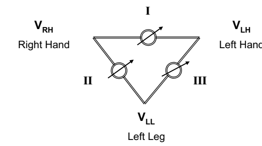

Fig. 2. Einthoven triangle

II. ECG WAVES AND RECORDING TECHNIQUES

The electrocardiogram describes the electrical activity of the heart over time. ECGs are recorded with electrodes, attached to specific locations on the body surface. Figure 1 labels the basic elements of a single heart beat. Each wave pictures the sequential polarization and depolarization of the heart. The *P* wave is generated when the right and left atria of the heart are depolarized and it corresponds to low frequency spectral components i.e., 10 Hz- 15 Hz. The *QRS* complex reflects the depolarization of the right and left ventricles. This complex has much steeper slopes compared to other waves, and for this reason its spectrum is concentrated in the interval 10 Hz - 40 Hz. Finally, the *T* wave corresponds to the ventricular repolarization and its position depends on the heart rate, appearing closer to the *QRS* complex when the rate increases [13].

There are more than one methods for ECG recording, such as orthogonal leads and synthesized leads. However, the most widely applied system is the *standard 12-lead ECG*. This system is determined by three main sets of lead orientations. The *bipolar limb leads* are usually denoted as I,II, and III and they track the electrical potential of the heart when three electrodes are attached at the right and left hand and left leg.

By convention, lead I measures the potential difference between the two arms. In lead II, one electrode is attached on the left leg and the other one on the right hand as depicted in Figure 2. Finally, in lead III configuration, the potential measured is between the left leg and hand.

Following the electrode position as pictured in Figure 2, the limb leads are measured in the following combinations:

$$I = V_{LH} - V_{RH} \tag{1}$$
$$II = V_{LL} - V_{RH} \tag{2}$$
$$III = V_{LL} - V_{LH} \tag{3}$$

Which suggest that having recorded any two of the bipolar limb lead signals, the third one can be directly derived.

The *augmented unipolar limb leads* fill the 60^o gaps in the directions of the bipolar limb leads. Using the same electrodes the augmented unipolar are measured as:

$$aVR = V_{RH} - \frac{V_{LH} + V_{LL}}{2} \tag{4}$$
$$aVL = V_{LH} - \frac{V_{RH} + V_{LL}}{2} \tag{5}$$
$$aVF = V_{LL} - \frac{V_{LH} + V_{RH}}{2} \tag{6}$$

The third category of lead orientation involved in the conventional 12-lead system are the *precordial leads* (V1, V2, V3, V4, V5, V6). These signals are recorded with 6 electrodes attached successively on the left side of the chest, thus capturing more detailed information in the electrocardiogram [13], [14].

III. METHODOLOGY

Human identification is essentially a pattern recognition problem consisted of three stages: *pre-processing*, *feature extraction* and *classification*. In the pre-processing stage, the ECG signals are filtered to remove noise and then subjected to windowing and computation of the normalized autocorrelation. Feature extraction, involves the application of linear discriminant analysis, for dimensionality reduction and design of distinctive signatures. Classification is the final stage of the identification process, where based on a distance measure, each feature vector is assigned to a class. The objective of this paper is to combine the information from different leads, and therefore a decision-based fusion will be evaluated before a subject is recognized.

A. Autocorrelation based feature extraction

The recorded ECG records contain a wide variety of noise effects. Noise can corrupt ECGs to a degree where further analysis is impossible without filtering. Generally, the electrocardiogram contains low frequency noise which causes baseline wander and high frequency noise components such as powerline interferences. To eliminate these effects, the signals are filtered using a Butterworth band-pass filter of order 4. The cutoff frequencies are 1Hz- 40Hz based on empirical results.

Windowing follows filtering, to partition the electrocardiogram into several non overlapping windows, allowing to blindly cut the signal even in the middle of a pulse. The only restriction is for the employed window to have an appropriate length, so that multiple pulses are included.

The autocorrelation of ECGs embeds very discriminative patterns associated directly to the *P*, *QRS* and *T* waves. The normalized autocorrelation is computed for every window of the electrocardiogram and for each one of the 12-leads. This way, samples that would have to be subjected to fiducial points detection, are blended into a sequence of sums of products:

$$\widehat{R}_{xx}[m] = \frac{\sum_{i=0}^{N-|m|-1} x[i]x[i+m]}{\widehat{R}_{xx}[0]} \tag{7}$$

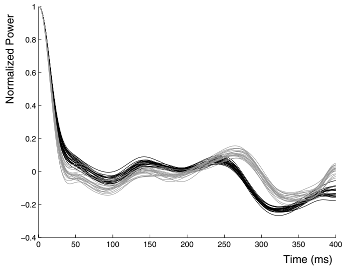

Fig. 3. AC ECG signals of two recordings of the same subject taken a few years apart. Sequences from the same record are plotted in the same shade.

where $x[i]$ is the windowed ECG for $i = 0, 1...(N-|m|-1)$, $x[i+m]$ is the time shifted version of the windowed ECG with a time lag of $m = 0, 1, ...(M-1)$; $M<<N$, and N is the length of the windowed signal. Our expectations for the autocorrelated signals to form characteristic intra-individual signatures are confirmed by the results of Figure 3.

The Linear Discriminant Analysis is a well known and efficient method for dimensionality reduction and feature extraction. It is a transform domain method that performs supervised learning. Given a training set $\mathcal{Z} = \{\mathcal{Z}_i\}_{i=1}^{U}$, containing U classes with each class $\mathcal{Z}_i = \{\mathbf{z}_{ij}\}_{j=1}^{U_i}$ containing a number of windows $\mathbf{z_{ij}}$ a set of K feature basis vectors $\{\psi_m\}_{m=1}^{K}$ is estimated by maximizing Fisher's ratio. This ratio is defined as the between-class to within class scatter matrix. The maximization is equivalent to the solution of the following eigenvalue problem:

$$\psi = \arg\max_{\psi} \frac{|\psi^T \mathbf{S}_b \psi|}{|\psi^T \mathbf{S}_w \psi|} \tag{8}$$

where $\psi = [\psi_1, ..., \psi_K]$, and $\mathbf{S_b}$ and $\mathbf{S_w}$ are the between and within class scatter matrices respectively. Linear Discriminant Analysis finds ψ as the K most significant eigenvectors of $(\mathbf{S}_W)^{-1}\mathbf{S}_b$ that correspond to the first K largest eigenvalues. Having obtained the basis vectors, any test input window $\mathbf{z}$ is subjected to the linear projection $\mathbf{y} = \psi^T \mathbf{z}$ [16].

B. Information Fusion

Information fusion is widely applied in multi-modal biometric systems, i.e. systems which take advantage of multiple biometric traits. For instance, [5] suggests that face characteristics can be combined with the electrocardiogram to increase the security levels of current approaches. When data is combined in the right framework, the recognition precision can be augmented.

In this paper, we demonstrate different levels of fusion of ECG information obtained from different leads. The motivation behind this implementation is that ECG windows which are recorded at the exact same time from different electrode orientations, can be combined to increase the distinctive information for every subject.

Fusion can be roughly performed in three different levels: the raw-data level, the feature level and the decision level.

Combining raw information suggests direct fusion of different sources for the same trait. In the electrocardiogram case for instance, one could average the ECG signals from different leads. However there is no practical reason why such a process would offer more substantial information for subject recognition.

Fusion at a feature extraction level can be performed in two ways. Data collected from different biometrics or different aspects of the same biometric can potentially be concatenated in one feature vector with higher dimensionality, provided that these features are in the same type of measurement scale [15]. Furthermore, feature level fusion includes a combination of scores that are produced from different classifiers, each specifically trained on features of the same origin. In other words, every classifier is trained on inputs from selected sensors, offering a distance (or score) measure when tested. Classifier fusion in that case dictates that scores are synthesized to make a final decision.

The third type of fusion is decision based. Different classifiers make decisions about specific feature vectors and the final decision is a result of a structured synthesis (such as majority voting). An extensive description of methods for combining the outcomes of different classifiers can be found in [17].

In this paper, features obtained when the AC/LDA method is applied on ECG segments from different leads, are combined at the decision level, based on variants of the voting principle. Specifically, 12 classifiers are trained each on signals recorded from the corresponding lead. We denote that classifier k is tested on an input x as $cl(x)^k$. The final decision where all classifiers are fused is noted as $CL(x)$. If the system has N registered subjects which can be identified, then every classifier makes a decision from the set $\Omega = 1, 2...$N. The following characteristic function is introduced to simplify the description on the fusion methodology:

$$\Phi_k(x \in C_i) = \begin{cases} 1, & \text{if } i \in \Omega \text{ and } cl(x)^k = i \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

We introduce here four rules that guide the decision fusion of different classifiers.

- *Case 1*:
  This rule is used to make conservative decisions. Voting takes place, but the system rejects (R) the input unless all classifiers agree on the same cluster. The final decision $CL(x)$ is given from:

$$CL(x) = \begin{cases} j, & \text{if } j \in \Omega \text{ and } \sum_{k=1}^{12} \Phi_k(x \in C_j) = 12 \\ R, & \text{otherwise} \end{cases} \tag{10}$$

- *Case 2*:
  A less conservative rule for decision synthesis can be given from:

$$CL(x) = \begin{cases} j, & \text{if } \Psi(x,j) = \max_i \Psi(x,i) > 6 \\ & \text{and } j, i \in \Omega \\ R, & \text{otherwise} \end{cases} \tag{11}$$

where $\Psi(x,j) = \sum_{k=1}^{12} \Phi_k(x \in C_j)$. Here an input x is identified as subject j if more than half of the classifiers agree on that (majority voting).

- *Case 3*:
  This case is a generalization of case 2, to accommodate more or less conservative decision fusions, based on the parameter α which takes values in (0,1]. The final estimation for the subject is given from:

$$CL(x) = \begin{cases} j, & \text{if } \Psi(x,j) = \max_i \Psi(x,i) > \alpha * 12 \\ & \text{and } j, i \in \Omega \\ R, & \text{otherwise} \end{cases} \tag{12}$$

  For α=0.5 cases 2 and 3 are equivalent, so this rule can be regarded as a generalization of majority voting.

- *Case 4*:
  To assist situations of equal votes for two or more classes, or cases where the final class is chosen with votes which are not considerably higher than the second maximal, the final decision can be made through:

$$CL(x) = \begin{cases} j, & \text{if } \Psi(x,j) = \max_1 \\ & \text{and } \max_1 - \max_2 \geq \alpha * 12 \\ R, & \text{otherwise} \end{cases} \tag{13}$$

  where

$$\max_1 = \max_i \Psi(x,i) \tag{14}$$

$$\max_2 = \max_{i-\{j\}} \Psi(x,i) \tag{15}$$

  When α is big, this rule becomes very conservative, since in order to assign an input to a class, it must be supported by many classifiers and not to have opponents [17].

IV. Experimental results

The performance of the proposed methodology was evaluated on the PTB [18] public database. This database contains 549 records from 294 healthy volunteers and patients with different heart diseases. The database is offered for public use from the National Metrology Institute of Germany and the signals were collected at the Department of Cardiology of University Clinic Benjamin Franklin in Berlin. Each record contains the conventional 12-leads and 3 Frank leads ECG. The signals were sampled at 1000 Hz, with a resolution of 16 bit over a range of 16.384 mV. For the current experimental setup, healthy subjects were studied only. Therefore, a subset of the PTB dataset containing 14 subjects of different age and gender was composed. Two records are offered for every subject, collected a few years apart. The older recording of a subject was included in the gallery set, and the newer one was utilized for testing.

A. Individual analysis of leads

In this section, we present the results of the AC/LDA method for feature extraction from 12 lead ECG signals. The framework begins by filtering the electrocardiogram recordings for each lead. The normalized autocorrelation is computed with Eq. 7 on a 5 sec ECG segment, and the linear discriminant analysis is applied for dimensionality reduction of an AC window. Several different autocorrelation windows have been tested as feature vectors, however we suggest a window of approximately the length of a *QRS* complex. This is because, the *QRS* complex is not affected by varying heart rates as much as the rest of the waves [19]. Following this observation, such a window will enable the system to perform well in cases of anxiety, stress and exercise, all of which increase the heart rate.

Lead	Subject Recognition Rate	Window Recognition Rate
I	100%	97.2%
II	100%	97.9%
III	100%	97.58%
αVR	100%	97.58%
αVL	100%	97.88%
αVF	100%	97.88%
V1	85.71%	82.47%
V2	100%	97.88%
V3	92.85%	92.74%
V4	85.71%	84.29%
V5	100%	98.48%
V6	100%	99.39%

TABLE I
Experimental results from classification of the PTB data of different leads

The similarity measure used in our simulations is the Euclidean distance, with the nearest neighbor as a classifier. The performance is measured in terms of *subject* and *window recognition rates*. When measuring window performance, a subject is identified based on one of his/her recordings only. On the other hand, for subject recognition, multiple ECG windows are studied, and result in a decision based on majority voting. The performance for every lead signal is shown in Table I which suggests that all leads embed discriminative power and that integration of this information in the right framework will enhance the overall identification procedure. In addition, Figure 5.A and 5.B presents the contingency matrices of two individual leads.

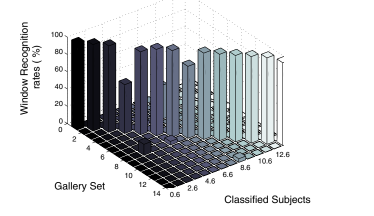

Fig. 4. Contingency matrix after feature-level fusion of leads. The darker the square the higher the recognition performance.

B. Feature level fusion of leads

By recording the electrocardiogram signal simultaneously from every lead, different aspects of the instantaneous potential

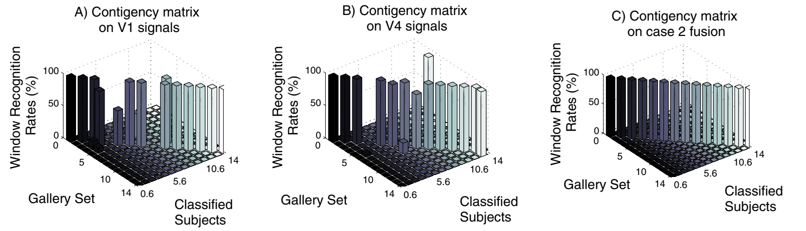

Fig. 5. A) Identification rates with the AC/LDA method applied on V1 signals B) Identification based on V4 signals. C) Decision based fusion of 12 leads

of the heart are captured. Depending on the electrode configuration, numerous details are pictured in each of the 12 lead signals. The purpose of the information fusion is to utilize this source of distinctive characteristics as much as possible.

To apply a feature-level fusion of the data, a segment from the autocorrelated ECG windows of every lead is subjected to dimensionality reduction with the LDA. Having obtained an optimum feature set, the vectors are concatenated since they are of the same measurement scale. This procedure is performed for all 12 instances of every 5 sec ECG recorded from a subject. The Euclidean distance between every concatenated vector in the test and gallery set is computed, and classification is performed with nearest neighbor. The contingency matrix in Figure 4 demonstrates the window identification rates for each subject in the test set. In a perfect system, it is expected that the diagonal would show 100% window recognition rate. However, even though the subject identification rate is *100%*, the window rate is *95.16%*. This implies that concatenation of the feature vectors leads to loss of discriminative information (less powerful leads overrule the results) and a decision based fusion will be more appropriate.

C. Decision level fusion

In order to combine the 12 leads at a decision level, 12 classifiers are trained, each on the corresponding lead ECG signals. The feature space is once again obtained from the normalized autocorrelation of ECG windows and the dimensionality is reduced with discriminant analysis. The output of every classifier can be regarded as binary for every class, given an input *x*. The four cases described earlier introduce rules which guide the fusion of the 12 decisions.

However, this kind of fusion brings up rejection (*R*) cases. Rejection takes place when the system doesn't make a decision because either it is too conservative, or the class of the input data is ambiguous. Rejection might be unacceptable for biometric identification systems, since the subject will need to be recognized with a different module. On the other hand, it reduces significantly the possibility of illegal penetration. When the system is not absolutely confident about a person's identity, it sets off the alarm rather than assigns someone to a false identity. However, it is useful to configure a fusion framework, which would be conservative enough to detect intruders, and at the same time have as low rejection rate as possible.

The window and subject identification results of the current experiments are obtained among those subjects which are not rejected for every specific case. The first case is conservative enough, since a window is identified only if all classifiers agree. As expected, this rule leads to very high window and subject rejection rates, as reported in Table II. A subject is rejected if all the corresponding windows are rejected. For the first case, classification among the remaining subjects provides 100% subject and window recognition rates.

The second rule is less conservative than the first one, since it is based on majority voting. This kind of fusion rule is expected to have less rejection losses. Table II shows that the window rejection rate is reduced to 0.9% while still being able to identify correctly all the subjects. The percentage of rejected windows in this case, is distributed among all subjects, and therefore no subject is excluded from the system. Figure 5.C pictures the contingency matrix when fusion is forced using majority voting as the decision rule.

Cases three and four introduce window and subject rejection rates as well. In these cases, the degree of rejection is controlled by parameter α. This measure mainly expresses the order of confidence about the decision which is made. However, there is a tradeoff between highly confident decisions and rejection rates. The greater the number of the classifiers that participate in the voting process, the bigger the probability of successful identification, especially for large datasets. Given that α lies in the interval (0,1], several values have been tested, offering 100% subject and window recognition rates. Figure 6 depicts the rejection rates for different values of α.

Even though the proposed framework was tested on 14 healthy subjects, the analysis was carried out for multiple ECG windows recorded from every individual. The training set consists of 331 electrocardiogram windows, and the corresponding testing was performed using 324 windows. The extracted features for recognition, can be also associated to authentication operational modes. In such applications, the system aims to find if the collected biometric and one which corresponds to an identity claimed by the user, make a good match or not. Authentication using 12 lead ECG signals is an *one to one* process thus independent of dataset's size. The

Case	Window Rejection Rate	Subject Rejection Rate	Subject Recognition rate	Window Recognition rate
1	32.32%	21.43%	100%	100%
2	0.9%	0	100%	100%

TABLE II
REJECTION AND IDENTIFICATION RATES WITH CASE 1 AND 2 DECISION LEVEL FUSION

framework described in this paper can be potentially applied for criminal investigation and access control, as ECG is soon expected to find its own niche in the biometric world.

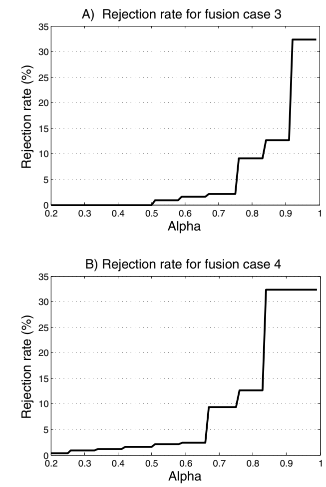

Fig. 6. Rejection rates when the 12 leads are combined in a decision level

V. CONCLUSION

In this paper, a human identification system based on the electrocardiogram signal is reported. Most of the current approaches study the applicability of this biometric trait using one lead signals only. It is shown in this study that all signals of the conventional 12 lead system embed discriminative power. Two approaches are suggested for fusion of this information. When the features are associated at a feature level, the identification performance is not as high as expected. This suggests that specific lead information with poor performance when tested independently, overrules highly discriminative information contributed by other leads. However, when combining the outcome of different classifiers at a decision level, the subject and window recognition performance increases while there is a tradeoff between the identifying and rejecting individuals.

We propose the employment of all the 12 leads for ECG based biometric identification, as this increases the security level significantly while capturing possible illegal penetration.

VI. ACKNOWLEDGMENTS

This work has been supported by the Natural Sciences and Engineering Research Council of Canada (NSERC) and partially by the Canadian National Medical Technologies Inc. (CANAMET).

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