Multimodal biometric system for ECG, ear and iris recognition based on local descriptors

Meryem Regouid[1] , Mohamed Touahria[1] , Mohamed Benouis[2] & Nicholas Costen[3]

Abstract

Combination of multiple information extracted from different biometric modalities in multimodal biometric recognition system aims to solve the different drawbacks encountered in a unimodal biometric system. Fusion of many biometrics has proposed such as face, fingerprint, iris…etc. Recently, electrocardiograms (ECG) have been used as a new biometric technology in unimodal and multimodal biometric recognition system. ECG provides inherent the characteristic of liveness of a person, making it hard to spoof compared to other biometric techniques. Ear biometrics present a rich and stable source of information over an acceptable period of human life. Iris biometrics have been embedded with different biometric modalities such as fingerprint, face and palm print, because of their higher accuracy and reliability. In this paper, a new multimodal biometric system based ECG-ear-iris biometrics at feature level is proposed. Preprocessing techniques including normalization and segmentation are applied to ECG, ear and iris biometrics. Then, Local texture descriptors, namely 1D-LBP (One D-Local Binary Patterns), Shifted-1D-LBP and 1D-MR-LBP (Multi-Resolution) are used to extract the important features from the ECG signal and convert the ear and iris images to a 1D signals. KNN and RBF are used for matching to classify an unknown user into the genuine or impostor. The developed system is validated using the benchmark ID-ECG and USTB1, USTB2 and AMI ear and CASIA v1 iris databases. The experimental results demonstrate that the proposed approach outperforms unimodal biometric system. A Correct Recognition Rate (CRR) of 100% is achieved with an Equal Error Rate (EER) of 0.5%.

Keywords ECG . EAR . IRIS. 1D-LBP. Shifted-1D-LBP. 1D-MR-LBP. CRR . EER

1. Introduction

Our biological, behavioral or morphological characteristics fall under the name of Biometrics, which is considered as a real alternative to passwords, signatures and other identifiers for identification purposes. Obviously, biometric systems is made to identify or verify certain individuals automatically based on their physical, physiological, or behavioral characteristics of a human being, such as their iris, face, gait, keystroke dynamics or other traits. Any algorithm in this area aims to meet most or all of these criteria: Universality, Uniqueness, Permanence, Measurability, Performance, Acceptability, and Circumvention [33]. The aim of the identification is to determine the identity of a person by comparing the biometric data (i.e. trait) of a person with biometric data of several other people enrolled in a database.

Biometric systems may run in two modes: identification and verification. In the verification mode, the system must answer a question: “are you who you are claiming?”, by comparing the input data with its own biometric template(s) stored in the system database using a one-to-one comparison to validate the person’s identity and check if the claim is true or not. Whereas, in the identification mode, the system must answer a different question: “who are you?” by comparing the input data with all biometric template(s) stored in the system database using a one-to-many comparison to achieve the individual’s identity [35].

To date, the state-of-the-art methods for biometric authentication are being incorporated into various access control and personal identity management applications. While physically-based biometrics (including the iris) have been the most commonly used technology, there is growing evidence that multi-modal biometrics, established through different biometric traits can be used for reliable person recognition. However, every separate biometric still faces the problems of improving accuracy, robustness, security, privacy, and further efforts are needed to develop efficient approaches that can be used for person identification in different contexts and applications.

Many mono-modal biometric systems have been proposed [4, 16, 54] in various areas, providing only one biometric trait. To the best of our knowledge, among the more popular biometric technologies, the iris recognition system is considered to be one of the more confident techniques for security in airports, government buildings, and research laboratories [4].

The use of the iris as the third biometric modality makes our system more robust and achieves a high level of security as a consequence of its advantages such as the uncorrelated nature of the iris codes for both unrelated persons and also identical twins or even between the left and right irises of the same person [16]. Despite its promising performance for these biometric tasks, iris-based biometric requires full cooperation on the part of the user and also has often not been fully accepted by them.

In recent years, newly emerging biometric technologies [54] have been used extensively for both human identification and security tasks [4]. Some of these technologies include gait, lip motion, skin reflection and ear shape. This last feature is simpler and more accepted by people; also it may be easier to acquire data using a simple camera [3, 23]. Moreover, biometric technologies, especially those using 3D representations [53], are proving particularly powerful and are now being employed in many state of-the-art face recognition systems [17]. In the case of the ear biometric, for instance Bhanu et al. successfully use 3D data to represent significant features in ear images [56], and Yanet et al. introduced a powerful search and retrieval method using ICP with 3D-PCA to find the relevant point in an ear shape volume [10]. As explained by several research papers in the ear recognition [11], even though 3D ear images are not affected by emotional expression, illumination, aging and poses, occlusion where the ear can be partially or fully covered by hair or by other items such as head-dress, and out-of-plane rotations are still an unsolved problem and remains an object of research.

In the biomedical engineering field, biological or behavioral data may be captured directly from diverse sensors (EMG sensor, EEG sensor, ECG sensor, microphone (voice), etc.). To capture high quality data, quite a few capturing sensors have been developed. Early sensors were generally less comfort and expensive. Indeed, they required a high degree of cooperation from the users. With the development and popularization of healthcare technology, ubiquitous smart sensors have become more compact, affordable and friendly, making it possible to embed them in smart watches, mobile phones and wearable devices (e.g., Google glass 6). To solve serious challenges, recently, mobile health objects and the Internet of Things provide new concepts involving the use of smart mobile devices to create efficient healthcare/smart-life services and solutions. Thus, we intend to investigate the benefit of these emerging biometric methods. These include a number of advantages which allow us to improve the overall performance of a biometric system, while maintaining strong user authentication, and is biometrically-based smart, and replaceable as a privacy concern.

In contrast to the approaches found in the literature and detailed above, analysis of electrocardiogram (ECG) is a new biometric measure for human identity recognition. The activity recorded by the ECG comes from extracellular currents related to the propagation of a depolarization front (atrial P wave, then ventricular QRS complex) across the heart. The strength of ECG based biometric authentication systems is that ECG can be directly utilized as a liveness detector. A remote login process by ECG signal captured from a finger, which improves security and privacy [31], unlike such traditional modalities as the face that can be found easily in public. As reported in reviews of the state-of-the-art ECG based biometric systems, such a biometric system must record more than 10 s of ECG data (long term) in order to make a reliable decision about human identity [8, 11, 25].

Due to its limitations, as well as problems concerning missing data and unreliable identification, some challenges commonly encountered by such unimodal biometric systems remain. These include:

(i) Environmental (e.g. may it effect the system during authentication due to changes in the prevailing conditions),

(ii) Noise in sensed data (e.g. dirty sensor, poorly illuminated or problems modalities like several ear or face poses),

(iii) Intra-class variations (e.g. multiple differences between enrolled and authenticated templates),

(iv) Interclass similarities,

(v) Non-universality (e.g. some people may do not have the desired modality due to

disabilities or illness),

(vi) Spoof attacks (e.g. the use of a single biometric modality makes it easier to mimic, also some biometric modalities are easy to spoof because of their use in public like face),

(vii) Upper bound on identification accuracy (e.g. cannot continuously improve the recognition rate) [9, 33].

An increasing number of researchers are motivated by the achievements of data fusion tools in multidisciplinary areas [45], applying multi biometric methods to the biometric field. The results (e.g. the use of multiple sources of information for authentication can help to solve the majority of these problems which is appointed as multimodal biometric systems, spoofing multiple biometric information at the same time will be very hard to imposter that improves recognition accuracy) also confirm the use of multimodal biometric approaches [33]. In the biometric field, the information of the biometric traits can be merged at different levels of fusion: sensor-level fusion, feature extraction-level fusion, score-level fusion and decision-level fusion. Moreover, the first two stages occur before the matching stage and the rest take place after the matching stage. In this present work, feature extraction level fusion is performed.

Despite the various improvements allowed by a multimodal system, these systems suffer from a number of weaknesses such as lengthy enrollment times and material costs. These issues are increased due to the use of multiples sensors, in addition to the disturbance of using several modalities. To tackle this issue, we propose a multimodal approach, which combines three traits: iris, ear and ECG. As the dimensionality of these modalities is large, their fusion by concatenation is difficult, inefficient and lacks robustness. It is well known in the literature that if the feature space has very high dimensionality, it is susceptible to the curse of dimensionality. This problem can be solved by feature extraction and dimensionality reduction. Local texture descriptors, namely 1D-LBP (One-Dimensional Local Binary Patterns), Shifted-1DLBP (Shifted One-Dimensional Local Binary Patterns) and 1D-MR-LBP (One-Dimensional Multi-Resolution Local Binary Patterns) are used in this study for features extraction purposes from 1D signals and 2D images after projecting these images into a 1D space. Researchers have used LBPs methods, proposed by Ojala in 1996 [41], in several studies addressing texture analysis for 2D image processing [27, 40]. LBPs methods can solve various computer vision problems, due to their invariance to monotonic gray level changes caused, by illumination variations. In addition, their simplicity of computation allows analyzing images in challenging real-time settings [43]. Following its numerous advantages on a 2D image, developers have proposed the application of LBPs to 1D processing signal. Chatlani et al. were the first who develop speech systems by using 1D-LBP to distinguish the important features from speech signals and proved its speed and applicability to a real problem which is computationally inexpensive [14]. Louis et al. [34]

demonstrate the use of 1D-MR-LBP to reduce noise and preserves the morphology of ECG waveforms. For all these multiple strengths and reasons, the use of these methods will drive our system to achieve the underlying targets.

The rest of the paper is organized as follows: in Section 2 there is a review of relevant literatures on unimodal and multimodal biometric systems. Section 3 presents the local descriptors used in our proposed system. Our architecture is discussed in Section 4. Then, Section 5 displays the experimental results evaluated and tested on several benchmarks: IDECG and USTB1, USTB2 and AMI ear and CASIA v1 iris databases besides a comparative study with the existents techniques. Then Section 6 concludes the paper.

2. Related work

Researchers have developed several biometrics techniques using unimodal and multimodal scheme concepts. Here, we presented the most related works are closely to our novel framework which consists of three traits such as iris, ear and ECG. As a unimodal system, for iris biometric, Daugman [19] is considered the pioneer in this field by developing the first automatic iris recognition system. His algorithms are now the baseline of several strands of research. Many systems have been developed using the iris biometric modality [5, 22, 36]. Because of their high accuracy and reliability, many researchers have been extensively investigated to use the iris modality in early multi biometric research.

Regarding the ear biometric, the French criminologist Bertillon [30] claimed that the ear has the most unique external design of body parts, and constitutes an important characteristic feature which can be used for identification purposes. Recently, Emeršič et al. [20] contributed an excellent survey on ear recognition. This summarizes the state-of-the-art ear recognition techniques and a selection of available databases. Due to its unique features, as well as the possibility of safe and reliable identification, ear biometrics seem to be a good choice to support well known technologies such as iris, fingerprint, gait or face identification [3, 4, 23].

For ECG biometrics, Biel et al. [11] developed a new approach using a 12-lead electrocardiogram (ECG) record for human identification. Twenty participants from an ECG-ID database were used in this approach, using fiducial features of heartbeat waves in the extraction phase. Experiments demonstrated that the features extracted from one lead can be used to identify a person with 98% accuracy. To date, ECG has seen significant attention in biometric recognition studies [8, 25, 34, 54], using both fiducial (specific anchor points such as P-QRST) and non-fiducial features. Despite the research efforts directed at ECG biometrics, at present there is only one commercial system available which exploits ECG or EMG biometrics for recognition, the B-secure [28]. Experimental evaluation performed by the authors shows that the ECG based biometric has become the focus of major research in the field of human identification technology.

Biometric systems remain a challenging problem if they are to be sited in public places or in unconstrained environments. The main weakness of unimodal biometrics are related to several factors, including variable environmental conditions, large intra-class variations, non-universality (due to accident, skin diseases, age) and spoof attacks (fake biometric data).

Multimodal biometric recognition systems have attracted recently attracted significant research attention, as they offer a method of solving the different drawbacks of unimodal systems. Hong and Anil [29] developed a prototype biometric authentication system using faces and fingerprints with decision-level fusion. Ross and Jain [48] proposed a multimodal biometrics system which includes face, fingerprint and hand geometry, using a matching score level fusion. Subsequently, many modalities have been fused to fulfil various application requirements [22, 35, 50]. Ear, ECG and iris biometric modalities fusions have been introduced in different combinations and fusion strategies, using various levels of fusion by these researchers.

A multimodal biometric system [38], has been constructed which integrates face, iris and ear data. This applies the Fisher image technique to the face and ear image databases for recognition and the Hough transform and Hamming distance techniques to iris recognition. A novel method based on Markov chain was then used for rank level fusion. In order to improve on the accuracy and reliability of other rank fusion methods, they also suggested a new Markov chain approach for fusing rank information in a multimodal biometric system. Using different rules (the min rule, max rule, product rule and sum rule) in decision level fusion, ECG features extracted via KPCA (Kernel Principal Component Analysis) and face features extracted using Principal Component Analysis (PCA) and Spectral Regression (SR) algorithms are combined to treat the problem of combining different biometric modalities in intelligent video surveillance systems [12],. An implementation of a multimodal system by Al Hamdani et al. [1], combined three modalities using score level fusion to reach a higher security level. Fusion of speech, ECG and PCG with sum score fusion was performed. SIFT (Scale Invariant Feature Transform) was exploited in order to extract features from both ear and iris data, fusing them at feature level. A FAR of 0 was achieved [22]. Fusion of fiducial features (peaks) from the first lead (I) of the ECG, with spectrum features from six different bands of the electroencephalogram (EEG) in order to construct a robust and secure multimodal biometric recognition system using sum, product and weighted sum operators. Then, the Euclidean norm distance was applied to match the fused features. A Hits at ERR of

0.93 was achieved [6]. In [50], game theory was used to combine ear, palm-print and signature features extracted using a Gabor filter to obtain optimal logistic regression weights for rank-level fusion. Face and ECG were also incorporated for an authentication system [13]. Using feature level fusion, in [32], face and ECG features were fused together for person identification.

Ear, iris and ECG biometric traits have been used in various works in the literature because of their different advantages. Iris recognition has emerged in several studies [9, 22, 35] due to its strength, robustness and efficiency in identification as well as verification systems. Ear biometrics has acquired a large interest because of its benefits such as a stable structure, robust information and rich features. Lately, ECG has become known as a new multimodal biometric for recognition purposes. This signal is universal since every living and functional person has his or her unique ECG signal [13], and ECG is characterized by stability over a long period of time. Also, it is robust in the context of security [31]; this can make it hard to spoof the liveliness measurement unlike other traditional modalities. At the moment, no one can mimic ear or ECG biometric features. This biological signal also allows the identification of emotions such as fear, happiness, sadness and anger [49]. As a result, the detection of these emotions can allow the system to launch a protection routine in from expecting spoof attack when user suffers from stress or fear for example.

As a feature extraction level, to improve the accuracy rate and achieve a maximum performance of the system, all the features are fitted in unique feature vector. As reported in the literature [44], the local binary pattern which has accumulated abundant contributions, particularly in computer vision, was also investigated for biometric field such as face, ear, iris, gait...etc. While using standard LBP to extract features a 2D data has a long history of research, recent important papers that have investigated new variant 1D LPB in signal and image processing applications areas. The motivation behind this implementation is that 1DLBP, which is well carried out on these three modalities and can be easily combined to increase the distinctive information for every subject.

In this paper, we propose a new multimodal recognition system integrating ear, iris and ECG biometric technologies. Our approach was implemented using local texture descriptors to extract features from each modality and fuse the extracted features at features level fusion. The fusion, at this level, has many strengths, the homogeneous extracted data don't require any normalization which reduces the complexity. Moreover, features level fusion outperforms matching score fusion [48]. There have been considerable variants of multi biometric strategy schemes proposed for human identification and recognition [27, 40, 43]. Until now, one of the most popular strategies is fusion modalities. Thus, methods based on score fusion have achieved remarkable performance, most of which fuses two modalities [11, 25, 34]. As for ECG with the conventional biometric, there are fewer studies. For this reason, a comparison was done with existing multimodal systems that use one or two out of three modalities. We aim to develop a system that will be able to:

- Take the advantage of the strengths and reduce the chance of the false alarm of each approach while increasing the accuracy of the biometric authentication process.
- Achieve better performance and high security level (minimum Equal Error Rate).
- Reduce the complicity weaknesses of a multimodal system by applying 1d-LBPs.
- Hard to imposer to spoof ear, iris and ECG traits in the same time.
- The uses of liveness measurements are not easily mimicked.
- Remote login process by ECG signal captured from a finger which improves security and privacy.
- Combination of hidden (ECG) and visible (EAR and IRIS) modalities in a multimodal system leads to form a robust and a secure system.

– make our biometric system become more robust against many various factors where are usually linked to diseases factors, accident, age, life condition, and will has the ability to meet the specific requirements expected in different contexts such as border control, mobile application, IOT and healthcare application, .etc.

3. Local texture descriptors

Local texture descriptors have proven their efficiency in Biometric domains which have been applied in a 3D shape, 2D image and also recently 1D signal. Researchers demonstrate the robustness of local texture descriptors in the multimodal biometric system especially in real-world applications as well as easy data acquisition [14, 27, 34]. The two major steps involved in biometric system are feature extraction and classification step. In this work, we have more investigated the first step which aims to reduce the data and selected the significant features which must be invariant against multiple issues that may be appeared in biometric task. Furthermore, feature extraction is one of the crucial step of biometric system as well as is related to dimensionality reduction and abstraction data (i.e., image, signal, etc.) to get features that will be useful in decision and identification of subjects. Although many studies on handcraft features have appeared in recent years, local binary pattern remains an interesting feature extraction and keep attracting the researchers particularly after his performance on biometric applications such as face, iris and ear [21, 34, 56]. In this purpose, three local texture descriptors namely 1D-LBP, Shifted 1D-LBP and 1D-MR-LBP have been implemented and detailed in this paper in an attempt to evaluate our multimodal biometric system. In this section, 1D- LBP, shifted 1D-LBP and 1D-MR-LBP based features are discussed below:

3.1 1D-lbp

LBP method has gained a great popularity since its first proposal by Ojala in 1996 [41] due to its efficiency of extracting important textures that exists in the processed image using its local neighborhood. LBP generate a binary code by thresholding each value of neighborhood with the value of the center pixel of an image based on the assumption that texture has locally two complementary aspects, a pattern and its strength [43]. While LBP method was used to process pixels of a 2D image, 1D-LBP was used to process samples data for the 1D signal. The first proposition of 1D-LBP method was introduced by Chatlani [14] for the purpose of extracting features from a speech signal and identifies the voiced and the unvoiced components. 1D-LBP generate a binary code, which named a 1D-LBP code, by thresholding each value of neighborhood with the value of each center samples from a signal. The formulation of 1DLBP on the i^{th} sample of processed signal x[i] is given as:

$$\mathrm{1DLBP}(x[i]) = \sum_{j=0}^{\frac{p}{2}-1} \{S(x[i+j-p/2]-x[i])2^{j} + S(x[i+j+1]-x[i])2^{j+p/2}\}$$

Where the S() indicates the sign function and is defined as:

$$S(x) = \begin{cases} 1 \; for \; x \geq 0 \\ 0 \; for \; x < 0 \end{cases}$$

And where P is the number of neighboring samples. The input parameter of S() is the result of the difference between each neighboring sample and the center sample. And its output parameter is a thresholding binary number which will be converted to an LBP code by applying a binomial weight. i represent the i^{th} sample where i = [(P/2) + 1:N-P/2], N is the length of processed signal x. An example of the 1-D LBP operator is given in Fig. 1 where P = 8 and the center sample PC is mentioned.

3.2 Shifted LBP

Shifted 1D-LBP method was adapted from a 1D-LBP method which was introduced by Chatlani et al. [14]. Both methods are applied to sensor signals for the purpose of extracting features or segmentation. They are inspired from 2D-LBP method proposed by Ojala 1996 [41]. The same process will be applied using 1D-LBP or Shifted 1D-LBP methods at each sample of signal, while 1D-LBP method use constant left and right neighbors of the central sample and obtained a limited macros patterns,Shifted 1D-LBP method use shifted left (PL) and right (PR) neighbors of the central sample Pc [21] after the selection of neighborhoods, Shifted 1D-LBP generate a binary code, which named a Shifted 1D-LBP code, by thresholding each value of left and right neighborhood with the value of each center samples from a signal x[i]. The formulation of Shifted 1D-LBP of center sample Pc of processed signal x[i] is given as:

$$\text{Shifted1DLBP}(\mathrm{P}_c) = \sum_{j=1}^{p} S(\mathrm{P}_j - \mathrm{P}_c)2^{j-1}$$

p

Where the S() indicates the sign function as mentioned in a1D-LBP method without modification and is defined as:

$$S(x) = \begin{cases} 1 \; for \; x \; \geq 0 \\ 0 \; for \; x \; < 0 \end{cases}$$

And where Pc and Pj represent the center sample and number of neighbors respectively.

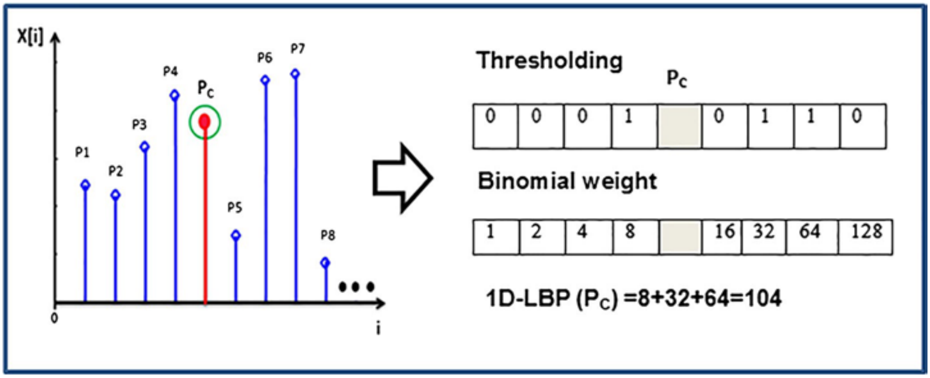


Fig. 1 An example of 1-D LBP operator

An example of Shifted-1D-LBP operator is given in Fig. 2 where PL = 5 and PR = 3, the center sample Pc is mentioned.

3.3 1D-MR-LBP (one-dimensional multi-resolution local binary patterns)

1D-MR-LBP methods, which is applied on a 1D signal, was proposed by Louis [34] to solve the problem of passing irregular signals to biometric system and of an unknown amplitude of a signal and achieve better performance.1D-MR-LBP methods were inspired by the 2-dimensional image Local Binary Patterns. While 1D-LBP and1D-Shifted LBP based on just the selection of neighbors on both left and right side for extraction, 1D-MR-LBP based on two variables p and d, where the first one represents the number of selected samples that are used for 1D-MR-LBP feature extraction from both side, which considered by neighbors on 1D-LBP method, and the second one represents the distance between the center sample x_c and the last/first selected sample pi used for 1DMRLBP feature extraction from left/right side. The formulation of 1D-MR-LBP on the i^{th} sample of processed signal x[i] is given as:

$$\text{1DMRLBP}(\text{x[i]}) = \sum_{j=1}^{p} S\big(\text{x(i+j-p-d)}\big)2^{j-1} + S\big(\text{x(i+j+d-1)}\big)2^{j+p-1}$$

Where the S() indicates the sign function by adding epsilon ε as a new parameter which makes ECG signals less influenced by noises beside to take on consideration the quantization error [34]. The S() function defined as:

$$S(x) = \begin{cases} 1 \; for \; x + \varepsilon \; \geq 0 \\ 0 \; for \; x + \varepsilon \; < 0 \end{cases}$$

And where p and d are defined above. The input parameter of S() is the result of the difference between each sample pj where j = [1,2,..,p] and the center sample. And its output parameter is a thresholding binary number which will be converted to an LBP code by applying a binomial weight. i represent the i^{th} sample where i = [p + d:N-p-d + 1], N is the length of processed signal x. An example of a 1-D-MR-LBP operator is given in Fig. 3 where P = 3 and d = 3 and the center sample PC is mentioned.

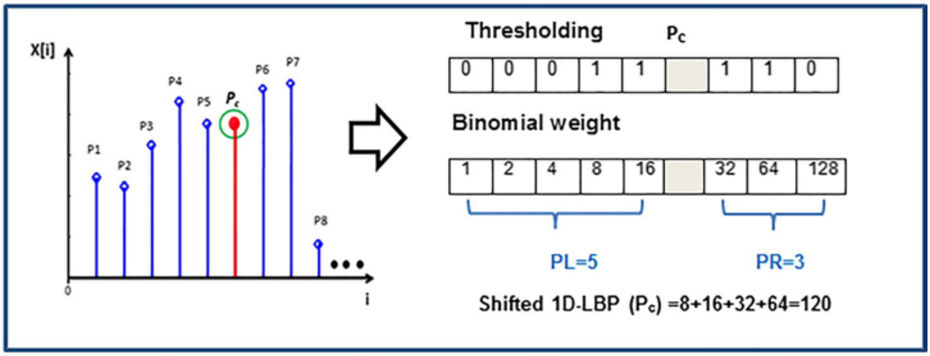


Fig. 2 An example of Shifted-1D-LBP operator

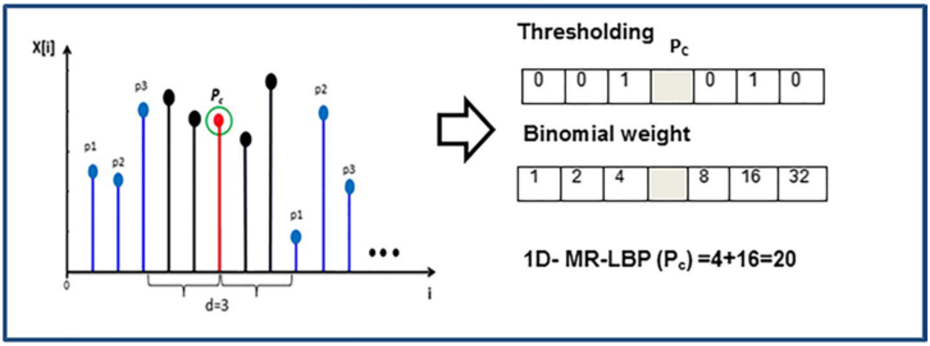


Fig. 3 An example of 1D-MR- LBP operator

4. Proposed approach

In this paper, new fusion approach of three modalities namely ECG, ear and iris was proposed in an attempt to develop a secure and robust multimodal biometric recognition system. The proposed modalities (ECG, ear or iris) used in the proposed approach was fused with other biometric modalities in many researches [1, 12, 22, 35, 38, 50] but there is no system fuses the three biometric modalities together.

1D-LBP, Shifted 1D-LBP and 1D-MR-LBP are applied in each unimodal algorithm with the aim to obtain high frequency information of ECG signal and ear and iris images beside to enhance recognition accuracy rate, moreover to reduce the equal error rate. Since the nature of biometrics modalities, Local texture features impose its existence in several approaches [14, 21, 27, 34]. In our study, 1D-MR-LBP will apply for the first time on ear and iris biometrics after projecting each image into a 1D signal with the purpose of demonstrating its efficiency compared with 1D-LBP and shifting 1D-LBP methods. The proposed recognition process is divided into four phases as described in Fig. 4.

4.1 Preprocessing step

4.1.1 ECG preprocessing

In the first step, the ECG signal obtained from different databases publicly available is frequency normalized using simple linear interpolation. The preprocessing step aims at reducing the noise from the ECG signal and removes various artifacts and improves the signal equality, derived from muscular interference or more commonly from the power grid (50 Hz or 60 Hz). Savitzky-Golay Finite impulse response (SG-FIR) recursive digital filters are the most used for attenuation of these noises. We apply SG-FIR technique to smooth the ECG signal specifying a polynomial order of 3 and a frame length of 11. Figure 5a shows about 10 s from the original ECG signal and its de-noised one in Fig. 5b.

The waveform signal ECG contain many information's which were located by either on fiducial or non-fiducial techniques, The QRS complex was considered one of the most important fiducial feature that might be used to learn the local and global variation of ECG signal and therefore to make easily the heartbeat segmentation task. in this fact, in our paper we have used Pan-Tompkins algorithm [42] to isolate the fiducial point (P, Q, R, S, and T) for each beat segment (due to the non-stationary and aperiodic nature of ECG signal, beat lengths for all of the ECG records are not equalized, each signal have different numbers of waveforms (heartbeat). In our segmentation, each wave R determines the center of the QRS complex by taking 94 samples before the R-peak and 150 samples after the R-peak which means that each ECG heartbeat has 245 samples and 490 ms segment duration as shown in Fig. 6a while Fig. 6b shows segmented heartbeats for different subjects aligned with the R peak.

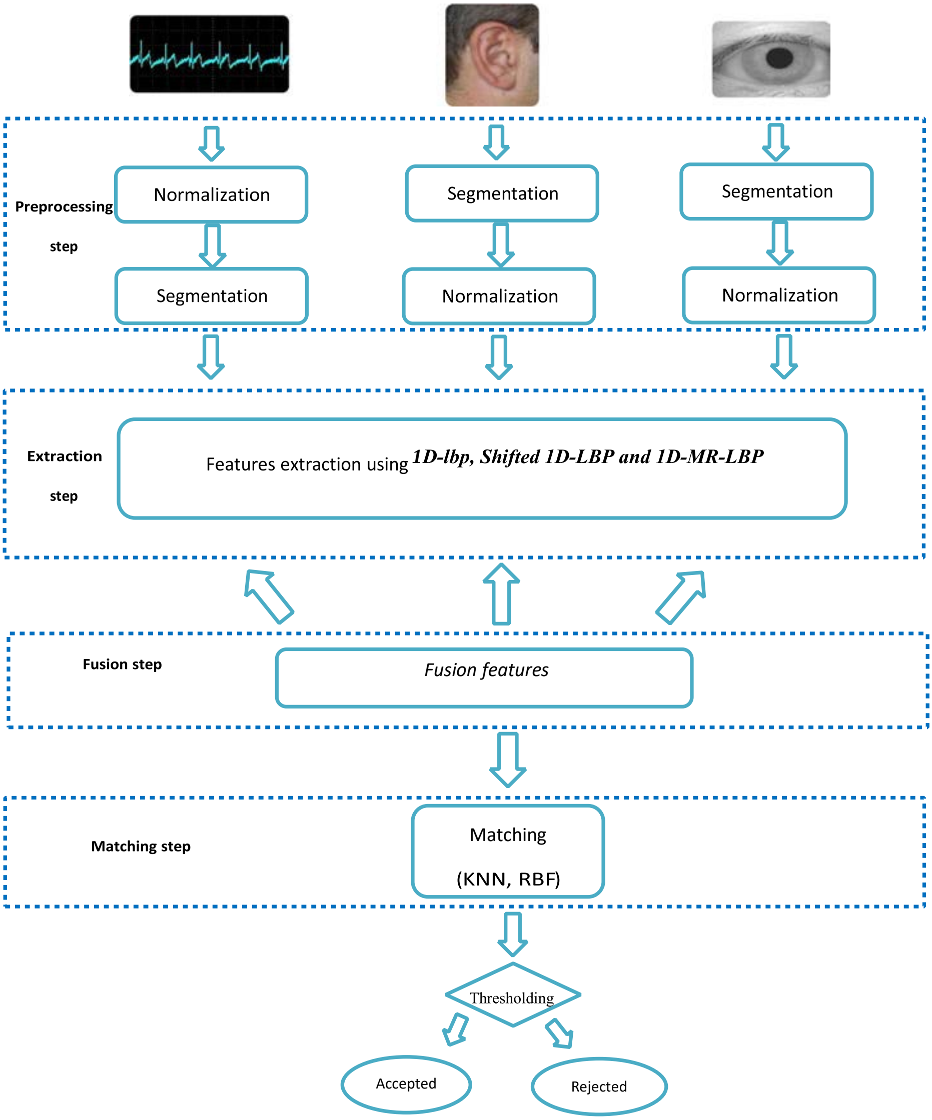


Fig. 4 The proposed recognition process

4.1.2 EAR pre-processing

For ear Segmentation phase, the ear is manually cropped from different artifacts that reduce the accuracy and maximize the EER such as hair and skin areas. Next step consists of converting

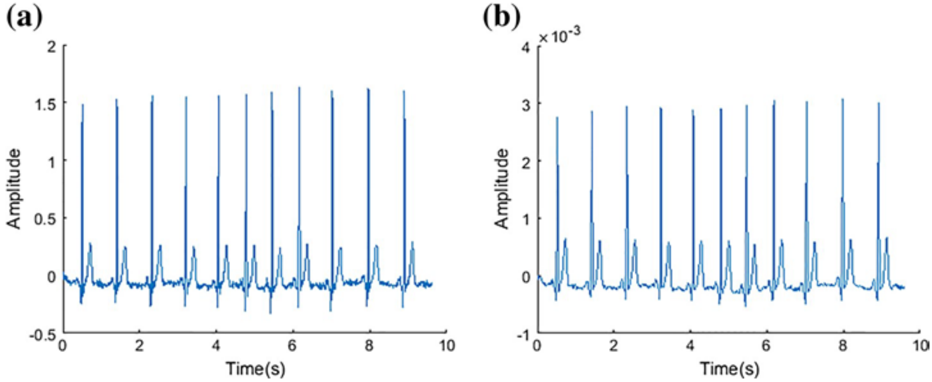


Fig. 5 A portion of ECG signal before (a) and after (b) preprocessing step

the different cropped ear images size to a fixed size of 50× 50 pixels. The resized images were converted then to a grayscale images. The preprocessed ear image can be appreciated from the Fig. 7b.

4.1.2 IRIS pre-processing

For iris Segmentation step, several algorithms were proposed in the literature for segmentation procedure. Daugman [27] develop an Integro-differential Operator algorithm which allows the location of the circular iris, pupil regions and the arcs of the upper and lower eyelids. Ritter et al. [46] propose Active Contour Models which allows the location of the pupil region. Wildes et al. [55], Masek [37] and other employ circular Hough transform technique for an automated segmentation algorithm in order to detect the iris and pupil boundaries. We decide to use circular Hough transform technique for the iris and pupil boundaries detection. This can be realized in the following phases [37]:

1. Detection of center coordinates and radius of the detected iris/pupil boundaries using Canny edge detection and Hough Transform

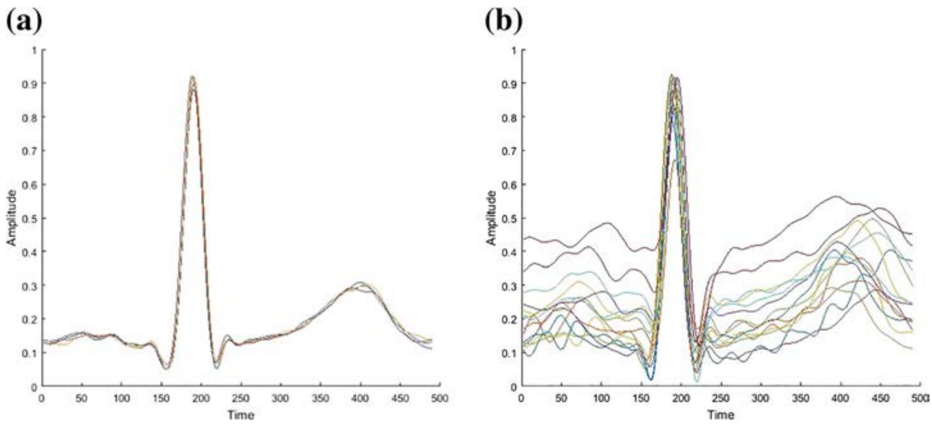


Fig. 6 Segmented heartbeats for the same (a) and different (b) subjects, aligned with the R peak

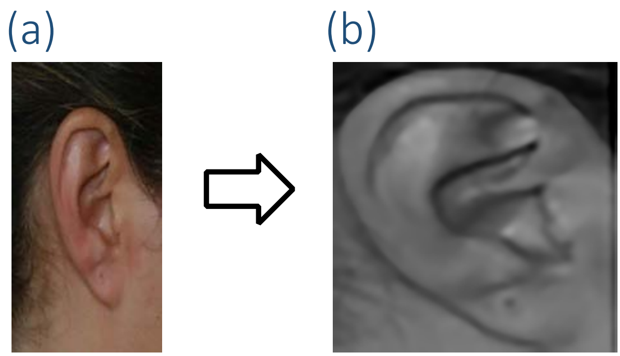


Fig. 7 The original (a) and the preprocessed (b) ear image

2. The use of linear Hough transform to isolate Eyelids by fitting a line to the upper and lower eyelid.

3. The use of thresholding technique to isolate eyelashes.

Next step consists of normalization process of segmented image aiming at solving the different problems such as pupil dilation caused by varying levels of illumination or camera's rotation. The normalized image will have the same constant by unwrapping the circular region into rectangular block dimensions. A technique based on Daugman's rubber sheet model was applied [37]. In Fig. 8, the different sub-steps of preprocessing iris stage were illustrated.

4.2 Features extraction

We have implemented 1D-LBP, Shifted-1D-LBP and 1D-MR-LBP methods on each preprocessed modality, ECG signal and preprocessed ear and iris images after converting them to 1D space, to extract local features. On 1D-LBP operators, we have set the number of neighbors p to 6 in ear and iris features extraction and to 5 in ECG features extraction. For the number of the obtained bins, which they are related to the choice of neighbors (p), will be equal to 22x p. In our case, we have 4096 bins for ear and iris converted signals and 1024 for ECG signal. Figures 9a and 10a show ear, iris images and ECG features extraction diagram applying 1d-LBP method.

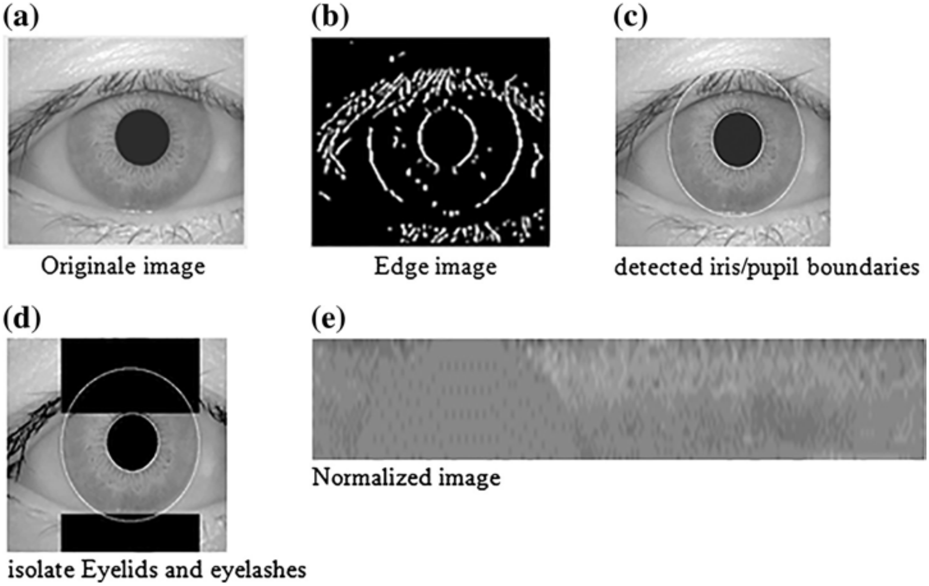


Fig. 8 The different sub steps of preprocessing iris stage

On Shifted-1D-LBP operators, we have set the number of left PL and right PR neighbors to 6 and 2, respectively for both ear and iris converted signals. A number of 5 and 3 were assigned to left PL and right PR neighbors respectively for ECG signal. Number of obtained bins was equal to 2PL + PR, therefore, in our case, we have 256 for ear, iris and ECG signals. Figures 9b and 10b show ear, iris images and ECG features extraction diagram applying Shifted-1d-LBP method.

On 1D-MR-LBP operators, the two variables p and d are assigned to 5 and 4 respectively for the three preprocessed ECG, ear and iris signals. Like 1D-

LBP, the number of bins obtained was 1024. Figures 9b and 10b show ear, iris images and ECG features extraction diagram applying 1D-MR-LBP method.

For ECG signal, the extracted non-fiducial features for each heartbeat, applying the three methods described above, were normalized by dividing it on addition of heartbeat length and its maximum value. Each constructed features vector was stored for the matching process.

4.3 Features fusion

Numerous identification systems based on different modalities have been proposed which utilize: sensor level, feature-extraction level, matching-score level, and decision level. In feature extraction level fusion, a new feature vector is formed by concatenation of different feature sets extracted from multiple biometric sensors. Here, the extracted features templates from the three modalities ECG, EAR and IRIS for each subject are concatenated together into a new fused feature vector aiming that this fused vector will have a higher dimensionality and contain more important information which allows us identifying the person.

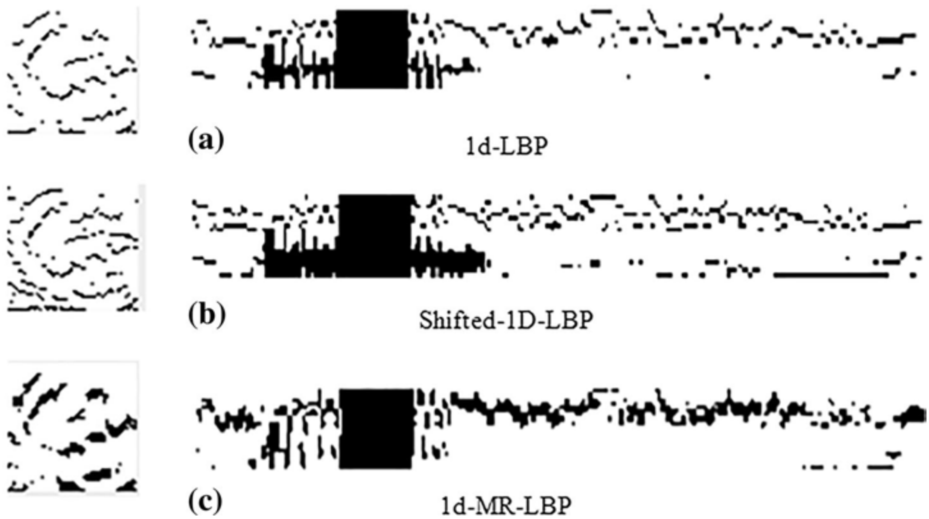
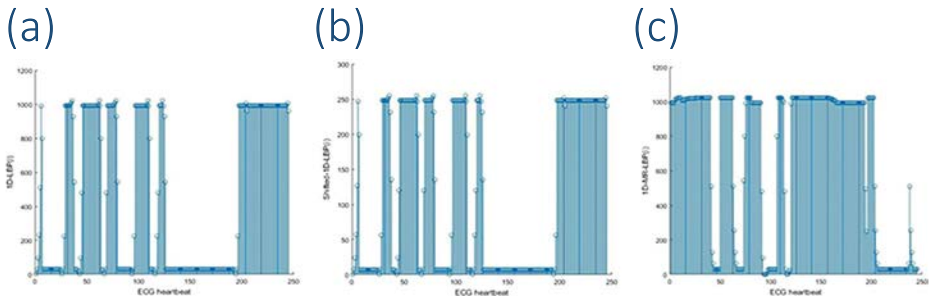


Fig. 9 Ear and iris images after applying (a) 1d-LBP (b) Shifted-1D-LBP (c) 1d-MR-LBP, respectively



1d-LBP Shifted-1D-LBP 1d-MR-LBP

Fig. 10 Features extraction diagram from an ECG heartbeats using (a) 1d-LBPwith parameters p = 6. (b) Shifted
-1d-LBP with parameters pl = 6 and pr = 2. (c) 1d-MR-LBP with parameters d = 4 and p = 5

Results of Ross research's [47] have proved that feature level fusion outperforms matching score fusion. Besides that, the merged vector represents richer information at an earlier stage of processing [22]. A popular technique for data fusion in feature level that was used in the proposed work is concatenation by a union. This process is well illustrated in Fig. 11.

$$V_{fusion} = \{V_{ECG} V_{ear} V_{iris}\}$$

4.4 Matching

In the matching step, the features extracted from the three input data (ECG, ear and iris) was fused in a new vector which will be compared with the templates collected during the enrollment phase. KNN (K nearest neighbors) and RBF (radius basis function) classifiers are used to match the input template with the registered templates [26]. Our neural network training algorithm used in ECG classification step did not require many parameters compared to other neural networks (MLP, LVQ), which usually uses the smoothing parameter σ to control the fitting of training of network. Obviously, to get a higher recognition rate, we have made a series of experiments to choose the best smoothing parameter σ used in RBF.

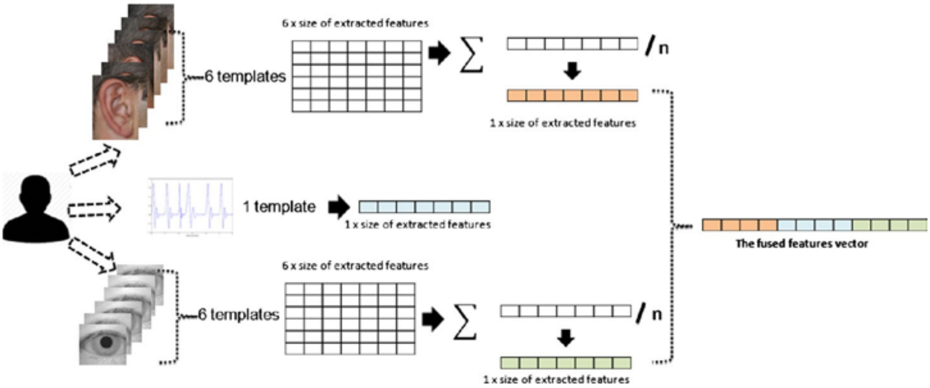


Fig. 11 The proposed fusion scheme

5. Experimental result

5.1 Databases

Our proposed approach is validated through applying different public databases. We have used ECG-ID database [51] for ECG biometric. AMI [2], USTB1 and USTB2 [52] database for ear biometric and CASIA database for iris biometric. The ECG-ID database was created by Tatiana Lugovaya who contributed this database in order to use it in her master's thesis. ECG-ID database contains signals from 90 subjects, each subject has at least two records and at most 20 records acquired for about 20 s and digitized at 500 Hz with 12-bit resolution. Both raw and filtered signals were included for each record. In our experiments, two records were used per subjects, one as a training set and the other as a testing set. Some signals of the database are shown in Fig. 12.

University of Science and Technology in Beijing (USTB) developed two databases namely USTB1 and USTB2 for ear recognition. The collected images are from Students and teachers from USTB. USTB 1 database contains images from 60 subjects. Each subject has three images of the right ear with different angle rotation and image under different lighting condition, whereas, USTB 2 contains images from 77 subjects. Each subject has four images of the right ear. Similarly to USTB 1,USTB 2 images were taken with different angle rotation and under different lighting condition. We have taken 2 images per subject as training set and one image as testing set from USTB 1 database and 3 images per subject as training set and one image as testing set from USTB 2 database. Sample image of USTB 1, USTB 2 database are shown in Fig. 13a and b respectively.

Mathematical Analysis of Images (AMI) Ear Database was created by Esther Gonzalez who contributed this database in order to use it in her PhD in Computer Science. AMI database contains images from 100 subjects collected from students, teachers and staff of the Computer Science department at Universidad de Las Palmas de Gran Canaria (ULPGC), each subject has seven images, six right ear images and one left ear image acquired under the same lighting conditions with a resolution of492 × 702 pixels. Concerning the division of data on train/test set, we have divided the AMI database into six images per subject as a training set and one image as testing set. Sample image of the database is shown in the Fig. 13c.

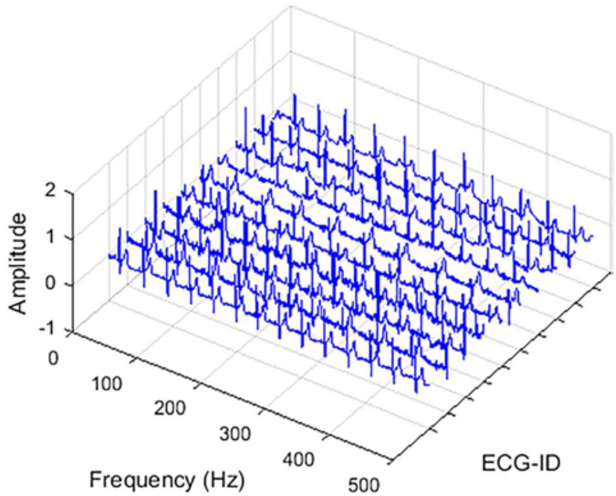


Fig. 12 ECG signals from different subjects from ECG-ID database

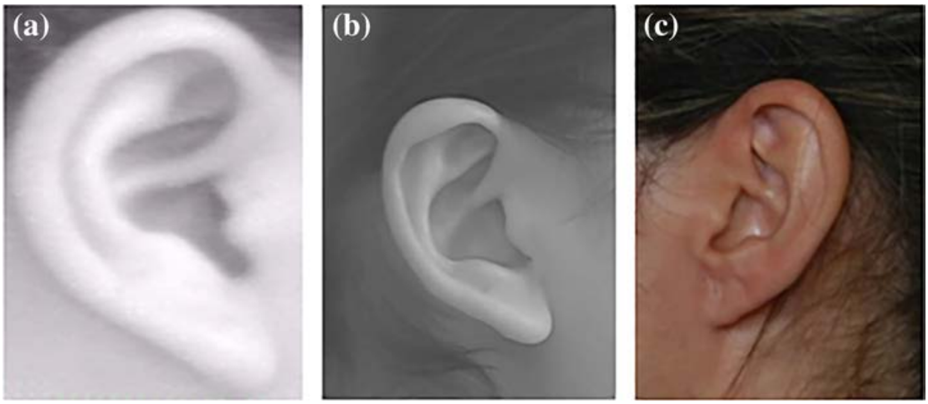


Fig. 13 Sample images from: (a) USTB1; (b) USTB; (c) AMI databases

Institute of Automation, Chinese Academy of Sciences (CASIA) developed the first version of Iris Image Database (CASIA Iris V1) since 2002. CASIA Iris V1 includes images from 108 eyes. Each eye has seven images are collected into two folders. Three images exist in the first folder and four in the second one. In our experiment, six images were taken as a training set and one as testing set. Sample image of the database is shown in the Fig. 14.

In our multimodal system, an equal number of subjects must be performed. Since three databases (AMI, USTB1 and USTB2) for EAR were done, three cases were considered. In the case of validating our proposed experiments using AMI databases, 90 subjects are chosen from ECG-ID, CASIA and AMI database. In the second case using USTB1 databases, 60 subjects are chosen from ECG-ID, CASIA and USTB1 database. The last case using USTB2, 77 subjects are chosen from the three databases.

5.2 Performance measures

To validate any biometric recognition system, FRR (False Rejection Rate), FAR (False Acceptance Rate), ERR (Equal Error Rate), ROC (Receiver Operator Characteristic) and

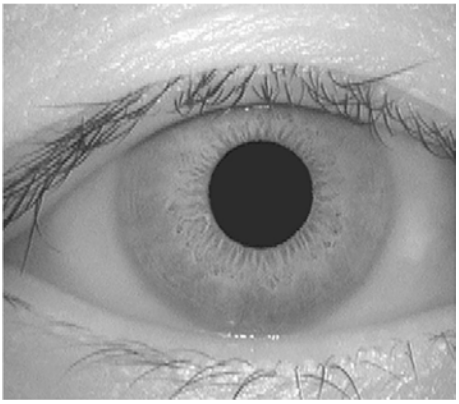


Fig. 14 Sample image from CASIA v1 database

Table 1 Comparison of performance measures for our proposed unimodal ECG systems with related systems

Authors	Extraction method	Database	CRR%	EER%	FAR%	FRR%
Biel et al. [11]	Fiducial features	ID-ECG	98	–	–	–
Louis et al. [34]	1D-MR-LBP	PTB	91	0.09	0.09	0.09
Boumbarov et al. [12]	PCA and LDA	own	95.7	–	–	–

Al.hamdani et al. [1]	Mel-Frequency Cestrum Coefficients	own	98.5	4.5	–	–
Barra et al. [6]	simple peak detection	PTB	96.15	1.33	–	–
Chakraborty et al. [13]	histogram based method	own	95	–	–	–
Bassiouniet al [7]	Fiducial features +DWT	ID-ECG	98	–	–	–
Nemirko et al. [39]	Fiducial features	ID-ECG	96	–	–	–
Daret al [18]	(DWT) and (HRV)	ID-ECG	83.88	–	16.1	0.3
Chun [15]	Guided filter + Simple distance measurements	ID-ECG	99	2.4	–	–
Our1st experiment	1D-LBP	ID-ECG	97	2.16	0. 71	5.56
Our2nd experiment	shifted 1D-LBP		97	2.16	0. 71	5.56
Our3rd experiment	1D-MR-LBP		98	3.10	1	6

accuracy must be calculated which indicate performance measures. Accuracy can be calculated by:

$$\text{Correct Recognition Rate}=100- \frac{\text{FRR+FAR}}{2}$$

Where: FRR indicates that genuine person considered as an imposter and FAR indicate that imposter was considered as a genuine person. ERR indicates the point where: FRR-FAR = 0. We also generate a ROC curve which allows for evaluating and comparing our algorithms with others and visualize their performances.

5.3 Numerical results and discussion

In this section, to assess the performance of the effectiveness of the methods that have been stated in this work, three experiences have been implemented and analyzed in this paper to distinguish the different strengths and weaknesses of these proposed methods in each unimodal system on the one hand, and their effects in multimodal system also implemented to compare our results against relevant literature on the other hand. MATLAB framework 2016b was used to implement the proposed multimodal biometric system and plot the desired figures.

Table 2 Comparison of performance measures for our proposed unimodal ear systems with related systems

Authors	Extraction method	Database	CRR%	EER%	FAR%	FRR%
Ghoualmi et al. [22]	SIFT	USTB2	91.36	–	0.6536	7.7419
Ghoualmi et al. [24]	SIFT	USTB1	97.15	–	0.8475	4.8387

Tahmasebi et al. [23]	Gabor filter	UND	–	–	18	10
Our 1st experiment	1D-LBP	USTB1	100	1.05	1.33	1.60
		USTB2	98.70	6.54	1	11
		AMI	98	0. 772	1.09	4.9
Our 2nd experiment	shifted 1D-LBP	USTB1	100	1.05	1.22	1.6
		USTB2	97.40	6	1	13.5
		AMI	98	0. 700	1	4.5
Our 3rd experiment	1D-MR-LBP	USTB1	100	2.03	1.05	3.33
		USTB2	97.40	6.22	1	14
		AMI	100	2.07	0.24	6,67

Table 3 Comparison of performance measures for our proposed unimodal iris systems with related systems

Authors	Extraction method	Database	CRR%	EER%	FAR%	FRR%
Daugman [19]	1D- Gabor filters	own	99.61	0.32	–	–
Goualmi et al. [22]	SIFT	CASIA v1	95.80	–	0.65	7.74
Barpanda et al. [5]	tunable filter bank	CASIA v3	91.65	8.35	8.45	8.25
Marciniak [36]	logarithmic Gabor filters	CASIA v1	97	–	3.25	3.03
Our 1st experiment	1D-LBP	CASIA v1	98.89	1.90	0.27	3.33
Our 2nd experiment	shifted 1D-LBP		98.89	1.88	0.21	3.22
Our 3rd experiment	1D-MR-LBP		100	1.19	0.16	2.22

Figure 4 shows the architecture of the proposed multimodal biometric system. As described above in section 4, each unimodal biometric system has three stages. The pre-processed stage has normalization and segmentation sub-stages including the conversion of pre-processed ear and iris images to 1D space as shown in Figs. 5, 6, 7 and 8 Then, the textures descriptors namely 1D-LBP, Shifted-1D-LBP and 1D-MR-LBP were extracted from the pre-processed signals, Figs. 9 and 10 illustrate the different extracted features from the three biometric modalities. Finally, KNN and RBF were adopted for the matching step. The results are tabulated in Tables 1, 2 and 3 for each unimodal biometric system and Table 4 summarizes the results of our three ECG-EAR-IRIS multimodal systems based on local descriptor textures. In Table 1, the proposed unimodal ECG biometric was tested over the three experiments. Different measures have been calculated to evaluate the performance of our unimodal system.

Table 4 Comparison of performance measures for our proposed multimodal systems with related systems

Authors		modalities	Fusin level	CRR%	EER%	FAR%	FRR%
Barra et al. [6]		ECG and EEG	Score	96.85	0.94	–	–
Goualmi et al. [22]		EAR and Iris	features	99.67	–	0	0.64
Monwar and Marina [38]		Ear, Iris and face	Rank	98.29	–	–	–
Boumbarov et al. [12]		ECG and face	decision	99.5	–	–	–
Al.hamdani et al. [1]		ECG and speech	score	–	0.7	–	–
Barra et al. [6]		ECG and EEG	score	96.79	0.956	–	–
Tahmasebi et al. [23]		Ear, Palmprint and signature	rank	99.63	0.37	0.17	0.37
Chakraborty et al. [13]		ECG and Face	feature	97.5	–	–	–
Our 1st experiment	1st case	ECG, ear and Iris	feature	100	0.82	0	1.57
	2nd case			99	2.08	1.28	2.60
	3rd case			100	0.54	0	1.110
Our 2nd experiment	1st case			100	0.81	0	1.64
	2nd case			99	2.07	1.28	2.60
	3rd case			100	0.56	0	1.111
Our 3rd experiment	1st case			100	0.82	0	1.42
	2nd case			99	0.73	0.09	1.30
	3rd case			99	0.57	0	2.022

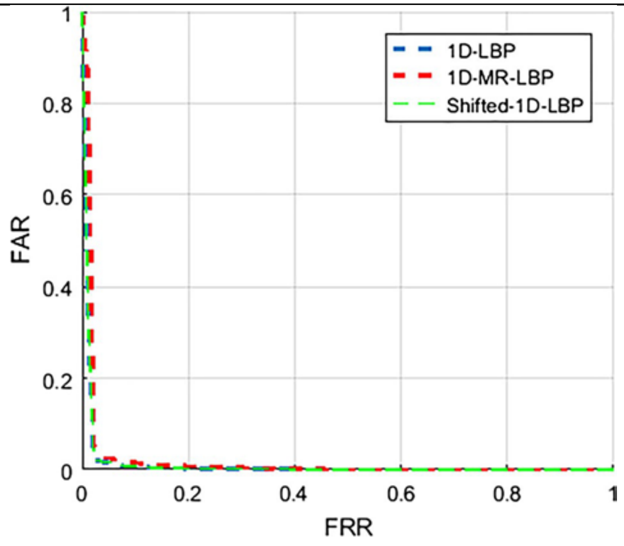
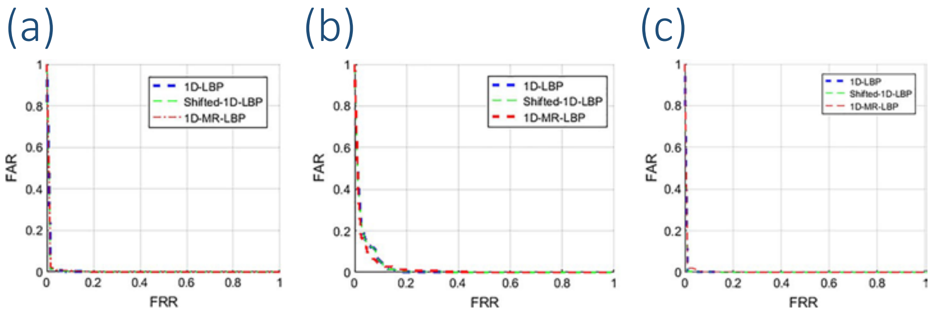


Fig. 15 ROC curve for unimodal ECG systems by the three experiments

Local descriptors textures, 1D-LBP, Shifted-1D-LBP and 1D-MR-LBP, extract rich and complex non-fiducial information from the segmented heartbeats. For classification, we can see that 1D-MR-LBP has achieved a CRR of 98%. The same result was obtained from the two classifiers whereas less CRR of 97% has obtained by 1D-LBP and Shifted-1D-LBP. Contrariwise, it can be noticed that the same results were obtained from 1D-LBP and Shifted-1D-LBP. These results were better than a 1D-MR-LBP method on terms of EER, FAR and FRR with a value of 2.16%, 0.71% and 5.56% respectively. Comparing the obtained results with state-ofthe-art work, we can see that the three methods have improved its efficiency, robustness and capability of extracting discriminative features. The ROC curve for the 1D- LBP (where p = 5), Shifted-1D-LBP (where PL = 5 and PR = 3) and 1D-MR-LBP (where p = 5 and d = 4) is presented in Fig. 14.

In Table 2, evaluation of the proposed unimodal EAR biometric was performed over the three experiments using USTB1, USTB2 and AMI database. After the enhancement of 2D ear image, the conversion on 1D space was accomplished to allow the1D-LBP, Shifted-1D-LBP and 1D-MR-LBP methods extracting features. The same results were obtained with KNN and



Performance comparison on Performance comparison on Performance comparison on USTB1
USTB2 AMI

Fig. 16 ROC curves for unimodal ear systems by the three experiments

).

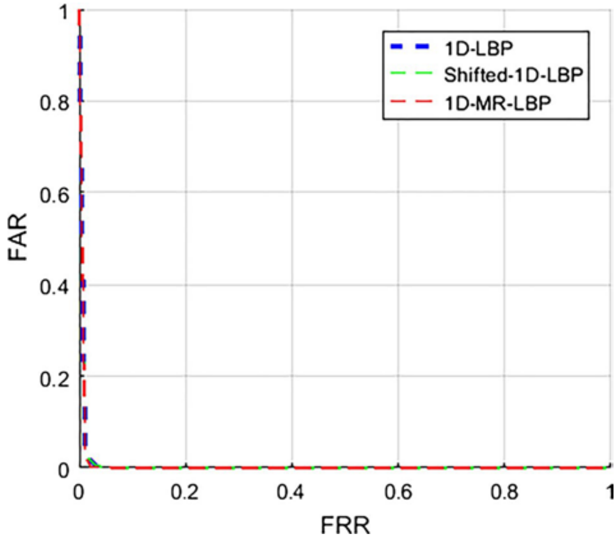
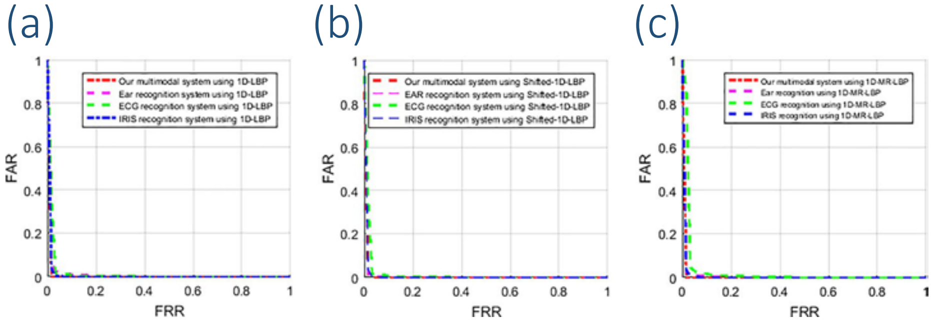


Fig. 17 ROC curves for unimodal iris systems by the three experiments

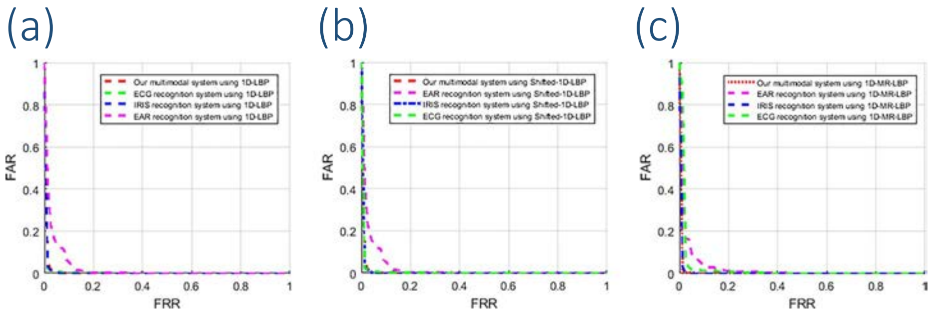
RBF classifiers. With USTB1 database, we got a CRR of 100% using the 3 methods, whilst, less CRR has been acquired from USTB2. It can be observed that USTB2 has significantly worse EER than USTB1 and also AMI. For AMI database, the better result was found using 1D-MR-LBP on term of CRR by having 100%, while Shifted-1D-LBP got a good result on term of EER by having 0.7%. The presented ROC curve allows us to visualize easily our results mentioned in Table 2 for 1D- LBP (where p = 6), Shifted-1D-LBP (where PL = 6 and PR = 2) and 1D-MR-LBP (where p = 5 and d = 4) is presented in Fig. 15.

In Table 3, we have tested the performance of our unimodal iris system over the proposed 3 experiments. CASIA database was used to validate our proposed approaches. It can be seen that 1D-MR-LBP has proved its efficiency in terms of CRR, EER, FAR and FRR with 100%, 1.19%, 0.16% and 2.22% respectively. From Table 3, it can be noticed that 1D-MRLBPachieve better results than 1D-LBP and Shifted-1D-LBP.Comparing our results with existing researches, local descriptors have proved its capability of extracting the discriminants and important information for iris recognition purpose (Fig. 16).



Performance comparison for Performance comparison for Performance comparison for the 1st
experiment the 2nd experiment the 3rd experiment

Fig. 18 ROC curves for multimodal systems by the three experiments on USTB1 database



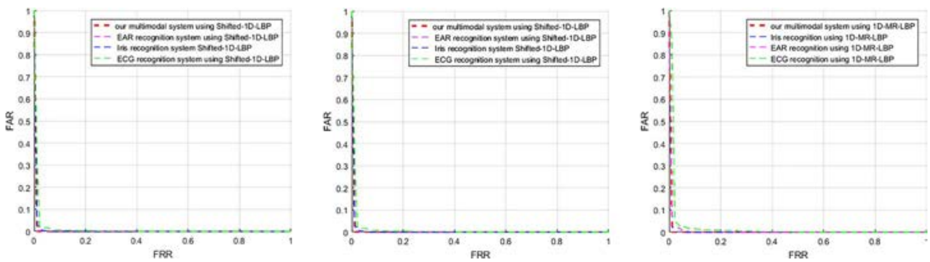
Performance comparison for Performance comparison for Performance comparison for the the 1st
experiment the 2nd experiment 3rd experiment

Fig. 19 ROC curves for multimodal systems by the three experiments on USTB2 database

In Table 4, three multimodal systems were evaluated, tested and compared with literature work. The difference between these systems is centered in the features extraction method where the first system use 1D-LBP, the second use Shifted-1D-LBP, while the third system extract features using 1D-MR-LBP.Because we have used 3 databases for Ear biometric, 3 cases in each multimodal system will be studied: the first case consists of fusing the ID-ECG, USTB1 and CASIAv1 databases, the second case consists of fusing the ID-ECG, USTB2 and CASIAv1 databases. Last case consists of fusing the ID-ECG, AMI and CASIAv1 databases.

In each experiment, as previously stated, the 1D-LBP, Shifted-1D-LBP and MR-LBP were applied on each preprocessed ECG, Ear and Iris biometric. The extracted features were fused together at feature level to obtain a single vector. The main advantage of fusion, at this level, is that our homogeneous data don't require any normalization which reduces the complexity that shortens the time. For classification step, we got the same result applying KNN and RBF classifiers. It can be observed, from Table 4, that the 3rd case achieves better result than the other two cases in all experiments in terms of EER with 0.5% where the CRR varies from 99% to 100% in the 3 experiments. From the obtained results, we can affirm that our multimodal systems perform better than different unimodal systems. Minimum EER was obtained with the 1st experiment using 1D-LBP descriptor in the 3rd case using ID-ECG, AMI and CASIA v1 databases. Comparing our experiments against the existing systems that use one or two of our modalities, it can be noticed that our multimodal systems achieved better result in terms of CRR and FAR and partly in term of EER. Figures 17, 18 and 19 show ROC curves for our experiments and its cases which allow us to visualize the obtained results clearly (Fig. 20).

(a) (b) (c)



Performance comparison for Performance comparison for Performance comparison for the the 1st
experiment the 2nd experiment 3rd experiment

Fig. 20 ROC curves for multimodal systems by the three experiments on AMI database

6. Conclusion

In this paper, a new multimodal ECG-EAR-IRIS biometric system was proposed. Three experiments have implemented and analyzed to discriminate the different strengths and weaknesses of 1D-LBP, Shifted-1D-LBP and 1D-MR-LBP methods in each unimodal system on the on hand and their effects in multimodal system also to compare our results against relevant literature on the other hand. In the preprocessing stage, different methods of segmentation, normalization and filtering were applied on our modalities. Then, the preprocessed Ear and IRIS were converted from 2D to 1D signal. Important information and features were extracted using three local descriptors called 1D-LBP, Shifted-1D-LBP and 1D-MR-LBP in extraction stage. A single vector was generated by fusing the ECG-EAR-IRIS extracted features. Finally, KNN and RBF were used in the matching stage.

The achieved result shows that our proposed multimodal system in the three experiments outperformed unimodal systems in terms of ERR, CRR, FAR and FRR. Better results were obtained with the first experiment using 1D-LBP descriptor in the 3rd case using ID-ECG, AMI and CASIA v1 databases obtaining 0.54%, 100%, 0%, 1.1% for ERR, CRR, FAR and FRR, respectively.

This work will be investigated on mobile and healthcare application. The detection of different claimed emotions using bio signal ECG will be our next step which improves security system besides to the use of ECG image in place of ECG signal for recognition purpose. Another perspective is also to validate our work on large datasets in order to further confirm the performance of the our proposed multibiometric framework.

References

1. Al-Hamdani O, Chekima A, Dargham J, Salleh S, Numan F, Hussain H et al (2013, 01). Multimodal Biometrics Based on Identification and Verification System. 04
2. AMI Ear Database, Esther Gonzalez,Luis Alvarez and Luis Mazorra CTIM. Centro de I+D de Tecnologias de l' Imagen Universidad de Las Palmas de G.C. http://www.ctim.es/research_works/ami_ear_database/
3. Annapurani K, Sadiq MA, Malathy C (2015) Fusion of shape of the ear and tragus–a unique feature extraction method for ear authentication system. Expert Syst Appl 42(1):649–656
4. Anwar AS, Ghany KK, Elmahdy H (2015) Human ear recognition using geometrical features extraction. Procedia Comput Sci 65:529–537
5. Barpanda SS, Sa PK, Marques O, Majhi B, Bakshi S (2018) Iris recognition with tunable filter bank based feature. Multimed Tools Appl 77(6):7637–7674
6. Barra S, Casanova A, Fraschini M, Nappi M (2017) Fusion of physiological measures for multimodal biometric systems. Multimed Tools Appl 76(4):4835–4847
7. Bassiouni MM, El-Dahshan E-SA, Khalefa W, Salem AM (2018) Intelligent hybrid approaches for human ECG signals identification. SIViP 12(5):941–949
8. Belgacem N, Nait-ali A, Fournier R, Bereksi Reguig F (2013) ECG Based Human Identification Using Random Forests. The International Conference on E-Technologies and Business on the Web (EBW2013). Bangkok, Thailand
9. Benaliouche H, Touahria M (2014) Comparative study of multimodal biometric recognition by fusion of iris and fingerprint. Sci World J 2014
10. Bhanu B, Chen H (2003) Human ear recognition in 3D. In Workshop on Multimodal User Authentication (Vol 12 pp 91–98)
11. Biel L, Pettersson O, Philipson L, Wide P (2001) ECG analysis: a new approach in human identification. IEEE Trans Instrum Meas 50(3):808–812
12. Boumbarov O, Velchev Y, Tonchev K, Paliy I (2011) Face and ECG based multi-modal biometric authentication. Dans Advanced biometric technologies. InTech
13. Chakraborty S, Mitra M, Pal S (2016) Biometric analysis using fused feature set from side face texture and electrocardiogram. IET Sci Meas Technol 11(2):226–233

14. Chatlani N, Soraghan JJ (2010) Local binary patterns for 1-D signal processing. Signal Processing Conference, 2010 18th European, (pp 95–99)
15. Chun SY (2016) Single pulse ECG-based small scale user authentication using guided filtering. Biometrics (ICB), 2016 International Conference on, (pp 1–7)
16. Czajka A, Bowyer KW, Krumdick M, VidalMata RG (2017) Recognition of image-orientation-based iris spoofing. IEEE Trans Inf Forensics Secur 12(9):2184–2196
17. Dagnes N, Vezzetti E, Marcolin F, Tornincasa S (2018) Occlusion detection and restoration techniques for 3D face recognition: a literature review. Mach Vis Appl 1–25
18. Dar MN, Akram MU, Shaukat A, Khan MA (2015) ECG based biometric identification for population with normal and cardiac anomalies using hybrid HRV and DWT features. IT Convergence and Security (ICITCS), 2015 5th International Conference on, (pp 1–5)
19. Daugman JG (1993) High confidence visual recognition of persons by a test of statistical independence. IEEE Trans Pattern Anal Mach Intell 15(11):1148–1161
20. Emeršič Ž, Štruc V, Peer P (2017) Ear recognition: more than a survey. Neurocomputing 255:26–39
21. Ertuğrul F, Kaya Y, Tekin R, Almal MN (2016) Detection of Parkinson's disease by shifted one dimensional local binary patterns from gait. Expert Syst Appl 56:156–163
22. Ghoualmi L, Chikhi S, Draa A (2014) A SIFT-based feature level fusion of iris and ear biometrics. IAPR Workshop on Multimodal Pattern Recognition of Social Signals in Human-Computer Interaction, (pp 102– 112)
23. Ghoualmi L, Draa A, Chikhi S (2015) Ear feature extraction using a dwt-sift hybrid. Dans Intelligent Data Analysis and Applications (pp 37–47). Springer
24. Ghoualmi L, Draa A, Chikhi S (2016) An ear biometric system based on artificial bees and the scale invariant feature transform. Expert Syst Appl 57:49–61
25. Gurkan H, Guz U, Yarman BS (2013) A novel biometric authentication approach using electrocardiogram signals. Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE, (pp 4259–4262)
26. Haykin, Neural Networks and Learning Machines, Pearson Education, 3rd Ed., 2009, ISBN13 9780131293762 ISBN10
27. He S, Soraghan JJ, O'Reilly BF, Xing D (2009) Quantitative analysis of facial paralysis using local binary patterns in biomedical videos. IEEE Trans Biomed Eng 56(7):1864–1870
28. Homepage of B-secure, (https://www.b-secur.com/ecg-next-generation-authentication/). Accessed: 201811-17
29. Hong L, Jain A (1998) Integrating faces and fingerprints for personal identification. IEEE Trans Pattern Anal Mach Intell 20(12):1295–1307
30. Iannerelli, Ear Identification, Forensic Identification Series, Paramount Publishing Company, Fremount, CA, 1989
31. Islam MS, Alajlan N (2017) Biometric template extraction from a heartbeat signal captured from fingers. Multimed Tools Appl 76(10):12709–12733
32. Israel SA, Scruggs WT, Worek WJ, Irvine JM (2003) Fusing face and ECG for personal identification. In Proceedings of the 32nd Applied Imagery Pattern Recognition Workshop, 226–231. Washington, DC, October 15–17
33. Jain AK, Flynn P, Ross AA (2007) Handbook of biometrics. Springer Science %& Business Media
34. Louis W, Hatzinakos D, Venetsanopoulos A (2014) One dimensional multi-resolution local binary patterns features (1DMRLBP) for regular electrocardiogram (ECG) waveform detection. Digital Signal Processing (DSP), 2014 19th International Conference on, (pp 601–606)
35. Lumini A, Nanni L (2007) When fingerprints are combined with Iris-a case study: FVC2004 and CASIA. IJ Netw Secur 4(1):27–34
36. Marciniak T, Dąbrowski A, Chmielewska A, Krzykowska AA (2014) Selection of parameters in iris recognition system. Multimed Tools Appl 68(1):193–208
37. Masek L, others (2003) Recognition of human iris patterns for biometric identification
38. Monwar MM, Gavrilova M (2013) Markov chain model for multimodal biometric rank fusion. SIViP 7(1): 137–149

39. Nemirko AP, Lugovaya TS (2005) Biometric human identification based on electrocardiogram. Proceedings of the XIIIth Russian Conference on Mathematical Methods of Pattern Recognition, Moscow, Russian, (pp 20–26)
40. Ojala T, Pietikäinen M (1999) Unsupervised texture segmentation using feature distributions. Pattern Recogn 32(3):477–486
41. Ojala T, Pietikäinen M, Harwood D (1996) A comparative study of texture measures with classification based on featured distributions. Pattern Recogn 29(1):51–59
42. Pan J, Tompkins WJ (1985) A real-time QRS detection algorithm. IEEE Trans Biomed Eng 3:230–236
43. Pietikäinen M, Hadid A, Zhao G, Ahonen T (2011) Computer vision using local binary patterns (Vol 40). Springer Science %& Business Media
44. Pietikäinen M, Hadid A, Zhao G, Ahonen T (2011) Computer vision using local binary patterns (Vol 40). Springer Science & Business Media
45. Raol JR (2015) Data fusion mathematics: theory and practice. CRC Press
46. Ritter N, Owens R, Cooper J, Van Saarloos PP (1999) Location of the pupil-iris border in slit-lamp images of the cornea. Image Analysis and Processing, 1999. Proceedings. International Conference on, (pp 740– 745)
47. Ross AA, Govindarajan R (2005) Feature level fusion of hand and face biometrics. Biom Technol Hum Identif II 5779:196–205
48. Ross A, Jain A (2003) Information fusion in biometrics. Pattern Recogn Lett 24(13):2115–2125
49. Shin D, Shin D, Shin D (2017) Development of emotion recognition interface using complex EEG/ECG bio-signal for interactive contents. Multimed Tools Appl 76(9):11449–11470
50. Tahmasebi A, Pourghassem H (2017) Robust intra-class distance-based approach for multimodal biometric game theory-based rank-level fusion of ear, palmprint and signature. Iran J Sci Technol Trans Electr Eng 41(1):51–64
51. The MIT-BIH ECG-ID database (October 2013), http://www.physionet.org/physiobank/database/ecgiddb/
52. The University of Science and technology in Beijing Database. http://www1.ustb.edu.cn/resb/en/news/news3.htm
53. Vezzetti E, Marcolin F (2012) Geometrical descriptors for human face morphological analysis and recognition. Robot Auton Syst 60(6):928–939
54. Webbeler G, Stavridis M, Kreiseler D, Bousseljot R-D, Elster C (2007) Verification of humans using the electrocardiogram. Pattern Recogn Lett 28(10):1172–1175
55. Wildes RP, Asmuth JC, Green GL, Hsu SC, Kolczynski RJ, Matey JR et al (1994) A system for automated iris recognition. Applications of Computer Vision, 1994. Proceedings of the Second IEEE Workshop on, (pp 121–128)
56. Yan P, Bowyer KW (2005) Ear biometrics using 2D and 3D images. In Computer Vision and Pattern Recognition-Workshops, 2005. CVPR Workshops. IEEE Computer Society Conference on (pp 121–121). IEEE

Meryem Regouid received his Masters degree in TIC from the Faculty of Mathematics and Computer Science, at the University of M'sila -Mohamed Boudiaf-, Algeria in 2015. She is currently in her third year of her Ph.D. in the department of sciences, Farhat Abbes Setif 1. Her research interests center on intelligent systems and machine learning. Her current research is focused on the development of a multimodal biometric recognition system using different biometrical modalities (ECG, EAR, IRIS…).

Mohamed Touahria Appointed in 2014 as Professor in the Computer Science Department of Ferhat Abbas University in Setif, Algeria. For the last 15 years, he has been in charge of computer science research teams in the field of artificial intelligence and knowledge engineering. He is the author of numerous publications and a member of international conference program committees. His fields of research are artificial intelligence, web applications and automatic translation of natural languages.

Mohamed Benouis received his Masters degree in TIC from the National Institute of Telecommunications and ICT (INT-TIC), Oran, Algeria in 2012. He received his PhD in Computer Science from the University of Oran 1 Ahmed Ben Bella in 2017. Since then, his work has focused on two areas, one being modeling of biometric data using bioelectrical signals (ECG, EMG, EEG), and the development of mobile applications for modeling human behavior, with a particular focus on health-related behaviors such as smoking. He is a Lecturer at the University of M'sila, Algeria where he was engaged in delivering lectures on data compression, artificial intelligence and telecom network.

Nicholas Costen received the BA degree in experimental psychology from the University of Oxford, and the PhD degree in mathematics and psychology from the University of Aberdeen. He has undertaken research with the Advanced Telecommunications Research Laboratory, Kyoto, and the Division of Imaging Science and Biomedical Engineering, University of Manchester. He is currently a Reader in Cognitive Computer Vision with Manchester Metropolitan University, where his interests include face recognition and human motion analysis.

Affiliations

Meryem Regouid[1] & Mohamed Touahria[1] & Mohamed Benouis[2] & Nicholas Costen[3]

Mohamed Touahria
mohamed.touahria@univ.setif.dz

Mohamed Benouis
mohamed.benouis@univ.msila.dz

Nicholas Costen
n.costen@mmu.ac.uk

[1] Computer Science Department, University of Ferhat Abbas Setif 1, Pôle 2 - El Bez, 19000 Setif, Algeria

[2] Computer Science Department, University of M’sila BP, 28000 M’sila, Algeria

[3] Manchester Metropolitan University, Manchester, UK