Score Level and Feature Level Fusion of Face and Ear Biometrics for Personal Authentication

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Abstract- Thepresent networked culture needs more naturally and consistency in provided to access in high level security and transaction management systems .so they move to the biometrics. We present to fusion the (L3DF) Local 3D features for 3D ear and face data using the score level and fusion level technique. The score and feature level techniques can used to fusion the face and ear data. For score-level fusion, to perform normalization the ear and face local 3Dimentional features (L3DFs) are take-out and coordinated separately. Matching scores from the two modalities traits are then fused rendering to a weighted sum rule technique. For feature level fusion technique, after extracting Local 3DFeatures from the face and ear data, we concatenate the face and ear data based on their local shape similarity (LSS). Formerly iterative closest point (ICP) used to fused data, according to the fused feature distance. Both these approaches are fully accurate and were found to be highly automatic and efficient.

Index term **-** score level, feature level fusion, L3DF, iterative closest point (ICP), weighted sum rule.

1. INTRODUCTION:

Thecurrent networked society are more naturally and reliability is providing high level security to access control and transaction management systems. [4, 6] Most of the modernhuman identity verification model i.e. based on token (ID card) an d knowledge based (password) can easily violation when the password is revelation or the card is stolen, so the traditional identification systems are not sufficiently reliable to satisfy current security, who the user illegally acquires the access privilege.

To overcome this problem, the concept of biometrics can be introduced.Biometrics methods easily deal with these problems since peoples are recognized by who they are, not by something they have to recall or convey with them. Science of launching the identity of an individual based on the bodily and behavioural attributes of the person.[14]There are many methods of users identification based on image examination. In general, these biometrics technique can be divided into physiological and behavioural regarding the basis of data. The first method is based on it identifies people by how they doing something and based on the behavioural features data of human actions.

In this work, we explore a method for fusing the 3D ear and face biometric data at the match score level and fusion level technique. Many no of year forensic science can be used in the human year for major featureEar does not change highly during face changes more meaningfully with age than any other part of human bodyand human life. [9]First we extract the face image using iterative closest point algorithm (ICP).

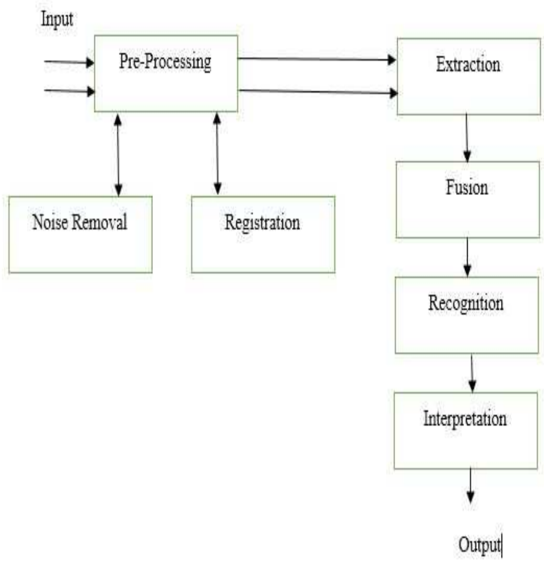

Fig 1: SYSTEM ARCHITECTURE

This method first acquire the image then pre-processed and find the neighbour pair then extract the face image and we extract ear image using our previous developed method AdaBoost technique. In this technique first classify the given ear data and classification the data then eliminate the noisy data and extract the clustered ear data. The feature level fusionis used to normalization and matching the 3D ear and face data using root mean square (RMS) distance technique and score level fusion is used to concatenate or integrate the extracted data using weighted sum rule. Both these techniques are fully automatic and highly accurate and efficient. [20]

2. LITERATURE REVIEW

[1]Dapinder Kaur, Gaganpreet Kaur was describe the advantages of multimodal biometrics fusion have appeared in the literature.Biometrics refers to an automatic identification of a person based on his physiological and behavioural characteristics. The single modal biometric recognition systems have a variety of problems and limited applications are used in singe or unimodel biometric system. Four important modules are used in the multimodal biometric system. The first sensor module acquiring the biometric data from a authentication person; second the data extraction module processes the acquired biometric data and extracts a data set to represent it [10]; third the matching modulecompares the extracted feature set with the database using a classifier or matching technique algorithm in order to generatematching scores; finally the decision level module the matching scores are used either to identify an enrolled user or verify a user's identity

[2]Xiaobo Zhang, Zhenan Sun, and Tieniu Tandescribe about the fusion of Face and Iris in order to improve the quality of the image. The Hierarchical fusion scheme process in the low Quality image under uncontrolled situation. The (CCA)Canonical correlation Analysis, is accepted to build a numerical mapping in Face and Iris in pixel level. The pixel level and Score level fusion are processed for the evaluation of the Fusion of Face and Iris. The construction of the regression model between two data sets is done by considering its canonical correlation analysis (CCA) from its efficient and effective results align to form mapping between two multidimensional variables. [5] The Score level fusion identification process is done, by Representing the Face and Iris traits and Fusion of those components results in the similarity measure between the problem sample and the gallery model can be explained by the residual between the original testing models.

[3]AtifBinMansoor, Salah-ud-din GhulamMohi-ud-Din, HassanMasood, MustafaMumtazdescribe the use of multi-instance feature level fusionThe modern network are not sufficiently dependable to satisfy the recent security supplies as they lack the ability to stop the fraud user who illegally acquires to access the data. To solve this problem move to the biometrics. In the biometrics the single model system suffers various problem like similar data occur, unacceptable error. These problems are effectively handled by multimodal biometrics system. [7, 6, 9] In this paper to fusion the palm print and finger-print by feature level and score level (Sum and Product rule).

[4]Nageshkumar.M, Mahesh.PK and M.N. ShanmukhaSwamy proposed an authentication system based on face and palm-print. The biometrics based personal identification is to regard an effective method for automatically identifying user data, with a high sureness a person's identity. [11, 13, 10] A multimodal biometric modalityjoined the evidence presented by multiple biometric sources data and typically improved recognition performance relate to system based on a unibiometric modality system. This paper is proposed todesign for application where the exercise data contains a palm-print and face.Integrating the palm-print and face data features improving robustness of the person authentication. The final choice is made by fusion at matching score level technique architecture in which features data are created unconventionally for query measures and are then compared to the enrolment pattern, which are stored during database preparation.

[5] Michal Choras describe the concept about human ear recognition. TheBiometrics authentication methods proved to be more natural, very efficient, and easy for users than standard methods of user identification. Actually, only biometrics methods truly identify humans. Because we can't remember any password and ID cards. In this biometrics very simple to acquisition the data easily and requires human data only camera, sensor or scanner. The physical biometrics methods to have many advantages over technique based on user behaviour. This article introduces to ear biometrics based recognition and presents its merits over face biometrics in inert user Identification method. The ear data is unique to extract the features. [8, 12] Because it's constant when changing the face expression.so easy to extract the data from ears. In the process of acquisition, ear images cannot be disturbed by glasses in contrast to face identification systems, stubble and make-up. Based on this method to recognize the data. But can't recognize when the image is low quality.

3. RELADED WORK:

The modern organizations like financial service area, telecommunication,e-commerce, government, traffic, health care the security concerns are more and more main. It is main to verify that people are allowed to pass some points or use some properties. The security issues are risen quickly after some basicmisuses. For these reason, organizations are interested in taking automated identity identification systems, which will improve the customers satisfaction and operating productivity. Basically there are three different methods for verifying identity: (i)knowledge, like userid, password, Personal authentication Number (PIN); (ii)possessions, like cards, badges, keys; (iii) biometrics similar fingerprint, face, and ear data. Biometrics is the verifying the identity of a person or science of finding based on behavioural or physiological characteristics.

The ear and face has been proposed as a biometric. In this we recognize face and ear in a single sensor. And extracting the feature using Iterative Closest Point (ICP) and AdaBoost algorithm. Then the extracted features are stored into the database. In the face and ear data are fused using score and feature level technique, so it will improving performance and robustness.

Active shape model is a statistical approach for facial feature extraction. In the original ASM the local structure of a feature point is modelled by assuming that the normalized first derivative of the pixel intensity values along a profile line satisfy multivariate Gaussian distribution. Gaussian model, respectively.

$$f_{P_{HSV}} = \sum_{i\in\{h,s,v\}} w_i \cdot (P_i - \overline{P_i})^T \Sigma_i^{-1} (P_i - \overline{P_i}) \quad (1)$$

The ear shape model is used to describe a shape and its typical appearances.The local appearance models describe the local gray features around each landmark. To be assumed that local gray models are distributed as a Gaussian multivariate. For the j_{th}landmark, we can derive the mean profile $\overline{k}_j$ and the sample covariance matrix M_j from thej_{th} profile example straight. The quality of the suitable a feature vector K_m at teat image location s to the j_{th}technique is given by calculating the MahalanobisGaussiandistance from the feature vector to the j_{th} model mean.

$$f_j(K_m) = (K_m - \overline{K}_j)^t M_j^{-1} (K_m - \overline{K}_j) \quad (2)$$

Similarly, in case of single modal identifiers, the extracted features data are co-ordinated with respective database using a Euclidian classifier in matching component, followed by the decision on the foundation of selected edge in the decision module method.

The score level and feature level fusion technique is used to fused the weighted sum rule technique. Thus, the new set of values covers more amount of data as compared to the individual single model systems, hence, giving more data to identify a person. Finally, the conclusion of input statement is established on the basis of present threshold by the classifier.

$$S_g = \sum_{j=1}^{R} f_{P_{HSV}} * f_j(K_m)$$
(3)

Where, $f_{P_{HSV}}$ active shape model for face recognition and $f_j(K_m)$ is ear shape model. R is a vector value for score level fusion. Finally, S_g is the fusion of face and ear value.

4. PROPOSED SYSTEM:

In the proposed system to collected and created the multimodal biometric datasets for evaluate the performance of fusion methods. In order to create the multimodal datasets, ear and face features are extracted from the frontal andprofile face images individually. The ear area is identified from 2D profile image based on Cascaded AdaBoost algorithm
technique

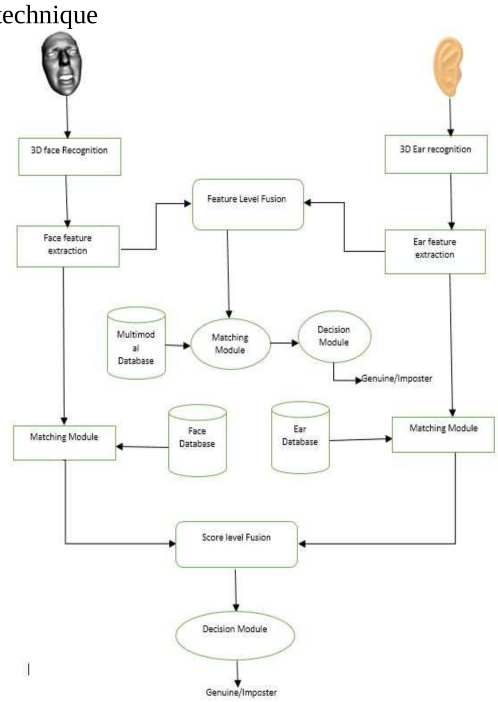

Fig 2: METHODOLOGY ARCHITECTURE

So, it is very perfect, fast and entirely automatic approach. During data collection, both the 2D surfaced colour image and 3D scanned object are captured simultaneously and available to the users in communication. Therefore, after the ear region is detected from the 2D shape image, the parallel 3D data are then extracted from the co-registered 3D profile feature data. The position of the nose point is then identified in the matching district of range image from which a sphere of radius of 80 mm is take out. Then eliminate spikes from the extracted 3D face feature data, resample it.

For feature-level fusion method of ear and face, feature vectors of face and ear are concatenated collected to make shared feature vector technique. The objective is to syndicate these two feature sets after standardisation in order to produce a joint feature vector (JFV). joint feature vector are produced and stored in order to make multimodal database which is consequently used for verification and identification purpose on a uniform grid of 160 mm by 160 mm, eliminate holes using cubic interpolation method.(Fig 2 describe) Local 3D features data are extracted from 3D face and ear data. A number of characteristic 3D feature point positions (key facts) are automatically selected on the 3D face and 3D ear region based on the irregular variations in depth around them. The Root Mean Square (RMS) distance technique is used to matching the Local 3D feature (L3DF) data.

5. EXPERIMENTS AND RESULTS:

Face and ear images were collected using Digitalized scanner or cameras. A database consisting of face and ear images of 60 individuals has been built. Sixteen prints are composed from lone individual with 10 records per biometric modalities. Thus, multimodal database consists of 990 proceedings, consisting of 440 face and 440 ear records. The database is recognised in two meetings with an average interval of two months to motivation on performance of multimodal system.

In our experimentations data, the developed database is divided into two non-overlapping sets: training and validation sets of 440 images each ear and face based multimodal system is applied in Matlab on a 1.0GB RAM, 2.5GHz Intel Core Duo processor for PC. Exercise set is first used to train the threshold determination and the system. Verification data set is then used to evaluate the performance of trained system model.

Table 1Comparison of equal error rates (EER) of multimodal and single modal systems

Biometric System	EER (%)
Face	2.823
Ear	2.554
Face and Ear (Feature level fusion)	0.540
Face and Ear (Score level fusion (Sum rule))	0.6145
Face and Ear (Score level fusion (Product rule))	0.5483

Table 1 gives the evaluation of Equal Error Rates (EER) of Multimodal systems with the single modal systems. Equal Error Rate, EER of feature-level fused method is 0.5400%, while that of score-level fusion with product and sum rules are 0.6145 and 0.5483%, respectively. The multimodal systems is far less than EER values of separate face (2.8234%) and ear (2.5543%) identifiers.

Table 2 score-level fusion results on the proprietary dataset using ICP.

The results of the	Ear		Face		Fusion	
Facial Expression	Id.rate (%)	Var.rate (%)	Id.rate (%)	Var.rate (%)	Id.rate (%)	Var.rate (%)
Neutral	92.86	91.07	98.21	98.21	100	100
Neutral	96.43	96.43	98.21	98.21	100	100
Angry	92.86	91.07	98.21	96.43	100	100
Angry	96.43	96.43	98.21	96.43	100	100
Smiling	92.86	91.07	92.86	91.07	98.21	96.43
smiling	96.43	96.43	92.86	91.07	98.21	98.21

It is obviousfrom the table that although single modal ear recognition results change when earphones are damaged, the fusion results remain at 100%. In the case of the face modality model, angry terminologies do not decrease the recognition rates much likened to smiling expression.

6.PERFORMANCE ANALYSIS:

The recognition presentation of our proposed score level fusion approach is estimated as follows.

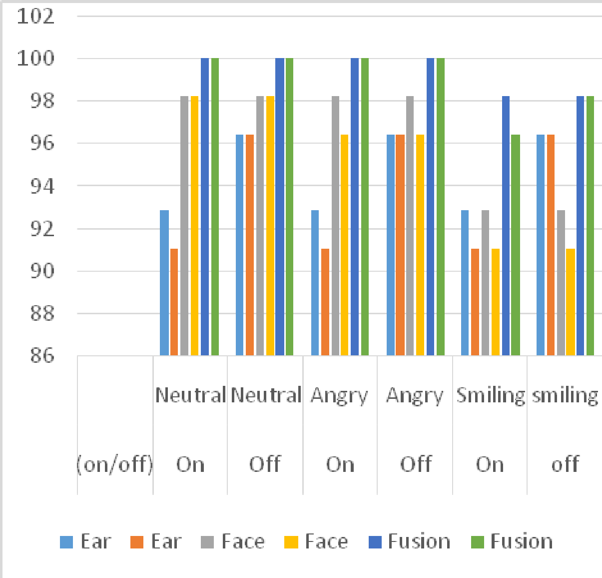

Fig 3.Identification results on the test dataset for score level and feature level fusion technique.

6.1. Results using L3DF-based measures only

The results calculated without including the ICP data scores. Only seeing the L3DF based scores are as follows. It will obtain rank one authentications rates of 90.1% and 96.89% unconnectedly for the face and ear data respectively on the dataset with animpartial facial expression. The score level fusion of two modalities, progresses the overall presentation to 99.9% accuracy for rank one authentication.

6.2. Identification results:

The feature level fusion of face and ear data on the examination data set with non-aligned facial expression, to obtain a rankone proof of identity rate of 98.9%. On the similar data set with non-neutralterminologies.

6.3. Verification results:

For the data with impartial facial expression on the examination dataset, to obtain a verification rate 99.9% at an FAR of 0.01. In case of non-neutral expressions, the accuracy decreases to 96.9%.

The fig 4 can be well-known that although results of aseparable modality increase with the use ofIterative Closest Point for neutral expression, the fusion result reduced slightly.

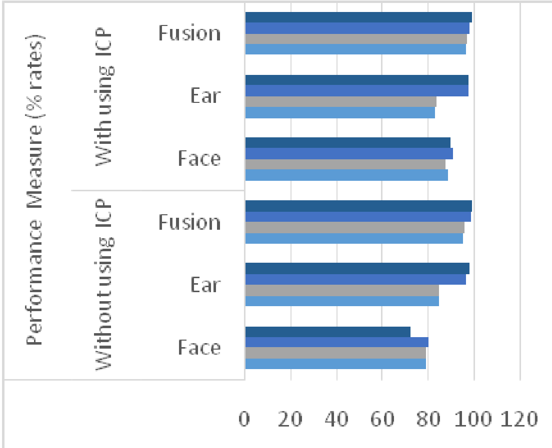

Fig 4. The Performance Measure for Rank one identification rate and verification rate.

7. CONCLUSION:

In this paper, two multimodal ear face biometric recognition approaches are proposed, one with fusion at the feature level and another at the score level. These methods are based on local 3D features (L3DF) which are very fast to calculateocclusions due to hair and earrings and robust to pose and scale differences. Then fusion with ear feature data meaningfully improves the face recognition results below non-neutral expressions. The feature and score level fusion techniques can used to fusion the ear and face data. For score level fusion, to perform standardisation the ear and face (L3DFs) are take-out and matched independently. Similar scores from the two modalities are then fused rendering to a weighted sum rule (WSR). For feature level fusion, next extracting Local 3D Features L3DFs from the face and ear data, in this to concatenate them based on their local shape similarity (LSS). It will combine the benefits of the different levels of fusion methods.

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