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Graph Application on Face for Personal Authentication and Recognition

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***Abstract*—This paper presents a novel face recognition technique with graph topology drawn on Scale Invariant Feature transform (SIFT) features and is compared with all the available well known techniques on SIFT features, and Elastic Bunch Graph Matching (EBGM) technique drawn on gabor wavelet feature. IITK face database is used for evaluation purpose. Test results show that the proposed graph matching technique will be an appropriate one for face recognition. Finally, the test results have been compared with the results found on BANCA face database following MC protocol only.**

***Keywords*—face recognition, graph matching constraints, SIFT features, correspondence graph, gabor wavelet, EBGM, euclidean distance metric, IITK face database, BANCA face database.**

I. INTRODUCTION

Biometric is a biologically inspired adaptive science where user is automatically recognized by their physiological or behavioral characteristics. Many machine vision researchers have made significant contribution to biometric authentication and recognition. From the past few years several biometric systems have been exploited, such as fingerprint, face, iris, signature, palmprint, retina, voice are the most widely accepted and common to use. Each biometric trait has its own merits and demerits. Although face recognition emerged as a critical biometric science due to variations in facial expression, occlusion and lighting conditions, illumination, clutter, and also variability in pose, and all these effects are made face recognition is a very challenging task in computer vision research. From the perspective of real life applications, face recognition has drawn significant attention in the field of human computer interaction, surveillance, criminal investigation, and authentication. Based on face representation, face recognition algorithms can be divided into three groups, viz. appearance-based approach, feature-based approach and model-based approach. Appearance-based approach uses holistic texture features and is applied to either whole-face or specific regions in a face image. Feature- based approach uses geometric facial features (mouth, eyes, brows, cheeks etc.) and geometric relationships between them. Model based approach uses active appearance models, shape models and fitting morphable models to either the whole-face or specific regions in a face.

Face recognition system is identified as passive biometric which does not require user's active participation. However, sometimes performance of face recognition systems degrades due to various threats occurred in recognition process. In many literatures, appearance based face recognition systems using component analysis has been exploited [1]-[3]. But, sometimes these techniques are incapable of capturing a substantial amount of variations existing in facial expressions. Apart from appearance based techniques, feature based elastic bunch graph matching is also been illustrated in [4]. However, the performance of the system has not been evaluated and tested under different constraints and furthermore, the overall recognition process produced quite complicated results. A probabilistic face recognition approach with a single training face sample is discussed in [5] that could compensate for the imprecise localization, partial occlusion, and extreme facial expressions. However, the illumination problem remained unsolved. Of late, the investigation of SIFT features in the context of face authentication has been explored in [6], [11]. The results are obtained from these SIFT-based techniques are found to be promising; but the need is felt for more robust and systematic way of capturing details and complementary information, that could be able to further improve the overall system performance.

The aim of this paper is to propose a novel face recognition system and compare the results with the two techniques presented in [11], all of which are implemented and developed in the same feature space (SIFT features) with the identical graph topology. Proposed graph matching technique is also being compared with another graph matching technique, namely elastic bunch graph matching (EBGM) that has been developed with Gabor filter feature. The experimental result shows that the proposed face recognition system outperforms other face recognition systems that are either based on SIFT features or on Gabor filter based EBGM while evaluation were made on IITK face database. The results are obtained from IITK face database are also being compared with results obtained from BANCA database and the proposed technique has been proved to be more effective and robust in any environment with very little cost to the system.

The paper is organized as follows. In Section 2, related work based on SIFT features with complete graph topology and Elastic Bunch Graph Matching technique have been presented. Section 3 describes the proposed technique. Experimental results are given in Section 4. The concluding remarks are drawn in Section 5.

II. RELATED WORKS

This paper presents a novel face recognition technique which has been designed by using the same identical graph topology with a robust and efficient approach. The technique is developed with the available of two graph matching techniques, namely gallery image based match constraint [11] and reduced point based match constraint [11]. In this section these two techniques along with the Elastic Bunch Graph Matching (EBGM) [4] have been discussed briefly. Two graph matching techniques illustrated here are based on SIFT features and complete graph topology [11]. First the face image is normalized by using histogram equalization. The rotation, scale and translation invariant SIFT features are then extracted from the normalized face images. Finally, the graph-based topology is used for matching two face images. The basic process of EBGM technique is also being illustrated that compare graphs between a pair of faces and generate new graphs for face recognition.

A. Graph Matching with SIFT Features

In the SIFT feature based graph matching technique each face image is represented with a complete graph drawn on feature points extracted using the SIFT operator [7], [10]. In this section two matching constraints [11] are presented: gallery image based match constraint and reduced point based match constraint. These techniques can then be applied to find the corresponding sub-graph in the probe face image given the complete graph in the gallery image.

In object recognition and image retrieval applications, affine-invariant features have recently been researched [8], [9]. These affine-invariant features are highly distinctive and matched with high probability against a large case of image distortions and illumination conditions.

The scale invariant feature transform, called SIFT descriptor, has been proposed by [7], [10] and proved to be invariant to image rotation, scaling, translation, partly illumination changes, and 3D projective transform. The SIFT operator is used to detect stable feature points in the scale-space through a staged filtering approach. First, select the candidate locations for feature points by searching peaks in the scale-space derived from difference of Gaussian (DoG) function. Then localize the feature points by using the measurement of their stability and assign orientations based on local image properties. Finally, calculate the feature descriptors which represent local shape distortions and illumination changes.

When candidate locations are 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 and describes it relative to this orientation. 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. Towards this end, the gradient magnitude and the orientation are smoothed by applying a Gaussian filter and then sampled over a 4 x 4 grid with 8 orientation planes.

The following sub-section defines correspondence graph in the context of graph matching constraints.

B. Correspondence Graph Definition

The correspondence graph problem 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 are two face graphs given by:

$$G1 = \{V^{G1}, E^{G1}, F^{G1}\}, G2 = \{V^{G2}, E^{G2}, F^{G2}\}; \qquad (1)$$

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:

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

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

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) Definition 2: Let, 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

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

and

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

$$\in_1 > 0, \in_2 > 0$$

for some small

The correspondence graph between G1 and G2 is defined as:

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

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

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

In order to find mapping function by correspondence graph each feature in one face image we compute the corresponding geometric characteristics in the other face image.

By considering correspondence graph definitions, two match constraints [11] are developed and thoroughly investigated in the following sub-section.

C. *Graph Matching Constraints*

In this work, SIFT operator is used for feature extraction and each feature point contains four types of information. Assume that these information are represented by $X(f_i)$, $K(f_i)$, $S(f_i)$ and $O(f_i)$, for spatial location (x, y), key point descriptor (K), scale (S) and orientation (θ), respectively. In addition to the proposed method, existing graph matching techniques drawn on invariant SIFT features and another is EBGM drawn on Gabor features are discussed in the subsequent sections.

1) Gallery image based match constraint: In this particular match constraint [11] an assumption has been made that the fidutial matching points would be available around similar positions on face image. By eliminating false matches using minimum Euclidean distance measure, a set of approximate match correspondence pairs is obtained. It is determined by experiment that, often multiple points on first face make correspondence to a single point on second face. When identical number of interest points are not found on both faces, then many points are might be discarded either from the second face or many repetitions might be available for a single point on second face. After computing distances between a pair of points, only the minimum pair distance would be taken (See Figure 1 and Figure 2).

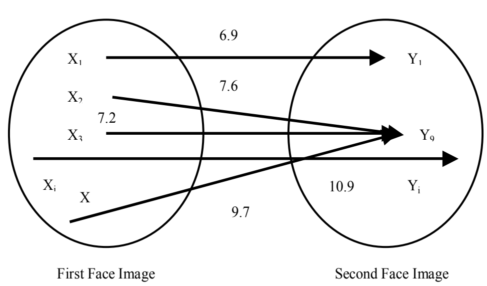

Figure 1. The corresponding points of First Face Image mapped into Second Face Image.

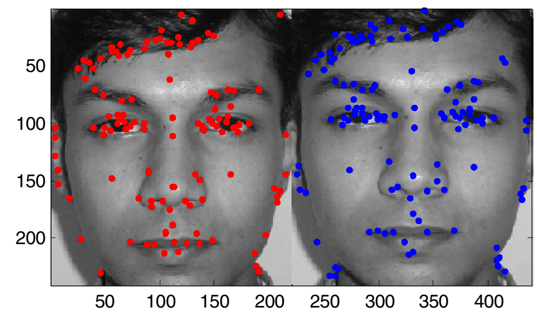

Figure 2. Feature points and their matches are shown for a pair of faces, computed from Euclidean distance metric.

2) Reduced point based match constraint: Limitations due to multiple assignments estimated in gallery image based match constraint is removed and the technique is furthermore extended by reduced point based match constraint [11]. It has been observed that in the gallery image based match constraint that there can still be some false matches. Usually, these false matches are found due to multiple assignments while more that one point are assigned to a single point on another face, or to one way assignments is exist (see Figure 3). The false matches due to multiple assignments are eliminated by pairing the points with the minimum distance. The false matches due to one way assignments are eliminated by removing the correspondence links that do not have any corresponding assignment from the other face. The graph on gallery face and the corresponding graph on the probe face have been shown in Figure 4. On top, all matches computed from left face to right face are shown. The bottom figure shows, resulted graphs with few false matches.

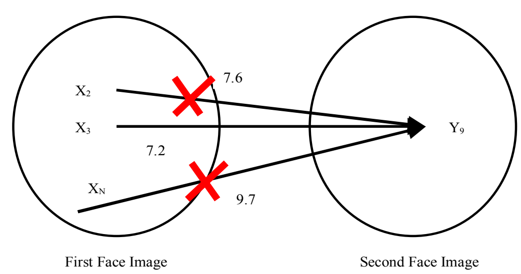

Figure 3. Elimination of false matches

3) Elastic bunch graph matching technique: In its simplest version of EBGM [4] a single labeled graph is matched onto an image. A labeled graph has a set of jets arranged in a particular spatial order. A corresponding set of jets can be selected from the Gabor-wavelet transform of the image. The image jets initially have the same relative spatial arrangement as the graph jets, and each image jet corresponds to one graph jet. The similarity of the graph with the image is simply the average jet similarity between image and graph jets. To increase the similarity one allows the graph to translate, scale and distort to some extent, resulting in a different selection of image jets. The distortion and scaling is limited by a penalty term in the matching cost function. The image jet selection which leads to the highest similarity with the graph is used to generate a new graph. When a bunch graph is used for matching, the procedure gets a little bit more complicated. Besides selecting different image locations the graph similarity is also maximized by selecting the best fitting jet in each bunch. This is done independently of other bunches to take full advantage of combinatory of the bunch graph representation.

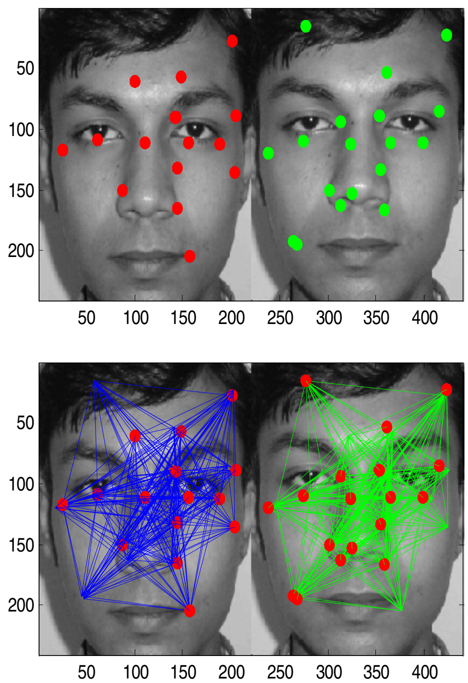

Figure 4. Reduced point based match constraint

III. PROPOSED 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 determined that if sub-images of dimensions 1/5 of width and 1/5 of height represent a good compromise between localization accuracy and robustness to registration errors on a face image. The overlapping was 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 and choosing a minimum distance assignment between a pair of points by applying Euclidean distance metric on two sub-images. 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. After selection of feature points 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:

$$D^{RGBMC}{}_V(F_{gallery}, F_{probe}) = \min_{i=1,2,\ldots,N}\{\min_{j=1,2,\ldots,M}(d(I_i(F_{gallery}), I_j(F_{probe}))\} \quad (7)$$

$$\Delta^{RGBMC}{}_V(F_{gallery}, F_{probe})^k = \frac{1}{T'}\sum_{t'=1}^{T'} D^{RGBMC}{}_V(F_{gallery}, F_{probe})^{t'} \quad (8)$$

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,……,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's take $E_1'(N)$ and $E_2'(N)$ are the number of edges for a pair of face sub-graphs, respectively. If N no. of vertices in face sub-graph of gallery face are paired with the same no. of vertices in face sub-graph of probe image, respectively, then $(c, c') \in E_1'(N)$ and $(d, d') \in E_2'(N)$ would be a pair of edges for a pair of face sub-graphs.

$$D^{RGBMC}{}_E(F_{gallery}, F_{probe}) = d(I_i(F_{gallery}(c, c')), I_j(F_{probe}(d, d'))) \quad (9)$$

where i= 1,2,3,…N and j = 1,23,...,N;

$$\Delta^{RGBMC}{}_E(F_{gallery}, F_{probe})^k = \frac{1}{E}\sum_{e=1}^{E} D^{RGBMC}{}_E(F_{gallery}, F_{probe})^e \quad (10)$$

where E 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,……,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 divided 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.

$$\Delta^{RGBMC}(I_{gallery}, I_{probe}) = \frac{1}{G}\sum_{k=1}^{G}(D^{GIBMC}(I^k{}_{gallery}, I^k{}_{probe})) \quad (11)$$

In the proposed method each feature is assigned a weight according to Gaussian empirical rule [12] and use of this rule further determines that the relevant features are having strong impact on classification. In order to compute the weighted distance between two graphs, the weights value are assigned by applying the Gaussian empirical rule in which three properties defined [12].

If the node and the geometric distance values lie within one, two and three times the standard deviation of the mean, they are multiplied by 0.075 or 0.05 or 0.03 respectively. These multiplication factors have been determined by a thorough testing on the subset of IITK face database.

IV. Experimental Results

The proposed graph matching strategy for face recognition has been evaluated and tested with IITK face database. The first two techniques presented in [11] have been evaluated with BANCA database consisting of 52 subjects of both male and female face images. But, in this paper all the three techniques including EBGM discussed in section 2 have been tested and evaluated on IITK database only. The IITK face database consists of 1000 facial images with five images per person (200 X 5) in different illumination and expressions taken in control environment. The images are acquired in light and dark background under different illumination conditions. The database comprises of Indian faces of frontal view. The sample images from IITK database is shown in Figure 6. In this experiment, algorithms are tested under different background and lightning conditions. These images are acquired in different sessions. However to maintain the consistency, the same setup is used for image acquisition. For the proposed three graph matching techniques, we cropped the face part from the background and then convert the image format from JPG to PGM. The invariant feature SIFT is used for feature extraction for the proposed techniques, that support PGM file format only at the level of implementation detail. In order to maintain consistency and robustness it is necessary to go through implementation details and parameters. But, in case of EBGM, JPG format has been used due to the ease of the algorithm. The test results have been computed and accuracy has been determined which is shown in Figure 5 in terms of ROC curve. False accept rate (FAR), false reject rate (FRR) and Equal error rate (EER) are shown in Table 1 with weighted Error Rate (WER) on the entire dataset for R=0.1, 1.0 and 10. Note that 'GIBMC', 'RPBMC', 'RGBMC' and 'EBGM' stand for gallery image based match constraint, reduced point based match constraint, proposed regular grid based match constraint and elastic bunch graph matching respectively.

From the receiver operating characteristics (ROC) curve, it can be clearly seen that among the techniques including EBGM method, RGBMC, the regular grid based match constraint outperform other methods. In case of regular grid based match constraint, the whole image is sub divided into several equal regions using a regular grid with overlapping. The matching between a pair of two face images is done by computing distances between all pairs of corresponding sub-image graphs, and finally averaging them with all dissimilarity scores for a pair of sub-images. So, the detail information is extracted from each sub-region with invariant features and for each region the graph representation drawn on SIFT feature points. The results are presented here by considering various constraints like – illumination changes, expressions, different backgrounds, lighting conditions. The proposed regular grid based match constraint has also been tested on BANCA database and finally, the results obtained from IITK face database are compared with the results obtained from BANCA database (For illustration, see Figure 7 and Table 2) and the proposed technique has been proved to be a superior less error rate to the system.

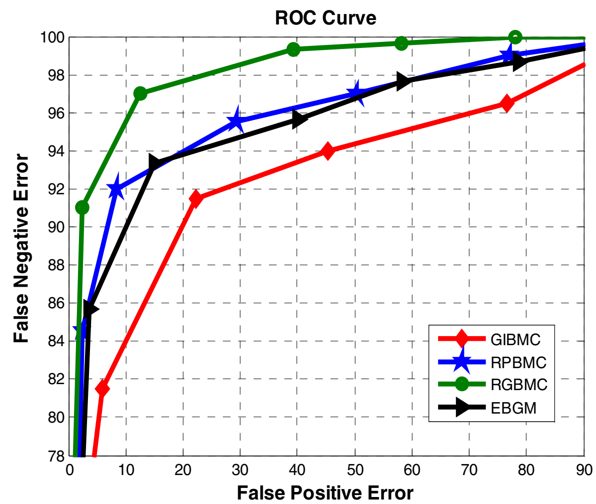

Figure 5. ROC curves are shown for different graph matching constraints along with the proposed technique computed on IITK face database.

Figure 6. Sample face images from IITK Face databse.

TABLE I. FRR, FAR, WER FOR DIFFERENT GRAPH MATCHING TECHNIQUES INCLUDING THE PROPOSED TECHNIQUE.

	FRR (%)	FAR (%)	WER (R=0.1)	WER (R=1.0)	WER (R=10)	Avg WER (%)
GIBMC	15	10.94	14.63	12.97	11.31	12.97
RPBMC	10.5	6.46	10.13	8.48	6.83	8.48
EBGM	12.07	7.87	11.68	9.97	8.25	9.97
Proposed RGBMC	7.31	4.65	7.06	5.98	4.89	5.98

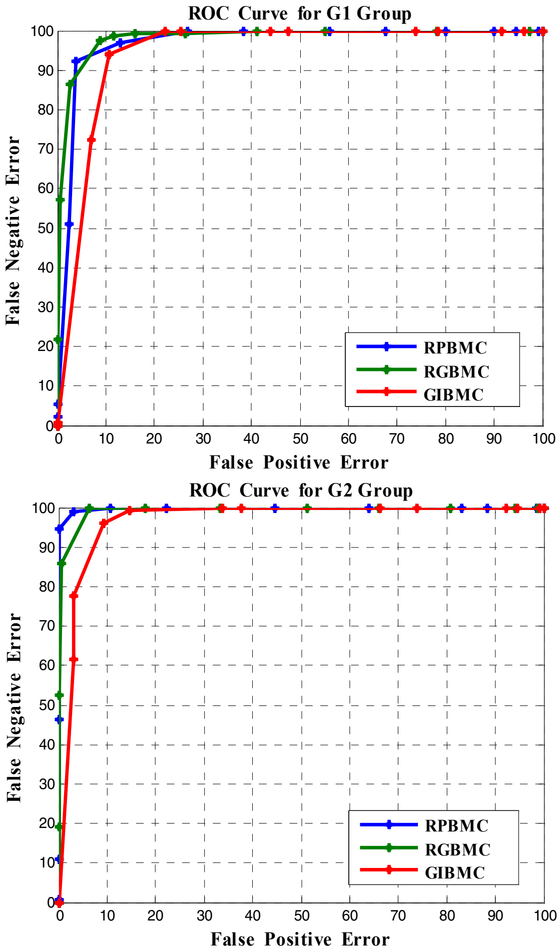

Figure 7. ROC curves (Top and bottom) for different graph matching constraints (GIBMC and RPBMC) along with the proposed technique shown are computed with BANCA face database (G1 and G2 groups). In particular, ROC curve for EBGM is not computed with BANCA database (The curve for EBGM technique is not shown here).

TABLE II. WEIGHTED ERROR RATES ARE SHOWN IN THE TABLE FOR THREE GRAPH MATCHING TECHNIQUES TESTED WITH BANCA FACE DATABASE.

	GIBMC (%)	RPBMC (%)	RGBMC (%)
WER (R = 0.1) on G1	10.24	7.09	4.07
WER (R = 0.1) on G2	6.83	2.24	3.01
WER (R = 1) on G1	10.13	6.66	4.6
WER (R = 1) on G2	6.46	1.92	2.52
WER (R = 10) on G1	10.02	6.24	4.12
WER (R = 10) on G2	6.09	1.61	2.02

V. CONCLUSION

This paper proposes a novel face recognition technique and results are compared with other techniques also. In the first topology, three graph matching techniques are developed based on the SIFT [7], [10] to generate a complete graph representation for face image. The results are obtained by testing the methods on the IITK face database. This work shows a remarkable increase in the performance of the system with respect to the previous work based on the SIFT features [6]. The obtained results show the capability of the system to cope for illumination changes and occlusions occurring in the database or the query face image. Among all techniques presented here the proposed regular grid based match constraint outperforms other techniques due to its detailed grid information of invariant feature SIFT. When the technique presented here compared with the EBGM technique [4] on a straightforward manner of image graphs on two different feature spaces, the suitability and superiority for a particular environment is shown in terms of robust performance. Experiment result with the EBGM are reported on the IITK face database, including recognition across different expressions, illumination changes, lighting conditions, different backgrounds, but the reported errors are higher than those obtained from the presented system using complete graph topology. It has been seen that when the proposed technique evaluated with BANCA database followed by match controlled (MC) protocol the technique shown more robust and more effective on small size of database. But, when database size is big (IITK face database), the proposed technique degrades a little which is ignorable compared to the results found on BANCA database. Due to invariant nature of SIFT features it is realized that even comparison made with some well known techniques with on different standard databases, the complete graph topology drawn on SIFT features is shown to be robust and efficient technique in terms of expressions, illumination changes, transformations, lighting conditions, occlusions, etc.

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