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ORIGINAL PAPER

ECG biometric analysis in cardiac irregularity conditions

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Abstract Biometric traits offer direct solutions to the critical security concerns involved in identity authentication systems. In this paper, a systematic analysis of the electrocardiogram (ECG) signal for application in human recognition is reported, suggesting that cardiac electrical activity is highly personalized in a population. Features extracted from the autocorrelation of healthy ECG signals embed considerable diacritical power, and render fiducial detection unnecessary. The central consideration of this paper is the evaluation of an identification system that is robust to common cardiac irregularities such as premature ventricular contraction (PVC) and atrial premature contraction (APC). Criteria concerning the power distribution and complexity of ECG signals are defined to bring to light abnormal ECG recordings, which are not employable for identification. Experimental results indicate a recognition rate of 96.2% and render identification based on ECG signals rather promising.

Keywords Electrocardiography · Discriminant analysis · Complexity measure · Cosine transform

1 Introduction

Automatic, reliable and accurate validation of human's identity is required in numerous civilian applications, such as criminal investigations, access authorization and surveillance. Traditional strategies for identification rely on entities (tokens, ID cards) or passwords. However, such strategies are based on something that the user knows or possesses and are vulnerable to certain security attacks.

Biometrics are characteristics extracted directly from human subjects to form signatures for identity verification systems. By designing the authentication key to be highly correlated to physiological or behavioral features of an individual's identity, this class of strategies offers airtight security [1]. Several biometrics modalities have been used so far, among which are fingerprints, the iris, the face, the voice, the keystroke and the gait. Although most of them have gained wide acceptance, the main limitation in their application is their defenseless nature against falsification.

According to [1], there are few criteria that a biometric feature has to meet. First, it must be universal i.e., applicable to all individuals. Also, it must be significantly reliable over the enrollees population, and stable over a sufficiently long period of time. Finally, the feature must be quantitatively measurable.

Lately, attention has been drawn in the employment of a new biometric trait, the electrocardiogram (ECG) [2–7]. ECG signals reflect the cardiac electrical activity and subsequently, have been studied for medical diagnostic purposes thoroughly. The idea of identifying subjects with the ECG is relatively young but it embraces considerable advantages. The key benefit is the robustness against falsified credentials as it is hard to steal ECG and impossible to mimic it. In addition, ECG itself is a liveness indicator, suggesting that potential applications will have a way to reassure that the subject who is offering the biometric is indeed the one who is carrying it. This is not the case with conventional biometrics such as fingerprint, iris, face and so on where additional mechanisms are needed to guarantee liveness.

To date, most of the reported methodologies, use features which picture morphological attributes of heart beat cycles (i.e. amplitude and temporal distances of successive fiducial

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points) [2–7]. Such methods rely heavily on the localization of wave boundaries among heart beats. Current fiducial detection algorithms are used in the medical field solely, where a rough approximation of their position is adequate for diagnosis. This is not the case with biometric applications, where in order to extract reliable features from heart beats, they have to be isolated and perfectly synchronized. Furthermore, there is no universally acknowledged rule to define fiducial points with precision [8], which often limits the effectiveness of underlying biometric systems.

The remainder of this paper is organized as follows. Sections 2 and 3 provide a brief introduction to ECG waveforms, to the sources of inter-individual variability and to common cardiac disorders. Section 4 reports existing approaches on ECG based identification. The proposed identification methodology is discussed in Sect. 5, and the ECG based authentication technique is described in Sect. 6. Our experimental results are reported in Sect. 7.

2 Inter-individual variability of ECG

In order to satisfy the requirements for universality and permanence, it is crucial to examine the uniqueness of ECG signals. When monitoring a population, different cardiac electrical signals conform to roughly the same repetitive pattern. However, further analysis of ECGs can reveal remarkably correlated trends among multiple recordings of a subject. Paradigms of ECG inter-individual distinctions can be found in the literature [9–15].

Electrophysiological and geometrical variations of the heart are embedded in ECG signals. Model studies have shown that physiological factors such as the heart mass orientation, the conductivity of various areas of the cardiac muscle and the activation order of the heart, can introduce significant variability among subjects [14,15].

Furthermore, geometrical attributes such as the exact position and orientation of the myocardium, and torso shape designate ECG signals with particularly distinct and personalized characteristics. Other attributes that operate on ECG signals are the timing of depolarization and repolarization and lead placement. In addition, except for the anatomic idiosyncrasy of the heart, unique patterns are related to physical attributes such as the body habitus and gender [9,13–16]. The electrical map of the area surrounding the heart may also be affected by variations of other organs in the thorax [15].

Various methodologies have been suggested to eliminate the differences among ECG recordings. The idea of clearing off inter-individual variability is standard when seeking to establish normal rates of the ECG morphology [10]. Automatic diagnosis of pathologies via the ECG becomes more feasible when the level of variability among healthy people is lower [14]. In such algorithms, personalized parameters of every subject are treated as random variables and a number of criteria have been defined to quantify the degree of subjects' similarities on a specific feature basis.

However, a critical consideration is the vulnerability of ECG waveforms to rhythm anomalies, referred to as cardiac arrhythmias. Several types of arrhythmias can be met, some of which are life-threatening [such as ventricular tachycardia (VT) or fibrillation (VF)]. Most often, a cardiac arrhythmia disrupts the healthy representation of the signals. Therefore, the invariance of an ECG biometric system to rhythm distortions is a basic prerequisite.

In this paper, motivated by both the cardiac irregularities problems and the fiducial detection inaccuracies, a new framework is presented for identification via the ECG. A windowing technique is adopted to eliminate the shortcomings of localizing fiducial points. A new approach capable to identify malignant ECGs by means of an irregularity screening process is proposed.

3 ECG waves and cardiac disorders

For the ECG to be recorded, electrodes are attached on the surface of the body in multiple configurations that provide representation of typical aspects of the heart cycle. The first ECG recorder apparatus was developed by the physiologist Wiliam Einthoven in the twentieth century. Up to now, the traits of heart's electrical behavior have been under analysis for clinical applications.

The ECG is a non periodic but highly repetitive signal that is mainly composed of three waves. Figure 1 shows the most significant components of an ECG signal i.e., the *P* wave, *QRS* complex and the *T* wave.

The *P* wave has usually positive polarity and a duration of 120 ms. This wave mainly reflects the depolarization of the right and left atria. The *QRS* complex describes the depolarization of right and left ventricles. In normal sinus rhythms, its duration varies between 70–110 ms. Finally, the *T* wave reflects a depolarization of the ventricles and is usually

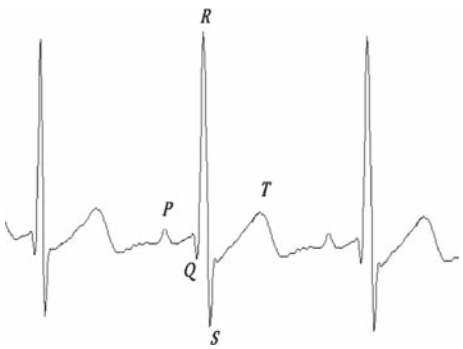

Fig. 1 Salient components of an ECG signal

observed about 300 ms after the *QRS* complex. However, its exact position relies on the heart rate and appears closer to the *QRS* complex at rapid rhythms [17].

The spectral characteristics of ECG waves are central to the application of signal processing algorithms. A healthy *P* wave is considered to contribute to the low frequency components at about 10–15 Hz. On the other hand, a *QRS* complex has a spectrum of comparately high frequencies due to its steep slopes. The spectral content of this complex is usually found in the 10–40 Hz band.

In ECG monitoring, commonly encountered types of premature heart beats are the premature ventricular contraction (PVC) and the atrial premature contraction (APC). These kinds of irregularities are not lethal but they indicate abnormalities of the heart.

In addition, there are cases refered to as arrhythmias, where the structure of the signals undergos severe alterations and require immediate medical assistance. Examples of this type of anomalies are the atrial or VT, atria flutter and VF.

4 Related works

Analysis of the ECG signal has been in the spotlight for clinical study and research for the past two decades. Only lately have ECGs been considered for biometric applications.

Biel et al. [2] were among the first to manifest the applicability of ECGs as biometric. Their approach is to extract a set of temporal and amplitude features from heart beats that are normally used in clinical diagnosis. The features were obtained directly from a SIEMENS ECG equipment and their dimensionality was reduced by simple analysis of the correlation matrix. Further selection was based on experiments. The experimental setup involved 20 subjects of varying ages. An 100% human identification rate was achieved but the major drawback of the method was the lack of automatic recognition, since specific apparatus was used for feature extraction.

Israel et al. [3] introduced an ECG based identification system where only temporal features were employed. An input ECG was filtered to eliminate the effects of noise and the signal's peaks were detected in the time domain by finding local maxima in the regions surrounding each of the *P*, *R* and *T* complexes. Then, 15 features were extracted that denote the time distances between detected features. Wilks' Lamda was used for feature selection and linear discriminant analysis (LDA) was used for classification. The system achieved 100% subject recognition and 81% heartbeat recognition rate for a total of 29 subjects. In a later work by Israel et al. [4], a framework that fuses face and ECG traits was reported. This method offers automatic identification, however, it may still experience shortcomings due to sensitivities in the localization of fiducial points.

Shen et al. [5] reported another method for one lead ECG identity verification. First, template matching was used to compute the correlation coefficient among *QRS* complexes in order to verify possible candidates. A decision based neural network (DBNN) was then used to strengthen the validation of the identity resulting from the first step. The experimental results of this system, tested on 20 subjects have provided a recognition rate of 95% for template matching, 80% for the DBNN and 100% for the combination of the two. This methodology was later extended by Shen [6] with a larger database containing 168 healthy subjects. The highest identification rate achieved in that work was 95.3%.

Wang et al. [7] suggested an integration of analytic and appearance features from heart beats. The preprocessed ECG signal was subjected to fiducial points detection to measure temporal and amplitude distances. The classification performance showed that even though amplitude features have discriminative ability, analytic features are not sufficient for identification. Experiments were conducted on the extraction of appearance related characteristics with the help of either the principal component or LDA. When the two types of features were combined in a hierarchical scheme, a 100% subject and 98.9% heart beat recognition rates were reported for 13 subjects.

In summary, the main drawback of the above systems is the low accuracy in the automatic detection of fiducial points. Healthy abnormalities of ECG recordings can lead to rejection of heart beats due to poor localization of their components. Figure 2a illustrates ECG heart beats collected from the same subject and synchronized at the *QRS* complex, revealing large variation around the *P* and *T* waves. Figure 2b shows an example of inaccurate detection of *T* wave's boundaries.

In addition, these works did not account for cardiac irregularities. This can be a limiting factor for such technologies. There are some kinds of abnormalities (PVC, APC) caused by every day factors such as caffeine consumption or stress, which affect the ECG. Previously proposed ECG identification systems did not address this issue. Furthermore, the recognition features considered in [2–7] are themselves vulnerable to common cardiac irregularities.

Among the earliest works on arrhythmia detection is Chen et al. [19]. The suggested methodology makes use of the quantitative differences between the autocorrelation (AC) of healthy and arrhythmia records. A regression test was applied on the peak magnitudes of autocorrelated ECGs to reveal the aperiodic nature of VF and tachycardia signals. Even though the system achieved high detection rates it did not address irregularity types such as PVC and APC.

To improve the identification accuracy including abnormal heart beat scenarios, we propose a new technique for ECG recognition. We suggest that classification features are derived from the AC of ECG windows [20,21]. A power

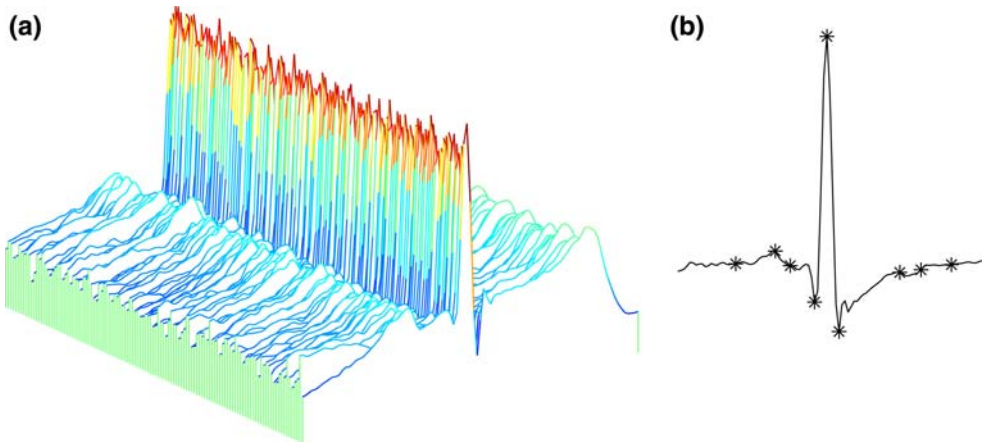

Fig. 2 **a** Waterfall diagram of ECG pulses collected from the same subject of the MIT-BIH Normal Sinus Rhythm database [18]. **b** Ambiguous localization of fiducial points

criterion for the autocorrelated ECG is applied in conjunction with a complexity measure (Cm), to distinguish and discard those irregular segments not suitable for recognition. Automatic detection of cardiac disorders is a very active area of research. However, in order to control complexity, our framework for arrhythmia detection is based once more on AC to seek for malignant ECG segments. As a final step, classification is carried out among healthy recordings brought to light by LDA. The proposed approach completely eliminates the need for fiducial point localization and provides improved operability.

5 Identification methodology

Human identification is essentially a pattern recognition problem involving three main steps: preprocessing, feature extraction and classification. The framework described in this paper is graphically depicted in Fig. 3. Preprocessing can be regarded as a noise and artifact removal step. Feature extraction operates directly on the AC of a few seconds of ECG to form distinctive personalized signatures for every subject. As in most pattern recognition problems, classification among a gallery set is the last step of the identification process.

The AC of repetitive signal like the ECG, exhibits diacritical characteristics in a population. However, before extracting features for classification, it is essential to examine various windows from the ECG records and verify only those with healthy AC structure. This step reassures the robustness of the system to the presence of pathological records. During screening, the algorithm discards those segments that have abnormal AC, through a careful detection of irregular heart beats.

5.1 Preprocessing

The ECG data in raw format contain a lot of noise which has to be eliminated. The most common types of noise in ECGs are the baseline wander and the powerline interference. Baseline wander is caused by low frequency components that force the signal to extend away from the isoelectric line. The source of this kind of artifacts is the respiration, body movement or inadequate electrode attachment. Furthermore, power line interference is generated by poor grounding or conflicts with nearby devices [17].

To reduce these effects, a Butterworth band pass filter of order 4 is used in the current experimentation. The cutoff frequencies of the filter are 1–40 Hz based on empirical results.

5.2 PVC Screening

The repetitive property of the ECG signal is not distorted in cases where atrial premature contraction heart beats appear. An APC results in pulses that are morphologically healthy but occur earlier in time than expected. Since the signal preserves its quasi-periodic property the structure of the AC does not change significantly (Fig. 4) and thus the ECG is suitable for identification. The methodology used for screening is tolerant to APC ECG windows.

On the other hand, a PVC results in beats whose appearance deviates substantially from healthy heart beats. A PVC usually inhibits the next normal beat and introduces a pause of almost twice the length of a cycle [17]. This kind of irregular heart beats force the AC to deviate from that of a repetitive signal as illustrated in Fig. 5, where a healthy and a PVC ECG segment along with the respective ACs are plotted. It is crucial to detect and dismiss PVC ECG segments before proceeding to the identification stage.

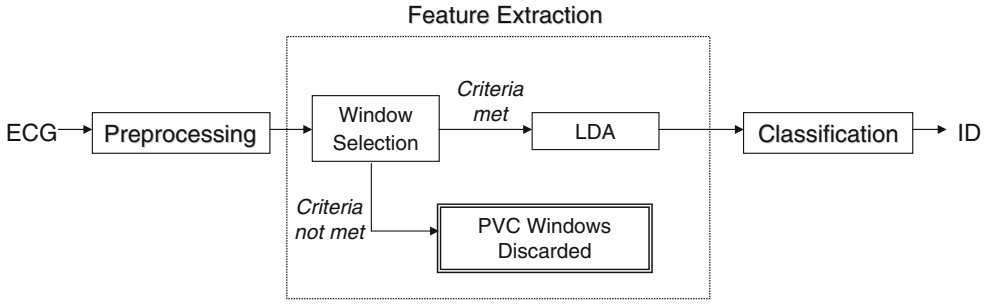

Fig. 3 Block diagram of proposed method

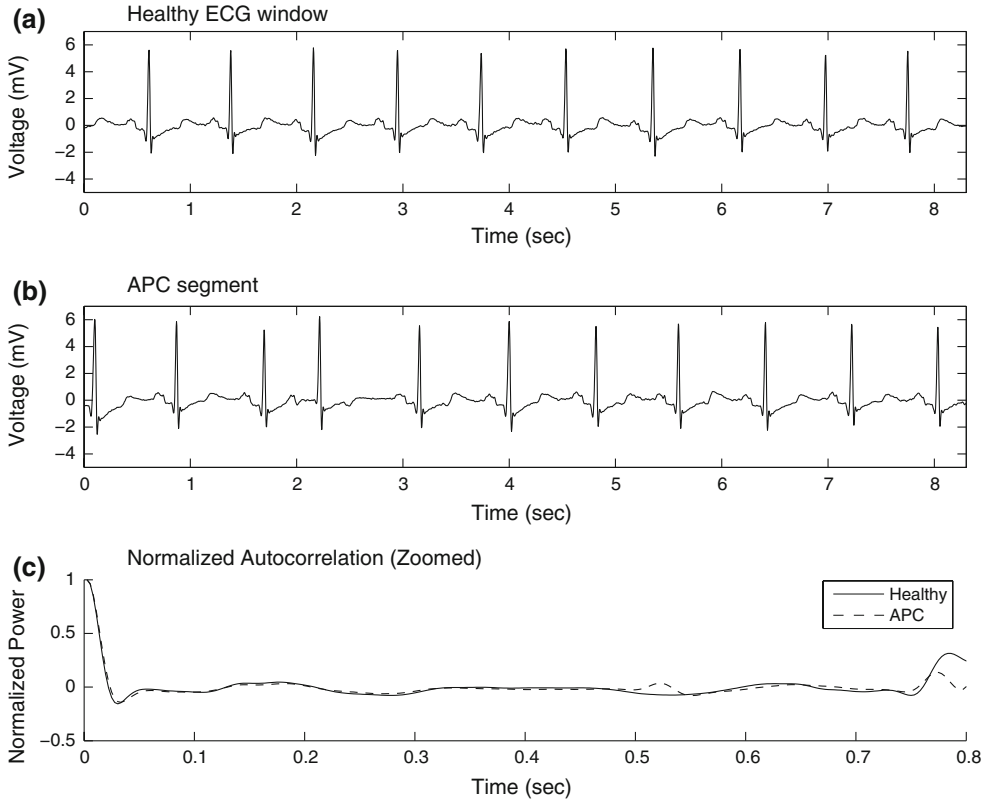

Fig. 4 **a** Lead II healthy ECG segment from a subject in the MIT-BIH Arrhythmia database [22]. **b** Lead II ECG segment with APC around the second from the same subject. **c** Normalized autocorrelations of the ECG windows from **a** to **b**

PVC screening acts complementary to the identification module. In the remainder of this paper we will refer to ECG windows with PVCs (and not APCs) as irregularities, suggesting that they are not qualified for identification.

A window based method is adopted for feature extraction both to extract identity related features and to detect malignant segments. This releases the need for fiducial points detection. Windowing is allowed to blindly cut the recording even in the middle of a pulse. The only restriction is for the window length to be greater than the average heart rate so that multiple pulses are included.

The AC of ECG segments has been reported to contain distinctive information of individuals [20,21]. The motivation behind the use of AC is to capture the repetitive property of the ECG and to operate on ECG samples which would otherwise need to be scanned by a fiducial detector.

PVC screening encapsulates two modules. As a first step, a power criterion is placed on the AC spectrum. For those ECG windows that meet this criterion, a second process based on an entropy measure which indicates the degree of complexity in the AC is then applied.

Both the arrhythmia screening and identity verification processes depend on the AC of ECG windows. This commonality allows to better control the overall computational effort of the system. The AC is computed for every ECG window to provide a shift invariant representation of similarity features

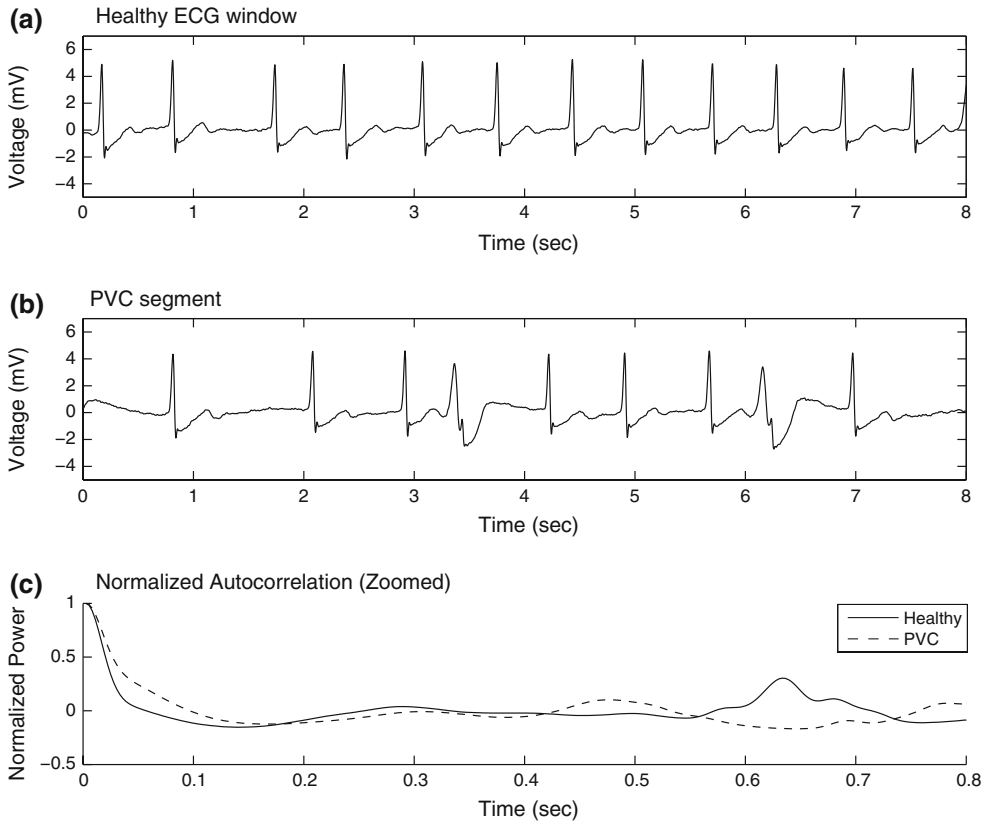

Fig. 5 **a** Lead II healthy ECG segment from a subject in the MIT-BIH Arrhythmia database [22]. **b** Lead II ECG segment with PVC from the same subject. **c** Normalized autocorrelations of the ECG windows from **a** and **b**

over multiple heart cycles. The AC coefficients $\widehat{R}_{yy}[m]$ are computed as:

$$\widehat{R}_{yy}[m] = \sum_{i=0}^{N-|m|-1} y[i]y[i+m] \tag{1}$$

where $y[i]$ is the windowed ECG for $i = 0, 1, \ldots (N-|m|-1)$, and for different time lags $m = 0, 1, \ldots (M-1)$; $M \ll N$. To normalize, the AC $\widehat{R}_{yy}$ is divided by its maximum value at zero lag. Normalization is necessary because even though the major contributors to the AC distribution are the P, T waves and the QRS complex, large variations in amplitudes might appear even among the heart beats of the same subject.

5.2.1 Power criterion

When exposing an ECG window to a premature ventricular heart beat, the morphology of the AC is distorted as illustrated in Fig. 5. The regularity of the AC peaks is strongly affected, and the spectrum of the signal is penetrated by smaller frequencies. The discrete cosine transform (DCT) is used at this point, to define a criterion for the power distribution. The frequency coefficients of the AC are estimated as follows:

$$Z[u] = G[u] \sum_{i=0}^{N-1} z[i] \cos \frac{(2i+1)u\pi}{2N} \tag{2}$$

where N is the length of the signal. For the screening algorithm $z[i]$ is the autocorrelated ECG obtained from Eq. 1. The $G[u]$ is given by:

$$G[u] = \begin{cases} \sqrt{\frac{1}{N}}, & u = 0 \\ \sqrt{\frac{2}{N}}, & 1 \le u \le N-1 \end{cases} \tag{3}$$

Figure 6a demonstrates the normalized ACs of 24 healthy and PVC diagnosed ECGs, while Fig. 6b shows the corresponding frequency distribution with DCT.

To distinguish between healthy and malignant DCT waveforms, the criterion considered in this paper measures the concentration of power. It has been observed that the AC of arrhythmic ECG segments has half of its total power concentrated in the frequency interval 0.5–7.2 Hz. For any power distribution, the DCT coefficient where half of the total power is contained can be found by:

$$k = \min\left(\left| \sum_{i=1}^{k} Z(i) - \sum_{i=k}^{N} Z(i) \right| \right) \tag{4}$$

where $Z(i)$ are the coefficients of the DCT.

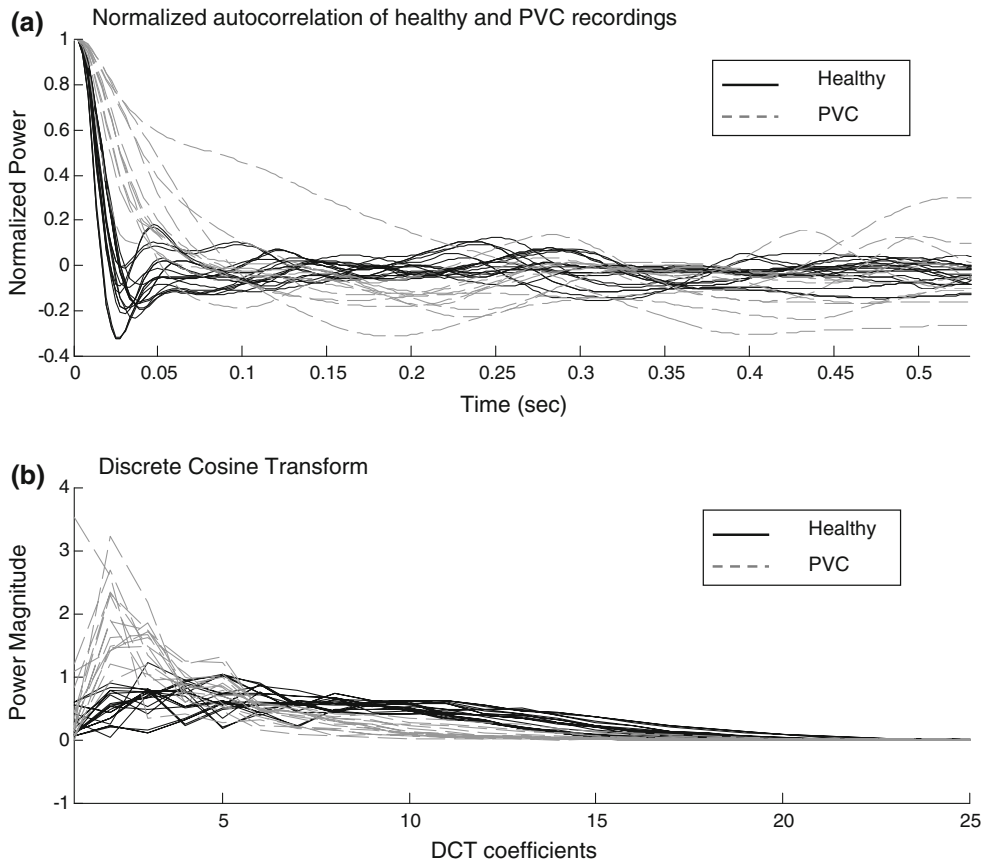

Fig. 6 **a** Normalized autocorrelation (zoomed) of healthy and PVC ECG windows. **b** Frequency spectrum of healthy and PVC ECG windows with the discrete cosine transform

In principle, the Discrete Fourier Transform (DFT) can be used instead of DCT. However, a criterion concerning the distribution of the power spectrum applies better to DCT coefficients, because of the energy compaction property of DCT. In addition, experimental results have shown that the DFT is less distinctive between normal and abnormal signals.

5.2.2 Complexity measure

The Cm of finite sequences has been proposed by Lempel and Ziv [23]. Few works have been reported about its applicability in analyzing ECG signals [24–26]. In this paper, Cm is associated to the AC of ECG signals because it is computationally efficient.

A Cm reveals the number of patterns that are hidden in a finite sequence, to describe the degree of disarrangement. In this work, Cm is used to capture essential morphological structures of the autocorrelated ECG. By acknowledging that the AC of quasiperiodic or repetitive signals has peaks recurring periodically, Cm is expected to reveal their frequency of appearance.

Prior methodologies have utilized the Cm to detect VF and VT arrhythmias [24–26]. In this class of arrhythmias, not only the rhythm but the total of the ECG's physiological properties may change.

On the other hand, premature atrial and ventricular contractions result in isolated abnormal heart beats, while healthy pulses also appear. The Cm cannot be used to detect localized differences between healthy ECGs and PVC or APC, however, it is suitable for the detection of VT and VF.

To apply this measure on the AC, with the mathematical definitions provided by Lempel and Ziv [23], it needs to be translated into a binary sequence. In this binary projection, local maxima are represented by ones while all the remaining samples by zeros. For peak detection, AC waveforms are passed through a lowpass filter with a cutoff frequency at 5 Hz so that small peaks of less interest are eliminated. Our expectations that the complexity of arrhythmic AC will be higher than that of healthy records are verified by the results of Fig. 7.

According to [23], the algorithm for the computation of the Cm proceeds as demonstrated in Fig. 8 and the following definitions:

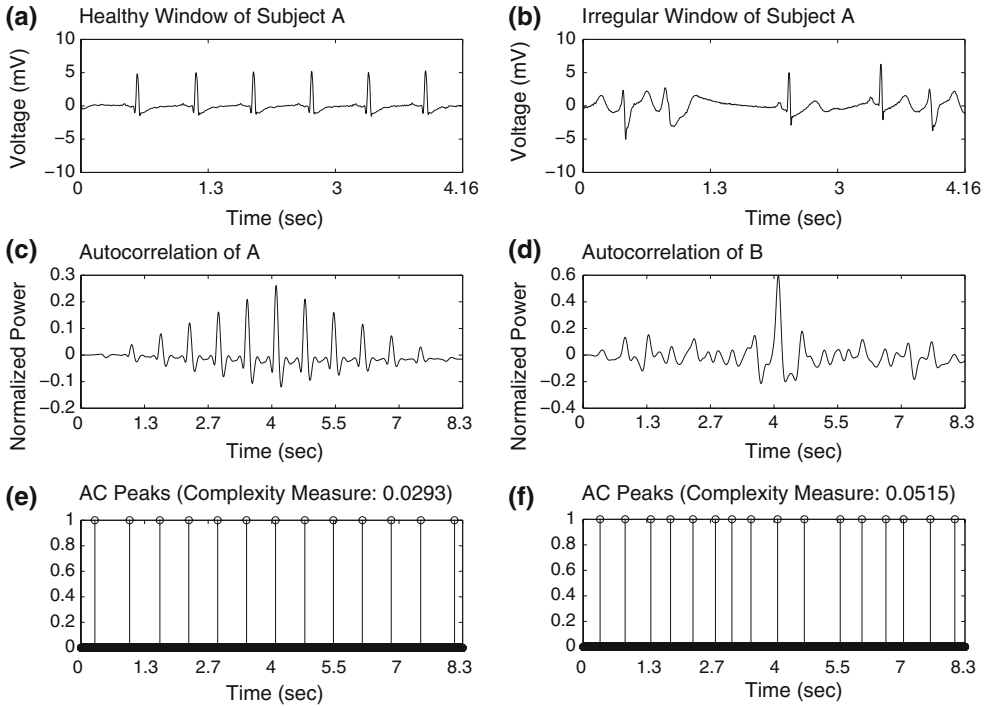

Fig. 7 **a–b** A healthy and a malignant ECG window (Lead II). **c–d** The corresponding normalized ACs after filtering. **e-f** Binary sequences showing the peaks of the autocorrelated ECGs

- x is the binary AC sequence
- S and Q are two binary strings
- SQ is the concatenation of S and Q
- $l(SQ)$ is the length of sequence SQ
- $SQ\pi$ is SQ where the last character is deleted
- $v(SQ\pi)$ is the vocabulary of $SQ\pi$, i.e. different substrings that $SQ\pi$ embeds

When the algorithm begins, the Cm is set to one. S and Q are set to be the first and second characters of the sequence x, respectively. In the midst of the computations, if Q is an existing word in the $v(SQ\pi)$ vocabulary, then Q is appended with the next symbol of x, while Cm and S remain the same. However, if Q does not exist in $v(SQ\pi)$, Cm is augmented by one, SQ is assigned to S, and Q becomes the next character of the x sequence. This process stops when the sequence x is scanned.

Lempel and Ziv [23] have also shown that the upper limit of Cm for a binary sequence x of length $l(x) = n$ is:

$$\lim_{n\to\infty} \mathrm{Cm}(n) = b(n) \equiv \frac{n}{\log_2(n)} \tag{5}$$

A normalized complexity measure C which is independent of the sequence length is utilized instead:

$$C = \frac{\mathrm{Cm}(n)}{b(n)} = \mathrm{Cm}(n)\frac{\log_2(n)}{n} \tag{6}$$

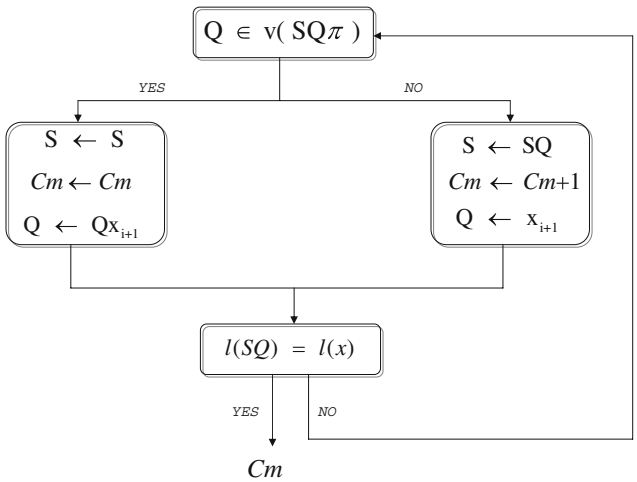

Fig. 8 Block diagram depicting the steps of the algorithm for the computation of Cm

Note that $0 \leq C \leq 1$ with values closer to one indicating higher complexity.

5.3 Feature extraction and identification

Having acquired an optimal set of suitable windows for identification, the next step toward recognition is to design feature vectors and classify. As mentioned earlier, features for identification are based on the AC coefficients. However the

Table 1 (A) Variance matrices, mean and projection of linear discriminant analysis. (B) Covariance matrix, ensemble mean and projection of principal component analysis

(A)	(B)
$S_b = \frac{1}{N}\sum_{i=1}^{U} U_i(\overline{z_i} - \overline{z})(\overline{z_i} - \overline{z})^T$	$S_{\text{cov}} = \frac{1}{N}\sum_{i=1}^{U}\sum_{j=1}^{U_i}(z_{ij} - \overline{z})(z_{ij} - \overline{z})^T$
$S_w = \frac{1}{N}\sum_{i=1}^{U}\sum_{j=1}^{U}(z_{ij} - \overline{z_i})(z_{ij} - \overline{z_i})^T$	
$\overline{z_i} = \frac{1}{N_i}\sum_{j=1}^{U_i} z_{ij}$	$\overline{z} = \frac{1}{N}\sum_{i=1}^{U}\sum_{j=1}^{U_i} z_{ij}$
$y = \psi^T z$	$y_{ij} = \psi^T(z_{ij} - \overline{z})$

dimensionality of such a feature space is considerably high and inappropriate for cost efficient systems.

To reduce the dimensionality, the LDA is utilized. LDA is a well-known statistical method for feature extraction. Supervised learning is performed in a transform domain so that eventually the feature space is projected in lower dimensions and the classes are better distinguishable.

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 autocorrelated windows $\mathbf{z_{ij}}$ a set of K feature basis vectors $\{\psi_m\}_{m=1}^{K}$ can be estimated by maximizing Fisher's ratio. Maximizing this ratio is equivalent to solving the following eigenvalue problem:

$$\psi = \arg\max_{\psi} \frac{|\psi^T \mathbf{S}_b \psi|}{|\psi^T \mathbf{S}_w \psi|} \tag{7}$$

where $\psi = [\psi_{\mathbf{1}}, \ldots, \psi_{\mathbf{K}}]$, and $\mathbf{S_b}$ and $\mathbf{S_w}$ are the between and within class scatter matrices respectively, computed as shown in Table 1(A). LDA finds ψ as the K most significant eigenvectors of $(\mathbf{S}_W)^{-1}\mathbf{S}_b$ which correspond to the first K largest eigenvalues. A test input window $\mathbf{z}$ undergoes the linear projection $\mathbf{y} = \psi^T\mathbf{z}$, prior to classification [27].

6 Authentication

Identity authentication (or verification) is a very critical procedure performed by biometric systems other than identification. The major difference between identification and verification is the state of knowledge in which the system stands concerning the identity of the subject.

During the identification mode, the purpose is to find the best match between someone's biometric characteristic and all subjects stored in the gallery set. However, during the verification procedure the person to be verified claims an identity and the system decides on the validity of the claim.

In the present work, authentication is accomplished by setting a threshold with respect to the distance between an input subject and the gallery set. When applying LDA the similarity measure employed is the Euclidean distance, and a threshold is selected for that metric. In cases where the resemblance of a pair is unacceptable (higher in distance than allowed) the system denies the validation of the so claimed identity. On the other hand, an individual is positively authenticated when there is an adequately small distance between a pair.

LDA is a supervised learning technique and is thus appropriate for identification as this is a difficult one to many problem. Authenticating, on the other hand, is an one to one process and class-dependent methodologies are not required.

A well known unsupervised technique to provide optimal projection in lower dimensions, is the principal component analysis (PCA). PCA does not engage class information, while managing to retain useful data (principal components) and eliminate redundancies. The route of computations is depicted in Table 1(B) following the notation for LDA.

When PCA is applied for authentication, the cosine distance is used to associate input ECG windows and windows belonging to the target identity. By applying a threshold on this measure, validation or rejection decisions can be made. It is expected that the LDA will outperform PCA, because class information is not embedded in the latter. However, the computational effort of PCA is smaller compared to that of the LDA. This makes PCA more appropriate for real time applications.

7 Experimentation

An evaluation of the proposed framework is reported in this section. The experimentation proceeds as depicted in Fig. 9. The electrode configuration used to test this method corresponds to Lead II. However, all lead signals can be used and combined as they have approximately equal discriminative power [28].

The similarity measure considered is the Euclidean distance. Classification is performed with the nearest neighbor (NN) classifier. The PVC screening performance is measured in (healthy/malignant) classification rates. The overall identification performance is measured in window or multiple window recognition rates. The difference is that when measuring window recognition rates, an individual is

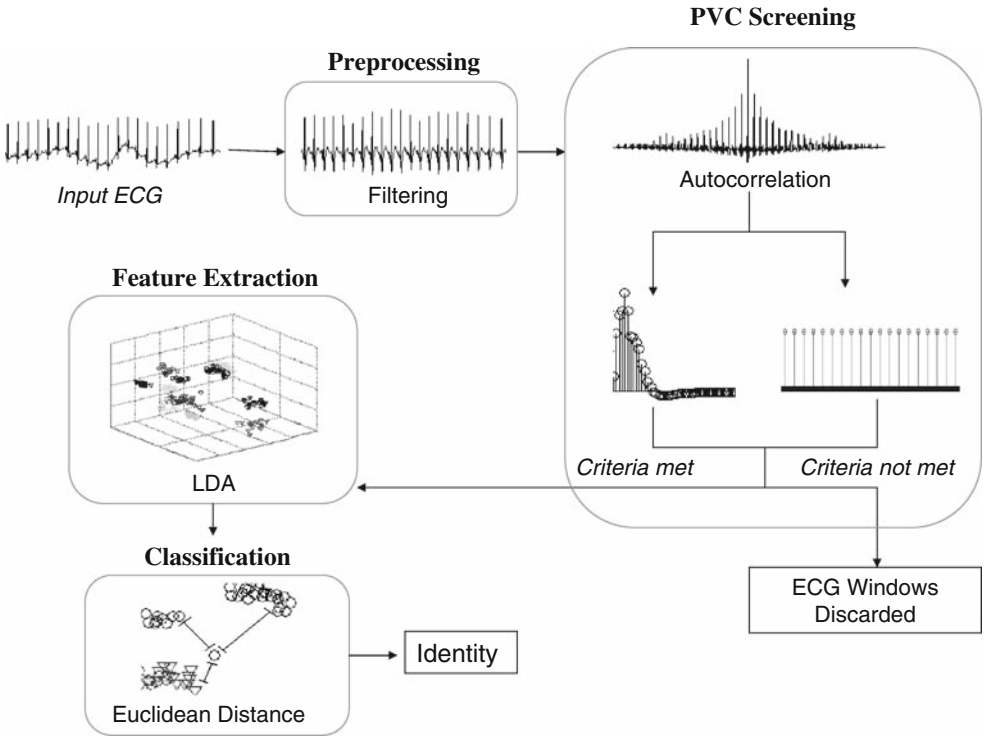

Fig. 9 Flow chart of the experimentation procedure

identified based on only one ECG recording, while for multiple window recognition more than one readings are considered using voting.

7.1 ECG data

To evaluate the performance of the proposed framework in healthy and arrhythmia settings, a series of experiments was conducted on three public databases: the MIT-BIH Normal Sinus Rhythm [18], the MIT-BIH Arrhythmia database [22] and the PTB database [29].

The MIT-BIH Arrhythmia database contains 48 ECG signals that were recorded between 1975 and 1979 at the Beth Israel Hospital Arrhythmia Laboratory. Each of the records is around 30 min long, and they show various kinds of arrhythmias. The sampling frequency of this database is 360 Hz. For our experimental setup, 30 subjects were selected to form a subset of the MIT-BIH Arrhythmia database. This selection was performed in a way that the subset is consisted of ECGs which show mostly PVC and APC. Since the database offers only one recording for every subject, we partitioned the ECG signals into two halves, one for the gallery set and one for testing.

The MIT-BIH Normal Sinus Rhythm database contains 18 ECG recordings from subjects that did not exhibit significant arrhythmias. The recordings were collected at the Laboratory of Boston's Beth Israel Hospital and the sampling frequency is 128 Hz. For our experimental setup, a subset of the database containing 13 subjects was composed. The selection of the subjects for our experiments was based on the length of the recordings. The waveforms of the remaining recordings had many artifacts that reduced the valid heart beat information and for this reason they were not used in our experiments. Once again, the signals were partitioned into two halves, one to build the gallery set, along with the arrhythmia records, and one to test the system. In order to provide comparative results between the two databases, the records of the MIT-BIH Normal Sinus Rhythm Database were re-sampled to 360 Hz.

The PTB database is offered from the National Metrology Institute of Germany and it contains 549 ECG recordings from 294 subjects. This database contains ECG signals diagnosed with a variety of clinical conditions (myocarditis, valvular diseases, myocardial infraction and so on). The recordings that match the requirements of the current simulations are those marked as healthy. Every record includes the conventional 12-leads and 3 Frank leads ECG. The sampling frequency of these recordings is 1 kHz and it was resampled to 360 Hz for our experiments. In addition, for every subject in the PTB database, at least two recordings are available which were collected a few years apart. A subset of 13 healthy subjects was formed from the PTB database for

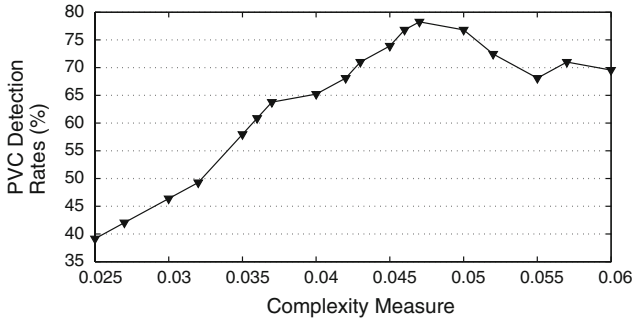

Fig. 10 Classification rates for different complexity measure thresholds

our experiments. The criteria for the selection of the records were, to demonstrate healthy ECG waveforms and to have at least two recordings for every subject. The older recording of every subject was used to built the gallery set and the newer one to test the performance of the method.

7.2 Identification experimental results

For the experimental setup, the window length examined is approximately 10 s. Since the available datasets offer longer recordings, a number of ECG windows is acquired from every subject's recording.

Autocorrelation. The normalized AC is computed for every window using Eq. 1. Out of this sequence, only a segment beginning at zero lag is retained for further analysis. The length of this segment is approximately equal to the duration of a *QRS* complex (the average for all recordings).

A longer AC segment can be used, however, we suggest a length corresponding to the main pulse complex. The rational is that the *QRS* complex exhibits the less variability in time under different heart rate scenarios [3,30]. Such a prearrangement makes the system more robust in cases where anxiety, stress and exercise increase the average heart rate.

Power criterion. To apply the power criterion as introduced in the methodology section, the DCT of every AC segment is computed. For each DCT feature vector the power convergence is approximated through Eq. 4. Analyzing a test set, it was observed for malignant ECG segments that 7.2 Hz is roughly the frequency where half of the total power of the distribution is reached. By adjusting a threshold for classification, and by categorizing a subject as non-healthy if at least one of his/her windows meets the PVC standards, 80% of the subjects are classified correctly. When this principle is combined with the identification procedure, a 94.7% window recognition rate is achieved.

Complexity criterion. Another option for isolating healthy ECG segments is to apply the Cm as discussed earlier. Filtering the autocorrelated ECGs makes the AC peaks easier to detect and convert them into a binary sequence. To capture information about the uniformity of AC peaks, the Cm is evaluated on the entire AC waveform and not just a segment.

For the Cm a classification threshold of 0.048 signifies arrhythmic and healthy records. Figure 10 demonstrates the system's performance in detecting non-healthy subjects. Following the definition for the power criterion, a subject's ECG is considered to be malignant if at least one of the corresponding ECG windows have AC complexity higher than the threshold. By employing the Cm, 78% of the subjects are correctly classified as healthy or not. Moreover, when the Cm alone is combined with the identification mechanism, a 92.5% window recognition rate is achieved.

Integration of the two principles enhances the precision of system. To integrate the two criteria a rule is introduced to dictate that healthy ECG segments are those for which both criteria agree. Roughly speaking, two criteria in stead of one reassure that the treated ECGs have indeed healthy AC structures. By applying strict thresholds for both of them, a more accurate assessment for ECG windows is obtained.

Linear discriminant Analysis. The final phase of the recognition procedure is to assign inputs to clusters. By applying the above mentioned procedure, a set of 2,905 healthy ECG windows is formed. These windows serve for testing the LDA, which is previously trained on a separate but equal amount of healthy training ECGs. For identification among C subjects, LDA can reduce the dimensionality down to C-1 which corresponds to 55 samples for the current experimental setup. A feature vector of that length forms the signature of every testing subject.

Having acquired personalized signatures for the testing subjects, the system proceeds to classification. The window recognition rate accomplished is 96.2% which indicates that a finer selection took place in the screening step, when the two criteria were integrated. Finally, multiple window recognition is estimated with majority voting, to offer an identification performance of 54 subjects out of 56 (26 healthy and 30 arrhythmic).

The overall performance of the described framework is presented in Fig. 11. In this Figure, the classification percentages between every subject in the gallery set and the rest of the subjects including himself is demonstrated in terms of window recognition rates. Cases of misclassified ECG windows appear mostly among non-healthy subjects. More specific, Figs. 11d and e illustrate the recognition performance for healthy and malignant ECG cases independently.

The screening algorithm is highly efficient in detecting and discarding inappropriate windows for identification. However, the misclassification error at that step is propagated

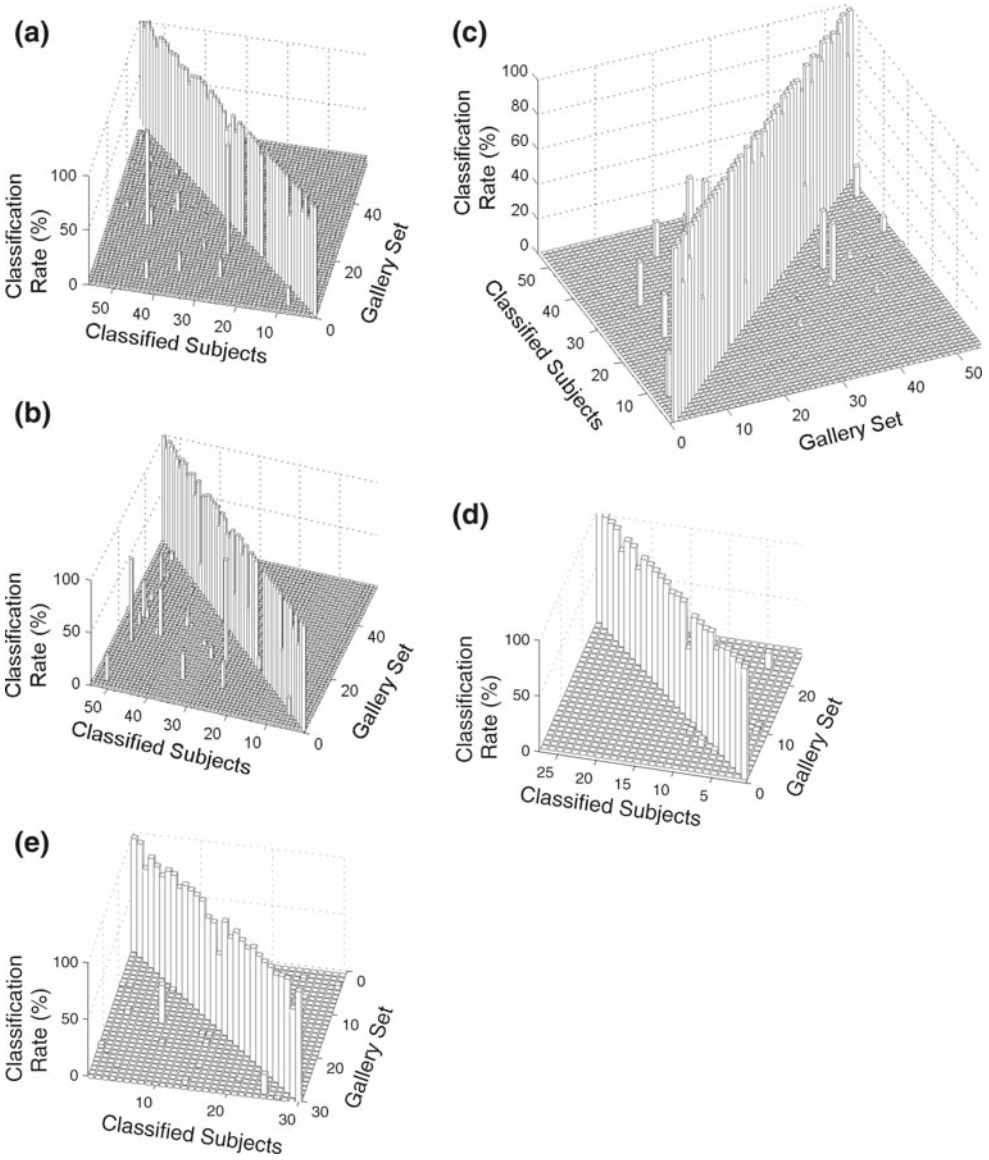

Fig. 11 Classification percentages of every subject against all subjects in the gallery set. **a** Identification performance when only the power criterion is applied during PVC screening. **b** Performance on the complexity measure for screening. **c** Identification performance of the overall system (combined criteria) both for healthy and malignant subjects. **d** Contingency matrix of the overall system tested on healthy subjects only (PTB and MIT-BIH Healthy database). **e** Contingency matrix of the overall system tested on subjects with cardiac irregularities only (MIT-Arrhythmia Database)

to the identification phase, affecting the performance of the system.

Nevertheless, the experimental results demonstrate that ECG based human identification in heart beat disorder scenarios is feasible. A comparison of the current scheme with other frameworks found in literature is summarized in Table 2. The confidence of the decision made by the recognizer can potentially increase if more than one instances of a subject's ECG is stored in the database. In such a case, a K-nearest neighbor $K > 1$ technique or simple majority voting can be employed.

7.3 Authentication experimental results

Both the linear discriminant and principal component analyses have been tested for identity authentication purposes. The selection of a threshold for the Euclidean and cosine distances can be performed empirically based on results from a small training set, however this section presents results for various threshold choices.

Figure 12a shows the validation performance of the system i.e., the rate at which legitimate subjects are verified when reducing dimensionality via discriminant analysis.

Table 2 Table associating the performance of the current approach with other works in the field

		Israel et. al	Biel et. al	Shen et. al	Wang et. al	Proposed method
Feature extraction	Fiducial detection	✓	✓	✓	✓	X
	Feature origin	Heart beats	Heart beats	Heart beats	Heart beats	ECG windows
	Feature specifics	Temporal	Temporal + amplitude + slopes	Temporal + amplitude	Temporal + amplitude + appearance	autocorrelation
	Extraction method	Automatic	Machine based	Automatic	Automatic	Automatic
Feature selection		Wilks' Lamda	Inspection of the correlation matrix	–	PCA or LDA	LDA
Classification		LDA and Majority voting	SIMCA model based on PCA	Prescreening and distance classification	Nearest centre, nearest neighbor, LDA	Nearest neighbor on Euclidean distance
Electrode orientation		Neck, chest	limb leads (I, II, III)	Lead I	Lead II	Lead II
Special experiments		(1) Electrode configurations (2) Anxiety conditions	Different operators	Analysis of the effects of age, gender weight, height and BMI	Integration of analytic and appearance features	Arrhythmia scenarios
Performance	Subject rates	100%	100%	95, 30%	100%	96.42%
	Heart beat/window rates	82%	–	–	98, 90%	96.2%
	Number of subjects	29	20	168	13	56 (2905 windows)

Correspondingly, Fig. 13a demonstrates the verification rates with PCA. The validation rates achieved support the perspective of application in larger ECG databases.

However, authentication has undesired effects, such as false rejections and acceptances. A false rejection takes place when the system denies an identity claim made by a legitimate user. False acceptance is the case where the system verifies the identity of an intruder. The false acceptance and false rejection rates (FAR and FRR) are plotted against different distance thresholds in Figs. 12b and 13b for LDA and PCA features, respectively. It is usually up to the designer to choose a distance threshold for the system. For instance, if a system has a means to reassure that no intruders will claim an identity, a larger selection of the distance threshold seems more appropriate.

According to a related NIST internal report [31], an accurate face recognition system of 1% FAR corresponds to a verification rate of 90.3%. Furthermore, a fingerprint recognizer with 1% FAR offers a verification rate of 99.9%. For the current LDA based system, the verification rate is 87% when FAR is 1%. These findings suggest that ECG can potentially be a powerful biometric characteristic, analogous to more traditional and advanced biometrics.

8 Conclusion

In this paper, an identity recognition system based on ECG is reported and evaluated. It is demonstrated that human identification via the ECG is feasible and highly effective. The ECG's robust nature against falsification makes it rather promising for security systems, as it offers airtight security in all situations. it has been found that although using multiple heart beats of an individual can increase the accuracy of the decision, identification can still be carried out by using just a 10 s ECG recording.

To completely eliminate the need for fiducial points detection, the AC of ECG segments is utilized as a source of highly distinctive signatures among subjects. Discriminant analysis operates on the AC signals to project the features into a lower dimensional space while preserving significant information.

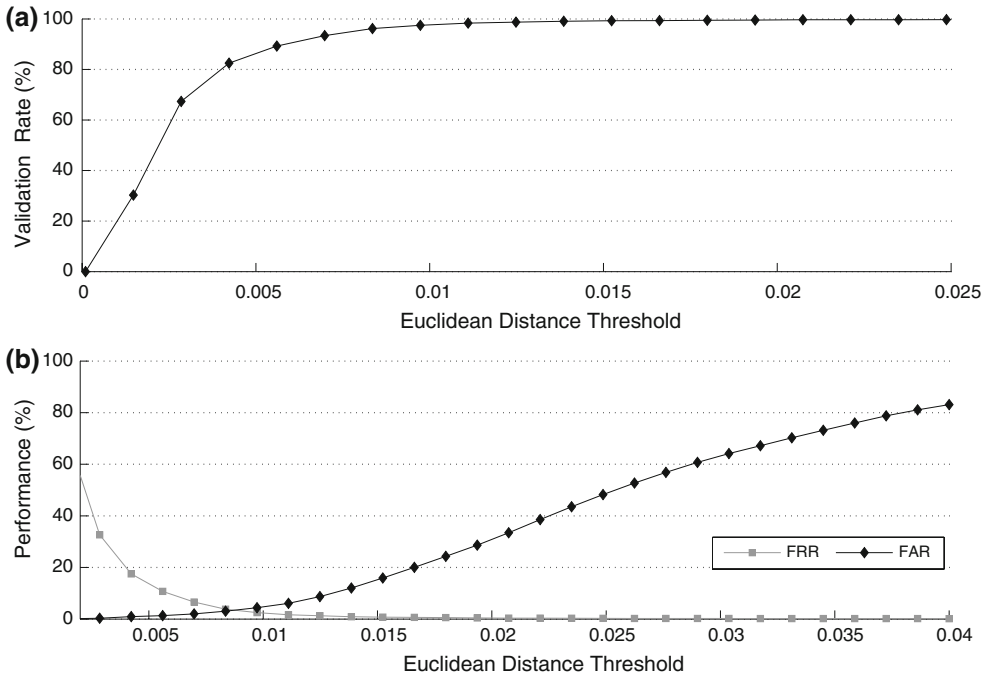

Fig. 12 Linear discriminant analysis **a** Window verification performance for different Euclidean distance thresholds. **b** Corresponding false acceptance and rejection rates

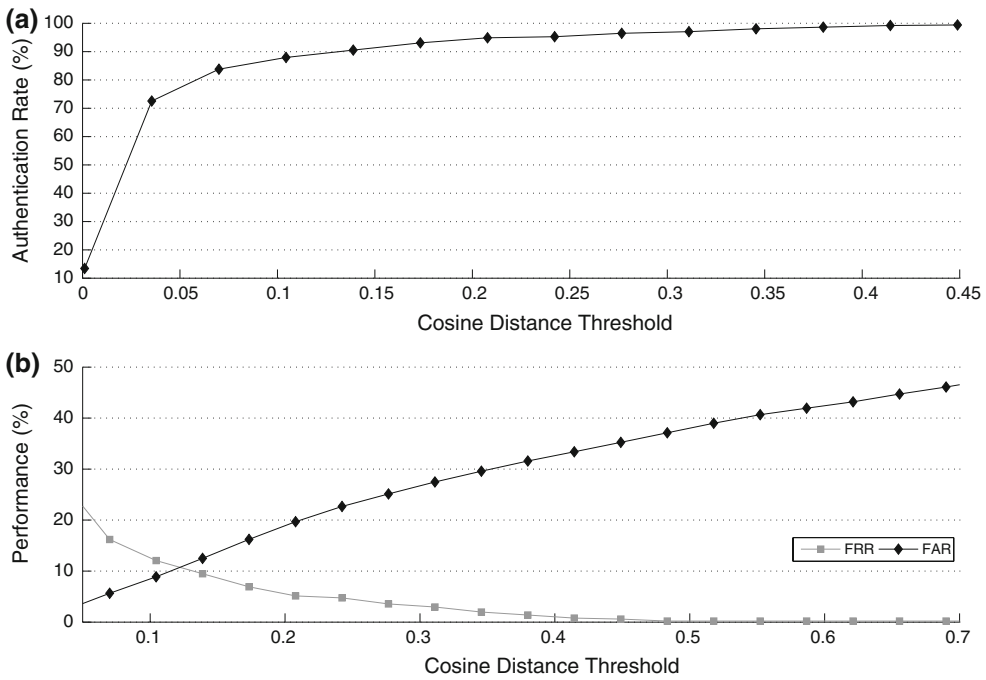

Fig. 13 Principal componet analysis **a** Window verification performance for different cosine distance thresholds. **b** Corresponding false acceptance and rejection rates

No pulse synchronization is needed, keeping this way the computational effort of the system in low levels.

The major novelty of the current work lies in addressing identification in presence of cardiac irregularities which are often encountered and which would otherwise jeopardize recognition. The methodology discussed is invariant to the presence of atrial premature heart beats, while an arrhythmia screening algorithm is proposed to discard windows which

involve ventricular originated heart beats. It is suggested that a power and a Cm criterion constitute a strong combination in isolating pathological ECG segments and resulting in a recognition performance of 96.2%.

It is expected that the ECG will soon find the niche in the biometric world. Future works will investigate the potential of applying ECG based identification under nonfunctional factors, such as stress aging and drug usage.

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