AUTHENTICATION USING FACE AND EAR RECOGNITION BASED ON PRINCIPAL COMPONENT ANALYSIS

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Abstract

Authentication of users is an essential and difficult to achieve in all systems. Shared secrets like Passwords and key devices such as Smart cards are not presently sufficient in some situations. Traditional security methods have largely been overtaken by biometrics. Vein pattern characteristics have become the forefront of biometric research because of its uniqueness, stability and immunity to frauds. Researchers are pioneering methods of processing and matching vein patterns. For the last few years, hand vein unimodal biometric has been explored. However, to address the challenges such as intra-class variations, unacceptable error rates and noisy data posed by the latter, multimodal biometrics has to be developed. Motivated by the fact that multimodal biometrics improve the accuracy of biometric system, a dorsal hand vein biometric and face biometric has been implemented in this work. The proposed system used the extracted face and dorsal hand vein images to develop the respective feature spaces via Independent Component Analysis (ICA) algorithm. Later the individual scores are generated by individual matchers and then fused using score level fusion which is easy to access and combine the scores obtained from the different modalities. The proposed system showed promising results than individual face or hand vein biometrics investigated in the experiments. The final result was then used to affirm the person as genuine or an impostor. System was tested on several databases and gave an overall accuracy of 92.24% with FAR of 10% and FRR of 6.1%. The results obtained from the combination of face and hand vein is a good technique because it offered a high accuracy and security.

Key words: *Face Recognition, Dorsal Hand Vein Recognition, ICA, and Pattern Recognition*

1. Introduction

Biometrics refers to the use of physiological or biological characteristics to measure the identity of an individual. These features are unique to each individual and remain unaltered during a person's lifetime. These features make biometrics a promising solution to the society. The access to the secured area can be made by the use of ID numbers or password which amounts to knowledge based security. But such information can easily be accessed by intruders and they can breach the doors of security. The problem arises in case of monetary transactions and highly restricted to information zone. Thus to overcome the above mentioned issue biometric traits are used.

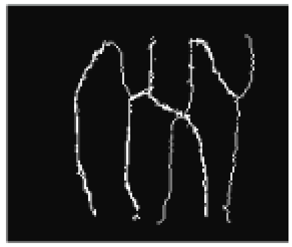
The various biometrics traits available are face, fingerprint, iris, palm print, hand geometry and ear. Among the available biometric traits some of the traits outperform others. The reliability of several biometrics traits is measured with the help of experimental results. The biometric system is basically divided into two modes i.e., uni modal biometric system and multimodal biometric system. In case of uni modal biometric system the individual trait is used for recognition or identification. The most successful applications of image analysis and understanding, face recognition has recently received significant attention, especially during the past several years, for example, recognition of face images acquired in an outdoor environment with changes in illumination and/or pose remains a largely unsolved problem. In other words, current systems are still far away from the capability of the human perception system, research in biometric systems has been increasing significantly due to international insecurity environment. One recent emerging potential biometrics that is competing with fingerprints, hand geometry, iris scans, faces or handwritten signatures is the hand vein pattern. Hand vein pattern is a distinct pattern beneath the skin, stable and immune to forgery. So Research groups around the world are developing algorithm and systems based on face and hand vein biometrics. In this research recognition with face and dorsal hand vein and their implementations on different databases are studied. Face and Vein recognition algorithm is mainly based on Independent Component Analysis (ICA).

The main steps involved in a biometric security system are image capture, pre processing, processing and matching. Cross et al. have developed a low cost automatic thermographic imaging system and have used grid based matching to match the images [1]. A shift and add architecture have been developed by Im et al. for filtering vein pattern[2]. Badawi has developed a hand vein biometric verification where pixel by pixel technique was used to recognize individuals[3].Cellular Neural Network was used by Malki et al.[4] to extract dorsal hand vein features. Kisku et al. have developed Face recognition by fusion of local and global matching scores using DS theory[5].

2. Face and Hand Vein Capture and Feature Extraction

No public dorsal database is available to public community. Hence, dorsal hand vein patterns have been captured to develop a multimodal biometric security system. Since these vein patterns are found beneath the skin and cannot be seen with naked eyes, a CMOS digital camera, an infrared filters and LEDs have been used to capture these images. But for Face images many public databases are available online.

Here the face images are taken from ORL database. For Hand vein Images cameras were used to capture the vein images which were obtained from 200 individuals from different ethnic and age group, where 6 dorsal veins were taken for both fair and dark skin.Preprocessing steps that are then applied on dorsal vein patterns are hand segmentation, vein pattern segmentation, noise filtering and thinning.The background is first subtracted from the hand vein image. The dorsal veins are then obtained by using thresholding where “graythresh” function in Matlab has been applied. To remove noises and to enhance the quality of the vein images, the thresholded images are subjected to match filter, Wiener and smoothing filters[no]. Suen and Zhang [no] thinning algorithm has been applied to generate a skeletal image of the vein patterns to represent the veins in 1 bit pixel.The following figure shows an example of a thinned dorsal hand vein pattern.



2. Background and Related research

An overview on the major human face recognition techniques are applied mostly to frontal faces, advantages and disadvantages of each method are also given. The methods considered are eigen faces and multimodal f The approaches are analyzed in terms of the facial representations they used. Eigen face is one of the most thoroughly investigated approaches to face recognition. It is also known as Karhunen-Loève expansion, eigen picture, eigenvector and principal component. Some references used principal component analysis to efficiently represent pictures of faces. They argued that any face images could be approximately reconstructed by a small collection of weights for each face and a standard face picture (eigen picture). The weights describing each face are obtained by projecting the face image onto the eigen picture. Another used eigen faces, which was motivated by the technique of Kirby and Sirovich, for face detection and identification. In mathematical terms, eigen faces are the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images. The eigenvectors are ordered to represent different amounts of the variation, respectively, among the faces. Each face can be represented exactly by a linear combination of the eigen faces. It can also be approximated using only the "best" eigenvectors with the largest eigen values. The best M eigen faces construct an M dimensional space, i.e., the "face space".

As the images include a large quantity of background area, the above results are influenced by background. Many authors explained the robust performance of the system under different lighting conditions by significant correlation between images with changes in illumination. Recently, experiments with ear and face recognition, using the standard principal component analysis approach, showed that the recognition performance is essentially identical using ear images or face images and combining the two for multimodal recognition results in a statistically significant performance improvement.

3. Eigen faces technique

3.1 Description

Principal Component Analysis (PCA, also known as "Eigen faces"), is one of the most known global face recognition algorithm. The main idea is to de correlate data in order to highlight differences and similarities by finding the principal directions (i.e., the eigenvectors) of the covariance matrix of a multidimensional data. In this paper experiments are performed by using several datasets in which the first dataset is provided by the Massachusetts Institute of Technology (MIT), second is ORL face database, third Yale face database. Each Gallery Set contains train subjects and test subjects. For testing the system, some face images from test subjects (same persons of the train Set but with changes in facial expressions) are used.

3.2 Training the PCA

From a theoretical point of view, a face image Γi can be seen as a vector is a huge dimensional space, concatenating the columns. Pre processed normalized face images are used for the research. In this system MIT normalized face and ear images are used which is shown in Fig. 1. A new code with MATLAB to combine the face and ear recognition in one algorithm using PCA and GUI has been written.

The first step is to train the PCA using the Training Set, in order to generalize the ability of the system and generate eigenvectors. Compute the mean image of the training data:

$$\Psi = \frac{1}{M} \sum_{m=-1}^{M} \Gamma_m \qquad (1)$$

Then each training image is mean-subtracted:

$$\Phi_i = \Gamma_i - \Psi_{train} \quad i = 1, 2, \ldots, M \qquad (2)$$

This set of very large vectors is then subject to principal component analysis, which seeks a set of M ortho normal vectors, Un, which best describes the distribution of the data. The kth vector, Uk, is chosen such that:

$$\lambda_k = \frac{1}{M} \sum_{n=1}^{M} (U_k^T \Phi_n)^2 \qquad (3)$$

The vectors Uk and scalars λk are the eigenvectors and eigenvalues, respectively of the Covariance Matrix
(CM):

$$C = \frac{1}{M} \sum_{n=1}^{M} (\Phi_n \Phi_n^T) = AA^T \qquad (4)$$

Fig. 1: An example of a MIT normalized face and ear image used in this system

The mean image Ψ of the gallery set is computed. Each mean-subtracted gallery image, Φi = Γi-Ψ, i = 1….M is Then projected onto the “Face Space” spanned by the M' eigenvectors deriving from the training set. This step leads to

$$\omega_k = U_k^T \Phi_i \quad k = 1 \ldots M' \tag{5}$$

This describes a set of point-by-point image multiplication and summations. The weight from the vectors:

$$\Omega = [\omega_1, \omega_2, \ldots, \omega_k] \tag{6}$$

That describes the contribution of each eigen face or eigen ear in representing the input face or ear image treating the eigen faces or eigen ears as a basis set of face or ear images. Calculating a Euclidian distance is the simplest way to classify the new face or ear class as follows:

$$d_k = \left\| \Omega - \Omega_k \right\| \tag{7}$$

where, Ωk is a vector describing the kth face or ear class. A face is classified as belonging to class k when the minimum dk is in the defined threshold limit of εk. Otherwise, the new face or ear is defined as 'unknown'. The unknown face or ear can be used for developing further database. PCA computes the basis of a space which is represented by its training vectors. These basis vectors, actually eigenvectors, computed by PCA are in the direction of the largest variance of the training vectors. As it has been said earlier, it is called as eigen faces. Each eigen face can be viewed a feature. When a particular face is projected onto the face space, its vector into the face space describes the importance of each of those features in the face. The face is expressed in the face space by its eigen face coefficients (or weights). One can handle a large input vector, facial image, only by taking its small weight vector in the face space. This means that one can reconstruct the original face with some error, since the dimensionality of the image space is much larger than that of face space. In this study, let's consider face identification only. Each face in the training set is transformed into the face space and its components are stored in memory. The face space has to be populated with these known faces. An input face is given to the system and then it is projected onto the face space. The system computes its Euclidian distance from all the stored faces. However, two issues should be carefully considered:

- What if the image presented to the system is not a face?
- What if the face presented to the system has not already learned, i.e., not stored as a known face?

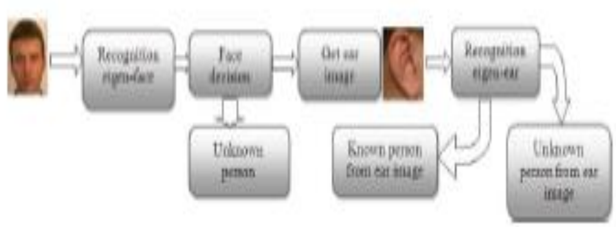


Fig. 2: Pictorial representation of the operations followed in the proposed method

The first defect is easily avoided since the first eigen face is a good face filter which can test whether each image is highly correlated with itself. The images with a low correlation can be rejected. Or these two issues are altogether addressed by categorizing following four different regions:

- Near eigen face and near stored face → known faces
- Near eigen face but not near a known face → unknown faces
- Near eigen ear and near stored ear → known-faces from ear
- Near eigen ear but not near a known ear → unknown-faces from ear

This is clear in Fig. 2 shows a representation of the operations followed in the proposed method .

4. RESOURCES & METHODOLOGY

4.1 The datasets

The research in this study was done using several datasets. The first dataset is provided by the Massachusetts Institute of Technology (MIT) containing a collection of facial images and side images used to construct the ear images from them (10 individuals with 4 face images and 4 ear images per individual). Figure 3 shows an example of images used in this research from the MIT dataset which is composed of 40 individuals with 10 face images per individual. Figure 4 shows an example of images used in this research from the ORL dataset which is composed of 15 individual with 11 face images per individual. Figure 5 shows an example of images used in this research from the SEARCH ear dataset. Images for individuals that are considered for this research were taken from different datasets to insure that they are taken on different sessions, different days and at different times of day. Some of the images were excluded from the datasets due to poor quality or movement distortions.

4.2 Recognition process

In this study, the recognition process is divided into two main steps. Each step is treated as a separate recognition problem. This means that if it is decided to identify an individual, we need to have two images for him, one for his face and other for his ear, representing each image to be recognized separately, Fig. 6 shows a general view of the recognition process for individual images. To recognize that individual correctly each image will have to be classified correctly to be belonging to that individual. In the following of this study the different datasets used with their corresponding recognition rates are presented. It is also presented a method for combining the results of classification of individual images to come to a unified decision about the classification of the individual in question.

Fig. 3: Example of images from the MIT database used in this research

Fig. 4: Example of images from the Yale database used in this research

Fig. 5: Example of images from the SEARCH ear database used in this research

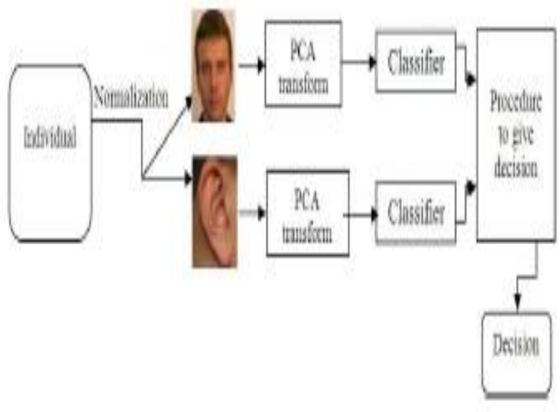


Fig. 6: A general view of the recognition process for individual images

5. RESULTS

5.1 Experimental results and analysis

Experimental results that were obtained from the proposed face and ear recognition system are given.At first level face and ear algorithms are tested individually. At this level the individual results are computed. At this level the individual accuracy for face is found to be 68.16% as shown in Table 1.

However in order to increase the accuracy of the biometric system as a whole the individual results are combined at matching score level. At second level of experiment the matching scores from the individual traits are combined and final accuracy graph is plotted as shown in Fig. 7. Table 1 shows the accuracy and error rates obtained from the individual and combined system. The overall performance of the system has increased showing accuracy for face and ear of 92.24% with FAR of 10% and FRR of 6.1% respectively. FAR graph is plotted as shown in Fig. 8 and FRR graph is plotted as shown in Fig. 9.

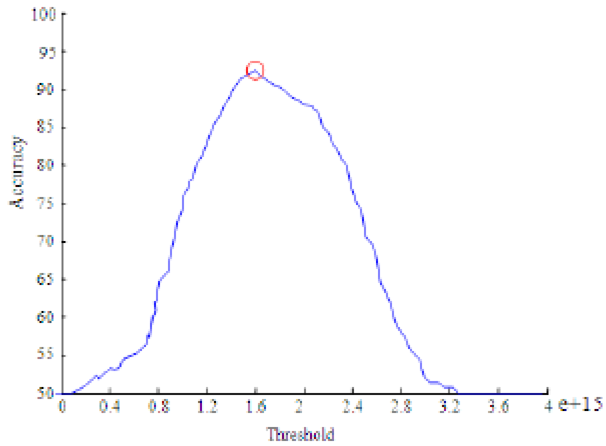


Fig. 7: Accuracy curve for combined face and ear

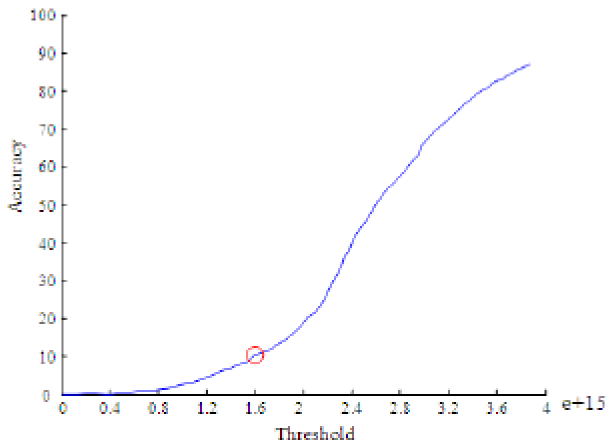


Fig. 8: FAR curve for combined face and ear

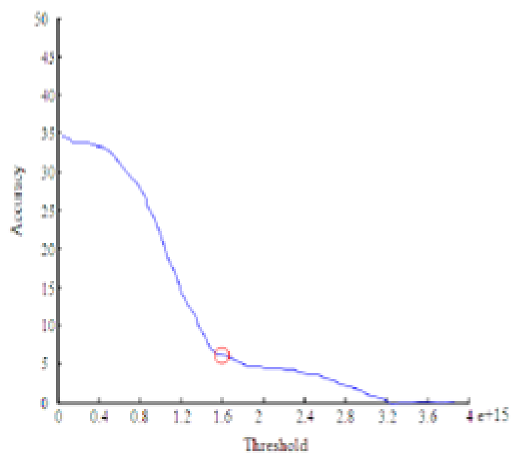


Fig. 9: FRR curve for combined face and ear

5.2 Applying recognition procedure on used datasets

Each image database used in this research is divided into two training set images, face and ear images and their two corresponding test set images. Images for 3 individuals were put in the test set of each dataset to construct the set of imposters and the images for a 10 chosen individuals from every dataset where divided into training and test face and ear sets as follows: The first two images per individual will construct the training set and the last two images per individual will be part of the test set. Principal components will be calculated for each individual image separately and the images will be transformed to the PCA space using their corresponding transformation matrix as discussed previously in Eigen faces technique.

The individual images are normalized and pre processing operations performed and then clear face and ear images are constructed. The individual images are transformed to the PCA space. Every image is recognized with its corresponding classifier. A Procedure is applied for reaching a unified decision.

Trait	Algorithm	Accuracy %	FAR (%)	FRR (%)
Face	PCA	68.16	31.2	14.1
Face and Ear	PCA	92.24	10.0	6.1

Table 1: Result Showing Individual and Combined Accuracy

6. DISCUSSION

What's wrong with using face recognition Alone? Face recognition has been researched a lot in the past years and a lot of algorithms, feature extraction techniques and classification techniques have been developed for that purpose, but it all comes down to the efficiency of the feature extraction. Facial features are susceptible to many factors such as mood, health, facial hair and facial expressions. This is a natural barrier in using face as a reliable means for human identification. The feature extraction technique used will have to deal with the material at hand, so no matter how good the feature extraction process used is, the condition of the face presented will determine the outcome.

Why preferred ears for fusion? The use of ears as a biometric for human identification has not been researched as intensively as other biometrics has been researched. Although research in this area is relatively small, the research that has been done showed a lot of promise in using the ear as a biometric for human identification.

The ear much like the face is a visible part of the human body that can be used for a non invasive biometric technique. Humans most likely will have to keep their ears uncovered to be able to hear. The ears unlike the face are unaffected by ageing, in fact the ear undergoes very slight changes from infancy to adulthood, in fact the only change that happens is elongation due to gravity. The ears also do not suffer the change in appearance by hair growth like the face does.

Although these are all pros for using the ears as a biometric, but using the ears for human identification has some disadvantages. These disadvantages are embodied in occlusions. Sources of occlusion may be long hair, earrings and multiple piercings.

7. CONCLUSION

In this paper, the present study has aimed to develop a multimodal biometric system for personal identification. Experimental results have shown that combined face and ear recognition system offers high accuracy and security. This system, after studying is implemented on different databases. In a near future, it is planned to combine dorsal hand vein features also with the combination of face and ear to develop a still more accurate multimodal biometric system for recognition. Research is also going on by applying other algorithms to make a significant comparison.

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