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Research Paper

PERSON IDENTIFICATION USING FACE AND FOOT MODALITIES

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ABSTRACT

Person identification is a necessary application implemented in government sector and private organization such as attendance record system, traffic and toll monitoring system and AADHAR card. Biometrics system provides these facilities for person identification and verification. The biometrics give the best solution to improve security using combination of two or more biometrics is knows as multimodal biometric which helps to remove all the limitations of single biometric.
In this paper I used two modalities face and foot for calculating matching score using different approaches like PCA based neural network classifier for face and modified sequential harr transform for foot. I calculated .result for each modalities and after that I applied fusion strategies sum rule to combine of data and matching score is calculated. Results prove the better performance when I combined the data. This all work performs on self created database of 100 parsons.

KEYWORDS Multimodal biometrics, Principal component analysis (PCA), Modified sequential harr transform, Euclidian distance.

INTRODUCTION

Recently many applications based on biometrics technology used for authentication purposes. biometrics or person authentication system usually uses two mechanisms for verification and identification. Verification deals with one-to-one matching whereas identification ensures one-to-many matching. Use of password, key, or PIN (personal identification number) has many drawbacks. all biometric verifiers may be considered combinations of physiological and behavioral characteristics due to the interaction between the user and the system. Any physiological or behavioral feature may be used as a biometric verifier as long as it satisfies the requirements [1]. Some of the modalities are related to physical structure or properties of human body; and some other traits are associated with human behavior. Multimodal biometrics system involves various levels of fusion, namely, sensor level, feature level, matching score level, decision level and rank level. [2-3].Biometric systems are designed to make sure the decisions- person is authorized or not. Figure 1, 2 shows the biometric system and multimodal biometric system.

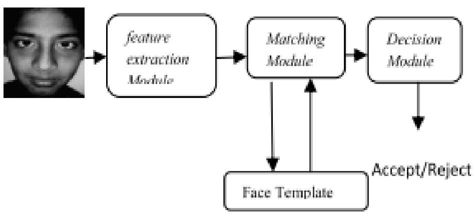

Fig 1: Biometric system

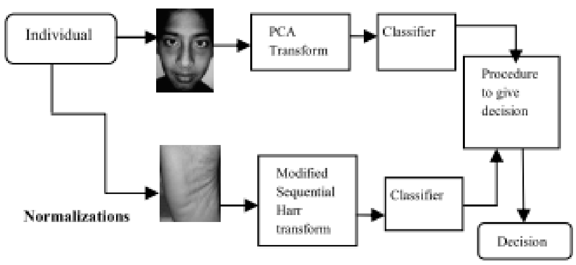

Fig 2: Multimodal biometric system

In this paper I proposed PCA classifier is used to obtain the features by input face imges and modified sequential harr transform for input foot images. Decision is made by matching the test image with the images registered in the database.
Section 2 describes related research in this field. Section 3 gives description of Identification process. Section 4 Explain the method which is applied to the modalities. Section 5 Show Experimental outcome. Section 6 shows results and section 7 conclusion has been discussed.

RELATED RESEARCH

From the last 30 years, several approaches have been proposed and developed for multimodal biometric authentication system. In 1998, a bimodal approach was proposed by L. Hong and A. K. Jain for a PCA-based face and a minutiae-based fingerprint identification system with a fusion method at the decision level [4]. In 2000, R. Frischholz and U. Dieckmann developed a commercial multimodal approach, BioID, for a model-based face classifier, a VQ- based voice classifier and an optical-flow-based lip movement classifier Lip motion and face images were extracted from a video sequence and the voice from an audio signal. Accordingly to the security level, experiments on 150 persons for verifying persons [5].In 2000 Zhao et al. implemented a multimodal biometric system using face and palm print at feature level. Gabor features of face and palm prints are obtained individually. Extracted Gabor features are then analyzed using linear projection scheme such as PCA to obtain the dominant principal components of face and palm print separately [6]. In 2003, J. Fierrez-Aguilar and J. Ortega-Garcia proposed a multimodal approach including a face verification system based on a global appearance representation scheme, a minutiae-based fingerprint verification system and an on-line signature verification system based on HMM modeling of temporal functions, with fusion methods, sum-rule and support vector machine (SVM) user-independent and user-dependent, at the score level [7]. In 2003 Jain et al. proposed a multimodal approach for palm print and hand geometry, with fusion methods at the feature level by combining the feature vectors by concatenation, and the matching score level by using max rule. Only the fusion approach at the matching score level outperforms the monomodal systems [8].There were also some PCA-based multimodal biometric systems proposed in 2003, Wang et al. Proposed a multimodal approach for a PCA-based face verification system and a key local variation-based iris verification system, with fusion methods at the matching score level by using un- weighted and weighted sum rules. Aiming at the same issue, i.e., to reduce false acceptance and false rejection error rates [09].In 2004, Toh et al. developed a system using hand geometry, fingerprint, and voice biometric with weighted-sum rule based match-score-level fusion. They treated the multimodal biometric decision fusion problem as a two-stage problem learning and decision. A reduced multivariate polynomial model was introduced to overcome the tedious recursive learning problem, as seen in neural network training. The four learning and decision paradigms were investigated, adopting the reduced polynomial model for biometric decision fusion. Experiments on fingerprint, speech, and hand-geometry biometric [10]. In 2005, Snelick et al. developed a multimodal approach for face and fingerprint; with fusion methods at the score level three fingerprint recognition commercial systems and one face recognition commercial system were used in this study. Seven score normalization techniques (min–max, z-score, tanh, adaptive, two quadrics, logistic, and quadric-line-quadric) and five fusion techniques on the normalized scores (simple sum, min score, max score, matcher weighting, and user weighting) were tested in this study. Data showed that local learning alone can improve verification [11] in 2005 year; Jain et al. proposed a multimodal approach for face, fingerprint, and hand geometry, with fusion at the score level. The attaching approaches for these modalities are the minutiae-based matcher for fingerprint, which has similarity scores as output, the PCA-based algorithm for face recognition, which has Euclidean distance as output, and a 14- dimensional feature vector for hand geometry, which also has Euclidean distance for output. Seven score normalization techniques (simple distance-t- similarity transformation with no change in scale, min–max normalization, z-score normalization, median-MAD normalization, double-sigmoid normalization, tanh normalization, and Parzen normalization) and three fusion techniques on the normalized scores (simple sum rule, max rule, and min rule) were tested in this study. Except for one normalization technique (the median MAD), all fusion approaches outperform the monomodal approaches. For example, the fingerprint system, which is the best monomodal system [12]. In 2007year Jing et al. employed Gabor transform for feature extraction and then Gabor features are concatenated to form fused feature vector. Then, to reduce the dimensionality of fused feature vector, non linear transformation techniques such as Kernel discriminate Common Vectors are employed [13]. In 2009 year Kisku et al. proposed a sensor level fusion scheme for face and palm print biometrics where face and palm print are decomposed using Haar wavelet and then average of wavelet coefficients is fused as image of face and palm print. Finally, inverse wavelet transform is carried out to form a fused image of face and palm print. Feature level fusion involves consolidating the evidence presented by two biometric feature sets of the same individual. The majority of the work reported on feature level fusion is related to multimodal biometric system [14]. In 2014 year Snehlata, et al developed multimodal biometrics system for face and ear modalities using PCA neural network, Eigen Images classifier to reduce FAR of single biometrics [15]. In same year she developed and analysis multimodal biometrics system for face, iris and ear using different classifier PCA based neural network for face, Hamming distance calculation for iris template and Eigen images for ear modalities calculating matching score after fusion[16].

FUSION TECHNIQUES

Person Identification

In the identification the system recognizes an individual by searching the templates of the entire database for a match. Therefore the system performs a one-to-many comparison. Identification ensures presence of an individual inside the database but does not indicate the exact identity of the person subjected for authentication.

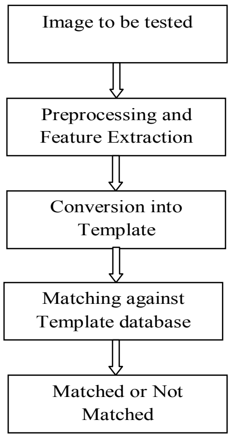

Fig.3 : Testing process in biometrics

A match score is known as genuine scores (GS) if it is a result of matching two sample of a biometric trait of the same user. It is known as an imposter score (IS) if it is the result of matching two sample of a biometric trait originating from different users. An imposter score that exceeds the predefined threshold (Th) results in a false accept, while a genuine score that falls below the predefined threshold (Th) results in a false reject. The false accept rate FAR and false reject rate FRR is calculated by using the formula.

$$FAR = \frac{IS}{Th}$$

$$FRR = \frac{GS}{Th}$$

The EER (Equal Error Rate) refers to the point where the FAR equals the FRR.

Fusion strategy

In fusion process different traits are combined into single traits. Normalization is must required because the output of individual trait may not be homogeneous. We use Min-Max normalization technique to produce traits scores to 0 and 1 respectively. The Min-Max technique computes as

$$y = \frac{x - \min(Sx)}{\max(Sx) - \min(Sx)}$$

Where Sx is the set of all possible matching scores generated by a particular trait. Different weights (Wi) are assigned on the basis of their Equal Error Rate (EER).

$$Wi = \frac{1/_{EERi}}{\sum_{j=1}^{n}(1/_{EERj})}$$

Where EERj is the equal error rate for jth and n represents the number of traits participating in fusion. The fusion score S is computed as

$$S = \sum_{j=1}^{n}(W_j \times S_j)$$

Where Sj is the match score of jth trait.

METHEDOLOGY

Principal Component Analysis

Person recognition algorithms are Principal Component Analysis (PCA). 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. For testing the biometric system, face images were used from the training set of face images. Before going to next step first train the PCA using the training set of images, The mean image is computed of the training data as:

$$\Psi_{Train} = \frac{1}{M}\sum_{n-1}^{M}\Gamma_n \qquad (1)$$

Each training image is subtracted by mean image as:

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

It is large vectors set subjected to PCA which seeks a set of M ortho-normal vectors, U_n. The k^{th} vector, U_k, is chosen such that:

$$\lambda_K = \frac{1}{M}\sum_{n-1}^{M}(U_K^T\Phi_n)^2 \qquad (3)$$

The vectors U_k and scalars λ_k are the eigenvectors and Eigen values respectively of the following covariance matrix (CM):

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

The mean image Ψ of the gallery set is computed. This is projected onto the "face space" by the M Eigen vectors derived from the training set. This gives:

$$\omega_K = U_K^T\Phi_i \quad K = 1 \ldots.M \qquad (5)$$

Euclidian distance is calculated for face as follows:

$$d_K = \| \Omega - \Omega_k \| \qquad (6)$$

Modified Sequential Harr Transform Techniques

Footprint identification is the measurement of footprint features for recognizing a person. Footprint is universal, easy to capture and does not change much across time.

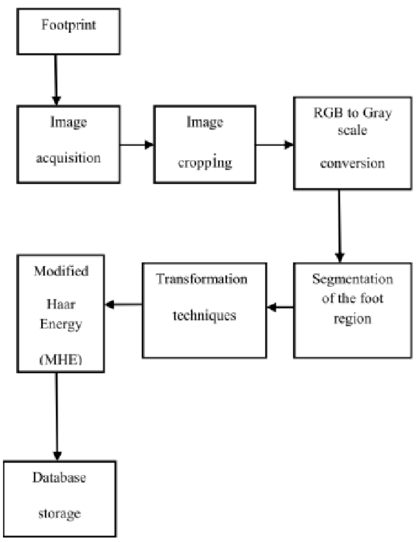

Fig. 4: Footprint identification system.

Sequential modified Haar wavelet is used to find the modified Haar energy feature in which sequential modified Haar transform is applied to the resize footprint image to get MHE. . The modified Harr energy of image is obtained by dividing the image into 4 x 4 blocks. The detailed coefficients of every image are then determined. The modified Haar energy for each of the block is calculated as:

$$MHEi,j,k = \sum_{p=1}^{p}\sum_{q=1}^{Q}(C_{p,q})^2 \qquad (1)$$

EXPERIMENTAL OUTCOME

A database is created that consists of 100 person's images. In which I take face and foot images. first all image converts RGB to gray scale and resize After that I applied PCA classifier for face and modified sequential haar transform for foot image Figure 5 to 13 shows the experimental results using MATLAB software

Figure 5 to Figure 10 present results for face images

Fig 5: Training set of face images

Fig 6: Normalized Training set of faces.

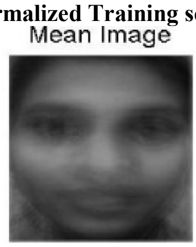

Fig. 7: Mean image

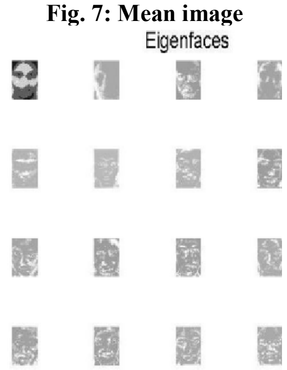

Fig. 8: Eigen faces

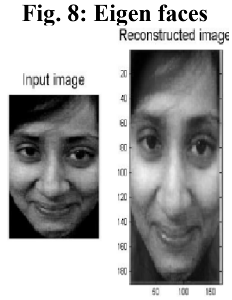

Fig. 9: Input image and reconstructed image

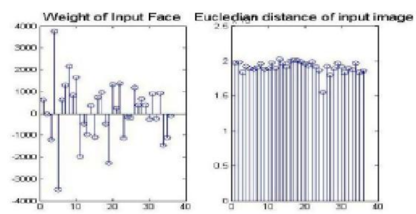

Fig. 10: Weight of input face and the Euclidian distance.

Figure 11 to Figure 13 present results for foot images

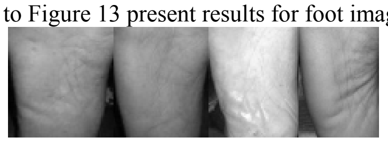

Fig. 11: Cropped and resized data sample of foot

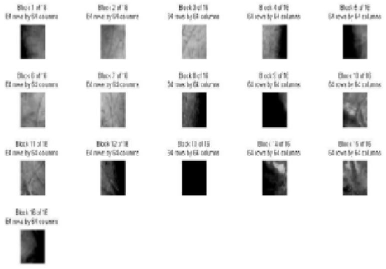

Fig: 12 foot image in 4x4 blocks

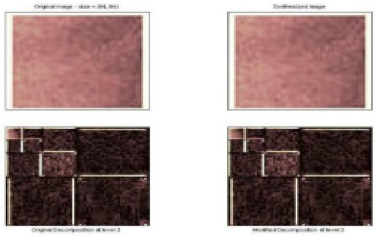

Fig. 13: (a) Original foot image, (b) Synthesized foot image, (c) Original Decomposition of image at level 3, (d) Modified Decomposition of image at level 3

RESULTS

MATLAB software is used to calculate results. Shown in previous the minimum-distance is calculated by Euclidian distance for faces and foot shown in Table 1

Table 1 : Euclidian distance for Faces and Foot

Faces	Minimum Euclidian distance for faces	Foot Image	Minimum Euclidian distance for foot
Pf1	1.5488E+04	Pfo1	6.7719E+003
Pf2	1.5485E+04	Pfo2	6.6783E+003
Pf3	1.5483E+04	Pfo3	7.0295 E+003
Pf4	1.5504E+04	Pfo4	7.0445 E+003
Pf5	1.5488E+04	Pfo5	6.6188 E+003
Pf6	1.5495E+04	Pfo6	6.9126 E+003
Pf7	1.5492E+04	Pfo7	6.8937 E+003
Pf8	1.5515E+04	Pfo8	6.8419 E+003
Pf9	1.5496E+04	Pfo9	6.7982 E+003
Pf10	1.5502E+04	Pfo10	6.7911 E+003

Face and foot algorithms are tested individually and the results of individual modalities are calculated in term of weight, EER, FAR, FRR shown in Table 2:

Table 2: Individual Trait Face and Foot

Traits	Weight	EER	FAR	FRR
Faces	0.92	1.0852	1.17	0.99
Foot	0.91	1.099	1.25	0.94

At fusion stage we apply min-max normalizations for similarity score because all recognition scores are dissimilar. Table 3 shows the weights assigned to different traits in possible fusion and matching score of traits. The sing + denotes the fusion. Maximum matching score 0.21 calculated for face and foot modalities.

Table 3: Calculate weight for each traits in all possible fusion of two traits

Traits	Face	Foot	Score
Face+ Foot	0.50	0.49	0.21

CONCLUSIONS

Many researchers gave their contributions in the multimodal biometric system field.When multiple biometric modalities are combined using different fusion methods have been achieved optimal result. In this paper shown, PCA and modified sequential harr transform approaches for face and foot biometrics modalities. All work is performed on self created database using MATLAB software. At finally matching score of two combine modalities face + foot is 0.21 which is optimal result prove the highest identification of person.(+) sign indicate combination of two modalities face anfoot.

REFERENCES

1. R. Arun, Jain Anil, et al. Multimodal Biometrics: An Overview[C]. *Proceedings of 12th European Processing Conference, 2004.1221-1224(Vienna, Austria)*
2. A.Ross, A.K.Jain, et al. Information fusion in biometrics. *Pattern Recognition Letters, 2003, 24(13):2115 –2125.*
3. Jain, A.K., Ross, A. et al. Biometric: A tool for information security. *IEEE Transactions-on Information Forensics and Security. 2006, 4(1): 125-143.*
4. A. K. Jain and L. Hong et al. integrating faces and fingerprints for personal identification, *IEEE Trans. Pattern Anal. Mach. Intell., 1998: 20(12): 1295–1307.*
5. R. Frischholz and U. Dieckmann et al. BiolD: A multimodal biometric identification system," *Computer, 2000,33(2) : 64–68*
6. W. Zhao, R. Chellappa, A. Rosenfeld, P. J. Phillips, et al. Face Recognition [J]. *An ACM Computing Surveys, 2003, 35(4):399-458.*
7. J. Fierrez-Aguilar, J. Ortega-Garcia, D. Garcia-Romero, and J. Gonzalez-Rodriguez et al. A comparative evaluation of fusion strategies for multimodal biometric verification*, in Proc. 4th Int Conf. Audio- Video-Based Biometric Person Authentication,2003, 2688: 830–837.*
8. A.Ross, R.Govindarajan et al. Feature level fusion using hand and face biometrics[C].*Proceedings of SPIE Conference on Biometric Technology for Human Identification, 2004, 5779:196 –204(Orlando ,USA*
9. T. Wang, T. Tan, and A. K. Jain et al. Combining face and iris biometrics for identity verification, *in Proc. 4th Int. Conf. Audio- Video-Based Biometric Person Authentication, 2003 LNCS 2688: 805–813.*
10. K. A. Toh, X. D. Jiang, and W. Y. Yau et al. Exploiting global and local decisions for multi-modal biometrics verification, *IEEE Trans. Signal Process., 2004,52(10) : 3059–3072*
11. R. Snelick, U. Uludag, A. Mink, et al. Large scale evaluation of multimodal biometric authentication using state-of the-art systems*, IEEE Trans. Pattern Anal. Mach. Intell., 2005, 27(3): 450–455.*
12. A. K. Jain, K. Nandakumar, and A. Ross, "Score normalization in multimodal biometric systems," *Pattern Recognition. 2005. 38(12): 2270–2285.*
13. X. Y. Jing, Y.F. Yao, J.Y. Yang, M. Li, D. Zhang et al. Face and palm print pixel level fusion and kernel DCVRBF classifier for small sample biometric recognition [J]. *Pattern Recognition, 2007, 40 (3): 3209-3224.*
14. D.R. Kisku, J. K. Singh, M. Tistarelli,et al. Multisensor biometric evidence fusion for person authentication using wavelet decomposition and monotonic decreasing graph[C]. *Proceedings of 7th International Conference on advances in Pattern Recognition (ICAPR)2009:205-208 (Kolkata, India)*
15. Snehlata, G.R.Sinha ET al.PCA based Multimodal Biometrics using Ear and Face Modalities [J] *International Journal of Information Technology and Computer Science (IJITCS).2014, 6(5), 43-49.*
16. Snehlata, G.R.Sinha et al.Multimodal Biometrics using Face, Ear and Iris Modalities[c] *International Journal of Computer Applications Recent Advances in Information Technology NCRAIT (2),2014:9-15.*

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