Face Recognition using SIFT Descriptor under Multiple Paradigms of Graph Similarity Constraints[1]

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Abstract

Biometric systems are considered as human pattern recognition systems that can be used for individual identification and verification. The decision on the authenticity is done with the help of some specific measurable physiological or behavioral characteristics possessed by the individuals. Robust architecture of any biometric system provides very good performance of the system against rotation, translation, scaling effect and deformation of the image on the image plane. Further, there is a need of development of real-time biometric system. There exist many graph matching techniques used to design robust and real-time biometrics systems. This paper discusses two graph matching techniques that have been successfully used in face biometric traits.

Keywords: *Biometrics, Face recognition, SIFT descriptor, Graph constraints.*

1. Introduction

There exist several graph matching techniques [1], [2], [3] for identity verification of biometric samples which can solve problems like orientation, noise, non-invariant, etc that often occurred in face. Different graph topologies are successfully used for feature representations of these biometric cues [1], [2], [4]. Graph algorithms [5] can be considered as a tool for matching two graphs obtained from feature sets extracted from two biometric cues. To describe the topological structure of biometric pattern, the locations at which the features are originated or extracted are used to define a graph. The small degree of distortions of features can easily be computed during matching of two graphs based on the position and distances between two nodes of the graph and also with the adjacency information of neighbor's features.

This paper makes an attempt and explains the way a graph can be used in the designing efficient biometric systems. Section 2 presents some preliminaries. Robust face recognition using complete graph topology is discussed in Section 3. Next section

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proposed a probabilistic graph based face recognition. Experimental results are presented in Section 5 and concluding remarks are made in the last section.

2. Preliminaries

2.1. Scale Invariant Feature Transform (SIFT) Descriptor

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 has introduced a technique called Scale Invariant Feature Transform (SIFT) [7] to extract features from images. 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 features provide a set of features of an object that are not affected by occlusion, clutter and unwanted noise in the image. In addition, 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 steps of computation used to generate the set of image feature based on SIFT.

- **Scale-Space Extrema Detection:** 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 locating scale space extrema by taking difference between two images, one with scaled by some constant time of the other. 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 this point is an extrema.

- **Keypoints Localization in Laplacian Space:** To localize keypoints, 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, 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, the poor extrema is localized and eliminated.

- **Assignment of Orientation:** 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.

- **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.

2.2. Correspondence Graph Definitions

The correspondence graph problem [6] is the problem of finding a match between two structural descriptions, i.e., a mapping function between elements of two set of feature points which preserve the compatibilities between feature relations of face images. Let *G1* and *G2* be two face graphs given by:

$$G1 = \{V^{G1}, E^{G1}, F^{G1}\}, G2 = \{V^{G2}, E^{G2}, F^{G2}\} \quad \textbf{(1)}$$

where V^{Gk}, E^{Gk} and F^{Gk} represent the set of vertices, edges and SIFT features, respectively, in terms of each feature points associated to the graph, with two face images $k = 1, 2$. Let us define the directional correspondence between two feature points as follows:

2.2.1. Definition 1: Let us assume that the i^{th} $(i=1,2,..,N)$ feature of first face graph *G1* has correspondence to the j^{th} $(j =1,2,...,M)$ feature point on the second face graph *G2* in respect of conditional probability $V_i^{G1} \rightarrow V_j^{G2}$, if

$$\left| p(V_i^{G1} = V_j^{G2}, V_{i+1}^{G1} = V_j^{G2}, ... \middle| G1) - 1 \right| \leq \in; \qquad \in > 0 \quad \textbf{(2)}$$

Note that $V_i^{G1} \rightarrow V_j^{G2}$ does not imply $V_j^{G2} \rightarrow V_i^{G1}$. Therefore, to avoid false correspondences, one-to-one correspondence is defined as the extension of the Equation (2).

2.2.2. Definition 2: Let the i^{th} feature point of the first face graph *G1* has one-to-one correspondence to the j^{th} feature point on the second face graph *G2* in terms of conditional probability $V_i^{G1} \leftrightarrow V_j^{G2}$ if

$$\left| p(V_i^{G1} = V_j^{G2} \middle| G1) - 1 \right| \leq \in_1 \quad \textbf{(3)}$$

and

$$\left| p(V_j^{G2} = V_i^{G1} | G2) - 1 \right| \leq \in_2 \qquad \textbf{(4)}$$

for some small $\in_1 > 0, \in_2 > 0$

The correspondence graph between *G1* and *G2* is defined as:

$$G^{G1 \leftrightarrow G2} = \left(V^{G1}, V^{G2}, E^{G1}, E^{G2}, F^{G1}, F^{G2}, C^{G1 \leftrightarrow G2} \right) \qquad \textbf{(5)}$$

where $\overline{G}k \subseteq Gk$ is a sub-graph of the original graph G_k, $k = 1,2$, in which all the nodes have the one-to-one correspondence to each other such that $V_i^{G1} \leftrightarrow V_j^{G2}$ and $C^{G1 \leftrightarrow G2}$ is the set of node pairs which have the one-to-one correspondence, given by:

$$C^{G1 \leftrightarrow G2} = \left\{ (V_i^{G1}, V_j^{G2}) \middle| V_i^{G1} \leftrightarrow V_j^{G2} \right\} \qquad \textbf{(6)}$$

2.3. Probabilistic Relaxation Graph

In order to interpret a pattern with feature points and graph relaxation topology [10], each extracted feature can be thought as a node and the relationship between points can be considered as edge between two nodes. Relaxation graphs are then drawn on the feature points extracted from the pattern. These relaxations are used for matching and verification.

Thus, the graph can be represented by G = $\{V,E,K,\zeta\}$, where V and E denote the set of nodes and the set of edges, respectively and K and ζ are the sets of attributes associated with nodes and edges in the graph, respectively. K denotes the set of keypoint descriptors associated with various nodes and ζ denotes the relationship between two keypoint descriptors.

Suppose, $G_R = \{V_R,E_R,K_R,\zeta_R\}$ and $G_Q = \{V_Q,E_Q,K_Q,\zeta_Q\}$ are two graphs. These two graphs can be compared to determine whether they are identical or not. If it is found that $|V_R| = |V_Q|$ for the given two graphs, the problem is said to be exact graph matching problem. The problem is to find a one-to-one mapping $f: V_Q \rightarrow V_R$ such that $(u,v) \in E_Q$ iff $(f(u),f(v)) \in E_R$. This mapping f is called an isomorphism and G_Q is called isomorphic to G_R. In this case, isomorphism is not possible because identical feature points may not be present on two different patterns. Hence, it is forced to apply inexact graph matching problem in the context of probabilistic graph matching where either $|V_R| < |V_Q|$ or $|V_R| > |V_Q|$. This may occur when the number of points or vertices is different in both the graphs.

The similarity measure for vertex and edge attributes can be defined as the similarity measure for nodes $v_R^i \in V_R$ and $v_Q^j \in V_Q$ as $s_{ij}^v = s(v_R^i, v_Q^j)$ where $v_R^i \in K_R \in V_R$ and $v_Q^j \in K_Q \in V_Q$, and the similarity between edges $e_R^{ip} \in E_R$ and $e_Q^{jq} \in E_Q$ can be denoted as $s^e_{ipjq} = s(e_R^{ip}, e_Q^{jq})$, where $e^{jp}_R \in \zeta_R \varepsilon E_R$ and $e^{jq}_Q \in \zeta_Q \in E_Q$.

Now, v^j_Q would be best probable match for v^i_R when v^j_Q maximizes the posteriori probability of labeling. Thus for the vertex $v^i_R \in V_R$, we are searching the most probable label or vertex $v^{-i}_R = v^j_Q \in V_Q$ in the graph. Hence, it can be stated as

$$\overline{v}_R^i = \arg \max_{j, v_Q \in V_Q} P(\psi_i^{v_Q^j} \mid K_R, \varsigma_R, K_Q, \varsigma_Q) \quad \textbf{(7)}$$

For efficient searching of matching probabilities from the query sample, we use relaxation technique which simplifies the solution of matching problem. Let $\overline{P}_{ij}^v$ denote the matching probability for vertices $v^i_R \in V_R$ and $v_Q^j \in V_Q$. Now, by reformulating Equation (7) one gets

$$\overline{v}_R^i = \arg \max_{j, v_{Q_j} \in V_Q} \overline{P}_{ij}^v \quad \textbf{(8)}$$

Equation (8) is considered as an iterative relaxation algorithm for searching the best labels for v^i_R. This can be achieved by assigning prior probability $\overline{P}_{ij}^v$ proportional to $s_{ij}^v = s^v(k_R^i, k_Q^j)$. The following iterative relaxation rule can be used to define $\overline{P}_{ij}^v$;

$$\hat{P}_{ij}^v = \frac{\overline{P}_{ij}^v . Q_{ij}}{\sum_{j, v_Q^j \in V_Q} \overline{P}_{ij}^v . Q_{ij}} \quad \textbf{(9)}$$

where, Q_{ij} is given by

$$Q_{ij} = \overline{P}_{ij}^v \prod_{v_i \in V_R} \sum_{v_j \in V_Q} s_{ij}^e . \overline{P}_{ij}^v \quad \textbf{(10)}$$

In Equation (10), Q_{ij} conveys the support of the neighboring vertices and $\hat{P}_{ij}^v$ represents the posteriori probability. The relaxation cycles are repeated until the difference between prior probability $\overline{P}_{ij}^v$ and posteriori probabilities $\hat{P}_{ij}^v$ becomes smaller than certain threshold Φ. When it is achieved then it is assumed that the relaxation process is stable.

3. Face Recognition using Complete Graph Topology

The proposed face recognition technique has been designed by using the complete graph topology which makes use of invariant SIFT features. The technique is developed with the three graph matching constraints, namely Gallery Image based Match Constraint [6], Reduced Point based Match Constraint [6] and Regular Grid based Match Constraint [6]. Initially the face image is normalized by using histogram equalization. The rotation, scale and partial illumination invariant SIFT features are then extracted from the normalized face images. Finally, the graph-based topology is applied for matching two face images.

3.1 Gallery Image based Match Constraint

It is assumed that matching points can be found around similar positions i.e., fiducial points on the face image. To eliminate false matches a minimum Euclidean distance measure is applied. It may be possible that more than one point in the first image correspond to the same point in the second image. Let us consider, $X_1, X_2, \ldots, X_N$ are the interest points found in the first image and $Y_1, Y_2, \ldots, Y_M$ are the interest points found in the second image. Whenever $N \leq M$, many interest points from the second image are discarded, while if $N \geq M$, many repetitions of the same point would be occurred as corresponding points in the second image. In both cases, one interest point of the second image may correspond to several points in the first image. After computing all the distances, only the point with the minimum distance from the corresponding point in the second image is paired (It has been illustrated in Fig. 1 and Fig. 2).

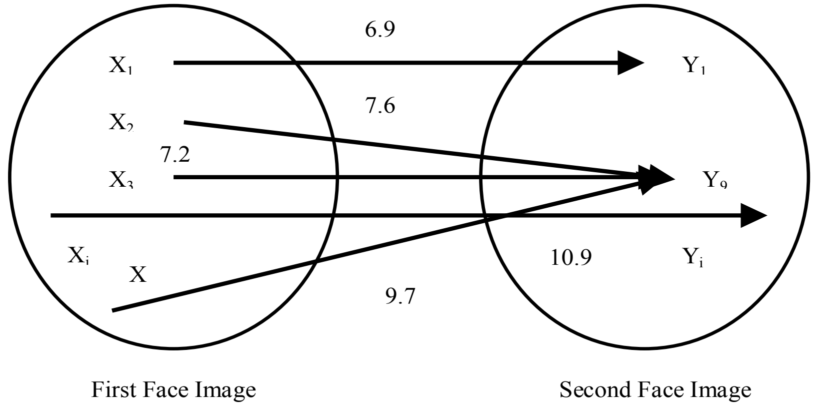


Figure 1. The Corresponding Points of Image 1 are Mapped into Image 2 using the Minimum Euclidean Distance Measure

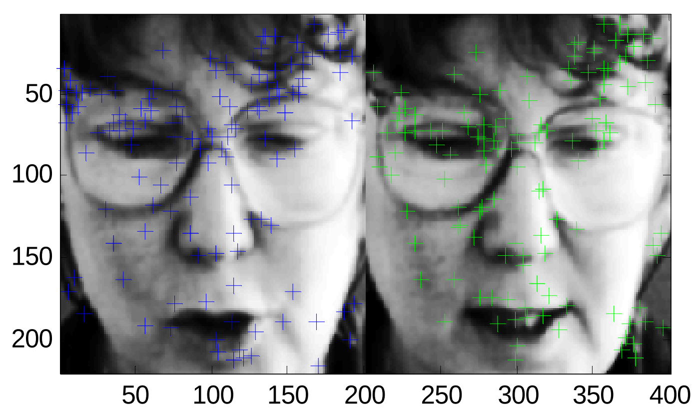


Figure 2. All Feature Points and their Matches for a Pair of Images, based on Euclidean Distance Measure

The distances are computed based on the Hausdorff distance between two images. The dissimilarity scores are computed between all pairs of nodes of two face images after constructing the complete graph for each face image.

Suppose, $F_{gallery}$ and F_{probe}, are two images representing the gallery and probe image, respectively and I is the compact information composed of all the four types of information generated by the SIFT descriptor. Then we have,

$$I(F_{gallery}) = \{X^{F_{gallery}}(f_i), K^{F_{gallery}}(f_i), S^{F_{gallery}}(f_i), O^{F_{gallery}}(f_i)\}$$

$$I(F_{probe}) = \{X^{Fprobe}(f_j), K^{Fprobe}(f_j), S^{Fprobe}(f_j), O^{F_{probey}}(f_j)\}$$

where i = 1,2,…….,N; j = 1,2,………,M;

The dissimilarity scores $D^{GIBMC}{}_V(F_{gallery}, F_{probe})$ and $D^{GIBMC}{}_E(F_{gallery}, F_{probe})$ are computed for both the vertexes and the edges as:

$$D^{GIBMC}{}_V(F_{gallery}, F_{probe}) = \min_{i=1,2,..,N}\{\min_{j=1,2,...,M}(d(I_i(F_{gallery}), I_j(F_{probe}))\} \quad \textbf{(11)}$$

$$\Delta^{GIBMC}{}_V(F_{gallery}, F_{probe}) = \frac{1}{T}\sum_{t=1}^{T} D^{GIBMC}{}_V(F_{gallery}, F_{probe})^t \quad \textbf{(12)}$$

where T is the total number of all is minimum distances. To find the correspondences between two graphs in terms of edge information, let us take $E_1(N)$ and $E_2(N)$ are the number of edges in the two face graphs respectively and the number of nodes for two images are same. After finding the corresponding points between the feature points of the first and the second image, we construct complete graph for each face image. We try to find out the correspondences and compute the dissimilarity scores for a pair of edges. If nodes $a,a' \epsilon N^{gallery}$ and $b,b' \epsilon N^{probe}$ belong to gallery and probe images, respectively, then $(a,a') \epsilon E_1(N)$ and $(b,b') \epsilon E_2(N)$ would be a pair of edges for the gallery image and the probe image, respectively and score is given by

$$D^{GIBMC}{}_E(F_{gallery}, F_{probe}) = d(I_i(F_{gallery}(a,a')), I_j(F_{probe}(b,b'))) \quad \textbf{(13)}$$

where $i,j = 1,2,\ldots,N$;

$$\Delta^{GIBMC}{}_E(F_{gallery}, F_{probe}) = \frac{1}{E}\sum_{e=1}^{E} D^{GIBMC}{}_E(F_{gallery}, F_{probe})^e \quad \textbf{(14)}$$

where $d(I_i(F_{gallery}(a,a'))I_j(F_{probe}(b,b')))$ is the distance between a pair of edges and $D^{GIBMC}{}_E(F_{gallery}, F_{probe})$ is the average distance of all pairs of edges.

3.2. Reduced Point based Match Constraint

After eliminating the points that do not satisfy the gallery image point based match constraints, there can still be some false matches. Usually, the false matches are due to multiple assignments. These false matches can be eliminated by the help of an example shown in Fig. 3. Note that more than one point (e.g, *X2*, *X3* and *XN*) are assigned to a single point (e.g. *Y9*) in the other image.

These false matches can be eliminated by applying another constraint, namely the reduced point based match constraint which guarantees that each assignment from an image X to another image Y has a corresponding assignment from image Y to image X. With this constraint, the false matches due to multiple assignments are eliminated by choosing the match with the minimum distance. The false matches due to one way assignments are eliminated by removing the links which do not have any corresponding assignment from the other side. Examples showing the matches before and after applying the reduced point based match constraints are given in Fig. 4.

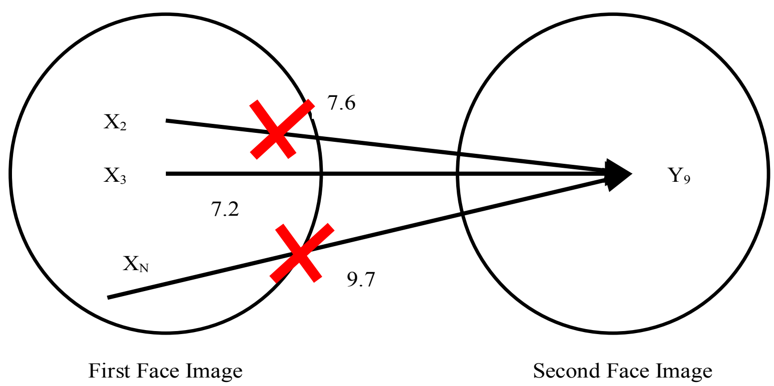
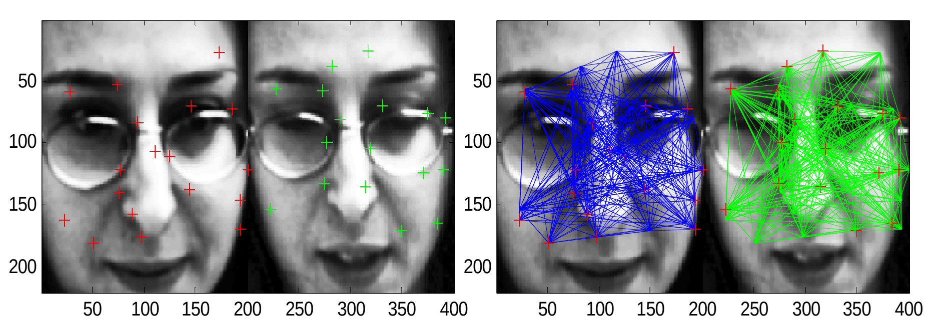


Figure 3. An Example of Multiple Assignments of points of First Image to a Single Point of Second Image

In this graph matching strategy, the same approach is followed which is described in the gallery image based match constraint. False matches, due to multiple assignments, are removed by choosing the match with the minimum distance between two face images. The dissimilarity scores on reduced points between two face images for nodes and edges are computed in the same way as for the gallery based constraint.



4(a) **4(b)**

Figure 4. An Example of Reduced Point based Match Constraint. (a) All Matches Computed from the Left to the Right Image. (b) The Resulting Complete Graphs with a Few Numbers of False Matches

3.3. Regular Grid based Match Constraint

The graph matching technique presented in this section has been developed with the concept of matching of corresponding sub-graphs for a pair of face images. First the face image is divided into sub-images, using a regular grid with overlapping regions. The matching between a pair of face images is performed by comparing sub-images and computing distances between all pairs of corresponding sub-image graphs in a pair of face images and finally averaging the dissimilarity scores for a pair of sub-images. From an experimental evaluation, we have considered sub-images of dimensions 1/5 of width and 1/5 of height as a good compromise between localization accuracy and robustness to registration errors on a face image. The overlapping is set to 30%.

When we compare a pair of corresponding sub-image graphs for a pair of face images, we eliminate false match pair assignments by choosing a minimum distance assignment between a pair of points. Let us consider face image is divided into G number of equal regions and for each pair of sub-regions invariant SIFT features are selected. We construct sub-graphs on a pair of corresponding sub-regions. While a direct comparison is made between a pair vertices and a pair of edges for a pair of sub-regions, the dissimilarity scores are computed. These dissimilarity scores represent distance between corresponding sub-graphs. The dissimilarity scores $D^{RGBMC}{}_{V}(F_{gallery}, F_{probe})$ are computed for a pair of vertices as:

$$D^{RGBMC}{}_{V}(F_{gallery}, F_{probe}) = \min_{i=1,2,..,N}\{\min_{j=1,2,...,M}(d(I_i(F_{gallery}), I_j(F_{probe}))\} \quad \textbf{(15)}$$

$$\Delta^{RGBMC}{}_{V}(F_{gallery}, F_{probe})^k = \frac{1}{T'}\sum_{t'=1}^{T'} D^{RGBMC}{}_{V}(F_{gallery}, F_{probe})^{t'} \quad \textbf{(16)}$$

where T' is the total number of minimum distances between a pair of face sub-graphs and $\Delta^{RGBMC}{}_{V}(F_{gallery}, F_{probe})^k$ (where $k = 1,2,3,\ldots,G$) is the mean distance between a pair of face sub-graphs in terms of composed invariant values which are associated to each vertex.

Similarly, to find the dissimilarity scores $D^{RGBMC}{}_{E}(F_{gallery}, F_{probe})$ for a pair of edges, let us take $E_1{}'(N)$ and $E_2{}'(N)$ are the number of edges for a pair of face sub-graphs, respectively. If N vertices in face sub-graph of gallery face are paired with the same number of vertices in face sub-graph of probe image, respectively, then $(c,c') \epsilon E'_1(N)$ and $(d,d') \epsilon E'_2(N)$ would be a pair of edges for a pair of face sub-graphs.

$$D^{RGBMC}{}_{E}(F_{gallery}, F_{probe}) = d(I_i(F_{gallery}(c,c')), I_j(F_{probe}(d,d'))) \quad \textbf{(17)}$$

where i= 1,2,3,…N and j = 1,23,...,N;

$$\Delta^{RGBMC}{}_{E}(F_{gallery}, F_{probe})^{k} = \frac{1}{E}\sum_{e=1}^{E} D^{RGBMC}{}_{E}(F_{gallery}, F_{probe})^{e} \quad \textbf{(18)}$$

where E is the total number of minimum distances between a pair of face sub-graphs and $\Delta^{RGBMC}{}_{E}(F_{gallery}, F_{probe})^{k}$ (where $k = 1,2,3,\ldots,G$) is the mean distance between a pair of face sub-graphs for a pair of edges. By adding mean distances $\Delta^{RGBMC}{}_{V}(F_{gallery}, F_{probe})^{k}$ and $\Delta^{RGBMC}{}_{E}(F_{gallery}, F_{probe})^{k}$ for vertices and edges respectively and dividing by 2, we get a mean dissimilarity value $D^{RGBMC}(I_{gallery}, I_{probe})$ for a pair of face sub-graphs. Finally, the weighted matching score $\Delta^{RGBMC}(I_{gallery}, I_{probe})$ is computed as the mean distance between a pair of face images. Weight assignment to each feature is done by Gaussian Empirical Rule.

3.4. Weighting the Score Reliability

The quality of the features has a significant impact on the performance of any learning based recognition algorithm. The way to improve the quality of features has been one of the critical issues concerned with the instance-based learning. Various approaches have been proposed in the past to address this issue. These approaches can be mainly divided into feature selection and feature weighting.

This work proposes a feature weighting method that is based on the Gaussian empirical rule. In this method, the relevance of a feature is determined by assigning a weight using the Gaussian empirical rule. The rationale behind this idea is that a relevant feature should have strong impact on classification. One advantage of using the Gaussian empirical rule for feature weighting is its rich expressiveness in representing hypotheses. In order to determine the weighted distance between two graphs, the weights can be assigned by applying the Gaussian empirical rule which satisfies the properties describe in [6].

Before generating the weighted dissimilarity scores, for each pair of face images, the mean and standard deviation are computed for a set of nodes and for a set of edges on the face graph.

If the node and edge values lie within one, two and three times of the standard deviation of the mean, they are multiplied by 0.075 or 0.05 or 0.025 respectively. These values have been determined by a through testing on the BANCA database.

3.5. Fusion of Matching Scores

Since Regular Grid based and Reduced Point Based match constraints show increase in accuracy, therefore we fuse these two match constraints using sum rule [15] in terms of matching scores obtained from these two methods. Prior to fusion of these two matchers, scores are normalized by min-max normalization rule [15]. Let n_i^k normalized score for matcher k ($k = 1,2,3, \ldots, K$; K be the number of matchers) and i ($i = 1,2,3,\ldots,I$) is the user. The fused score F_i for user i can be given by

$$F_i = \sum_{k=1}^{K} n_i^k, \forall i \quad \textbf{(19)}$$

Therefore, the match scores obtained from RGBMC and RPBMC methods can be fused by using the Equation (19) and the score F_i for user i can be given by

$$F_i^{(RGBMC\ +RPBMC\ )} = n_i^{RGBMC} + n_i^{RPBMC} \ ,\forall\, i \qquad \textbf{(20)}$$

4. Face Recognition using Probabilistic Relaxation Graph

This section proposes a novel local feature based face recognition technique which makes use of dynamic (mouth) and static (eyes, nose) salient features of face obtained through SIFT operator [7]. Differences in facial expression, head pose, illumination, and partly occlusion may result to variations of facial characteristics and attributes. To capture the face variations, face characteristics of dynamic and static parts are further represented by incorporating repetitive probabilistic graph relaxations drawn on SIFT features extracted from localized mouth, eyes and nose facial parts.

To localize the major facial features such as eyes, mouth and nose, positions are automatically located by applying the technique in [8], [9]. A circular region of interest (ROI) centered at each extracted facial landmark location is considered to determine the SIFT features of the landmark. The face recognition system can use SIFT descriptor for extraction of invariant features from each facial landmark, namely, eyes, mouth and nose shown in Fig. 5.

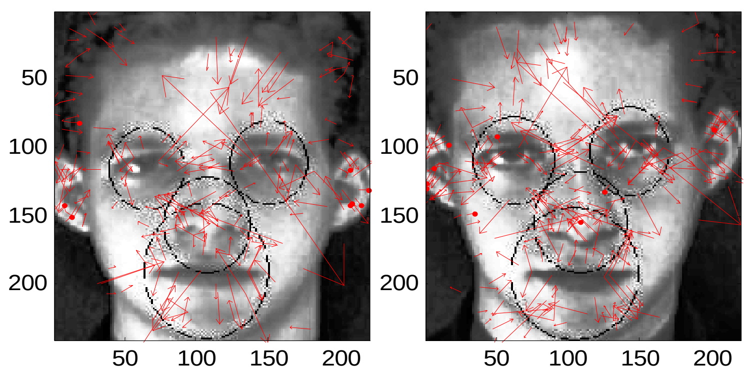


Figure 5. SIFT Features on Facial Landmarks

4.1 Fusion of Matching Scores

The Dempster-Shafer decision theory [11] which is applied to combine the matching scores obtained from individual landmark is based on combining the evidences obtained from different sources to compute the probability of an event. This is obtained by combining three elements: the basic probability assignment function (*bpa*), the belief function (*bf*) and the plausibility function (*pf*).

Let $\Gamma^{left-eye}$, $\Gamma^{right-eye}$, Γ^{nose} and Γ^{mouth} be the individual matching scores obtained from the four different matching of salient facial landmarks. In order to obtain the combine matching score from the four salient landmarks pairs, Dempster combination rule has been applied. First, we combine the matching scores obtained from the pairs of left-eye and nose landmark features and then the matching scores obtained from the pairs of right-eye and mouth landmark features are combined. Finally, the matching scores determined from the first and second processes are fused. Also, let $m(\Gamma^{left-eye})$, $m(\Gamma^{right-eye})$, $m(\Gamma^{nose})$ and $m(\Gamma^{mouth})$ be the *bpa* functions for the Belief measures $Bel(\Gamma^{left-eye})$, $Bel(\Gamma^{right-eye})$, $Bel(\Gamma^{nose})$ and $Bel(\Gamma^{mouth})$ for the four classifiers, respectively. Then the Belief probability assignments *(bpa)* $m(\Gamma^{left-eye})$, $m(\Gamma^{right-eye})$, $m(\Gamma^{nose})$ and $m(\Gamma^{mouth})$ can be combined together to obtained a Belief committed to a matching score set $C \in \Theta$ using orthogonal sum rule [11].

The final decision of user acceptance and rejection can be established by applying threshold to the final match score.

5. Experimental Results

To verify the efficacy and robustness of graph matching techniques discussed in the paper, three face databases such as BANCA [12], ORL [13] and IIT Kanpur [14] databases are used for evaluation. This paper describes two different graph based matching techniques, namely, complete graph based match constraints and probabilistic graph based matching technique.

5.1 Experimental Results Determined from Complete Graph based Matching

The proposed complete graph based matching technique for face recognition has been used the BANCA database for testing. BANCA face database [12] consists of 4160 face images obtained from 208 subjects of 4 different languages with 52 subjects (26 males and 26 females) for each language and each subject having 20 face images. Each language-gender specific population of 26 subjects is divided itself into two groups and each having 13 subjects each. The two groups are denoted as g1 and g2. Face images of each subject have recorded in controlled, degraded and adverse conditions with over 12 different sessions spanning three months.

Face images in different conditions are shown in Fig. 6. The face images are presented with changes in pose, in illumination and in facial expression. The BANCA face database considered as one of the complex databases for experiment. There are seven different protocols are constructed for evaluation. Such as Matched Controlled (MC), Matched Degraded (MD), Matched Adverse (MA), Unmatched Degraded (UD), Unmatched Adverse (UA), Pooled Test (PT) and Grand Test (GT). For this experiment, the Matched Controlled (MC) protocol is followed where the images from the first session are used for training and second, third, and fourth sessions are used for testing and generating client and impostor scores. Three graph matching constraints which are Gallery Image based Match Constraint (GIBMC), Reduced Point based Match Constraint (RPBMC) and Regular Grid based Match Constraint (RGBMC) have been tested with BANCA face database. The test images are divided into two groups, G1 and G2, of 26 subjects each.

Figure 6. Face Images from BANCA Database in different Scenarios. First Row: Controlled, Second Row: Degraded, Third Row: Adverse.

The error rates [14] have been computed using the following procedure:

- For getting scores of *G1*, perform the experiment on *G1*.
- Perform the experiment on *G2*, to get scores of *G2*.
- Compute the ROC curve using *G1* scores; determine the Prior Equal Error Rate and the corresponding client-specific threshold for each subject or each individual from several instances.
- Use the threshold T_{G1} to compute False Acceptance Rate ($FAR_{G2}(T_{G1})$) and False Rejection Rate ($FRR_{G2}(T_{G1})$) on the *G2* scores. The threshold is client-specific i.e, is computed specifically for each individual from the several instances of his/her images.
- Compute the weighted Error Rate (*WER(R)*) on *G2*:

$$WER(R) = \frac{FRR_{G2}(T_{G1}) + R \times FAR_{G2}(T_{G1})}{1 + R} \quad \textbf{(20)}$$

for $R = 0.1$, 1 and 10 (R is defined as the cost ratio for three different operating points, namely, $R = 0.1$, $R = 1$ and $R = 10$). *WER(R)* is computed on *G1* by a dual approach where the parameter R indicates the cost ratio between false acceptance and false rejection.

Prior Equal Error Rates for *G1* and *G2* are presented in Table 1 and Table 2 showing WER for three different values of *R*.

Table 1. Prior EER on G1 and G2 for the Four Methods: 'GIBMC' Stands for Gallery Image Based Match Constraint, 'RPBMC' Stands for Reduced Point Based Match Constraint, 'RGBMC' Stands for Regular Grid Based Match Constraint and the Fusion of RPBMC and RGBMC

Methods → EER ↓	GIBMC (%)	RPBMC (%)	RGBMC (%)	Fusion (%)
Prior EER on G1	10.13	6.66	4.6	2.02
Prior EER on G2	6.46	1.92	2.52	1.56
Average	8.29	4.29	3.56	1.79

From Table 2 it can be seen that WER for Reduced Point based Match Constraint determined on *G2* is very low while it is compared with other two match constraints. On the other hand, WER on *G1* determined with Regular Grid based Match Constraint shows low as it is compared with GIBMC and RPBMC. For *G1*, Regular Grid based Match Constraint outperforms others and for G2, Reduced Point based Match Constraint performance is better than other two techniques. Therefore, the significant number of features that forming better matched pair of SIFT feature points can be efficiently used in Reduced Point based Match Constraint (RPBMC) and Regular Grid based Match Constraint (RGBMC). Further RGBMC uses grids on face image which are formed by dividing the image into 5×5 equal regions with the consideration of 30% overlapping of sub-region boundaries. However, the fusion of RGBMC and RPBMC methods outperforms the RGBMC and RPBMC. Fusion method achieves 1.79% EER.

Table 2. WER for the Four Different Matching Techniques: 'GIBMC' Stands for Gallery Image Based Match Constraint, 'RPBMC' Stands for Reduced Point Based Match Constraint, 'RGBMC' Stands for Regular Grid Based Match Constraint and Fusion Method

Methods → WER ↓	GIBMC (%)	RPBMC (%)	RGBMC (%)	Fusion (%)
WER (R = 0.1) on G1 WER (R = 0.1) on G2	10.24 6.83	7.09 2.24	4.07 3.01	3.01 2.95
WER (R = 1) on G1 WER (R = 1) on G2	10.13 6.46	6.66 1.92	4.6 2.52	3.34 1.09
WER (R = 10) on G1 WER (R = 10) on G2	10.02 6.09	6.24 1.61	4.12 2.02	3.76 1.21

5.2 Experimental Results Determined from Probabilistic Graph Matching

The IITK face database [14] consists of 1200 face images with four images per person (300X4). These images are captured under control environment with ±20-30 degree changes of head pose and with at most uniform lighting and illumination conditions and with consistent facial expressions. For the face matching, all probe images are matched against all target images. From the ROC curve in Fig. 7 it has been observed that the recognition accuracy is 93.63%, with the false accept rate (FAR) of 5.82%.

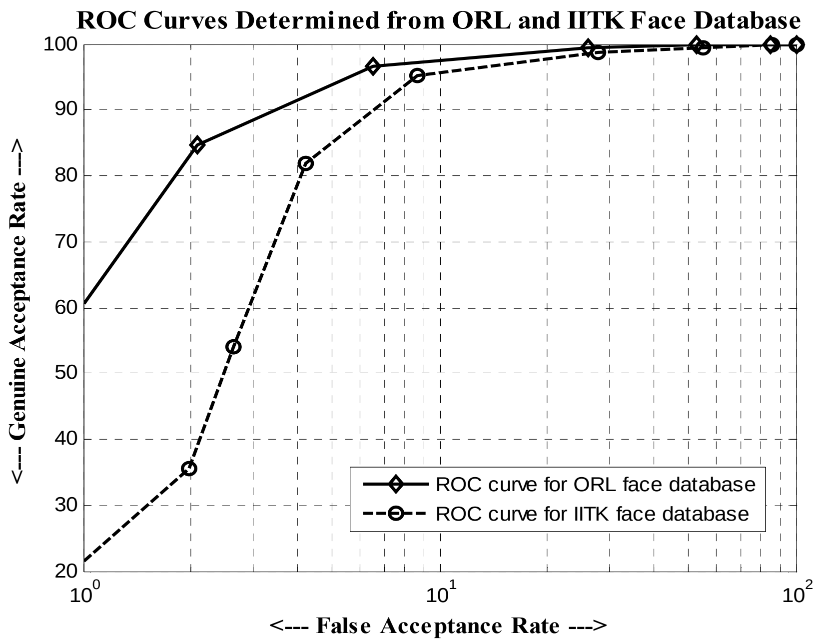


Figure 7. ROC Curves

The ORL face database [13] consists of 400 images taken from 40 subjects. Out of these 400 images, 200 face images are considered for experiment. It has been observed that there exist changes in orientation in images which lying between -20^0 and 30^0. The face images are found to have the variations in pose and facial expression (smile/not smile, open/closed eyes). The original resolution of the images is 92 x 112 pixels. However, for the experiment, the resolution is set to 120×160 pixels. From the ROC curve in Fig. 7 it has been observed that the recognition accuracy for the ORL database is 97.33%, yielding 2.14% FAR. The relative accuracy of the matching strategy for ORL database increases of about 3% over the IITK database.

6. Conclusion

In this paper, two face recognition systems have presented using complete graph topology and probabilistic relaxation graph matching respectively. The proposed systems exhibit robustness towards recognize the users. The results of the Reduced Point based Match Constraint and the Regular Grid based Match constraint show the capability of the system to cope for illumination changes and occlusions occurring in the database or the query face image. Moreover the fusion of these two method exhibits robust performance which outperforms these two methods. From the second face recognition it has been determined that when the face matching accomplishes with the whole face region, the global features (whole face) are easy to capture and they are generally less discriminative than localized features. In the face recognition method, local facial landmarks are considered for further processing. The optimal face representation using graph relaxation drawn on local landmarks allows matching the localized facial features efficiently by searching the correspondence of keypoints using iterative relaxation.

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