A Multimodal Approach for Face and Ear Biometric System

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Abstract

Multi modal biometric system is one of the major areas of study identified with large applications in recognition system. Single modal biometric systems have to challenge with a variety of problems such as noisy data, Intra-class variations, non-universality, spoof attacks, and unacceptable error rates. Some of these limitations can be solved with multi modal biometric systems. The major purpose of the study is to review and analyze the prime works in multimodal biometric system and its efficiency in recognition rate. The proposed framework of the multimodal biometric system using face and ear is given. This paper also discusses the levels of fusion that are possible and understand the types of challenges focused by prior research work in this area.

Keywords: *Face recognition, Ear recognition, biometric recognition, multi-modal recognition.*

1. Introduction

Biometric techniques are being used increasingly as a hedge against identity theft. The premise is that a biometric is a measurable physical features or behavioral trait and is a more trustworthy indicator of identity than bequest systems such as passwords and PINs [3]. Biometrics first came to renown in 1879 when Alphonse Bertillon (1853–1914), a French Criminologist, introduced his anthropometrical signalment or Bertillonage system for identifying criminals [22]. A method of identification based on anthropometry of different parts of the human body had developed including head, ear, fingers etc., the size of which remain constant throughout life after attaining full growth [3]. However, greater accuracy and robustness is desired in biometric identification.

A method of identifying or verifying the identity of an individual person or subject based on the physiological and behavioral characteristics is biometric recognition. Physiological biometrics is based on data derived from direct dimension of a part of the human body [6]. It involves fingerprint, iris-scan, DNA, retina scan, hand geometry, and facial recognition. Behavioral biometrics is based on data derived from an action taken by a person or individuals behavioral characteristic. Behavioral biometrics characteristics involve voice recognition, keystroke-scan, and signature-scan. Any physiological or behavioral characteristic of human can be used as a biometric characteristic as long as it is Universal, Unique, Collectable and Permanent [22].

Biometrics recognition features can be either passive or active. The recognition of Face and ear feature are Passive biometrics. Users participation is not require. It can be analyzed and successful even without any explicit action of the part of the user. But Active biometrics like fingerprint, retina scanning, signature recognition, DNA etc. however, do require some voluntary action by the user and will not work if one reject participating in the process. Biometric-based personal recognition systems can be classified into two main categories: Verification and Identification. Biometric verification ("one-to-one matching") compares the registered template of identity against an input image of an unknown person, whether the person is claims to be. Biometric Identification ("one-to-many matching") compares the input image of an unknown person against all records in a registered template [6]. The system identifies the individual from the database gallery. This category is usually associated with law enforcement applications.

Biometrics is a fast growing technology which can be useful in criminal justice system like mug-shot, post-event analysis, forensics. It provides security to prevent unauthorized access to ATMs, computer networks, cellular phones, email authentication on multimedia workstations, PDA, medical records management and distance learning. The voice biometric can be used during transactions conducted via telephone and internet commerce and banking. Retinal patterns of an individual provide medical information about diabetes or high blood pressure. In automobiles, keys can be replaced with key-less entry devices by the fingerprint biometric system. Face biometric is used in smart card applications [10]. The face-print can be stored in a smart card, bar code or magnetic stripe. Active biometrics like iris, fingerprint, and retina are most widely used and well-known biometrics. The passive biometric, face recognition is used in forensic applications such as terrorist identification, corpse identification etc. The other biometric applications such as social security, national ID card, border control and passport control.

2. Issues in Unimodal Biometric

The successful installation of biometric systems in different civilian applications does not entail that biometrics is a completely solved problem. Single modal biometric traits have plenty of error rates and they may not achieve the desired performance requirements. There are many factors which degrades the recognition performance. Researchers are addressing to enhance the usability of biometric system. Some of the issues imposed by single modal biometric are given below:

2.1 Noise in sensed data

Biometric system has different sensed data. The sensed data might be noisy or deformed. A voice altered by cold, iris recognition with wearing glasses. Finger print with a scar, might be too oily, dry, wet or damaged temporally or permanently. Face sensed weaknesses due to variations in light, pose or illumination. Gait sensed with fluctuation in body weights. Noisy sensed biometric data may be false matched with templates in database resulting in a false rejection.

2.2 Distinctiveness

Biometric trait is expected to vary significantly across two individuals. The characteristics of the individuals are represents with the large inter-class similarity in the feature sets. The information content (number of distinguishable patterns) in two of the most commonly used representations of hand geometry and face are only the order of and, respectively [13].

2.3 Nonuniversality

Problems regarding the quality or consistency of the capture of biometric data may not necessarily due to a fault or error in the sensor [20]. About 4% of the population may have poor quality fingerprints, due to scars or cuts and it shows erroneous result. Intra-class variations, the biometric data acquired from an person during testing may be different from template data during enrollment. The users are incorrectly interacting with the sensor. This may affect the matching result.

2.4 Spoof attacks

Biometric traits of the legitimate user are enrolled in the template database; an imposter may attempt to spoof the sensed data of the biometric system when the traits such as signature [25] and voice [2] are used. The fingerprint traits can also be spoof with the artificial fingers/finger print to thwart a fingerprint verification system [24].

3. Multimodal Biometric System

Multi-modal biometrics increase accuracy by considering other highly specific biological traits to limit the number of applicant for an identity. This system is expected to be more reliable due to the presence of multiple, independent trait and not easy to forge multiple biometric trait. Variety of biometric scenarios is depending on the traits, feature sets and sensors applied. Some of the scenarios are multiple sensors, multiple algorithms, repeated instances, multiple modalities. Multimodal system functions in three different modes. In Serial mode, the output of the one modality is used to reduce the number of possible identities before the next modality is used. In parallel mode, sensed data from multiple modalities are used concurrently. In hierarchical mode, individual modality is combined in a hierarchy structure.

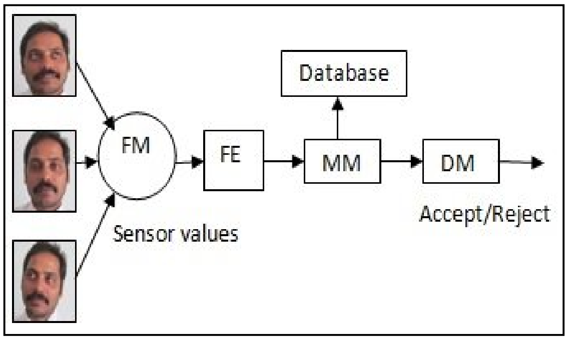
The performance of the multimodal system is expressed in terms of matching errors and image acquisition errors. Matching errors consist of false match rate (FMR), in which an impostor's sample matches a legitimate user's template, and False Non Match Rate (FNMR), in which a legitimate user's sample does not match his/her own template. Image acquisition errors consists of Failure to Enroll (FTE) which is defined as a user that is unable to successfully enroll in a biometric system, and Failure to Acquire (FTA) is a user that is unable to provide a good quality biometric trait at verification.

4. Level of Fusions

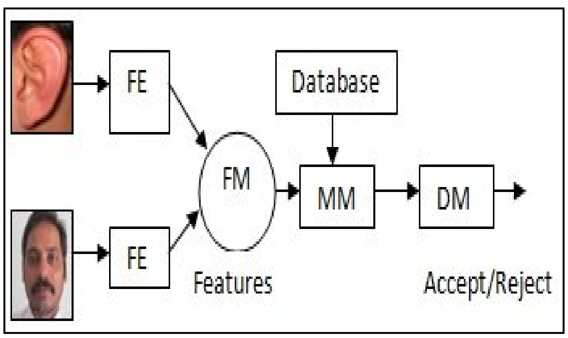
The Biometric fusion is the technique to integrate the classification results from each biometric channel. Multimodal biometric fusion combines the aspect from various biometric features to improve the strengths and reduce the limitations of the individual aspects. The efficiency of the fusion scheme greatly influences the accuracy of a multimodal biometric system. The various levels of fusion are:

4.1 Sensor level fusion

The raw data obtained from multiple sensors can be practiced and merged to generate new biometric data from which trait can be extracted. Biometric traits from different sensors like fingerprint, video camera, iris scanner, digital signature etc, are fused to form biometric trait to process. Sensing a speech signal concurrently with two various microphones may be fused and then be subjected to feature extraction and matching. Sensor level is projected to improve the recognition accuracy; it remains possible problems related with unimodal biometric system because of incompatibility of data from various modalities [12].



(a)



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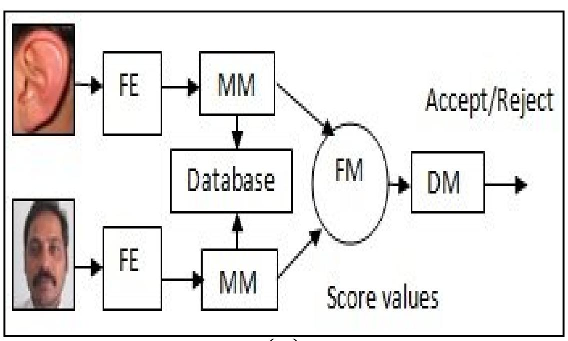

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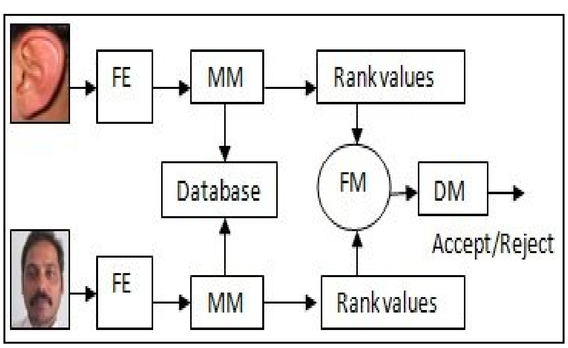

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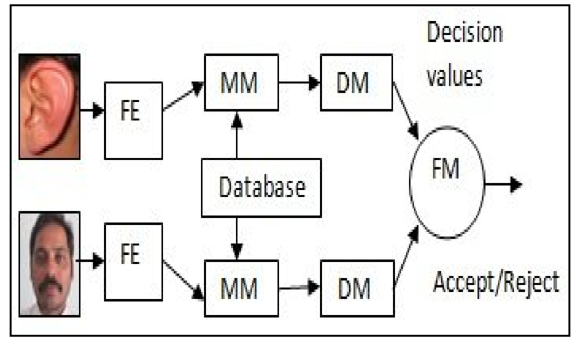

(e)

Fig 1. Level of Fusions: (a) Sensor Level fusion, (b) Feature Level fusion, (c) Match Score Level fusion, (d) Rank Level fusion, and (e) Decision Level fusion. FE: Feature Extraction Module; MM: Matching Module; DM: Decision-Making Module; FM: Fusion Module.

4.2 Feature level fusion

The feature sets are extracted from different biometric channels can be fused using specific fusion algorithm to form a composite feature set. The feature collections of different modalities agree to extract a minimal feature set from the high-dimensional feature vector. The feature vectors extracted from the face and ear modalities can be fused is an example of multimodal system. The feature level fusion is the extraction of correlated feature from the different modalities and in course identifies a prominent set of features that can improve recognition accuracy [7]. The feature level fusion is likely to achieve superior result in comparison with score level and decision level fusion.

4.3 Match score level fusion

Feature vectors are generated separately for each modality. Extracted feature vectors compared with the templates residing in the database individually for each biometric trait to generate match scores. Depending on the accuracy of each biometric channel, output set of match scores which are fused to create composite matching score. As an example, face and hand modalities match score may be combined by the use of simple sum rule in order to obtain a new match score which is then sent to the decision module [4].

4.4 Rank level fusion

Rank level fusion is a new fusion approach where each classifier associates a rank with every enrolled identity. Fusion involves consolidating the rank output by individual biometric subsystems and determining a new rank that would support in establishing the final decision. However, these fusions have one weakness. In multimodal biometric, more different identities output from two or three matching modules which are designed to appear some identities of only one matcher. In this case, the rank level fusion shows the risk of wrong results [11].

4.5 Decision level fusion

In multimodal biometric system, the final decision is based on the separate decision of different modalities using techniques such as majority voting, behavior knowledge space, weighted voting, AND rule, OR rule. Decision level fusion is least powerful due to availability of inadequate information and limits the basis for enhancing the system accuracy.

5. Prior Research Work

The prior works of the researches in multimodal biometric system are reviewed. Features of the face or other parts of the human have dissimilar properties for different sensors. Each parameter of the biometric can be characterized as better or worse depending on the data of the individual is acquired for identification purposes. The important features of multi-modal biometric studies are summarized in Table 1.

Muhammad Imran Razzak et al. [18] combined the face and finger veins, in which multilevel score level fusion is performed to increase the robustness of the authentication system. The score level fusion of client specific linear discriminant analysis (CSLDA) for fusion of face and finger veins result is performed. CLSDA uses the PCA and LDA to generate a client specific template. The score of face and finger veins are combined using weighted Fuzzy fusion. This system is efficient in reducing the FAR 0.05 and increasing GAR 91.4.

A human recognition method combined face and speech information in order to improve the problem of single biometric authentication are proposed by Mohamed Soltane et al. [16]. Gaussian mixture modal (GMM) is the main tool used in text-independent speaker recognition, in which it can be trained using the Expectation Maximization (EM) and Figueiredo-Jain (FJ) algorithms for score level data fusion. The use of finite GMM based Expectation Maximization (EM) estimated algorithm for score level data fusion is proposed. Extracted face and extracted audio is fused to achieve recognition rate. Face speech biometric EER is reduced to 0.087.

A multi-biometric system using lip movement and gestures is proposed by Piotr Dalka et al. [19]. . Lip gesture recognition is performed by an artificial neural network (ANN) approach. ANN contains parameters like no gesture, mouth opening, forming puckered lips, sticking out the tongue and all gestures. The experiment used 6120 image frames. The entire feature vector for ANN contains lip region only. ANN is trained with a resilient back propagation algorithm (RPROP). The result shows that the recognition rate is 93.7%.

A multi-biometric system using face and ear is presented by A.A. Darwish et al. [1]. PCA deccorrelate data by finding the eigen vectors of the covariance matrix. MIT, ORL and Yale databases are used for implementation. The individual face and ear images are normalized and preprocessed and then transformed to the PCA space. The system performance is 92.24% with FAR of 10% , FRR of 6.1%, Because of high accuracy and security, it concluded that the fusion of face and ear is a good technique.

The schedule extraction of local 3D features (L3DF) from ear and face biometrics and their arrangement at the feature and score levels for identification has been presented by S.M.S. Islam *et al.* [23]. 3D features removed from ear and frontal face information are fused at feature level. Scores from L3DF and iterative closest point algorithm were fused at matching level by means of a weighted sum rule. This system achieved recognition and verification (at 0.001 FAR) rates of 99.0% and 99.4%, respectively, with neutral and 96.8% and 97.1% with non-neutral facial expressions.

The multimodal system of face and ear at feature level fusion by Sparse Representation (SR) are proposed by Zengxi Huang *et al.* [27]. SR-based classification methods used in classification phase were Sparse Representation based Classification (SRC) and Robust Sparse Coding (RSC). Finally, they have obtained a group of SR-based multimodal recognition techniques, together with Multimodal SRC with feature Weighting (MSRCW) and Multimodal RSC with feature Weighting (MRSCW).

A novel kernel-based feature fusion algorithm method in combination of face and ear is proposed by Xu Xiaona et al. [26]. Combining with KPCA or KFDA algorithm, the feature fusion method were presented and applied to multimodal biometrics based on fusion of ear and profile face biometrics. This system defines the Average rule, Product rule, Weighted-sum rule in kernel-based fusion feature method and USTB database is analyzed. The experimental shows that the recognition rate of KPCA is 94.52% and KFDA is 96.84%, and this method is efficient for feature fusion level.

H. Mahoor et al. [15] proposed with a 2D face and 3D ear fusion at the match scores level using weighted sum technique. Active Shape Model is used to extract a set of facial landmarks from frontal facial images. For the ear recognition, a set of frames is extracted from a video clip and ear region in each frame is restructured in 3D using Shape from Shading (SFS) algorithm. The resulting 3D ear models are aligned using the iterative closest point (ICP) algorithm. The experiment performed on a database of 402 subjects. The performance of the system is increased to 100%; FAR 0.01%, EER of the multi-modal system is .01%.

M. Kawulok et al. [14] presents a face and eyes using multi-level ellipse detector combined with a SVM verifier. The main contribution is in increasing the accuracy of eye detection in high-quality images. The authors show that the detection error propagation considerably influences the face recognition performance. With the proposed improvements, face recognition increase the rate by 0.5 % for FERET and 7.7% for AR database compared with the publicly available implementation of the well established Viola-Jones face and eye detector.

Linlin shen et al. [23] proposed improve the accuracy by integrating multiple modal biometrics i.e face and palmprint. The both face and palmprint feature are represent by feature code, namely FPCode. FPCode uses fixed length 1/10 bits coding scheme that is very efficient in matching, and at the same time achieves higher accuracy than other fusion methods available. This approach compares with the Gabor+PCA and Gabor+KDRC. Experimental results show that both feature level and decision level strategies achieve much performance with the accuracy of 91.52% and 91.63%.

There are different ways of integrating different modality and they are depends on the number of samples, multiple matches, multiple snapshots, multiple sensors and the number of biometric features in the context of multi-biometric studies. Ear feature provide better biometric performance. Ear undergoes very slight changes from the childhood to adulthood. Due to ears semi-rigid shape and robustness against change over time, the ear has become an increasingly popular biometric feature. It has been shown that combining individual biometric methods face and ear into multi-biometric systems improves recognition.

6. Multiple Biometrics using Face and Ear

Multimodal biometrics based on the fusion of two different biometric modalities face and ear; provide a new approach of non- invasive biometric authentication. There are several inspirations to choose face and ear for a multi-modal biometric recognition. During image acquisition, ear and face data can be captured using conventional cameras. The data collection for face and ear does not require participation or cooperation from the user. The traits face and ear are in close physical proximity to each other. Both biometric features are jointly present in an image or video captured of a user's head and are both available to a biometric system. In prior literature work, the fusion of face and ear biometric shows the good performance in accuracy and recognition.

7. Proposed Framework

Multimodal Face and ear are combined to increase the robustness of the recognition system. The proposed model includes a training phase and recognition phase. In training phase, the samples of data on which the system needs to recognize are trained. Figure 2 present the proposed framework of multimodal recognition system. Figure 3 shows the sample face and ear image tested in the proposed system. Two different modalities face and ear are applied here. Recognition phase comprise with preprocessing, feature extraction and authorization. The input face and ear images are preprocessed, to reduce or eliminates some of the variations in input image. It enhances the image to improve the recognition performance of the system. Shape and texture features are extracted from the input images. A shape feature is to extract the shape of face and ear by using modified region growing algorithm. Texture feature are extracted by LGXP Technique. The authorization is done with the fuzzy vault. For decoding, the constructed face and ear image is combined with the stored fuzzy vault to generate the final key. The performance will be evaluated with the False Matching Rate (FMR), False Non Matching Rate (FNMR) and Genuine Acceptance Rate (GAR).

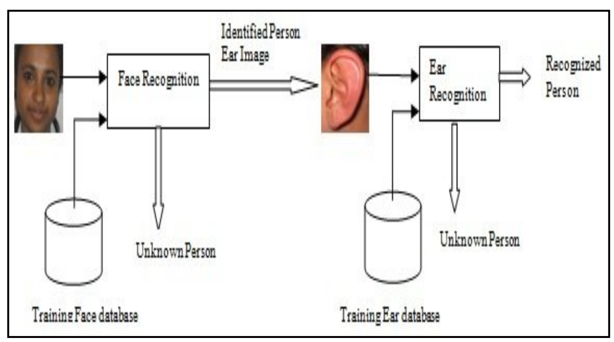

Fig. 2 Proposed framework of the system

Fig. 3 Sample Face and Ear image

TABLE 1: MULTI - MODAL BIOMETRIC STUDIES

Source (year)	***Databases***	***Biometric sources***	***Technique Adopted***	***Performance of Classification in percentage***	***No. of subjects***
Muhammad Imran Razzak(10') [18]	CAIRO	Face + Finger Veins	client specific linear discriminant analysis (CSLDA)	FAR 0.05% and GAR 91.4%	35 subjects,
Mohamed Soltane(10') [19]	UYVY. AVI 640 x 480, 15.00 fps	Face + Speech	Gaussian mixture modal (GMM)	EER: Face 0.44935, Speech 0.00269, Face + Speech (fusion) 0.08728	30 subjects
Piotr Dalka(10') [16]	Faces are recorded using web camera	Lip movement + Gestures	Artificial Neural Network (ANN)	Recognition Rate 93.7%	176 subjects
Darwish (09') [1]	MIT, Yale	Face + Ear	Principal Component Analysis (PCA)	Accuracy of 92.24% with FAR of 10% and FRR of 6.1%	MIT – 40 subjects ORL – 15 YALE-10.
S.M.S. Islam (13') [23]	UWA, UND-FRGC, UND-F and FRGC V2	Face + Ear	L3DF, Iterative closet point	FAR 0.001 Recognition: 96.8% Verification: 97.1%	UWA – 56 subjects UND-FRGC : 326 UND-F and FRGC V2: 100
Zengxi Huang (13') [27]	MD I: Yale B and USTB. MD II : AR and USTB	Face + Ear	Sparse Representation based Classification (SRC), Robust Sparse Coding (RSC)	MDI MSRCW : 95.732% MRSCW:97.86% MD II MSRCW: 98.39% MRSCW: 99.0%	MD I : 38 MD II: 79
Xu Xiaona(09') [26]	USTB database	Face + Ear	KPCA, Kernel Fisher Discriminant Analysis (KFDA)	Recognion Rate fusion KPCA 94.52%, KFDA 96.84%	79 subjects
M.H. Mahoor(09') [15]	West Virginia University database	2D Face + 3D Ear	Weighted sum technique	EER .01%, FAR .01%, Rank one identification 100%,	402 subjects
M. Kawulok (12')[14]	FERET, AR database	Face + Eye	multi-level ellipse detector combined with a SVM verifier	Increase the recognition rate by 0.5% for FERET and 7.7% for AR.	FERET: 3657 images AR: 3313 images
Linlin shen(11') [23]	AR, PolyU database	Face + Palmprint	FPCODE	Feature level fusion : 91.52% Decision level fusion : 91.63%	AR : 119 subjects PolyU : 386 palms

8. Comparison with Other Biometrics

Gait: Gait is a behavioral biometric. Gait is not supposed to be very distinctive, but is sufficiently discriminatory to allow verification in some low-security applications. It may not remain invariant, especially over a long period of time, due to fluctuations in body weight, major injuries involving joints or brain.

Iris: Iris is much smaller than the ear, a high resolution camera device is required in order to acquire image of acceptable quality. In general, the capturing sensor device is usually placed far from the subject. Iris recognition also can fail when the subject wear glasses.

Fingerprint: Fingerprint biometric system entails the use of specially designed sensors and computational resources which maybe too expensive for large scale deployment, especially when operating in the identification mode. Fingerprints of a small fraction of the population may be unsuitable for automatic identification because of genetic factors, aging, environmental, occupational reasons. Manual workers may have a large number of cuts and marks on their fingerprints that keep changing.

Voice: The voice of a person changes over time due to age, health conditions and emotional state, etc. Voice is also not very unique and may not be appropriate for large-scale identification. A disadvantage of voice-based recognition is that speech features are sensitive to a number of factors such as background noise.

Keystroke: This behavioral biometric is not expected to be unique to each individual. The keystroke dynamics may vary depends on the health condition. It is expect to observe large variations in typical typing patterns. The keystrokes of a person using a system could be monitored quietly as that person is keying in information.

Palmprint: The palmprints scanners need to capture a large area; they are more expensive than the fingerprint sensors. The physical size of a palmprint based system is large, and it cannot be embedded in certain devices.

Signature: The signature of a person is to be a characteristic of that individual. Signatures require contact with the writing instrument and an effort on the part of the user, which have been accepted in government, legal, and commercial transactions as a method of verification. It changes over a period of time and is influenced by physical and emotional conditions of the signatories. Signatures of some people vary significantly. Professional forgers may be able to reproduce signatures that fool the system.

8.1 Face biometric

Face recognition has potential applications in security control, surveillance, office automation, prevention of fraud, video indexing, automatic personalization of environments, etc. [21]. Face recognition is passive and non-intrusive unlike other active biometric techniques such as those using fingerprints, speech and signature [17]. There are two main categories of face recognition systems: First, Face detection and normalization, the face image database contains one image per person. System identifies a person and returns a list of names that most likely matches the query face image. Secondly, Face identification, System identifies a person from a smaller face databases so that they can gain entry to a particular resource. The face recognition techniques can be modified and used for gender classification. The high accuracy of the biometric system is to identify faces in real time under different facial expressions, hairstyle, and image background.

8.2 Ear Biometric

Ear is a new class of human biometrics for physiological identification with uniqueness and permanence. Ear has information rich anatomical feature and unaffected by ageing. Its location on the side of the head makes extraction easier. Ear biometric is convenient in collecting data comparison to other technologies like retina, iris, fingerprint [5]. The combination of ear and face show high recognition results. The ear features and ear identification were using in forensic for more than 10 years [1, 8]. In the absence of fingerprint, due to lack of expression and less effect of aging, the ear biometric is suggested for the identification. The recognition is similar to face recognition and it consists of image acquisition, preprocessing, feature extraction, model training and template matching.

7. Conclusion

Multimodal biometric systems address numerous problems observed in single modal biometric systems. The complex methods employed to find a good combination of multiple biometric modality and various level of fusion applied to get the best possible recognition result are discussed in this paper. The prior work has shown the performance evaluation of the multimodal system under the different trait combination scheme, identification rate and databases. The combination of face and ear modality are suggested and the proposed framework of the biometric system is given. In this paper, table 1 claims that multi-biometrics improve over a single biometric system and uncorrelated modalities are used to achieve performance in multimodal system.

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