10

Heart Biometrics: Theory, Methods and Applications

Foteini Agrafioti, Jiexin Gao and Dimitrios Hatzinakos
The Edward S. Rogers Sr. Department of Electrical and Computer Engineering University of Toronto 10 Kings College Road, Toronto
Canada

1. Introduction

Automatic and accurate identity validation is becoming increasingly critical in several aspects of our every day lives such as in financial transactions, access control, traveling, healthcare and other. Traditional strategies to automatic identity recognition include items such as PIN numbers, tokens, passwords and ID cards. Despite the wide deployment of such tactics, the authenticating means is either entity or knowledge-based which rises concerns with regard to their ease of acquisition and use from unauthorized third parties.

According to the latest *The US Federal Commission Report, Frebruary 2010* (n.d.), in 2009 identity theft was the number one complaint category (a total of 721,418 cases of consumer complaints). As identity theft can take different forms, credit card fraud was the most prominent (17%), followed by falsification of government documents (16%), utilities fraud (15%), employment fraud (13%) and other. Among these cases, true-identity theft constitutes only a small portion of the complaints, while ID falsification appears to be the greatest threat. Unfortunately, the technology for forgery advances without analogous counterfeit improvements.

Biometric recognition was introduced as a more secure means of identity establishment. Biometric features are characteristics of the human body that are unique for every individual and that can be used to establish his/her identity in a population. These characteristics can be either physiological or behavioral. For instance, the face, the iris and the fingerprints are physiological features of the body with identifying information. Examples of behavioral features include the keystroke dynamics, the gait and the voice. The fact that biometric features are directly linked with the users presents an extraordinary opportunity to bridge the security gaps caused by traditional recognition strategies. Biometric features are difficult to steal or counterfeit when compared to PIN numbers or passwords. In addition, the convenience by which a biometric feature can be presented makes the respective systems more accessible and easy to use.

However, biometric recognition has a drawback that rises from the nature of the authenticating modality. As opposed to static PIN numbers or passwords, biometric recognition may present *false rejection* since usually no two readings of the same biometric feature are identical. Anatomical, psychological or even environmental factors affect the appearance of the biometric feature at a particular instance. For instance, faces may be presented to the recognizers under various expressions, different lighting settings or with occlusion (glasses, hats etc). This may introduce significant variability (commonly referred to as *intra-subject* or *intra-class* variability) and the challenge is to design algorithms that can find robust biometric patterns.

Although the intra-subject variability is universal for all biometric modalities, every feature has unique characteristics. For instance, face pictures may be acquired from distance which makes them suitable for surveillance. On the opposite, fingerprints need direct contact with the sensing device, and despite the robust biometric signature that there exists, most of the error arises from inefficient processing of the image. Therefore, given a set of standards it is difficult, if not impossible, to choose one feature that satisfies all criteria. Every biometric feature has its own strengths and weaknesses and deployment choices are based on the characteristics of the envisioned application environment.

On the assumption that intra-subject variability can be sufficiently addressed with appropriate feature extraction, another consideration with this technology is the robustness to circumvention and replay attacks. Circumvention is a form of biometric feature forgery, for example the use of falsified fingerprint credentials that were copied from a print of the original finger. A replay attack is the presentation to the system of the original biometric feature from an illegitimate subject, for example voice playbacks in speaker recognition systems. Biometric obfuscation is another prominent risk with this technology. There are cases where biometric features are intentionally removed to avoid establishment of the true identity (for example asylum-seekers in Europe *Peter Allen, Calais migrants mutilate fingerprints to hide true identity, Daily Mail* (n.d.)). With the wide deployment of biometrics, these attacks are becoming frequent and concerns are once again rising on the security levels that this technology can offer.

Concentrated efforts have been made for the development the next generation of biometric characteristics that are inherently robust to the above mentioned attacks. Characteristics that are internal to the human body have been investigated such as vein patterns, the odor and cognitive biometrics. Similarly, the *medical biometrics* constitutes another category of new biometric recognition modalities that encompasses signals which are typically used in clinical diagnostics. Examples of medical biometric signals are the electrocardiogram (ECG), phonocardiogram (PPG), electroencephalogram (EEG), blood volume pressure (BVP), electromyogram (EMG) and other.

Medical biometrics have been actively investigated only within the last decade. Although the specificity to the individuals had been observed before, the complicated acquisition process and the waiting times were restrictive for application in access control. However, with the development of dry recoding sensors that are easy to attach even by non-trained personnel, the medical biometrics field flourished. The rapid advancement between 2001-2010 was supported by the fact that signal processing of physiological signals (or *biosignals*) had already progressed for diagnostic purposes and a plethora of tools were available for biometric pattern recognition.

The most prominent strength of medical biometrics is the robustness to circumvention, replay and obfuscation attacks. If established as biometrics, then the respective systems are empowered with an inherent shield to such threats. Another advantage of medical biometrics is the possibility of utilizing them for continuous authentication, since they can provide a fresh biometric reading every couple of seconds. This work is interested in the ECG signal, however the concepts presented herein may be extended to all medical biometric modalities.

2. ECG biometrics: Motivation and challenges

The ECG signal describes the electrical activity of the heart over time. It is recorded non-invasively with electrodes attached at the surface of the body. Traditionally, physicians use the ECG to gain insight on heart conditions, usually with complementary tests required in order to finalize a diagnosis. However, from a biometrics perspective, it has been demonstrated that the ECG has sufficient detail for identification.
The advantages of using the ECG for biometric recognition can be summarized as universality, permanence, uniqueness, robustness to attacks, liveness detection, continuous authentication and data minimization. More precisely,

1. *Universality* refers to the ability of collecting the biometric sample from the general population. Since the ECG is a vital signal, this property is satisfied naturally.
2. *Permanence* refers to the ability of performing biometric matches against templates that have been designed earlier in time. This essentially requires that the signal is stable over time. As it will be discussed later, the ECG is affected by both physical and psychological activity, however even though the specific local characteristics of the pulses may change, the overall diacritical waves and morphologies are still observable.
3. *Uniqueness* is guaranteed in the ECG signal because of its physiological origin. While ECG signals of different individuals conform to approximately the same pattern, there is large inter-individual variability due to the various electrophysiological parameters that control the generation of this waveform. Uniqueness will be further discussed in Section 3.1.
4. *Robustness to attacks*. The particular appearance of the ECG waveform is the outcome of several sympathetic and parasympathetic factors of the human body. Controlling the waveform or attempting to mimic somebody else's ECG signal is extremely difficult, if not impossible. To the best of our knowledge there is currently no means of falsifying an ECG waveform and presenting it to a biometric recognition system. Obfuscation is also addressed naturally.
5. *Liveness detection*. ECG offers natural liveness detection, being only present in a *living* subject. With this modality the recognizer can trivially ensure sensor liveness. Other biometric modalities, such the iris or the fingerprint require additional processing to establish the liveness of the reading.
6. *Continuous authentication*. As opposed to static iris or fingerprint images, the ECG is a dynamic biometric feature that evolves with time. When deployed for security in welfare monitoring environments, a fresh reading can be obtained every couple of second to re-authenticate an identity. This property is unique to medical biometrics and can be vital in avoiding threats such as field officer impersonation.
7. *Data minimization*. Privacy intrusion is becoming increasingly critical in environments of airtight security. One way to address this problem is to utilize as less identifying credentials as possible. Data minimization is a great possibility with ECG biometrics because there are environments where the collection of the signal is performed irrespective of the identification task. Examples of such environments are tele-medicine, patient monitoring in hospitals, field agent monitoring (fire-fighters, policemen, soldiers etc).

Despite the advantages, notable challenges are presented with this technology when envisioning large-scale deployment:

1. *Time dependency*. With time-varying biosignals there is high risk of instantaneous changes which may endanger biometric security. Recordings of the cardiac potential at the surface of the body are very prone to noise due to movements. However, even in the absence of noise, the ECG signal may destabilize with respect to a biometric template that was constructed some time earlier. The reason for this is the direct effect that the body's physiology and psychology have on the cardiac function. Therefore, a central aspect of the ECG biometrics research is the investigation of the sources of intra-subject variability.
2. *Collection periods*. As opposed to biometrics such as the face, the iris or the fingerprint, where the biometric information is available for capturing at any time instance, this is not the case with the ECG signal. Every heart beat is formed within approximately a second, which essentially means that longer waiting times are expected with this technology especially when long ECG segments are required for feature extraction. The challenge however is to minimize the number of pulses that the algorithm uses for recognition, as well as the processing time.
3. *Privacy implications*. When collecting ECG signals a large amount of sensitive information is collected inevitably. The ECG signal may reveal current and past medical conditions as well as hints on the instantaneous emotional activity of the monitored individual. Traditionally, the ECG is available to physicians only. Thus, the possibility of linking ECG samples to identities can imply catastrophic privacy issues.
4. *Cardiac Conditions*. Although cardiac disorders are not as a frequent damaging factor as injuries for more conventional biometrics (fingerprint, face), they can limit ECG biometric methods. Disorders can range from an isolated irregularity (Atria and ventricle premature contractions) to severe conditions which require immediate medical assistance. The biometric challenge is therefore to design algorithms that are invariant to tolerable everyday ECG irregularities Agrafioti & Hatzinakos (2008a).

3. Electrocardiogram fundamentals

The electrocardiogram (ECG) is one of the most widely used signals in healthcare. Recorded at the surface of the body, with electrodes attached in various configurations, the ECG signal is studied for diagnostics even at the very early stage of a disease. In essence, this signal describes the electrical activity of the heart over time, and pictures the sequential depolarization and repolarization of the different muscles that form the myocardium.

The first recording device was developed by the physiologist Williem Einthoven in the early 20th century, and for this discovery he was rewarded with the Nobel Prize in Medicine in 1924 Sornmo & Laguna (2005). Since then, ECG became an indispensable tool in clinical cardiology. The deployment of this signal in biometric recognition and affective computing is relatively young.

Figure 1 shows the salient components of an ECG signal i.e., the *P* wave, the *QRS* complex and the *T* wave. The *P* wave describes the depolarization of the right and left atria. The amplitude of this wave is relatively small, because the atrial muscle mass is limited. The absence of a *P* wave typically indicates ventricular ectopic focus. This wave usually has a positive polarity, with a duration of approximately 120 ms, while its spectral content is limited to 10-15 Hz, i.e., low frequencies.

The *QRS* complex corresponds to the largest wave, since it represents the depolarization of the right and left ventricles, being the heart chambers with substantial mass. The duration of this complex is approximately 70-110 ms in a normal heartbeat. The anatomic characteristics

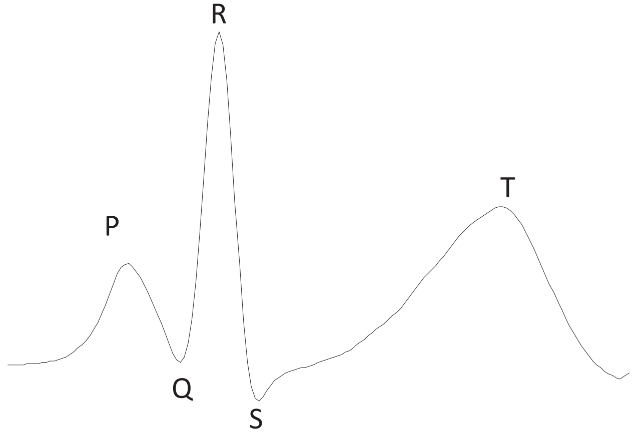


Fig. 1. Main components of an ECG heart beat.

of the *QRS* complex depend on the origin of the pulse. Due to its steep slopes, the spectrum of a *QRS* wave is higher compared to that of other ECG waves, and is mostly concentrated in the interval of 10-40 Hz.

Finally, the *T* wave depicts the ventricular repolarization. It has a smaller amplitude, compared to the *QRS* complex, and is usually observed 300 ms after this larger complex. However, its precise position depends on the heart rate, e.g., appearing closer to the *QRS* waves at rapid heart rates.

3.1 Inter-individual variability

This section will briefly discuss the physiological rationale for the use of ECG in biometric recognition. Overall, healthy ECG signals from different people conform to roughly the same repetitive pulse pattern. However, further investigation of a person's ECG signal can reveal notably unique trends which are not present in recordings from other individuals. The inter-individual variability of ECG has been extensively reported in the literature Draper et al. (1964); Green et al. (1985); Hoekema et al. (2001); Kozmann et al. (1989; 2000); Larkin & Hunyor (1980); Pilkington et al. (2006).

More specific, the ECG depicts various electrophysiological properties of the cardiac muscle. Model studies have shown that physiological factors such as the heart mass orientation, the conductivity of various areas and the activation order of the heart, are sources of significant variability among individuals Hoekema et al. (2001); Kozmann et al. (2000).

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 factors affecting the ECG signal are the timing of depolarization and repolarization and lead placement. In addition, except for the anatomic idiosyncrasy of the heart, unique patterns have been associated to physical characteristics such as the body habitus and gender Green et al. (1985); Hoekema et al. (2001); Kozmann et al. (1989; 2000); Simon & Eswaran (1997). The electrical map of the area surrounding the heart may also be affected by variations of other organs in the thorax Hoekema et al. (2001).

In fact, various methodologies have been proposed to eliminate the differences among ECG recordings. The idea of clearing off the inter-individual variability is typical when seeking to establish healthy diagnostic standards Draper et al. (1964). Automatic diagnosis

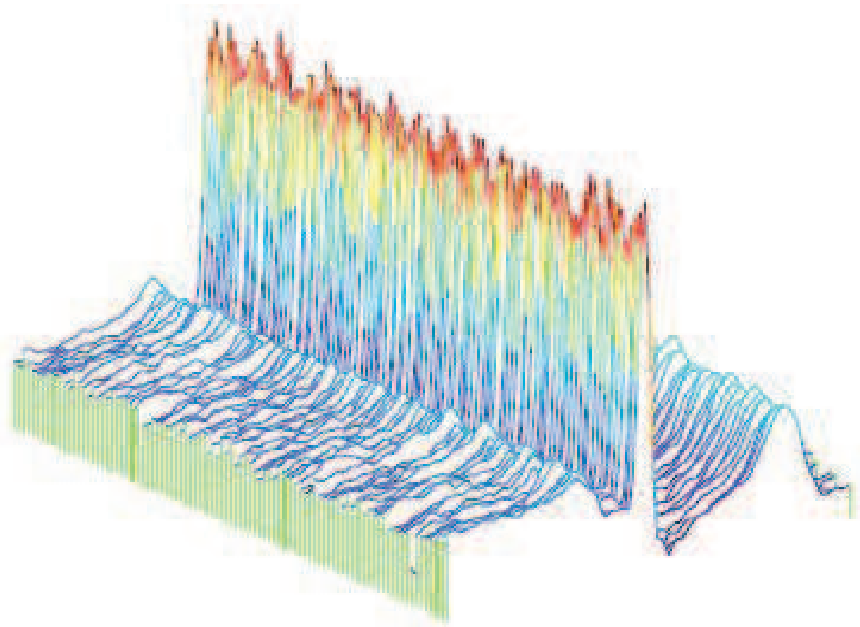


Fig. 2. Variability surrounding the *QRS* complex among heart beats of the same individual.

of pathologies using the ECG is infeasible if the level of variability among healthy people is high Kozmann et al. (2000). 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.

4. Related research

Prior works in the ECG biometric recognition field can be categorized as either fiducial points dependent or independent. Fiducials are specific points of interest on an ECG heart beat such as the ones shown in Figure 1. Therefore, fiducial based approaches rely on local features of the heart beats for biometric template design, such as the temporal or amplitude difference between consecutive fiducial points. On the other hand, fiducial points independent approaches treat the ECG signal or isolated heart beats holistically and extract features statistically based on the overall morphology of the waveform. This distinction has a direct analogy to face biometric systems, where one can operate locally and extract biometric features such the distance between the eyes or the size of the mouth. A holistic approach in this case would then be to analyze the facial image globally.
Both approaches have advantages and disadvantages. While fiducial oriented features risk to miss identifying information hidden behind the overall morphology of the biometric, holistic approaches deal with a large amount of redundant information that needs to be eliminated. The challenge in the later case, is remove this information in a way that the intra-subject variability is minimized and the inter-subject is maximized. For the ECG case, detecting fiducial points is a very obscure process due to the high variability of the signal. Figure 2 shows an example of aligned ECG heart beats which belong to the same individual. Even

though the *QRS* complex is perfectly aligned there is significant variability surrounding the *P* and the *T* wave, rendering the localization of these waves' onsets and offsets very difficult. In fact, there is no universally acknowledged rule that can guide this detection Hoekema et al. (2001).
This section provides an overview of fiducial dependent and independent approaches to ECG biometrics that are currently found in the literature. A comparison is also provided in Tables 1 and 2.

5. Fiducial based approaches

Among the earliest works in the area is Biel et al. (2001) proposal, in 2001, for a fiducial feature extraction algorithm, which demonstrated the feasibility of using ECG signals for human identification. The standard 12 lead system was used to record signals from 20 subjects of various ages. Special experimentation was carried out to test variations due to lead placement in terms of the exact location and the operators who place the electrodes.
Out of 30 clinical diagnosis features that were estimated for each of the 12 leads, only 12features were retained for matching by inspection of the correlation matrix. These features pictured local characteristics of the pulses, such as the *QRS* complex and *T* wave amplitudes, *P* wave duration and other. This feature set was subsequently fed to SIMCA for training and classification. Results of combining different features were compared to demonstrate that the best case classification rate was 100% with just 10 features.
Kyoso & Uchiyama (2001), also proposed fiducial based features for ECG biometric recognition. Overall, four feature parameters were selected i.e., the *P* wave duration, *PQ* interval, *QRS* complex and *QT* durations. These features were identified on the pulses by applying a threshold to the second order derivative. The subject with the smallest Mahalanobis distance between each two of the four feature parameters was selected as output. The highest reported performance was 94.2% for using just the *QRS* and *QT* intervals.
In 2002, Shen et al. (2002) reported an ECG based recognition method with seven fiducial based features defined based on the *QRS* complex. The underlying idea was that this wave is less affected by varying heart rates, and thus is appropriate for ECG biometric recognition.
The proposed methodology encompassed two steps: During a first step, template matching was used to compute the correlation coefficient among *QRS* complexes in the gallery set in order to find possible candidates and prune the search space. A decision based neural network (DBNN) was then formed to strengthen the validation of the identity resulting from the first step. While the first step managed to correctly identify only 85% of the cases, the neural network resulted in 100% recognition.
More complete biometric recognition tests were reported in 2004, by Israel et al. (2005). This work presented the three clear stages of ECG biometric recognition i.e., preprocessing, feature extraction and classification. In addition, a variety of experimental settings are described in Israel et al. (2005) such as, electrode placement and physical stress.
The proposed system employed only temporal features. A filter was first applied to retain signal information in the band 1.1- 40 Hz and discard the rest of the spectral components which were attributed to noise. By targeting to keep discriminative information while applying a stable filter over the gallery set, different filtering techniques were examined to conclude to a local averaging, spectral differencing and Fourier band-pass filter. The highest identification rate achieved was close to 100% which generally established the ECG signal as a biometric feature that is robust to heart rate variability.

A similar approach was reported in the same year by Palaniappan & Krishnan (2004). In addition to commonly used features within QRS complex, a form factor, which is a measure of signal complexity, was proposed an tested as input to a neural network classifier. An identification rate of 97.6% was achieved over recordings of 10 individuals, by training a MLP-BP with 30 hidden units.

Kim et al. (2005), proposed a method to normalize time domain features by Fourier synthesizing an up-sampled ECG heart beat. In addition, the *P* wave was excluded when calculating the features since it disappears when heart rate increases. With this strategy, the performance improved significantly when the testing subjects were performing physical activities.

Another work that addressed the heart rate variations was by Saechia et al. (2005) in 2005. The heart beats were normalized to a the healthy durations and then divided into three sub-sequences: *P* wave, *QRS* complex and *T* wave. The Fourier transform was applied on a heart beat itself and all three sub-sequences. The spectrum were then passed to a neural network for classification. It was shown that false rate was significantly lower (17.14% to 2.85%) by using the three sub-sequences instead of the original heart beat.

Zhang & Wei (2006), suggested 14 commonly used features from ECG heart beats on which a PCA was applied to reduce dimensionality. A classification method based on BayesŠ Theorem was proposed to maximize the posterior probability given prior probabilities and class-conditional densities. The proposed method outperformed Mahalanobis' distance by 3.5% to 13% depending on the particular lead that was used.

Singh & Gupta (2008), proposed a way to delineate the *P* and *T* waveforms for accurate feature extraction. By examining the ECG signal within a preset window before *Q* wave onset and apply a threshold to its first derivative, the precise position of *P* was revealed. In addition the onset, peak and offset of the *P* wave were detected by tracing the signal and examining the zero crossings in its first derivative. The system's accuracy was 99% as tested over 25 subjects.

In 2009, Boumbarov et al. (2009), investigated different models, such as HMM-GMM (Hidden markov model with Gaussian mixture model), HMM-SGM (Hidden markov model with single Gaussian model) and CRF (Conditional Random Field), to determine different fiducial points in an ECG segment, followed by PCA and LDA for dimensionality reduction. A neural network with radial basis function was realized as the classifier and the recognition rate was between 62% to 94% for different subjects.

Ting & Salleh (2010), described in 2010 a nonlinear dynamical model to represent the ECG in a state space form with the posterior states inferred by an Extended Kalman Filter. The Log-likelihood score was used to compare the estimated model of a testing ECG to that of the enrolled templates. The reported identification rate was 87.5% on the normal beats of 13 subjects from the MIT Arrhythmia database. It was also reported that the method was robust to noise for SNR above 20 dB.

The Dynamic time warping or FLDA were used in Venkatesh & Jayaraman (2010), together with the nearest neighbor classifier. The proposed system was comprised of two steps as follows: First the FLDA and nearest neighbor operated on the features and then a DTW classifier was applied to additionally boost the performance (100% over a 12-subject database). For verification, only features related to *QRS* complex were selected due to their robustness to heart rate variability. Same two-stage setting was applied together with a threshold and the reported performance was 96% for 12 legitimates and 3 intruders.

Another fiducial based method was proposed by Tawfik et al. (2010). In this work, the ECG segment between the *QRS* complex and the *T* wave was first extracted and normalized in the time domain by using Framingham correction formula or assuming constant *QT* interval. The DCT was then applied and the coefficients were fed into a neural network for classification. The identification rate was 97.727% for that of Framingham correction formula and 98.18% for that with constant QT interval. Furthermore, using only the *QRS* complex without any time domain manipulation yielded a performance of 99.09%.

6. Fiducial independent approaches

On the non-fiducial methodologies side the majority of the works were reported after 2006. Among the earliest is Plataniotis et al. (2006) proposal for an autocorrelation (AC) based feature extractor. With the objective of capturing the repetitive pattern of ECG, the authors suggested the AC of an ECG segment as a way to avoid fiducial points detection. It was demonstrated that the autocorrelation of windowed ECG signals,embeds highly discriminative information in a population. However, depending on the original sampling frequency of the signal, the dimensionality of a segment from the autocorrelation was considerably high for cost efficient applications. To reduce the dimensionality and retain only useful for recognition characteristics, the discrete cosine transform (DCT) was applied. The method was tested on 14 subjects, for which multiple ECG recordings were available, acquired a few years apart. The identification performance was 100%.

Wübbeler et al. (2007), have also reported an ECG based human recognizer by extracting biometric features from a combination of Leads I, II and III i.e., a two dimensional heart vector also known as the characteristic of the electrocardiogram. To locate and extract pulses a thresholding procedure was applied. For classification, the distance between two heart vectors as well as their first and second temporal derivatives were calculated. A verification functionality was also designed by setting a threshold on the distances. Authenticated pairs were considered those which were adequately related, while in any other case, input signals were rejected. The reported false acceptance and rejection rates were 0.2% and 2.5% corresponding to a 2.8% equal error rate (EER). The overall recognition rate of the system was 99% for 74 subjects.

A methodology for ECG synthesis was proposed in 2007 by Molina et al. (2007). An ECG heartbeat was normalized and compared with its estimate which was constructed from itself and the templates from the claimed identity. The estimated version was produced by a morphological synthesis algorithm involving a modified dynamic time warping procedure. The Euclidean distance was used as a similarity measure and a threshold was applied to decide the authenticity. The highest reported performance was 98% with a 2

In 2008, Chan et al. (2008), reported ECG signal collection from the fingers by asking the participants to hold two electrode pads with their thumb and index finger. The Wavelet distance (WDIST) was used as the similarity measure with a classification accuracy of 89.1%, which outperformed other methods such as the percent residual distance(PRD) and the correlation coefficient(CCORR). Furthermore, a new recording session was conducted on several misclassified subjects which improved the system performance to 95%.

In the same year,Chiu et al. (2008), proposed the use of DWT on heuristically isolated pulses. More precisely, every heart beat was determined on the ECG signal, as 43 samples backward and 84 samples forward from every *R* peak. The DWT was used for feature extraction and the Euclidean distance as the similarity measure. When the proposed method was applied to a database of 35 normal subjects, a 100% verification rate was reported. The author also pointed out that false rate would increase if 10 subjects with cardiac arrhythmia were included in the database.

Fatemian & Hatzinakos (2009), also suggested the Wavelet transform to denoise and delineate the ECG signals, followed by a process wherein every heart beat was resampled, normalized, aligned and averaged to create one strong template per subject. A correlation analysis was directly applied to test heart beats and the template since the gallery size was greatly reduced. The reported recognition rate was 99.6% for a setting were every subject has 2 templates in the gallery.

The Spectogram was employed in Odinaka et al. (2010) to transform the ECG into a set of time-frequency bins which were modeled by independent normal distributions. Dimensionality reduction was based on Kullback-Leibler divergence where a feature is selected only if the relative entropy between itself and the nominal model (which is the spectrogram of all subjects in database) is larger than a certain threshold. Log-likelihood ratio was used as a similarity measure for classification and different scenarios were examined. For enrollment and testings over the same day, a 0.37% ERR was achieved for verification and a 99% identification rate. For different days, the performance was e 5.58% ERR and 76.9% respectively.

Ye et al. (2010), applied the discrete wavelet transform (DWT) and independent component analysis (ICA) on ECG heart beat segments to obtain 118 and 18 features respectively (the feature vectors were concatenated). The dimensionality of the feature space was reduced from 136 to 26 using a PCA which retained 99% of the data's variance. An SVM with Guassian radial basis function was used for classification with a decision level fusion of the results from the two leads. Rank-1 classification rate of 99.6% was achieved for normal heart beats. Another observation was that even though dynamic features such as the *R-R* interval proved to be beneficial for arrhythmia classification, they were not as good descriptors for biometric recognition.

Coutinho et al. (2010), isolated the heart beats and performed 8-bit uniform quantization to map the ECG samples to strings from a 256-symbol alphabet. Classification was based on finding the template in the gallery set that results in the shortest description length of the test input (given the strings in the particular template) which was calculated by the Ziv-Merhav cross parsing algorithm. The reported classification accuracy was 100% on a 19-subject database in presence of emotional state variation.

Autoregressive modeling was used in Ghofrani & Bostani (2010). The ECG signal was segmented with 50% overlap and an AR model of order 4 was estimated so that its coefficients are used for classification. Furthermore, the mean PSD of each segment was concatenated as add-on features which increased the system performance to 100% using a KNN classifier. The proposed method outperformed the state-of-art fractal-based approach such as the Lyapunov exponent, ApEn, Shanon Entropy, and the Higuchi chaotic dimension.

Li & Narayanan (2010), proposed a method to model the ECG signal in both the temporal and cepstral domain. The hermite polynomial expansion was employed to transform heart beats into Hermite polynomial coefficients which were then modeled by an SVM with a linear kernel. Cepstral features were extracted by simple linear filtering and modeled by GMM/GSV(GMM supervector). The highest reported performance was 98.26% with a 5% ERR corresponding to a score level fusion of both temporal and cepstral classifiers.

Tables 1 and 2 provide a high level comparison of the works that can currently be found in the literature.

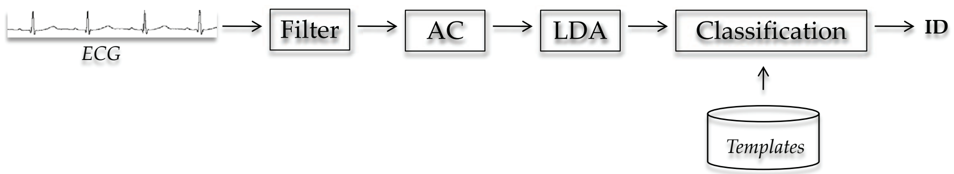


Fig. 3. Block diagram of the AC/LDA algorithm.

7. The AC/LDA algorithm

The AC/ LDA, is a fiducial points independent methodology originally proposed in Agrafioti & Hatzinakos (2008b) and later expanded to cardiac irregularities in Agrafioti & Hatzinakos (2008a). This method, relies on a small segment of the autocorrelation of 5 sec ECG signals. The 5 sec duration has been chosen experimentally, as it is fast enough for real life applications, and also allows to capture the ECG's repetitive property. The reader should note that this ECG window is allowed to cut the signal even in the middle of pulse, and it does not require any prior knowledge on the heart beat locations. The autocorrelation (AC) is computed for every 5 sec ECG using:

$$\widehat{R}_{xx}(m) = \sum_{i=0}^{N-|m|-1} x(i)x(i+m) \tag{1}$$

where $x(i)$ is an ECG sample for $i = 0, 1...(N - |m| - 1)$, $x(i + m)$ is the time shifted version of the ECG with a time lag m, and N is the length of the signal.
Out of $\widehat{R}_{xx}$ only a segment $\phi(m)$, $m = 0, 1...M$, defined by the zero lag instance and extending to approximately the length of a *QRS* complex[1] is used for further processing. This is because this wave is the least affected by heart rate changes, thus utilizing only this segment for discriminant analysis, makes the system robust to the heart rate variability. Figure 3, shows a block diagram of the AC/LDA algorithm.
In a distributed system, such as human verification on smart phones, every user can use his/her phone in one of the two modes of operation i.e., *enrollment* or *verification*. During enrollment, ECG sensors located on the smart phone, first acquire an ECG sample from a subject's fingers and then a biometric signature is designed and saved. Similarly, during verification a newly acquired sample is matched against the store template. Essentially, the verification decision is performed with a threshold on the distance of the two feature vectors. Although verification performs one-to-one matches, false acceptance can be controlled by learning the patterns of possible attackers. Therefore for smart phone based verification the objective is *to optimally reduce the within class variability while learning patterns of the general population*. This can be done with LDA training over a large generic dataset, against which a new enrollee will be learned.
More specific, given a generic dataset (which can be anonymous to ensure privacy) the autocorrelation of every 5 sec ECG segment is computed using Eq. 1. This results into a number of AC segments $\Phi(m)$ against which an input AC feature vector $\phi_{input}(m)$ is learned.

[1] A QRS complex lasts for approximately 100 msec

Method	Principle
Kyoso & Uchiyama (2001)	Analyzed four fiducial based features from heart beats, to determine those with greater impact on the identification performance
Biel et al. (2001)	Use a SIEMENS ECG apparatus to record and select appropriate medical diagnostic features for classification
Shen et al. (2002)	Use template matching and neural networks to classify *QRS* complex related characteristics
Israel et al. (2005)	Analyze fiducial based temporal features under various stress conditions
Palaniappan & Krishnan (2004)	Use two different neural network architectures for classification of six *QRS* wave related features
Kim et al. (2005)	By normalizing ECG heartbeat using Fourier synthesis the performance under physical activities was improved
Saechia et al. (2005)	Examined the effectiveness of segmenting ECG heartbeat into three subsequences
Zhang & Wei (2006)	Bayes' classifier based on conditional probability was used for identification and was found supurior to Mahalanobis' distanc
Plataniotis et al. (2006)	Analyze the autocorrelation of ECGs for feature extraction and apply DCT for dimensionality reduction
Wübbeler et al. (2007)	Utilize the characteristic vector of the electrocardiogram for fiducial based feature extraction out of the *QRS* complex
Molina et al. (2007)	Morphological synthesis technique was proposed to produced a synthesized ECG heartbeat between the test sample and template
Chan et al. (2008)	Wavelet distance measure was introduced to test the similarity between ECGs

Table 1. Summary of related to ECG based recognition works.

Method	Principle	Pe
Singh & Gupta (2008)	A new method to delineate *P* and *T* waves	
Fatemian & Hatzinakos (2009)	Less templates per suject in gallery set to speed up computation and reduce memory requirement	
Boumbarov et al. (2009)	Neural network with radial basis function was employed as the classifier	
Ting & Salleh (2010)	Use extended Kalman filter as inference engine to estimate ECG in state space	
Odinaka et al. (2010)	Time frequency analysis and relative entropy to classify ECGs	
Venkatesh & Jayaraman (2010)	Apply dynamic time warping and Fisher's discriminant analysis on ECG features	
Tawfik et al. (2010)	Examined the system performance when using normalized *QT* and *QRS* and using raw *QRS*	
Ye et al. (2010)	Applied Wavelet transform and Independent component analysis, together with support vector machi as classifier to fuse information from two leads	
Coutinho et al. (2010)	Treat heartbeats as a strings and using Ziv-Merhav parsing to measure the cross complexity	
Ghofrani & Bostani (2010)	Autoregressive coefficient and mean of power spectral density were proposed to model the system for classification model the system for classification	
Li & Narayanan (2010)	Fusion of temporal and cepstral features	

Table 2. (Continued) Summary of related to ECG based recognition works

Let the number of classes in the generic dataset be C. The training set will then involve $C + 1$ classes as follows:

$$\Phi(m) = [\Phi_1(m), \Phi_2(m)...\Phi_C(m), \Phi_{input}(m)] \tag{2}$$

and for every subject i in $C + 1$, a number of C_i AC vectors are available. This is because during enrollment, longer ECG recordings can be acquired, so that multiple segments of the user's biometric participate in training. The longer the training ECG signal the lower the chances of false rejection. Furthermore, since this is only required in the enrollment mode of operation, it does not affect the overall waiting time of the verification.

Given $\Phi(m)$, LDA will find a set of k feature basis vectors $\{\psi_v\}_{v=1}^{k}$ by maximizing the ratio of between-class and within-class scatter matrix. Given the transformation matrix Ψ, a feature vector is projected using:

$$Y_i(k) = \Psi^T \Phi_i(m) \tag{3}$$

where eventually $k << m$ and at most C.

An advantage of distributed verification is that smart phone can be optimized experimentally for the intra-class variability of a particular user. This can be done during enrollment, by choosing the smallest distance threshold at which an individual is authenticated. Essentially, rather than imposing universal distance thresholds for all enrolles, every device can be "tuned" to the expected variability of the user.

8. ECG signal collection

The performance of the framework discussed in Section 7 was evaluated over ECG recordings collected at the BioSec.Lab[2], at the University of Toronto. Overall, two recording sessions took place, scheduled a couple of weeks apart, in order to investigate the permanence of the signal in terms of verification performance. During the first session, 52 healthy volunteers were recorded for approximately 3 min each. The experiment was repeated a month later for 16 of the volunteers.

The signals were collected from the subject's wrists, with the Vernier ECG sensor. The wrists were selected for this recording so that the morphology of the acquired signal can resemble the one collected by a smart phone from the subject's fingers. The sampling frequency was 200Hz. During the collection, the subjects were given no special instructions, in order to allow for mental state variability to be captured in the data. The recordings of the 36 volunteers who participated to the experiment only once were used for generic training. For the 16 volunteers that two recordings were available, the earliest ones were used for enrollment and the latter for testing.

9. Experimental performance

Preprocessing of the signals is a very important because ECG is affected by both high and low frequency noise. For this reason, a butterworth bandpass filter of order 4 was used, centered between 0.5 Hz and 40Hz based on empirical results. After filtering, the autocorrelation was computed according to Eq. 1, for the generic dataset, the enrollment records and the testing ones.

Each of the enrollees' recordings were appended to the generic dataset individually, and a new LDA was trained for every enrollee. The performance each recognizer was then tested with matches the respective subject's recordings in the test set. To estimate the False Acceptance

[2] http://www.comm.utoronto.ca/~biometrics/

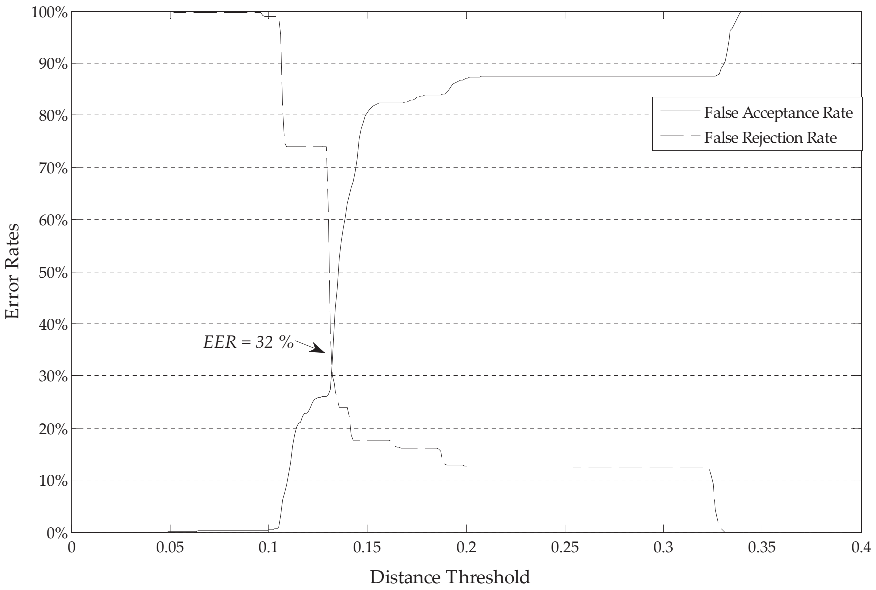


Fig. 4. False Acceptance and Rejection Rates when imposing universal recognition thresholds.

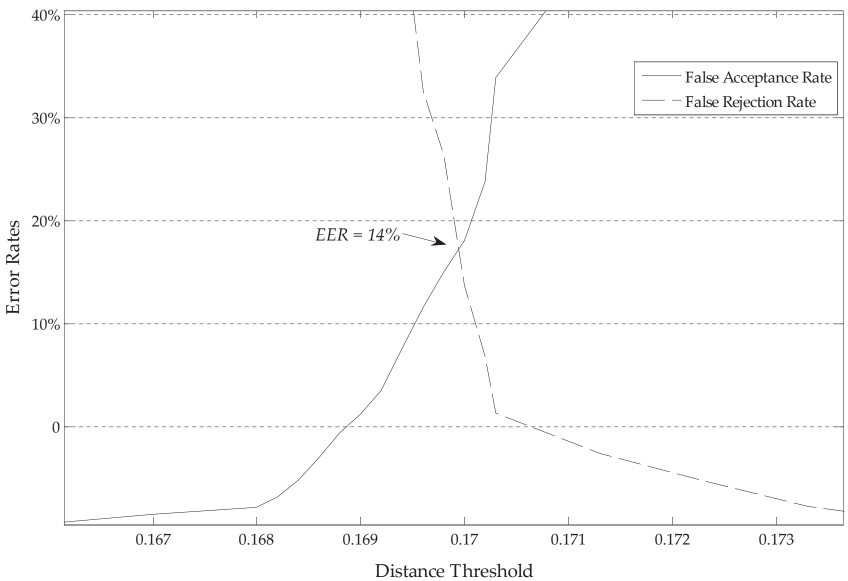


Fig. 5. False Acceptance and Rejection Rates after personalization of the thresholds.

Rate, the remaining enrolles (i.e., subjects who did not participate in the generic pool), acted as intruders to the system. This subset of recordings is unseen to the current LDA, and thus constitutes, the unknown population.

Figure 4 demonstrates the tradeoffs between false acceptance (FA) and rejection (FR) when the same threshold values are imposed for all users. The Equal Error Rate (EER) i.e., the rate at which false acceptance and rejection rates are equal is *32%*. This performance is generally unacceptable for a viable security solution.

When verification is performed locally on a smart device, one can take advantage of the fact that every card can be optimized to a particular individual. This treatment controls the false rejection since the matching threshold is "tuned" to the biometric variability of the individual. Figure 5 demonstrates the error distribution for the case of personalized thresholds, when aligning the individual ROC plots of the enrolles. The EER drops on average to *14%*, with a significant number of subjects exhibiting EER between *0%- 5%*. More details pertaining to this result can be found in Gao et al. (2011).

10. Conclusion

This chapter discussed on one of the most extensively studied medical biometric feature, the ECG. ECG reflects the cardiac electrical activity over time, and presents significant intra subject variability due to electrophysiological variations of the myocardium. However, as it was argued there are significant advantages of using ECG for human identification such as universality, permanence and uniqueness. Therefore, a number of approaches have been developed to address the challenges of designing templates that are robust to the heart rate variability.

The reported performance of the AC/LDA approach as well as of other methodologies in the literature, establish the ECG in the biometrics world and render its use in human recognition very promising. It is crucial however to perform large scale tests that can generalize the current performance as well as to address the privacy implications that arise with this technology.

11. References

Agrafioti, F. & Hatzinakos, D. (2008a). ECG biometric analysis in cardiac irregularity conditions, *Signal, Image and Video Processing* pp. 1863–1703.

Agrafioti, F. & Hatzinakos, D. (2008b). Fusion of ECG sources for human identification, *3rd Int. Symp. on Communications Control and Signal Processing*, Malta, pp. 1542–1547.

Biel, L., Pettersson, O., Philipson, L. & Wide, P. (2001). ECG analysis: a new approach in human identification, *IEEE Trans. on Instrumentation and Measurement* 50(3): 808–812.

Boumbarov, O., Velchev, Y. & Sokolov, S. (2009). ECG personal identification in subspaces using radial basis neural networks, *IEEE Int. Workshop on Intelligent Data Acquisition and Advanced Computing Systems*, pp. 446 –451.

Chan, A., Hamdy, M., Badre, A. & Badee, V. (2008). Wavelet distance measure for person identification using electrocardiograms, *Instrumentation and Measurement, IEEE Transactions on* 57(2): 248 –253.

Chiu, C. C., Chuang, C. & Hsu, C. (2008). A novel personal identity verification approach using a discrete wavelet transform of the ECG signal, *International Conference on Multimedia and Ubiquitous Engineering*, pp. 201 –206.

Coutinho, D., Fred, A. & Figueiredo, M. (2010). One-lead ECG-based personal identification using Ziv-Merhav cross parsing, *20th Int. Conf. on Pattern Recognition*, pp. 3858 –3861.

Draper, H., Peffer, C., Stallmann, F., Littmann, D. & Pipberger, H. (1964). The corrected orthogonal electrocardiogram and vectorcardiogram in 510 normal men (frank lead system), *Circulation* 30: 853–864.

Fatemian, S. & Hatzinakos, D. (2009). A new ECG feature extractor for biometric recognition, *16th International Conference on Digital Signal Processing*, pp. 1 –6.

Gao, J., Agrafioti, F., Mohammadzade, H. & Hatzinakos, D. (2011). ECG for blind identity verification in distributed systems, *IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP)*.

Ghofrani, N. & Bostani, R. (2010). Reliable features for an ECG-based biometric system, *17th Iranian Conference of Biomedical Engineering*, pp. 1 –5.

Green, L., Lux, R., Williams, C. H. R., Hunt, S. & Burgess, M. (1985). Effects of age, sex, and body habitus on qrs and st-t potential maps of 1100 normal subjects, *Circulation* 85: 244–253.

Hoekema, R., G.Uijen & van Oosterom, A. (2001). Geometrical aspect of the interindividual variaility of multilead ECG recordings, *IEEE Trans. Biomed. Eng.* 48: 551–559.

Israel, S. A., Irvine, J. M., Cheng, A., Wiederhold, M. D. & Wiederhold, B. K. (2005). ECG to identify individuals, *Pattern Recognition* 38(1): 133–142.

Kim, K. S., Yoon, T. H., L., J., Kim, D. J. & Koo, H. S. (2005). A robust human identification by normalized time-domain features of Electrocardiogram, *27th Annual Int. Conf on Eng. in Medicine and Biology Society*, pp. 1114 –1117.

Kozmann, G., Lux, R. & Green, L. (1989). Sources of variability in normal body surface potential maps, *Circulation* 17: 1077–1083.

Kozmann, G., Lux, R. & Green, L. (2000). Geometrical factors affecting the interindividual variability of the ECG and the VCG, *J. Electrocardiology* 33: 219–227.

Kyoso, M. & Uchiyama, A. (2001). Development of an ECG identification system, *23rd Annual International Conference of the Engin.g in Medicine and Biology Society*.

Larkin, H. & Hunyor, S. (1980). Precordial voltage variation in the normal electrocardiogram, *J. Electrocardiology* 13: 347–352.

Li, M. & Narayanan, S. (2010). Robust ECG biometrics by fusing temporal and cepstral information, *20th International Conference on Pattern Recognition*, pp. 1326 –1329.

Molina, G. G., Bruekers, F., Presura, C., Damstra, M. & van der Veen, M. (2007). Morphological sythesis of ECG signals for person authentication, *15th European Signal Proc. Conf.*, Poland.

Odinaka, I., Lai, P.-H., Kaplan, A., O'Sullivan, J., Sirevaag, E., Kristjansson, S., Sheffield, A. & Rohrbaugh, J. (2010). Ecg biometrics: A robust short-time frequency analysis, *IEEE International Workshop on Information Forensics and Security*, pp. 1 –6.

Palaniappan, R. & Krishnan, S. (2004). Identifying individuals using ECG beats, *International Conference on Signal Processing and Communications*, pp. 569 – 572.

Peter Allen, Calais migrants mutilate fingerprints to hide true identity, Daily Mail (n.d.). http://www.dailymail.co.uk/news/worldnews/article-1201126/Calais-migrants-mutilate-fingertips-hide-true-identity.html.

Pilkington, T., Barr, R. & Rogers, C. L. (2006). Effect of conductivity interfaces in electrocardiography, *Springer New York.* 30: 637–643.

Plataniotis, K., Hatzinakos, D. & Lee, J. (2006). ECG biometric recognition without fiducial detection, *Proc. of Biometrics Symposiums (BSYM)*, Baltimore, Maryland, USA.

Saechia, S., Koseeyaporn, J. & Wardkein, P. (2005). Human identification system based ECG signal, *TENCON 2005*, pp. 1 –4.

Shen, T. W., Tompkins, W. J. & Hu, Y. H. (2002). One-lead ECG for identity verification, *Proc. of the 2nd Conf. of the IEEE Eng. in Med. and Bio. Society and the Biomed. Eng. Society*, Vol. 1, pp. 62–63.

Simon, B. P. & Eswaran, C. (1997). An ECG classifier designed using modified decision based neural network, *Comput. Biomed. Res.* 30: 257–272.

Singh, Y. & Gupta, P. (2008). ECG to individual identification, *nd IEEE Int. Conf. on Biometrics: Theory, Applications and Systems 2*.

Sornmo, L. & Laguna, P. (2005). *Bioelectrical Signal Processing in Cardiac and Neurological Applications*, Elsevier.

Tawfik, M., Selim, H. & Kamal, T. (2010). Human identification using time normalized QT signal and the QRS complex of the ECG, *7th International Symposium on Communication Systems Networks and Digital Signal Processing*, pp. 755 –759.

The US Federal Commission Report, Frebruary 2010 (n.d.). http://www.ftc.gov /sentinel/reports/sentinel-annual-reports/sentinel-cy2009.pdf.

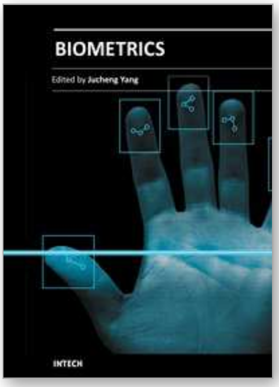
Ting, C. M. & Salleh, S. H. (2010). ECG based personal identification using extended kalman filter, *10th International Conference on Information Sciences Signal Processing and their Applications*, pp. 774 –777.

Venkatesh, N. & Jayaraman, S. (2010). Human electrocardiogram for biometrics using DTW and FLDA, *20th International Conference on Pattern Recognition (ICPR)*, pp. 3838 –3841.

Wübbeler, G., Stavridis, M., Kreiseler, D., Bousseljot, R. & Elster, C. (2007). Verification of humans using the electrocardiogram, *Pattern Recogn. Lett.* 28(10): 1172–1175.

Ye, C., Coimbra, M. & Kumar, B. (2010). Investigation of human identification using two-lead electrocardiogram (ECG) signals, *4th Int. Conf. on Biometrics: Theory Applications and Systems*, pp. 1 –8.

Zhang, Z. & Wei, D. (2006). A new ECG identification method using bayes' teorem, *TENCON 2006*, pp. 1 –4.



Biometrics

Edited by Dr. Jucheng Yang

ISBN 978-953-307-618-8
Hard cover, 266 pages
Publisher InTech
Published online 20, June, 2011
Published in print edition June, 2011

Biometrics uses methods for unique recognition of humans based upon one or more intrinsic physical or behavioral traits. In computer science, particularly, biometrics is used as a form of identity access management and access control. It is also used to identify individuals in groups that are under surveillance. The book consists of 13 chapters, each focusing on a certain aspect of the problem. The book chapters are divided into three sections: physical biometrics, behavioral biometrics and medical biometrics. The key objective of the book is to provide comprehensive reference and text on human authentication and people identity verification from both physiological, behavioural and other points of view. It aims to publish new insights into current innovations in computer systems and technology for biometrics development and its applications. The book was reviewed by the editor Dr. Jucheng Yang, and many of the guest editors, such as Dr. Girija Chetty, Dr. Norman Poh, Dr. Loris Nanni, Dr. Jianjiang Feng, Dr. Dongsun Park, Dr. Sook Yoon and so on, who also made a significant contribution to the book.

InTech Europe
University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China
Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821