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RESEARCH ARTICLE

HUMAN IDENTIFICATION USING FINGER PRINT AND FACE BIOMETRICS

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ABSTRACT

The objective is to compared at feature extraction level for face and fingerprint biometrics. The proposed approach is based on a compared to identify the human through, finger prints in automated manner and providing an efficient solution for very low resolution face recognition problem. It is performed by compared the biometric template extracted from every pair of fingerprints and face representing a user. The fingerprint and face images of different people may have different sizes, a fusion operation must be performed after ROIs extraction. Feature Extraction Level, information extracted from the different users is encoded into a joint feature vector, which is then compared to a casio data base template and assigned a matching score as in a Multibiometric system. Comparative experiments are conducted on casio database; it has feature extraction level, in compared to the matching score level.

Key words—Face, Feature extraction level, Fingerprint, Multimodal Biometrics

INTRODUCTION

Biometric authentication has seen considerable improvement in reliability, accuracy and security, with some offered good performance. The biometrics is 100% accurate. Multimodal biometric systems [1] remove some of the drawbacks of the unibiometric systems by grouping the multiple users of information. These systems utilize more than one physiological or behavioral characteristic for enrolment and verification/ identification. Multimodal Biometrics with various levels of fusion namely, feature level, matching score level, sensor level, and decision level [2].

It has been observed that, a biometric system that integrates information at an earlier stage of processing is expected to provide more accurate results than the systems that integrate information at a later stage. Since the feature set contains-much richer information on the user data than the matching score, fusion is expected to provide better recognition performances. Multimodal biometrics compared at feature level is a relatively to the problem.

A fusion or compared at feature level is relatively too complexity to achieve in practical because multi biometrics may have mismatched feature sets and the correspondence among the different feature set may be unknown, to compare the feature set may lead to the problem of dimensionality. Very complex matcher may be required and the compare the feature vector may contain noisy or redundant data, it is decrease of the classifier [5]. A novel approach to fuse face and fingerprint biometrics at feature extraction level. The improvement obtained applying the

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feature level fusion is presented over score level fusion technique. Experimental results on real and casio databases are comparison to fusion at score level.

FACE AND FINGERPRINT BIOMETRICS

A. Face Recognition based on Scale Invariant Feature Transform Features (SIFT): The face recognition system, preliminary introduced in [8] based on the SIFT features extracted from images of the query and database face. The SIFT features represent a compact representation of the local gray level structure, invariant to images are scaled, translated, and rotated, and partially invariant to illumination changes and affine or 3D projections. SIFT has emerge as a very powerful image descriptor and its service for face analysis and identification was systematically investigated where the fusion was performed using three techniques: (a) minimum pair distance, (b) matching eyes, nose and mouth, and (c) matching on a regular grid. The present system considers spatial, orientation and key point descriptor information of each extracted from SIFT point. Thus the input to the present system is the face image and the output is the set of extracted SIFT features s=(s 1, s 2 ….s m) where each feature point s_i=(x, y, θ, k) consist of the (x, y) spatial location, the local orientation θ and k is the key descriptor of size 1x128.

B. Fingerprint Verification and identification based on Minutiae matching technique: The fingerprint recognition module has been developed using minutiae based technique where fingerprint image is normalized, pre processed using Gabor filters, binarized and thinned, is then subjected to minutiae extraction [10]. However to achieve rotation invariance the following procedure is followed in the image segmentation module. The fingerprint is processed by first detecting the left, top and right boundaries of the centre. The overall slope of the centre is calculated by fitting a straight line to each edge by linear regression. The left and right edges of the line, which are expected to be roughly vertical, are fitted with lines of the form x = my + b and for the top edge the form y = mx + b is applied. The overall slope is determined as the average of the slopes of the left and right edge of the line, and a line of perpendicular to the top edge of the line. A rectangle is fitted to the and rotated to the same angle and the effect of rotation. The method is only depending upon the detection of edges. This improves the robustness to noise in the acquired fingerprint image. The input to this system is a fingerprint image and the output is the set of extracted minutiae m= (m 1, m 2 ….m m), where each feature point m_i=(x, y, θ) consist of the spatial location (x, y) and the local orientation θ.

FEATURE LEVEL FUSION SCHEME

The feature level fusion is realized by simply join the feature points obtained from different users of information. The joined feature point set has better discrimination power than the individual feature vectors. The concatenation procedure is described in the following sections

A. ***Feature set compatibility and normalization***: In order to be concatenated, the feature point sets must be well-matched. The minutiae feature point set is made well-matched with the SIFT feature point set by making it rotation and translation the key point descriptor, carrying the limited information, about the minutiae position. The limited regions are around each minutiae point is folded with a bank of filters with eight different equally spaced (0 , 23.5 , 47 , 70.5 , 94 , 117.5 ,141 , and 211.5) , eight different scales and two phases (0 and π/2), giving a key descriptor of size 1x130 . The rotation is handled during the pre processing step and the translation is handled by registering the casio database images with the query images [11]. Scale invariance is achieved by using the dpi specification of the sensors. The key point of each face and fingerprint points are normalized using the technique of (s_{norm}, m_{norm}), to scale all the 130 values of each key point descriptor within the range 0 to 1. This normalization also allows applying the same on the face and fingerprinting key point descriptors, when the matching pair of points is found for matching the fused point sets of casio database and query face and fingerprint images.

B. Feature Reduction and Concatenation:The feature level fusion is performed by joining the two feature point sets. This results in a fused feature point set concat= (s_{norm}, m_{norm} ,.).

C. Feature Reduction techniques:

1. *K-means clustering*. The normalized feature point sets (s_{norm}, m_{norm}) are first joined together (concat). Redundant features are then removed using the "k-*means*" clustering techniques [12] on the merged point set of an individual retaining only the centroid of the points from each cluster. These clusters are formed using spatial and orientation information of a point. The key point descriptor of each cluster's centroid is the average of key point descriptors of all the points in each cluster. The distance of the classifier used is euclidean distance. The number of clusters is determined using the cluster validity index. Since, the feature point set

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from the two classification i.e., face and fingerprint are invariant and moreover. The points belonging to an individual irrespective of whether they are extracted from face or fingerprint thus making K-means clustering possible.

2*. **Neighbourhood Elimination***. This technique is applied to the pointset of face and fingerprint (s_{norm}, m_{norm}) individually .For the each point of face and fingerprint, those point that lie within the neighbourhood of a certain radius are removed giving$(s_{norm'}, m_{norm'})$ the reduced face and fingerprint point set. Spatial information is used to determine the neighbours of each considered point. The result of neighbourhood elimination in fig 1.

3. Points belonging to specific regions. Only the points belonging to specific regions of the face i.e., specific landmarks like the eyes, the nose and the mouth lower portion. Face images in CASIO Database with respect to eyes and mouth lower portions are location. The core point in fingerprint is located using a reference point location algorithm. A radius equal to 85 and 120 pixels was set for the face and fingerprint feature points selection as shown in Fig. 2. The SIFT points around specific landmarks on face carry highly discriminative information. The region around core point accounts for combating the effect of skin elasticity and non-linear distortion due to varing pressure applied during image acquisition as it is the least affected region.

The aims of the " *k-means*" and "neighbourhood *elimination*" techniques are used to remove redundant information and at the same time retaining most of the information by removing only the points which are very near, as computed using euclidean distance, to a specific point. As these points may not provide any additional information because of being in vicinity. And the aim of "points belonging to specific region" is to consider only the points belonging to highly distinctive region.

D. ***Matching process***: The joined features pointset of the casio database and the query images concat and concat' respectively are processed by the matcher which gives matching score based on the no. of matching pairs found between the two pointsets.

1. Point pattern matching: This technique aims at finding the percentage of points "paired" between the joined feature pointset of the casio database and the query images. Two points are considered paired only if the spatial distance (1), the direction distance (2) and the Euclidean distance (3) between the corresponding key descriptors are all within some are within a pre-determined threshold, set with 4 pixels, 3°, 6 pixels for $r_0, \emptyset_0, k_0$ on the basis of experiments:

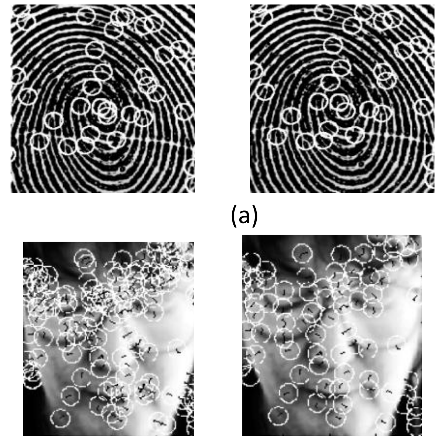

(a)
(b)

Fig.1 Effects of the neighborhood elimination on a) Fingerprint and b) Face

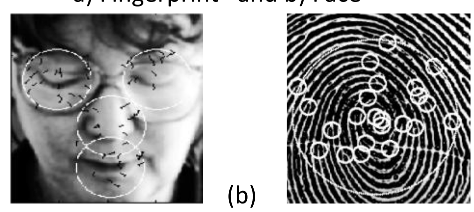

(a) (b)

Fig.2 Example of selected regions on a) face (left) and b) fingerprint (right)

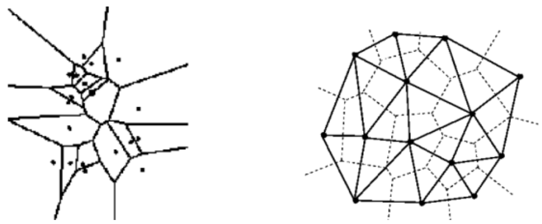
.

$$sd(concat'_j, concat_i) = \sqrt{(x'_j - x)^2 - (y'_i - y)^2} \le r_0 \quad (1)$$

$$dd(concat'_j, concat_i) = \min\left(\emptyset'_j - \emptyset_i, 360^0 - \emptyset'_j - \emptyset_i\right) \le \emptyset_0 \quad (2)$$

$$kd(concat'_j, concat_i) = \sqrt{\textstyle\sum_i (k'_j - k_i)^2} \le k_0 \quad (3)$$

Where the points i and j are represented by (x, y, θ, k) with k = k 1… k 128 of the concatenated database and query pointsets concat` and concat, sd is the distance of spatial, dd is the distance of direction, and kd is the distance of keypoint descriptor. The one to one correspondence is achieved by selecting among the candidates points lying within the threshold of spatial, direction and Euclidean distance, the one having minimum Euclidean distance for the keypoint descriptor. The feature pointsets are rotation, scale and translation invariant, in case of fingerprint, the registration is done at image pre processing level. This obviates the need to calculate transformation parameters for aligning the database and query fused pointsets. The final matching score is calculated on the basis of the ratio of the number of matched pairs to the total number of feature points found in the database and query sets, for both monomodal traits and for the fused feature pointset.



(a) (b)

Fig 3 Triangulation of pointset: (a) Voronoi diagram and (b) Delaunay triangulation

2. *Matching using the Delaunay Triangulation technique*: In this case, instead of considering individual points, triplet of points are grouped together as new features. Given a set S of points p, p 2, ..., pN, the Delaunay triangulation of S is obtained by first computing its *Voronoi diagram* [14] which decomposes the 2D space into regions around each point such that all the points in the region around pi are closer to pi than Delaunay triangulation is computed by connecting the centres of every pair of neighbouring Voronoi regions.

The *Delaunay triangulation* technique [15] is applied individually on the face and the fingerprint normalized pointset snorm and mnorm and then on the concatenated feature pointsets concat= (s_{norm},m_{norm}). Ten features are computed from the extracted the points. (a) The minimum and median angles (α_{min}, α_{med}) of each triangle (b) The triangle side (L) with the maximum length (c) The local orientation of the points at the triangle vertexes (d) The ratio (l1/l2) of the smallest side to the second smallest side of each triangle (e) The ratio (l2/l3) of the second smallest side to the largest side of each triangle.

All these parameters compose the feature vector fv= (t 1, t 2… t n), where ti = (α_{min} ,α_{med}), L, (l1/l2, l2/l3) is the triangle computed by the Delaunay triangulation. The process is repeated for the database and the query pointsets to get fv and fv'. The final score is computed on the basis of the number of corresponding triangles found between the two feature vectors fv and fv'. Two triangles are correctly matched if the difference between the attributes of the triangles ti and t i' are within a fixed threshold. As the fused pointset contain affine invariant and pre-normalized points thus making the application of Delaunay triangulation possible.

EXPERIMENTAL RESULTS

The proposed approach has been tested on two different databases: the first consists of 50 chimeric individuals composed of 10 face and fingerprint images for each individual. The face images are taken from the controlled sessions of the CASIO Database and the fingerprint images were collected by the real time data base. The fingerprint images were acquired using an optical sensor at 450 dpi.

The following procedure has been testing the mono-modal and multimodal algorithms:

Training: one image per person is used for enrolment in the face and fingerprint verification system; for each individual, one face-fingerprint pair is used for training the fusion classifier.

Testing: Four remaining samples per person are used for testing, generating client scores. Impostor scores are generated by testing the client against the first sample of all other subjects. For the multimodal testing, each client is tested against the first face and fingerprint samples of the rest of the chimeric users. In total 50x4=200 client scores and 50x49=2450 imposter's scores for each of the uni-modal and the multimodal systems are generated.

Evaluation: The best combination of feature reduction and matching strategy has been further tested on a real multimodal database acquired by the authors. The database consists of 150 individual with four face and fingerprint images per person. The first face and fingerprint combination is used for training and the rest three image pairs are used for testing, providing 150x3=450 client scores. Each individual is subject to imposter attack by ten random face and fingerprint pairs for a total of 150x10=1050 impostor scores. The experiments were conducted in four sessions recording False Acceptance Rate (FAR), False Rejection Rate (FRR) and Accuracy (which is computed at the certain threshold, FAR and FRR where the performance of the system is maximum ie., max (1-(FAR + FRR)/2) .

A. The face and the fingerprint recognition systems were tested alone, without any changes in the feature, i.e. SIFT features and minutiae features. The matching score is computed using point pattern matching independently for face and fingerprint. The individual system performance was recorded and the results were computed for each modality as shown in table 1.

B. In the second session, the effect of introducing the key descriptor around each minutiae point is examined. Once the feature sets are made well-matched the keypoint of SIFT and the minutiae points are normalized. The normalized feature pointsets are then joined and the k-means feature reduction is applied on each fused pointset. From the presented results (table 2), it is evident that the introduction of the key descriptor for the fingerprints increased the recognition accuracy by 1.66%, and the feature level fusion outperformed both single modalities, as well as the score level fusion, with an increase in the accuracy of 2.68% in comparison to score level. The score level fusion is performed scores independently for face and fingerprint are computed independently for face and fingerprints which are then normalized and added using sum of scores technique.

C. In the third session, to remove redundant features, two feature reduction strategies are applied prior to concatenation. The matching is performed with the point pattern matching technique. From the experimental results, presented in table 3, it is evident that the application of the neighbourhood removal technique does not increase the accuracy of the system. On the other hand, the reduction of points belonging to specific regions increased the recognition accuracy by 0.34%, while the FRR is dropped to 0%. Some statistics regarding the number of points retained in the fused poinsets, for all the three feature reduction techniques applied to one subject, are listed in table 4 and the performances are depicted in table 3.

TABLE 1. The FAR, FRR and Accuracy values obtained from the Monomodal Traits

Algorithm	FRR(%)	FAR(%)	Accuracy
Face SIFT	11.48	10.55	88.92
Fingerprint	7.43	12.21	90.19

TABLE 2. The FAR, FRR and Accuracy values obtained from the multimodal fusion

Algorithm	FRR (%)	FAR (%)	Accuracy
Fingerprint	5.388	10.98	91.85
(Face+Finger) score level	5.68	4.78	94.77
(Face+Finger) Feature Level	1.98	3.18	97.41

TABLE 3. FAR, FRR and Accuracy values for the feature reduction techniques

Algorithm	FRR (%)	FAR (%)	Accuracy
Neighbourhood removal technique	5.46	4.64	94.96
Points belonging to specific regions	0	4.57	97.75

TABLE 4. Statistics Regarding The Number of Points Retained In The Three Feature Reduction Techniques I .E., K -Means, neighbourhood elimination and points belonging to specific locations

Algorithm	Face (SIFT)	Finger (Minutiae)	Fused point set
The no. of Extracted features	145	50	195
K-means clustering technique	145	55	90
Neighbourhood removal technique	75	27	98
Specific regions	47	25	69

In the fourth session, the matcher based on the Delaunay triangulation of the poinsets is introduced. The reported results are computed for monomodal modalities and multimodal fusion at matching score and feature extraction level. In the first case, all the feature points were included for triangle computation, in a second case only the reduced set of points was used .Table 5, show that the application of the Delaunay triangulation enhances the performance of the face and fingerprint modalities alone by 5.07% and 0.85%, respectively. Moreover, the multimodal feature level fusion using the Delaunay triangulation outperforms all the feature level fusion experiments, with the increase in recognition accuracy of 0.39%. Finally, the combination of restricting the points to those belonging to specific regions and the Delaunay triangulation further enhanced the recognition accuracy by 0.46%. This last configuration was further tested on the multimodal database acquired by the authors with multimodal fusion at score level and feature level. The results, presented in table 6, also demonstrate that the feature level fusion outperforms the score level fusion of 0.67%, also for the multimodal database.

TABLE 5. FAR, FRR and Accuracy values for the delaunay triangulation technique

Algorithm	FRR (%)	FAR (%)	Accuracy
Face SIFT	2.24	9.85	93.95
Fingerprint	13.66	3.07	92.69
Face+Finger at Matching level	2.95	8.09	94.48
Face+Finger at Feature Level	2.95	0.90	98.09
Face+Finger at Feature level using specific region	1.97	1.02	98.59

TABLE 6. FAR, FRR and Accuracy of the best matching and feature reduction strategies

Algorithm	FRR(%)	FAR(%)	Accuracy
Best strategy at score fusion	2.56	5.48	95.99
Best strategy at feature fusion	1.15	4.99	96.68

CONCLUSIONS

A multimodal biometric system based on the integration of face and fingerprint traits at feature extraction level were presented. These two biometrics are the most widely accepted biometrics in most applications. There are also other advantages in multimodal biometric systems, including the ease of use, robustness to noise, and the availability of low- cost, off-the-shelf hardware for data acquisition. From a system point of view, redundancy can always be exploited to improve accuracy and robustness which is achieved in many living systems as well. Human beings, for example, use several perception cues for the recognition of other living creatures. They include visual and acoustic. The possibility to augment the verification accuracy by integrating multiple biometric traits. A novel approach has been presented where both fingerprint and face images are processed with well-matched feature extraction algorithms to obtain comparable features from the raw data. In fact, the real feasibility of this approach, in a real application scenario, may heavily depend on the physical nature of the acquired signal. The fusing information from independent/ uncorrelated sources (face and fingerprint) at the feature level fusion increases the performance as compared to score level.

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