Multibiometrics Feature Level Fusion by Graph Clustering

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Abstract

This paper presents a feature level fusion approach which uses the improved K-medoids clustering algorithm and isomorphic graph for face and palmprint biometrics. Partitioning around medoids (PAM) algorithm is used to partition the set of n invariant feature points of the face and palmprint images into k clusters. By partitioning face and palmprint images with scale invariant features SIFT points, a number of clusters are formed on both the images. Then on each cluster, an isomorphic graph is drawn. Most probable pair of graphs is searched using iterative relaxation algorithm from all possible isomorphic graphs for a pair of corresponding face and palmprint images. Finally, graphs are fused by pairing the isomorphic graphs into augmented groups in terms of addition of invariant SIFT points and in terms of combining pair of keypoint descriptors by concatenation rule. Experimental results obtained from the extensive evaluation show that the proposed feature level fusion with the improved K-medoids partitioning algorithm improves the performance of the system.

Keywords: *Biometrics, Feature Level Fusion, Face, Palmprint, Isomorphic Graph, Graph Clustering, K-Medoids Partitioning Algorithm.*

1. Introduction

In multibiometrics fusion [1], feature level fusion [2,3] makes use of integrated feature sets obtained from multiple biometric traits. Fusion at feature level is found to be useful as compared to other level of fusion such as match score fusion, decision fusion, rank level fusion [4]. Since feature set contains relevant and richer information about the captured biometric evidence, fusion at feature level is expected to provide more accurate authentication results. It is very hard to fuse multiple biometric evidences at feature extraction level in practice because the feature sets are sometime found to be incompatible. Apart from this reason, there are two more reasons to achieve fusion at feature extraction level such as the feature spaces are unknown for different biometric evidences and fusion of feature spaces may lead to the problem of curse of dimensionality problem [2]. Further, poor feature representation may cause to degrade the performance of recognition of users.

Multimodal systems acquire information from more than one source. Unibiometric identifiers [5] use single source biometric evidence and often are affected by problems like lack of invariant representation, non-universality, noisy sensor data and lack of individuality of the biometric trait and susceptibility to circumvention. These problems can be minimized by using multibiometric systems that consolidate evidences obtained from multiple biometric sources. Feature level fusion of biometric traits is a challenging problem in multimodal fusion. However, good feature representation and efficient solution to curse of dimensionality problem can lead to feature level fusion with ease.

Multibiometrics fusion at match score level, decision level and rank level have extensively been studied and there exist a few feature level fusion approaches. However, there is enough scope to design an efficient feature level fusion approach. The feature level fusion of face and palmprint biometrics proposed in [3] uses single sample of each trait. Discriminant features using graph-based approach and principal component analysis techniques are used to extract features from face and palmprint. Further, a distance separability weighting strategy is used to fuse two sets at feature extraction level. Another example of feature level fusion of face and hand biometrics has been proposed in [4]. It has been found that the performance of feature level fusion outperforms the match score fusion. In [5], a feature level fusion has been studied where phase congruency features are extracted from face and Gabor transformation is used to extract features from palmprint. These two feature spaces are then fused using user specific weighting scheme. A novel feature level fusion of face and palmprint biometrics has been presented in [6]. It makes use of correlation filter bank with class-dependence feature analysis method for feature fusion of these two modalities.

This paper proposes a feature level fusion of face [7] and palmprint [8] biometrics using isomorphic graph [9] and K-medoids [10]. SIFT feature points [11] are extracted from face and palmprint images as part of feature extraction work. Using the partitioning around medoids (PAM) algorithm [12] which is considered as a realization of K-medoids clustering algorithm is used to partition the face and palmprint images of a set of *n* invariant feature points into *k* number of clusters. For each cluster, an isomorphic graph is drawn on SIFT points which belong to the clusters. Graphs are drawn on each partition or cluster by searching the most probable isomorphic graphs using iterative relaxation algorithm [13] from all possible isomorphic graphs while the graphs are compared between face and palmprint templates. Each pair of clustered graphs are fused by concatenating the invariant SIFT points and all pairs of isomorphic graphs of clustered regions are further fused to make a single concatenated feature vector. The same set of invariant feature vectors is also constructed from query pair of samples of face and palmprint images. Finally, matching between these two feature vectors is determined by computing the distance using K-Nearest Neighbor [14] and normalized correlation [15] distance approaches. IIT Kanpur multimodal database has been used for evaluation of the proposed feature level fusion technique.

The paper is organized as follows. Next section discusses SIFT features extraction from face and palmprint images. Section 3 presents K-Medoids partitioning of SIFT features into a number of clusters. The method of obtaining isomorphic graphs on the sets of the SIFT points which belong to the clusters is discussed in Section 4. Next section presents feature level fusion of clustered SIFT points by pairing two graphs of a pair of clustered regions drawn on face and palmprint images. Experimental results are presented in Section 6 while conclusion is given in the last section.

2. Extraction of SIFT Keypoints

To recognize and classify objects efficiently, feature points from objects can be extracted to make a robust feature descriptor or representation of the objects. David Lowe [11] has introduced a technique to extract features from images which are called Scale Invariant Feature Transform (SIFT). These features are invariant to scale, rotation, partial illumination and 3D projective transform and they are shown to provide robust matching across a substantial range of affine distortion, change in 3D viewpoint, addition of noise, and change in illumination. SIFT image features provide a set of features of an object that are not affected by occlusion, clutter and unwanted noise in the image. In addition, the SIFT features are highly distinctive in nature which have accomplished correct matching on several pair of feature points with high probability between a large database and a test sample. Following are the four major filtering stages of computation used to generate the set of features based on SIFT [11].

2.1 Extrema Detection in Gaussian Scale-Space

This filtering approach attempts to identify image locations and scales that are identifiable from different views. Scale space and Difference of Gaussian (*DoG*) functions are used to detect stable keypoints. Difference of Gaussian is used for identifying key-points in scale-space and scale space extrema by taking difference between two images. To detect the local maxima and minima, each feature point is compared with its 8 neighbors at the same scale and in accordance with its 9 neighbors up and down by one scale. If this value is the minimum or maximum of all these points then the corresponding point is an extrema.

2.2 Keypoints Localization

To localize keypoints, a few points after detection of stable keypoint locations that have low contrast or are poorly localized on an edge are eliminated. This can be achieved by calculating the Laplacian space. After computing the location of extremum value, if the value of difference of Gaussian pyramids is less than a threshold value, then the point is excluded. If there is a case of large principle curvature across the edge but a small curvature in the perpendicular direction in the difference of Gaussian function, then the poor extrema is localized and eliminated.

2.3 Orientation Assignment

This step aims to assign consistent orientation to the key-points based on local image characteristics. From the gradient orientations of sample points, an orientation histogram is formed within a region around the key-point. Orientation assignment is followed by key-point descriptor which can be represented relative to this orientation. A 16x16 window is chosen to generate histogram. The orientation histogram has 36 bins covering 360 degree range of orientations. The gradient magnitude and the orientation are pre-computed using pixel differences. Each sample is weighted by its gradient magnitude and by a Gaussian-weighted circular window.

2.4 Keypoint Descriptor

In the last step, the feature descriptors which represent local shape distortions and illumination changes are computed. After candidate locations have been found, a detailed fitting is performed to the nearby data for the location, edge response and peak magnitude. To achieve invariance to image rotation, a consistent orientation is assigned to each feature point based on local image properties. The histogram of orientations is formed from the gradient orientation at all sample points within a circular window of a feature point. Peaks in this histogram correspond to the dominant directions of each feature point. For illumination invariance, 8 orientation planes are defined. Finally, the gradient magnitude and the orientation are smoothened by applying a Gaussian filter and then are sampled over a 4 x 4 grid with 8 orientation planes.

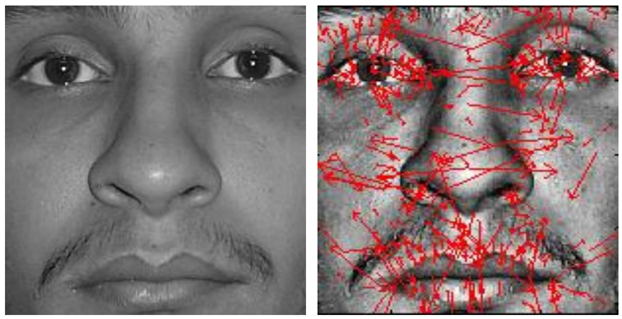

Figure 1. Face Image and SIFT Keypoints Extraction

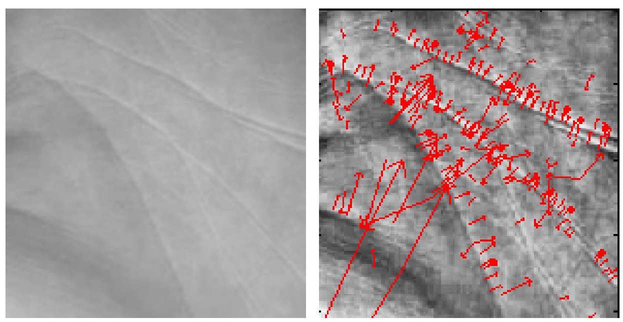

Figure 2. Palm Image and SIFT Keypoints Extraction

In the proposed work, the face and palmprint images are normalized by adaptive histogram equalization [2]. Localization of face is done by the face detection algorithm proposed in [16] while localization of palmprint is made by the algorithm discussed in [17]. After geometric normalization and spatial enhancement, SIFT features [11] are extracted from the face and palmprint images. Each feature point is composed of four types of information – spatial location (x, y), scale (S), orientation (θ) and Keypoint descriptor (K). For the experiment, only keypoint descriptor information has been considered which consists of a vector of 128 elements representing neighborhood intensity changes of each keypoint. More formally, local image gradients are measured at the selected scale in the region around each keypoint. The measured gradients information is then transformed into a vector representation that contains a vector of 128 elements for each keypoint calculated over extracted keypoints. These keypoint descriptor vectors represent local shape distortions and illumination changes. Figure 1 and Figure 2 show the extracted SIFT features for face and palmprint images respectively.

3. Feature Partitioning and Isomorphic Graph Representation

In most multimodal biometric applications, lack of well feature representation leads to the degradation of the performance. Therefore, well representation of feature space and template in terms of invariant feature points may help to exhibit robust and efficient solution towards user authentication. Instead of considering the whole biometric template and all the SIFT keypoints, clustering of all feature points into a number of clusters with limited number of invariant points can be an efficient approach of feature space representation. Clustering approach [18] often gathers together the keypoints which are most relevant and useful members of a particular cluster and association of these keypoints represents the relation within the keypoints in a cluster.

The proposed fusion approach partitions the SIFT keypoints which are extracted from face and palmprint images into a number of clusters with limited number of keypoints in each cluster and then isomorphic graph [9] is formed on each cluster with the keypoints of partitioned face and palmprint images. Prior to construct the isomorphic graphs on clusters, corresponding pairs of clusters are established in terms of relation between keypoints and geometric distance between keypoints regarded as vertices and edges respectively to itself as auto-isomorphism [9] for face and palmprint images. Three different steps are followed to make a correspondence between a pair of face cluster and a palmprint cluster after clustering of keypoints. Since the number of keypoints on face is more than that on palmprint, face image can be made as reference with respect to palmprint image. Later auto-isomorphism graph is built on each face cluster with the keypoints and the corresponding isomorphism is built on a palm cluster while point correspondences are established using point pattern matching approach [2]. Then a pair of clusters corresponding to a pair of face and palmprint images is searched by mapping the isomorphic graph of face cluster to the isomorphic graph of palmprint cluster. This process is carried out for all pairs of clusters of face and palmprint images. Lastly, the fusion of each pair of clusters of identical dimension of keypoints is done by sum rule approach [2]. Since each keypoint descriptor is a vector of 128 elements and each face and palm cluster is represented by an isomorphic graph. Isomorphic graphs for both the face and palm clusters contain same number of keypoints with one-to-one mapping. These two feature vectors containing SIFT keypoints are then fused using sum rule.

3.1 SIFT Keypoints Partitioning using PAM Characterized K-Medoids Algorithm

A medoid can be defined as the object of a cluster which means minimum dissimilarity to all the objects in the cluster. K-medoids [10] chooses data points as cluster centers (also called 'medoids'). It clusters the dataset of *n* objects into *k* clusters and is more robust to noise and outliers as compared to K-means clustering algorithm. This clustering algorithm is an adaptive version of K-means clustering approach and is used to partition the dataset into a number of groups which minimizes the squared error between the points that belong to a cluster and a point designated as the center of the cluster. The generalization of K-medoids algorithm is the Partitioning around Medoids (PAM) algorithm [12] which is applied to the SIFT keypoints of face and palmprint images to obtain the partitioned of features. It can provide more discriminative and meaningful clusters of invariant features. The algorithm can be given below.

Step 1: Select randomly k number of points from the SIFT points set as the medoids.

Step 2: Assign each SIFT feature point to the closest medoid which can be defined by a distance metric (i.e., Minkowski distance over the Euclidean space)

Step 3: for each medoid i, $i = 1, 2 \ldots k$

for each non-medoid SIFT point j
swap i and j and
compute the total cost of the configuration
Step 4: Select the configuration with the lowest cost
Step 5: Repeat Step 2 to Step 5 until there is no change in the medoid.

3.1.1 Improved version of PAM clustering using Silhouette approximations: Silhouette technique [12] can be used to verify the quality of a cluster of data points. After applying the PAM clustering technique to the sets of SIFT keypoints for face and palmprint images, each cluster can be verified by Silhouette technique. Let, for each keypoint i, $x(i)$ be the average distance of i with all the keypoints in cluster c_m. Consider $x(i+1)$ as an additional average distance next to $x(i)$. These two successive distances $x(i)$ and $x(i+1)$ are considered to verify the matching of these keypoints i and $(i+1)$ to the cluster where these points are assigned. The average distance of i and $(i+1)$ with the keypoints of another single cluster is found. This process is repeated for every cluster in which i and $(i+1)$ are not a member. If the cluster with lowest average distances to i and $(i+1)$ are $y(i)$ and $y(i+1)$ ($y(i+1)$ is the next lowest average distance to $y(i)$), the cluster is known to be the neighboring cluster of the former cluster in which i and $(i+1)$ are assigned. It can be defined by the following equation

$$S(i) = \frac{(y(i) + y(i+1))/2 - (x(i) + x(i+1))/2}{\max[((x(i) + x(i+1)), (y(i) + y(i+1))]} \tag{1}$$

From Equation (1) it can be written that $-1 \leq S(i) \leq 1$

When $x(i)+x(i+1) << y(i)+y(i+1)$, $S(i)$ would be very closer to 1. Distances $x(i)$ and $x(i+1)$ are the measures of dissimilarity of i and $(i+1)$ to its own cluster. If $y(i)+y(i+1)$ is small enough, then it is well matched; otherwise, when the value of $y(i)+y(i+1)$ is large then bad match is occurred. Keypoint is well clustered when $S(i)$ is closer to 1 and when that value of $S(i)$ is negative then it belongs to another cluster. Zero value of $S(i)$ means that keypoint is on the border of any two clusters.

The existing algorithm has been extended by taking another average distances of $x(i+1)$ and $y(i+1)$ for a pair of clusters and it has been determined that a better approximation could be made while PAM algorithm is used for partition the keypoints set. The precision level of each cluster is increased by this improved approximation method where more relevant keypoints are taken instead of the restricted number of keypoints for fusion.

3.2 Establishing Correspondence between Clusters of Face and Palmprint Images

To establish correspondence [7] between any two clusters of face and palmprint images, it has been observed that more than one keypoint on face image may correspond to single keypoint on the palmprint image. To eliminate false matches and to consider only minimum pair distance from a set of pair distances for making correspondences, first it needs to verify the number of feature points that are available in the cluster of face and that in the cluster of palmprint. When the number of feature points in the cluster for face is less than that of the cluster for palmprint, many points of interest from the palmprint cluster needs to be discarded. If the number of points of interest on the face cluster is more than that of the palmprint cluster, then a single interest point on the palmprint cluster may act as a match point for many points of interest of face cluster. Moreover, many points of interest on the face cluster may have correspondences to a single point of interest on the cluster for palmprint. After computing all distances between points of interest of face cluster and palmprint cluster that have made correspondences, only the minimum pair distance is paired.

After establishing correspondence between clusters for face and palmprint images, isomorphic graph representation [9] for each cluster has been formed while removing few more keypoints from the paired clusters. Further, iterative relaxation algorithm [13] is used for searching the best possible pair of isomorphic graphs from all possible graphs.

3.3 Isomorphic Graph Representations of Partitioned Clusters

To interpret each pair of clusters for face and palmprint, isomorphic graph representation has been used. Each cluster contains a set of SIFT keypoints and each keypoint is considered as a vertex of the proposed isomorphic graph. A one-to-one mapping function is used to map the keypoints of the isomorphic graph constructed on a face cluster to a palmprint cluster while these two clusters have been made correspondence to each other. When two isomorphic graphs are constructed on a pair of face and palmprint clusters with equal number of keypoints, two feature vectors of keypoints are constructed for fusion.

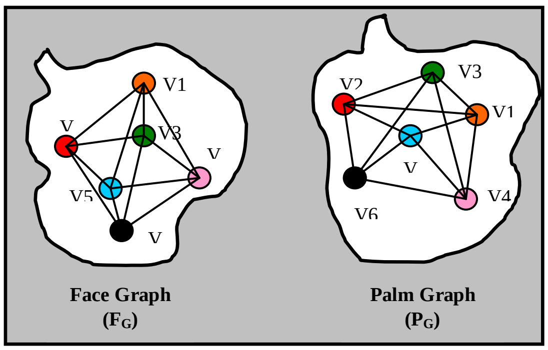

Figure 3. One-to-One Correspondence between Two Isomorphic Graphs

Let F_G and P_G be two graphs and also let f be a mapping function from the vertex set of F_G to the vertex set of P_G. When

- f is one-to-one and
- $f(v_k)$ is adjacent to $f(w_k)$ in P_G if and only if v_k is adjacent to w_k in F_G

then the function f is known as an isomorphism and two graphs F_G and P_G are isomorphic. Therefore the two graphs F_G and P_G are isomorphic if there is a one-to-one correspondence between vertices of F_G and those of P_G while two vertices of F_G are adjacent then so are their images in P_G. If two graphs are isomorphic then they are identical graph though the location of the vertices may be different. Figure 3 shows an example of isomorphic graph and one-to-one correspondence between two isomorphic graphs where each colored circle refers independent vertex.

4. Fusion of Keypoints

To fuse the SIFT keypoint descriptors obtained from each isomorphic graph for face and for palmprint images, two different fusion rules are applied serially, viz. sum rule [2] and concatenation rule [1]. Let $F_G(v_k) = (v_{k1}, v_{k2}, v_{k3},\ldots, v_{kn})$ and $P_G(w_k) = (w_{k1}, w_{k2}, w_{k3},\ldots, w_{kn})$ be the two sets of keypoints obtained from two isomorphic graphs for a pair of face and palmprint clusters. Suppose, there are m numbers of clusters in each of face and palmprint images. Then these two sets of clusters can be fused using sum fusion rule and the concatenation rule can be further applied to form an integrated feature vector. Suppose that $F_{G1}, F_{G2}, F_{G3},\ldots, F_{Gm}$ sets of keypoints are obtained from a face image after clustering and isomorphism and P_{G1}, P_{G2}, P_{G3},…, P_{Gm} are the sets of keypoints obtained from a palmprint image. The sum rule can be defined for the fusion of keypoints as follows

$$
\begin{array}{l}
S_{FP1} = F_{G1} + P_{G1} = \{(v_{k1}^{1} + w_{k1}^{1}), (v_{k2}^{1} + w_{k2}^{1}), (v_{k3}^{1} + w_{k3}^{1}), \ldots, (v_{kn}^{1} + w_{kn}^{1})\\
S_{FP2} = F_{G2} + P_{G2} = \{(v_{k1}^{2} + w_{k1}^{2}), (v_{k2}^{2} + w_{k2}^{2}), (v_{k3}^{2} + w_{k3}^{2}), \ldots, (v_{kn}^{2} + w_{kn}^{2})\\
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S_{FPm} = F_{Gm} + P_{Gm} = \{(v_{k1}^{m} + w_{k1}^{m}), (v_{k2}^{m} + w_{k2}^{m}), (v_{k3}^{m} + w_{k3}^{m}), \ldots, (v_{kn}^{m} + w_{kn}^{m})
\end{array}
\tag{2}
$$

In Equation (2), S_{FPj} ($i = 1,2,..,m$), v_{kj} ($j = 1,2,...,n$) and w_{kj} ($j = 1,2,...,n$) refer to a fused set of keypoint descriptors for a pair of isomorphic graphs obtained by applying sum fusion rule, a keypoint of a face graph and a keypoint of a palm graph respectively.

$$
Concat(S_{FP1}, S_{FP2}, \ldots, S_{FPm}) = \begin{bmatrix}
sum(v_{k1}^{1} + w_{k1}^{1}) & sum(v_{k2}^{1} + w_{k2}^{1}) & \ldots\ldots sum(v_{kn}^{1} + w_{kn}^{1})\\
sum(v_{k1}^{2} + w_{k1}^{2}) & sum(v_{k2}^{2} + w_{k2}^{2}) & \ldots\ldots sum(v_{kn}^{2} + w_{kn}^{2})\\
-------- & -------- & --------\\
-------- & -------- & --------\\
sum(v_{k1}^{m} + w_{k1}^{m}) & sum(v_{k2}^{m} + w_{k2}^{m}) & \ldots\ldots sum(v_{kn}^{m} + w_{kn}^{m})
\end{bmatrix}
\tag{3}
$$

In the next step, concatenation rule is applied to the sets of keypoints to form a single feature vector. Finally the concatenated set of keypoints is obtained as described in Equation (3).

5. Matching Criterion and Verification

The K-Nearest Neighbor (K-NN) distance [11] and correlation distance [12] approaches are used to compute distances from the concatenated feature sets. In K-NN approach, Euclidean distance metric is used to get K best matches. Let d_i be the Euclidian distance of the concatenated feature set of subject S_i, i = 1, 2,…, K, which belong to the K best matches against a query subject. Then S_t is verified against the query if $d_t \leq Th$ where d_t is the minimum of d_1, d_2,…, d_K and Th is the threshold.

On the other hand, the correlation distance metric is used for computing distance between a pair of reference set and probe set. Similarity between two concatenated feature vectors f_1 and f_2 can be computed as

$$
d = \frac{\sum f_1 f_2}{\sqrt{\sum f_1 \sum f_2}}
\tag{4}
$$

Equation (4) denotes the normalized correlation between feature vectors f_1 and f_2. Let d_i be the similarity of the concatenated feature set of subject S_i, i = 1, 2, … K, with respect to that of a query subject. Then the subject S_t is verified against the query subject if $d_t \geq Th$ where d_t is the maximum of d_1, d_2, ..., d_K and Th is the threshold. To determine the thresholds for both the distance measures, a subset of subjects is used.

6. Experimental Evaluation

6.1 Databases

The proposed approach has been tested on IIT Kanpur and chimeric multimodal databases. Chimeric database contains face images of ORL face database [20] and palmprint images of Hong Kong Polytechnic University (PolyU) database [21]. IIT Kanpur multibiometrics database consists of 800 face and 800 palmprint images and each subject contributes 2 face and 2 palmprint images. ORL face database contains 400 face images of 40 subjects while PolyU database contains 7,752 palmprint images of 193 subjects (386 palm impressions). From 400 face images of ORL database [20], only 160 face images are taken and 4 face images are taken for each subject. From PolyU database [21], only 160 palm images of 40 subjects having 2 right and 2 left palm images per subject are taken.

In IIT Kanpur face database, images are in controlled environment with maximum tilt of head by 20° from the origin. For evaluation, frontal view faces are used with uniform lighting and minor change in facial expression. These images are acquired in two different sessions. Among the two face images, one image is used as a reference face while the other one is used as a probe face. It uses the face detection algorithm [16] to get face portion only. On the other hand, face images in ORL database [20] are taken at different sessions with varying the lighting conditions, facial expressions (open/closed eyes, smiling/not smiling) and different facial details (glasses / no glasses). The face images are taken against a dark homogeneous background with the subjects in an upright, frontal position. For the experiment, only frontal view faces are taken with neutral facial expressions and uniform changes in lighting. Among the 4 face images, 2 images are used for reference and remaining two are used for probe face images. Since it contains cropped images, one does not require to get the face portion.

Palmprint images in IIT Kanpur database are also taken in controlled environment with a flat bed scanner having spatial resolution of 200 dpi. Impressions are taken on the scanner with rotation of at most $\pm 35^0$ to each user. There are 800 palmprint images of 400 subjects and each subject is contributed 2 images. An image enhancement technique is used to achieve uniform spatial resolution. Finally, palm portion is detected with the help of the technique proposed in [17]. In PolyU palmprint database [21], images are captured at two different sessions and these images are taken under different lighting conditions and by changing the focus of CCD camera. Change in focus is regarded as different palm capturing devices. The images which are of two different sizes, viz. 384×284 and 768×568, are resized to 160×160 and palm portion is detected by the algorithm presented in [17].

6.2 Experimental Results

The performance of the proposed approach is determined using one-to-one matching strategy. Experimental results are obtained with the help of two distance approaches namely, K-Nearest Neighbor (K-NN) distance [14] and normalized correlation [15]. We have also determined the performance of face and palmprint independently. Fused feature set which is obtained from reference face and palmprint images is matched with the feature set obtained from probe pair of face and palmprint images by computing the distance between these two sets. Experiments are for the six distinct cases: (i) face modality using K-NN, (ii) face modality using normalized correlation, (iii) palmprint modality using K-NN, (iv) palmprint modality using normalized correlation, (v) feature fusion using K-NN and (vi) feature fusion using normalized correlation.

Table 1. Different Error Rates on IIT Kanpur Database

Method	FAR (%)	Recognition Rate (%)
Face Recognition (K-NN)	7.0	92.50
Face Recognition (Correlation)	6.0	93.75
Palmprint Verification (K-NN)	4.5	94.75
Palmprint Verification (Correlation)	2.5	96.00
Feature Level Fusion (K-NN)	2.0	97.50
Feature Level Fusion (Correlation)	0.0	98.75

False Accept Rate (FAR), False Reject Rate (FRR) and recognition rate are determined from the IIT Kanpur database of 800 face and palmprint images of 400 subjects. Feature level fusion method using normalized correlation outperforms other proposed methods including individual matching of face and palmprint modalities. The correlation metric based feature level fusion has 98.75% recognition rate with 0% FAR while K-NN based method has the recognition rate of 97.5% with 2% FAR. It can be noted that FAR of all the proposed methods are found to be less than its corresponding FRR. On the other hand, palmprint modality performs better than face modality while K-NN and correlation metrics are used. The distance metrics play an important role irrespective of use of invariant features and isomorphic graphs representations. However, the robust representations of face and palmprint images using isomorphic graphs with the use of invariant SIFT keypoints and PAM characterized K-Medoids algorithm makes the proposed fusion method more efficient. In single modality, the same approach has been used. Therefore, the error rates obtained from the single modalities and fusion method are determined under a uniform framework. However, the methodology used for feature level fusion found to be not only superior to other methods but also shows significant improvements in terms of recognition rate and FAR. Table 1 shows different error rates determined on IIT Kanpur database for the methods while the Receiver Operating Characteristics (ROC) curves determined at different operating threshold points are given in Figure 4.

In the second phase, when the proposed fusion is applied to both the correlation based and K-NN based distance metrics for the chimeric multibiometric database, FAR is found to be much less than that of FRR. The correlation based distance metric has 99.5% recognition rate with 0% FAR while the K-NN distance metric has 99.25% recognition rate with 1.5% FAR. It is found that the palmprint modality performs better than face modality under both the distance metrics. The combination of SIFT features and isomorphic graph representation is found to be robust for the proposed feature level fusion approach while IIT Kanpur and chimeric multibiometric databases are used. However, the recognition rates determined from chimeric database is found to be more than that of IIT Kanpur database. This may be because of the small size compared to IIT Kanpur database. Table 2 shows the error rates and recognition rates for the proposed techniques on chimeric database.

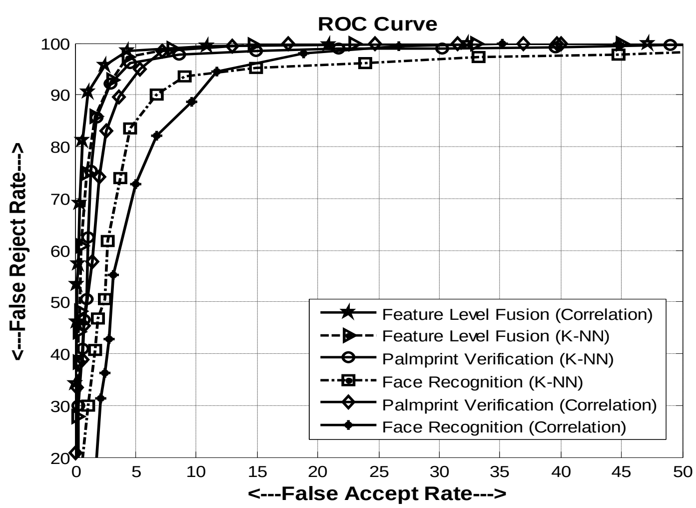

Figure 4. Receiver Operating Characteristics (ROC) Curves

Sub-graph isomorphism is robust and optimal routing representation where most of the feature points construct good representative graph for the other biometric sample on which the feature points of the first graph is mapped. This characteristic of subgraph isomorphism makes the feature level fusion more robust.

Table 2. Error and Recognition Rates Determined on Chimeric Database

Method	FAR (%)	Recognition Rate (%)
Face Recognition (K-NN)	5.5	93.75
Face Recognition (Correlation)	5	94.5
Palmprint Verification (K-NN)	4	95
Palmprint Verification (Correlation)	2.25	96.75
Feature Level Fusion (K-NN)	1.5	99.25
Feature Level Fusion (Correlation)	0.0	99.5

6.3 Comparison with a Well Known Technique

The proposed fusion of face and palmprint is compared with a multibiometrics system [19] where the features of face and hand evidences are fused. In the proposed fusion, SIFT features are extracted from face and palmprint and on these feature points, isomorphic graphs are drawn. These isomorphic representations are fused in terms of matched points found on isomorphic subgraphs. On the other hand, in [19] local facial features, such as eyes, mouth and nose features are localized using point distribution model and active shape models. Similarly, same methodology is applied to find some distinctive points on hand geometry. Gabor filter is applied to face image and feature vector is constructed by extracting the key points using active shape models. Similarly, the hand feature vector is constructed. To verify the identity of users, Support Vector Machine is used. The technique presented in [19] is tested on a multibiometrics database which contains 480 face images and 120 hand images of 30 peoples. 16 faces and 4 hand images are taken from each person. Two experiments are conducted on the entire database. In the first experiment, features of 12 faces and 2 hands are fused for training and for testing, feature of 4 faces and remaining 2 hands are fused. The system is trained on 12 feature vectors which contain information about face and hand geometry of each individual. One SVM is trained on each individual. In this experiment, numbers of hand features are fixed to every combination of features, whereas number of features for eyes, nose and mouth are changing in every combination. The best recognition accuracy obtained from the first experiment is 99.23%. In the second experiment features of 12 faces and 3 hands are fused. This combination achieves the best average accuracy while the system is trained with SVM. The best average accuracy is obtained by the feature vector which contains Gabor features of 8 eye points, 4 nose points and 9 hand geometry. Table 3 shows the best average accuracy of different combinations of feature points which is obtained from the second experiment and is 99.43%.

The proposed approach shows the best recognition accuracies (RR) on IIT Kanpur and chimeric databases. Test on IIT Kanpur reveals 98.75% and 97.5% accuracies under normalized correlation and K-NN distance metrics respectively. In case of the chimeric database, they are 99.5% and 99.25% respectively. The accuracies of the proposed approach are found to be better than that of the approach in [19]. Since the number of invariant features on both the face and palmprint images is not fixed, the performance shows outmost level of robust system. However, the fusion approach in [19] takes fixed number of features obtained from eyes, mouth and nose. And some distinctive features are determined from hand geometry. Number of SIFT feature points in the proposed fusion is changed dynamically and the combination of subgraph isomorphism and SIFT descriptor exhibits robustness of the fusion system. The system in [19] shows certain variations in selection of local feature points and it also shows good accuracies. However, due to fixed number of feature points and number of less feature points exhibit robustness to some extent. In the proposed fusion, the whole face is used for feature extraction while the fusion approach in [19] uses the local features only.

Table 3. Comparative Study: Best Recognition Accuracies Obtained from the Proposed Fusion Approach and from the Fusion Approach Discussed in [19]

Method	Database	Number of Feature Points Used	Recognition Rate (%)
Feature level fusion [Experiment I] [19]	Local database (480 faces, 120 hand geometry, 30 individuals)	21 points (8 points from eyes, 4 points from nose and 9 points from hand)	99.23
Feature level fusion [Experiment I] [19]	Local database (480 faces, 120 hand geometry, 30 individuals)	25 points (16 points from eyes, and 9 points from hand)	99.22
Feature level fusion [Experiment II] [19]	Local database (480 faces, 120 hand geometry, 30 individuals)	21 points (8 points from eyes, 4 points from nose and 9 points from hand)	99.43
Feature level fusion [Experiment II] [19]	Local database (480 faces, 120 hand geometry, 30 individuals)	21 points (8 points from eyes, 4 points from nose and 9 points from hand)	99.31
Feature Level Fusion (K-NN)	IIT Kanpur (800 faces, 800 palms, 400 individuals)	Feature points are not fixed	97.5
Feature Level Fusion (Correlation)	IIT Kanpur (800 faces, 800 palms, 400 individuals)	Feature points are not fixed	98.75
Feature Level Fusion (K-NN)	Chimeric (160 faces, 160 palms, 40 individuals)	Feature points are not fixed	99.25
Feature Level Fusion (Correlation)	Chimeric (160 faces, 160 palms, 40 individuals)	Feature points are not fixed	99.5

7. Conclusion

This paper has presented a feature level fusion system of face and palmprint traits using invariant SIFT descriptor and isomorphic graph representation. The performance of feature level fusion has been verified by two distance metrics namely, K-NN and normalized correlation metrics. However, normalized correlation metric is found to be superior to that of K-NN metric for all the proposed verification methods. This paper has presented a robust representation to invariant SIFT features for face and palmprint images which cannot only be useful to the individual verification of face and palmprint modality but has also proved to be useful to the proposed feature level fusion approach. Since isomorphic graph is used for representation of feature points extracted from face and palmprint images, identical numbers of matched pair points are to be used for fusion. In addition, PAM characterized K-Medoids algorithm as a feature reduction technique has also proved to be useful for keeping relevant nature of feature keypoints. Single modality palmprint method performs better than face modality while K-NN and correlation approaches are used. Feature level fusion approach attains 98.75% recognition rate with 0% FAR on IIT Kanpur multimodal database while that attains 99.5% recognition rate with 0% FAR on chimeric database. The proposed fusion approach is found to be an efficient one while it is compared with another fusion approach of different paradigm.

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