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An Enhanced Technique for Recognition of Disguised Face Images Using Granular Approach

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Abstract

A novel method for recognizing face images altered by disguise, using granular approach and classifiers is presented in this paper. In this method, global, local and granular features are used for recognizing the altered images. Global features are extracted from the whole face image by keeping the low frequency coefficients of Cosine transform, which encodes the holistic facial information, such as facial contours. These features are concatenated to form a global feature vector. For local feature extraction, Gabor wavelets are used considering their biological relevance. Gabor functions give optimal resolution in both frequency and time domain and is optimal for extracting the local features. These local features are concatenated to form a local Gabor feature vector. Granular features which are the non-disjoint features at three levels of granularity are also considered for the recognition purpose. The first level gives the global information about the face image. Second level gives the inner and outer facial information. At the third level, features from the local facial regions are extracted. These granular features are concatenated to form a granular feature vector. The local, global and granular features which are extracted are fed to a multiclass Support Vector Machine (SVM) classifier. This multiclass SVM trains and classifies the disguised face images based on these features. Testing on the standard AT&T and AR datasets shows that the proposed system outperforms state-of-the-art face recognition techniques.

Keywords: Face recognition, feature extraction, disguise, granular features, global features, local features

INTRODUCTION

Faces convey abundant information. The face is our primary focus of attention in social life playing an important role in conveying identity and emotions. Human beings can recognize a number of faces and also identify the faces at a glance even after years of separation. This is a strong skill that human beings possess that they can identify the person even if there is a large change in visual stimulus due to aging and modifications such as beard, glasses or changes in hairstyle. We need to analyze how machine recognize the people despite these changes. There are two main possibilities. Primarily, a three-dimensional, viewpoint invariant structural model of a face shall be constructed. Alternatively, an image-based description, which may be viewpoint dependent or pictorially dependent, may be formed. Computers are used in various machine vision applications such as to recognize and identify the faces in the case of criminal identification, security systems, image and film processing, identity verification, tagging purposes and human-computer interaction. But developing a computational model for face detection and recognition system is very difficult because faces are complex, multidimensional and meaningful visual stimuli [1].

Pantic, Maja, and Leon JM Rothkrantz.,et al.[3] has presented a Facial action recognition technique for facial expression investigation from static face images. An automatic system was proposed to recognize facial gestures in static, frontal or profile-view color face images. A multi detector approach to facial feature localization is used to spatially model the profile contour and the contours of the facial elements such as eyes and the mouth. Ten profile-contour fiducial points and 19 fiducial points of the facial component contours are extracted. In the light of these, 32 individual facial muscle actions occurring alone or in combination are recognized using rule-based reasoning.

Adini, Yael.,et al.[4] has presented a paper on face recognition, in which an empirical study has been presented that evaluates the sensitivity of these representations to variations in lighting, viewpoint and facial expression. The result showed that none of the representations considered is sufficient to overcome image variations due to a change in the direction of illumination. Similar results were obtained for changes due to viewpoint and expression.

Weng, Renliang, Jiwen Lu, and Yap-PengTan.,et al.[6] has presented a Robust Point Set Matching method for Partial Face Recognition. Given a pair of gallery image and probe face patch, first the key points are extracted and their local textural features are detected. Then, a robust point set matching method was proposed to discriminatively match these two extracted local feature sets, where both the textural information and geometrical information of local features are explicitly used for matching simultaneously. Finally, the similarity of two faces is converted as the distance between these two aligned feature sets.

Qian, Jianjun, Jian Yang, and Yong Xu., et al. [10] has presented local structure based image decomposition for feature extraction which applies to face recognition. A robust and simple image feature extraction technique is proposed, called image decomposition based on local structure (IDLS). It is assumed that in the local window of an image, the macro-pixel (patch) of the central pixel, and those of its neighbors, are locally linear. IDLS captures the local structural information by describing the relationship between the central macro-pixel and its neighbors. This relationship is represented with the linear representation coefficients determined using ridge regression. One image is actually decomposed into a series of sub images (also called structure images) according to a local structure feature vector. All the structure images, after being down-sampled for dimensionality reduction, are concatenated into one super-vector. Fisher linear discriminant analysis is then used to provide a low-dimensional, compact, and discriminative representation for each super-vector.

Chih-Hsueh Duan et al. has proposed a local sparse method for face component representation to handle the face recognition problem [26]. A dictionary of local patches of face images has been collected. A novel local descriptor has been introduced using sparse coefficients extracted from the dictionary and the local face patches extracted from the face elements. Performance of the face recognition system has been demonstrated by experiments on LFW and CMU PIE dataset. A novel robust kernel representation model with statistical local features (SLF) has been proposed by Meng Yang et al [27]. A multi partition max pooling method has been adopted to improve the invariance of SLF together with robust regression to handle occlusion in face images. Evaluation on LFW, FERET and FRGC databases have proved promising results.

A single sample face recognition technique based on locality preserving projection (LPP) feature transfer has been proposed by Jie Pan et al [24]. In this method, the source and target faces are projected onto the LPP feature subspace and the feature transfer matrix has been calculated, which is used on training samples for transferring the actual macro characteristics to the desired macro characteristics. The final face recognition step is realized by the nearest neighbor classifier. The results have been verified on AT & T, FERET and YALE databases. An analytic to holistic method has been proposed by Kin-Man Lam and Hong Yan to recognize faces at distinct perspective variations [22]. Fifteen feature points are located and a head model has been used to estimate the rotation of the face using geometric measurements. Using a similarity transform, these feature points are compared with that in the database. Using correlation, feature windows set up for eyes, mouth and nose is compared with those in the database. Results show good performance in different viewing angles of a face. The method proposed by Li Fei-Fei utilizes the fact that one can take advantage of the knowledge from previously learned object categories, and this technique was implemented using the Bayesian classifier [23]. Comparison with category models learned by Maximum Likelihood (ML) and Maximum A-Posteriori (MAP) methods shows that, for small training set, the Bayesian approach produces informative models than the other methods.

Majority of the existing methods utilize only global or local features. The Proposed system uses global, local and granular features for face recognition. Global feature gives overall information about the face image whereas Local feature gives information about the local facial regions like eyes, mouth and nose. Granular features extracted from three levels which have different sizes and shapes, help to gain a significant insight about the effect of alteration made by the disguise and hairstyle on the face image. These granular features are combined into a granular feature vector [2]. Then these local, global and granular feature vectors are combined and are given to a classifier to get better and accurate face recognition results. If we take two different images of the same person which is interpreted by two different system, one which use only global features and other which use only local features, it will fail to give the correct recognition. Global feature gives holistic information about the face image like facial contours, shape etc. while the local feature gives the information about the local facial regions like mouth, nose etc. It has been proved that a combination of these features give better results [1].Multiclass support vector machine (SVM) is used for training and testing the images to recognize face images.

PROPOSED SYSTEM

In Fig 1, the two input face images are simulated, whose eyes, nose, and mouth are actually from the same person. But they have varying hair style and facial contours. Consequently they look very different in terms of overall structural pattern, hairstyle and facial contours. A classifier which is built on global features will interpret them as different persons. But a classifier based on the local features will report them as same person since their individual components except hair style and facial contours are the same [1]. The conflicting results of the classifiers reflect the different roles of global and local information, which indicates that an ideal classifier should be the combination of the two [1].

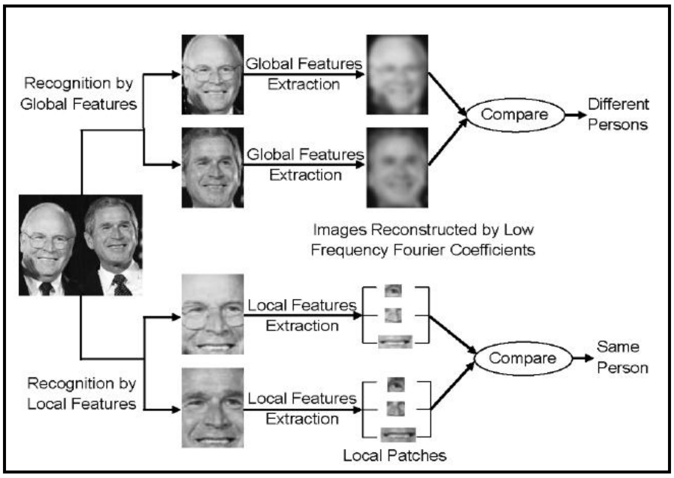


Figure 1. Illustration of the different roles of global and local features in face recognition [1].

One of the challenging forms of disguise present in face images is caused due to plastic surgery. Plastic surgery may cause alterations in multiple facial regions [28]. It has been reported that the variations caused by plastic surgery has certain intersection with the variations caused by disguise and aging [2]. Several existing part-based face recognition approaches does not handle concurrent variations in multiple features since these techniques generally analyses each feature independently. On the other hand, it has been reported that human problem solving is using perception and knowledge represented at various levels of granularity [28]. Human beings identify faces using holistic approaches together with discrete levels of features. Nineteen findings have been reported based on the face recognition abilities of human mind [28]. It has been found that humans can effectively recognize faces with noises and poor resolution. Besides, low and high frequency facial information is handled both locally and holistically. Reports show that inner and outer facial regions characterize diverse information that can be utilized for face recognition. Researchers working on cognitive science also suggest that local facial structures provide robustness towards partial occlusion and viewpoint variations [28], [29], [30].

Incorporating these observations, a granular approach had been proposed for facial feature extraction along with a multiobjective evolutionary granular algorithm to match faces altered by plastic surgery [2]. This method extracted non-disjoint face granules at three levels of granularity, comprising of local as well as global features. This work has been evaluated on the plastic surgery face dataset and the method has shown excellent recognition accuracy. The observation that the variations caused by plastic surgery and disguise share many common characteristics [2] motivated us to adopt the concept of granular feature set in the present work for resolving the problem of recognizing disguised face images.

In the proposed method, the enhanced granular feature set along with a hybrid two pass classifier has been used. With granulated information, more flexibility is achieved in analyzing the underlying information like nose, cheeks, ears, forehead and combination of multiple features [2] Fig. 2 shows an overview of the proposed system.

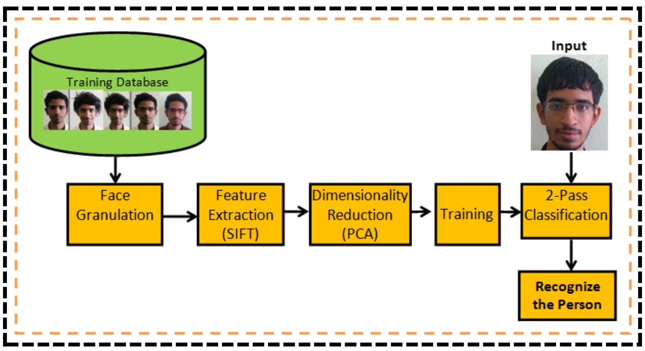


Figure 2. Block diagram of the different stages of the proposed system

The proposed disguised face recognition system comprises of five sections. They are face granulation, feature extraction, dimensionality reduction, training and classification. This technique generates non-disjoint face granules where each granule represents distinct information at varying size and resolution. Scale Invariant Feature Transform (SIFT) is used for extracting discriminating information from the face granules. Since SIFT returns features with very high dimensionality, PCA has been applied on the extracted features for dimensionality reduction, which in turn reduces computational complexity. The recognition task is performed by a hybrid two pass classifier [31]. The working of each section is detailed below.

A. Face Granulation

Let F be the detected frontal face image of size n x m. In the present work, it is selected as 196 x 224, adopting the values from the reports by Himanshu S Bhatt et al. [2]. The granulation process helps to examine various features concurrently. Moreover, the face granules of diverse shapes and sizes help to acquire insight about the effect of disguise on the various facial features. Face granulation is carried out at three levels of granularity, from which the features are extracted. The first level reports global information at numerous resolutions. The second level granules are obtained by subdividing the face into vertical and horizontal granules, and information about inner and outer facial areas are extracted from these granules. At the third level, local facial features are extracted. Details of feature extraction at three granularity levels are given in the following sections.

1. The First level of granularity

As already mentioned, global features need to be extracted at this level of granularity. A series of low pass filtered images are generated by a Gaussian operator by convolving the images iteratively with a two-dimensional Gaussian kernel. Since the resolution and sample density of the images are decremented after each iteration, the Gaussian kernel has to operate on a reduced version of the original image in each iteration [2].

Let F_{Gri} be the granules in the first granular level, where i represent the granule number. Three granules, viz. F_{Gr1} to F_{Gr3} are generated in this level. The facial features are segregated at different resolutions to provide edge information, smoothness, noise and blurriness present in each granule, thus compensating for the variations in facial texture. Fig 3 depicts the face granules in the first level of granularity, for a face image of size 196 x 224, selected from the AT&T dataset. The smallest granules will possess the size 49 x 56.The resulting granules may be considered as a pyramid with F_{Gr1} possessing the maximum resolution and F_{Gr3} possessing the minimum resolution.

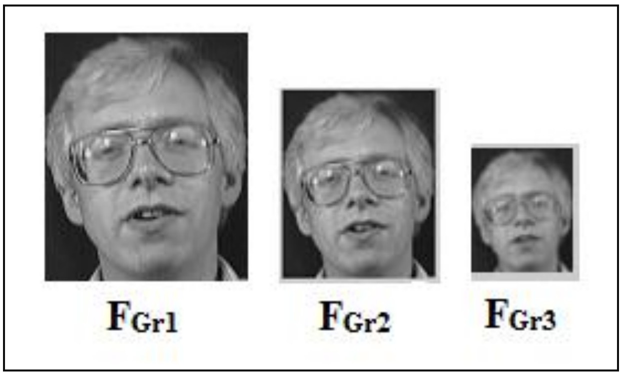
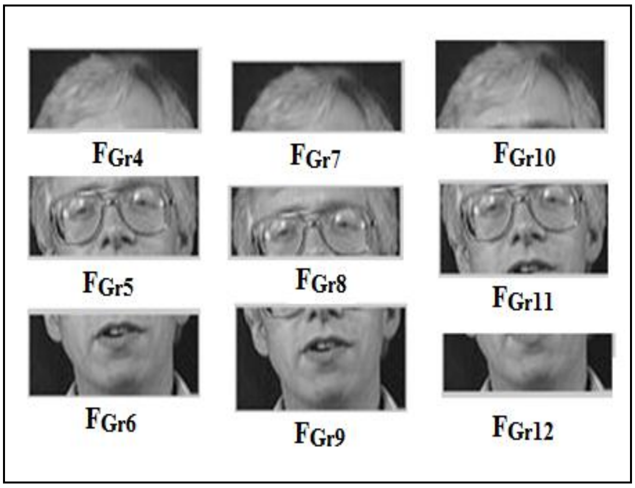


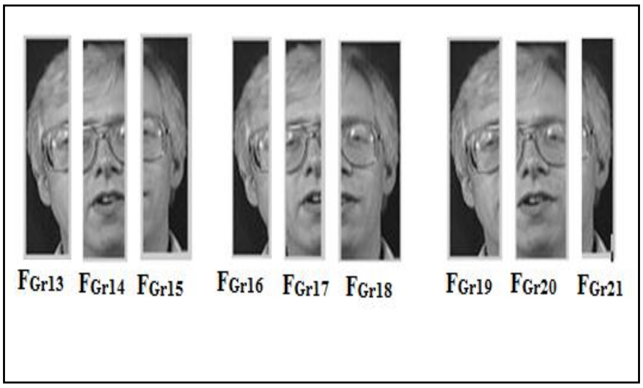
Figure 3. Face granules obtained in the first level of granularity

2. Second level of granularity

The second level of granularity provides information on inner and outer facial regions of the face image. The face image is subdivided into discrete regions to obtain 9 vertical and 9 horizontal face granules. F_{Gr4} to F_{Gr12} represents the horizontal face granules and F_{Gr13} to F_{Gr21} represent the vertical face granules as shown in Fig.4 (a) & (b) respectively. Among the nine horizontal granules, the first three granules, viz. F_{Gr4} to F_{Gr6} are of size $m/3 \ x \ n$ pixels [2]. The next three granules, F_{Gr7} to F_{Gr9}, are generated such that the size of F_{Gr7} and F_{Gr9} are $n \ x \ (m/3 - \varepsilon)$ and the size of F_{Gr8} is $n \ x \ (m/3 + 2\varepsilon)$. Further, F_{Gr10}, F_{Gr11} and F_{Gr12} are generated such that the size of F_{Gr10} and F_{Gr12} is $n \ x \ (m/3 + \varepsilon)$ and the size of F_{Gr11} is $n \ x \ (m/3 - 2\varepsilon)$. Nine vertical granules are also generated in the same manner. The value of ε has been fixed as 15 for optimum results [2]. Resilience for variations in inner and outer face regions is obtained at this level of granularity. The relations between vertical and horizontal granules are utilized to address the variations caused in ears, chin, cheeks and forehead [2].



a) Horizontal face granules obtained in the second level of granularity.

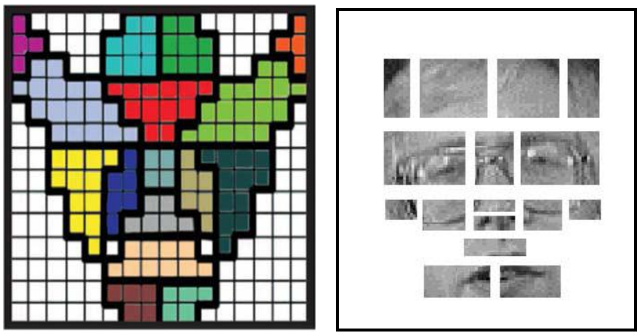


b) Vertical face granules obtained in the second level of granularity.

Figure 4. Horizontal and vertical face granules

3. Third level of granularity

Local facial features like eyes, nose and mouth play an important role while humans perform face recognition. Making use of this property, local facial fragments are extracted and used as granules in the third level of granularity. The idea of golden ratio face template has been adopted; from which sixteen local facial regions have been extracted [32]. Each of them provides unique local features for handling facial variations. Fig 5(a) shows golden ratio face template and the corresponding face granules in the third level of granularity is given in Fig. 5(b).



(a) (b)

Figure 5. Face granules obtained in the third level of granularity (a) Golden ratio face template [2] (b) Face granules corresponding to golden ratio template, in third granularity level ($F_{Gr22} – F_{Gr37}$)

The proposed granulation technique is used to create 37 non-disjoint facial granules from a face image of size 196 x 224. The reason for three levels of granularity is to handle the variations caused due to disguise in local facial regions. The face granules contain useful but diverse information, which when combined provides discriminating information useful for face recognition [2]. Table 1 provides a consolidated view of the three granular features.

Table 1. Overview of granular feature set and its information content

Granularity Level	Granule Number	Information content of the Granular feature
First	F_{Gr1} - F_{Gr3}	Global information at multiple resolutions
Second	F_{Gr4} – F_{Gr21}	Provides information on inner and outer facial region
Third	F_{Gr22} – F_{Gr37}	Analyses the local features to handle the variation in individual facial regions

B. Feature Extraction

SIFT is a scale and rotation invariant feature descriptor that generates a compact representation of an image based on magnitude, orientation and spatial vicinity of gradients of image [33]. These features are invariant to image scaling and rotation, and partially invariant to changes in illumination. Though SIFT is a sparse descriptor computed around detected interest points it can also be used in a dense manner computed around predefined interest points [2], which has been adopted in the present research. Here, SIFT has been computed over a set of uniformly distributed non-overlapping local regions of size 32 x 32, which are concatenated to form the feature vector.

A main benefit of SIFT is that it generates large numbers of features that densely cover the image over the full range of scales and locations. For image recognition and matching, SIFT features are initially extracted from a set of training images and stored in a database. The keypoint descriptors are highly distinctive, which allows a single feature to find the exact match with highest probability in a large database of features. But, in a cluttered image, many features from the background will not have any correct match in the database, giving rise to many false matches in addition to the correct ones. The correct matches can be filtered from the full set of matches by identifying subsets of keypoints that agree on the object and its location, scale, and orientation in the new image.

C. Dimensionality Reduction

Mikolajczyk and Schmid after evaluating a variety of approaches towards feature descriptors, identified SIFT as the technique most resistant to usual image deformations [34]. Further, Principal Component Analysis (PCA) along with SIFT is more compact and robust to deformations than standard SIFT [35]. High dimensionality is a major drawback of SIFT [36], which has also been observed while conducting experiments in the present research. The high dimensionalities of the features extracted using SIFT leads to very high training time which may even cause non-convergence. Principal Component Analysis can be used to resolve the problem of high dimensionality of SIFT feature descriptors [36]. Thus, in order to overcome the problem of high dimensionality and to enhance the benefits of SIFT, PCA has been used along with SIFT in the present research.

After extracting the SIFT features from all the three levels of granularity, dimensionality reduction has been performed using PCA. The dimension of the each feature extracted by SIFT was obtained as 128 x 224, which was reduced to 128 x 1 by PCA, by extracting only the most relevant information. After dimensionality reduction, all of the 37 features were concatenated to form a single feature vector, which has been used for training and further classification. The granular feature vector *GFV* can be defined as follows:

$$GFV = \bigcup_{i=1}^{37} \{V_{Gri}\}$$

In the above equation, V_{Gri} represents the feature vector comprising of 37 feature elements which corresponds to 37 granules extracted at three levels of granularity and U{*} is the concatenation operator. Fig 6 shows the schematic representation of computation of *GFV*.

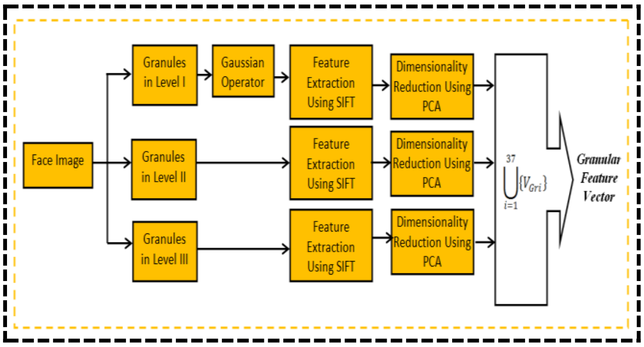


Figure 6. Block diagram of granular feature vector computation

D. Training and Classification

Now, the classifier has to be trained with the extracted features. Each face granule has varied and useful information, which when combined together provides discriminating information for disguised face recognition. The extracted feature set is trained using the suitable class labels. Training is performed both by Back Propagation Neural Network (BPNN) and Support Vector Machine (SVM), until the system converges to minimum error. The classifier used for the recognition process is the hybrid two pass classifier which combines BPNN and SVM [31] as shown in Fig 7. After the training process is complete, the system efficiently recognizes a disguised face image given as input.

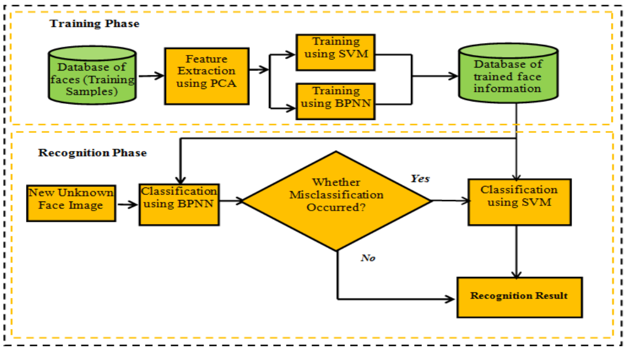
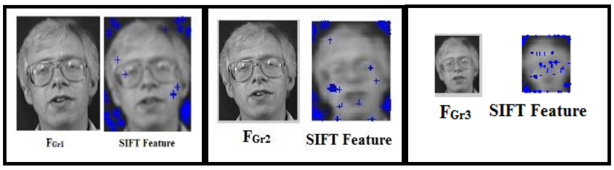


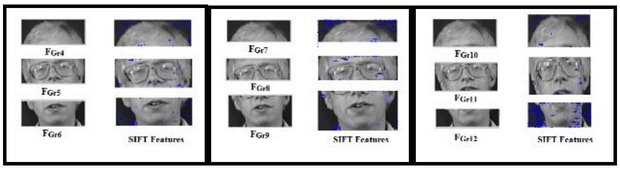
Figure 7. Hybrid Two-Pass Classifier using BPNN and SVM

SIMULATION EXPERIMENT AND RESULTS

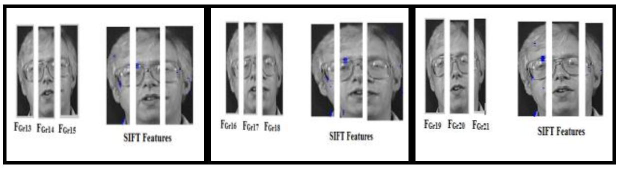
The simulations are performed on the standard AT&T, and AR datasets. Initially, the granules at three levels are created from the face image, as shown in Fig 3, 4 and 5. After the granulation process, SIFT features are extracted from all the three levels of granularity. The results of feature extraction on the sample AT & T dataset, at three levels of granularity using SIFT is shown in Fig 8.



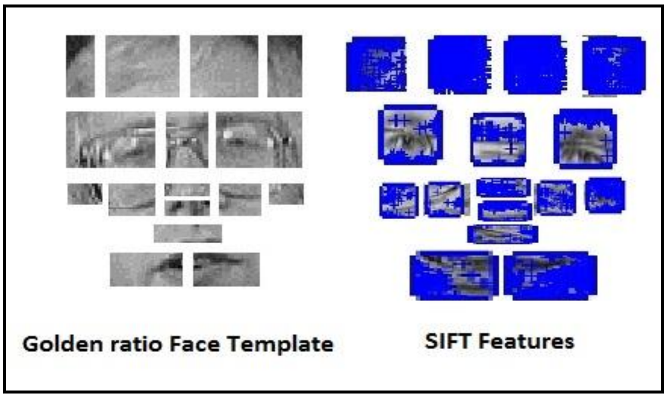
a) SIFT features extracted at first level of granularity



b) SIFT features extracted from horizontal granules at second level of granularity



c) SIFT features extracted from vertical granules at second level of granularity



d) SIFT features extracted at third level of granularity

Figure 8. SIFT features extracted at three levels of granularity

A. Evaluation on AT&T Dataset

The simulation experiments are performed on the standard AT&T face database that stores 400 face images of 40 different persons with 10 images per person. The standard evaluation protocol has two views, in which view 1 is used for modeling the prototype (training), and view 2 is employed for performance evaluation. 'Randomly choose N' scheme has been adopted in this experiment. In the present experiment, the prototype set consist of 5 randomly chosen images of each person (N=5). The rest of the 5 images of each person are used for testing. Table 2 shows the sample evaluation results of the proposed disguised face recognition system on the standard AT&T dataset.

Table 2 Evaluation Result on AT&T Database

Person IDs	No. of samples classified correctly	Recognition Rate in each class (%)
1-5	25	100
6-10	25	100
11-15	24 (Sample 12 misclassified)	96
16-20	25	100
21-25	25	100
26-30	25	100
31-35	25	100
36-40	24 (Sample 40 misclassified)	96
Overall Recognition Rate		99%

The evaluation results of the proposed face recognition technique using granular approach has been compared with the state of the art face recognition techniques. Table 3 shows the face recognition results of the competing methods on the AT&T database. The results of the existing techniques on both AT&T and AR databases have been taken directly from their published papers for comparison with the proposed method.

Table 3. Recognition Rates on AT&T database

Method	Recognition Rate (Percentage)
Block FLDA [22]	66
EPS-SEE [23]	76
FT-PCA [24]	74
FT-LDA [24]	86
FT-LPP [24]	92
HENN+SVM with ECOC [25]	98.1
Proposed Method	99

Fig. 9 shows the graphical comparison of the recognition rates of the proposed method with that of the state of the art techniques on AT&T dataset. From this analysis, we can see that the proposed method achieves the best performance over the listed techniques.

B. Evaluation on AR Dataset

For the purpose of studying the performance of the proposed system on disguised face images, evaluations were performed on disguised dataset too. Experiments were conducted using the images of 120 individuals captured in two different sessions in AR dataset. 13 images taken in the first session were used in view 1 for training and the other 13 images taken in session 2 were used in view 2 for testing. 3 fold validations have been applied to perform the experiments in the AR face database. The experimental results of the proposed disguised face recognition system on AR dataset are given in Table 4.

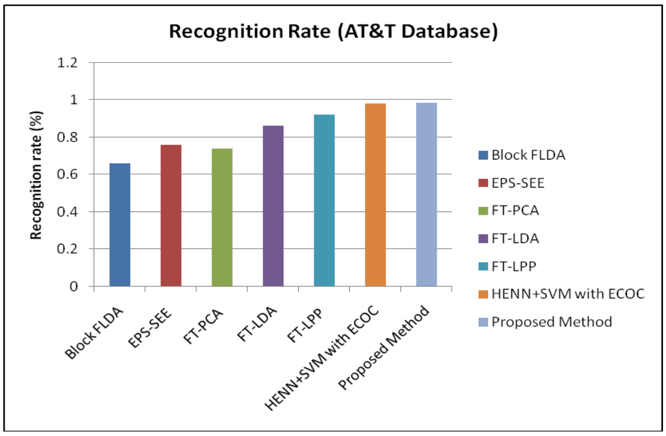


Figure 9. Comparison of the proposed method with the state of the art techniques on the AT&T database

Table 4. Evaluation Result on AR Database

Fold 1			Fold 2			Fold 3		
Person ID	No. of samples classified correctly	Recognition Rate in each class (%)	Person ID	No. of samples classified correctly	Recognition Rate in each class (%)	Person ID	No. of samples classified correctly	Recognition Rate in each class (%)
1	12	92.31	41	12	92.31	81	10	76.92
2	13	100	42	10	76.92	82	12	92.31
3	11	84.62	43	13	100	83	13	100
4	10	76.92	44	11	84.62	84	12	92.31
5	12	92.31	45	12	92.31	85	12	92.31
6	12	92.31	46	12	92.31	86	12	92.31
7	12	92.31	47	11	84.62	87	11	84.62
8	11	84.62	48	12	92.31	88	12	92.31
9	12	92.31	49	12	92.31	89	12	92.31
10	9	69.23	50	13	100	90	12	92.31
11	12	92.31	51	12	92.31	91	10	76.92
12	12	92.31	52	12	92.31	92	12	92.31
13	12	92.31	53	12	92.31	93	11	84.62
14	11	84.62	54	13	100	94	12	92.31
15	12	92.31	55	11	84.62	95	12	92.31

Fold 1			Fold 2			Fold 3		
Person ID	No. of samples classified correctly	Recognition Rate in each class (%)	Person ID	No. of samples classified correctly	Recognition Rate in each class (%)	Person ID	No. of samples classified correctly	Recognition Rate in each class (%)
16	12	92.31	56	12	92.31	96	12	92.31
17	12	92.31	57	11	84.62	97	12	92.31
18	13	100	58	9	69.23	98	10	76.92
19	12	92.31	59	12	92.31	99	13	100
20	12	92.31	60	12	92.31	100	11	84.62
21	12	92.31	61	12	92.31	101	13	100
22	11	84.62	62	12	92.31	102	12	92.31
23	12	92.31	63	9	69.23	103	12	92.31
24	12	92.31	64	11	84.62	104	10	76.92
25	6	46.15	65	7	53.85	105	12	92.31
26	12	92.31	66	12	92.31	106	10	76.92
27	12	92.31	67	8	61.54	107	10	76.92
28	13	100	68	11	84.62	108	10	76.92
29	13	100	69	12	92.31	109	12	92.31
30	12	92.31	70	12	92.31	110	12	92.31
31	12	92.31	71	11	84.62	111	12	92.31
32	12	92.31	72	13	100	112	11	84.62
33	7	53.85	73	12	92.31	113	12	92.31
34	12	92.31	74	8	61.54	114	13	100
35	13	100	75	11	84.62	115	12	92.31
36	8	61.54	76	10	76.92	116	11	84.62
37	12	92.31	77	12	92.31	117	12	92.31
38	11	84.62	78	12	92.31	118	12	92.31
39	12	92.31	79	9	69.23	119	12	92.31
40	9	69.23	80	7	53.85	120	10	76.92
Recognition Rate		87.89			85.58			89.04
Average Recognition Rate (ARR)						87.50		

Table 4. continued..

Table 5. Recognition Rates on AR Database

Method	Recognition Rate
EDBP with NN [21][17]	86.5
Eigen faces with NN [21][13][17]	56.2
Eigen faces with NS [21][13][18]	60.2
Eigen faces with SRC [21][13][19]	50.7
Eigen faces with CRC [21][13][20]	53.8
Randomfaces with NN [21][15][17]	50.8
Randomfaces with NS [21][15][18]	54.3
Randomfaces with SRC [21][15][19]	37.8
Randomfaces with CRC [21][15]	40.5
LBP with NN + Chi-Square [21][14]	69.7
Proposed Method	87.5

The evaluation results of the proposed disguised face recognition technique have been compared with the state-of-the-art face recognition techniques on AR database. Table 5 lists the face recognition results of the recent face recognition techniques on the AR database

Fig.10 shows the graphical comparison of the performance of the proposed method with that of the state-of-the-art techniques on AR database.

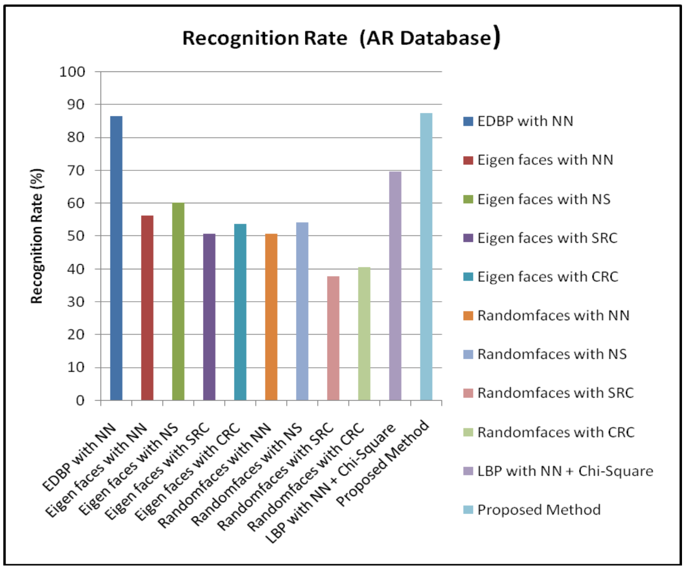


Figure 10. Comparison of the proposed method with the state of the art techniques on AR database

The simulation experiments proved that the proposed disguised face recognition technique performs better not only in the standard AT&T dataset, but also on the more difficult disguised AR dataset.

CONCLUSION

The enhanced granular feature set at three levels of granularity has been utilized efficiently to perform the disguised face recognition task successfully. Non disjoint features has been extracted at three granular levels using the SIFT feature extractor. Dimensionality reduction of the extracted features has been performed using Principal Component Analysis (PCA). With the granulated information, more flexibility has been achieved in analyzing the underlying information such as nose, ears, forehead, cheeks, etc. The hybrid two pass classifier is used for the final recognition of disguised face images. The advantage of the proposed system is that it extracts entire information from the whole face image using granular feature set so as to handle the variations caused by disguise. The results of the proposed method have been compared with that of state-of-the-art techniques and found to be superior in performance. Thus, the enhanced granular feature set obtained at three levels of granularity, extracted using SIFT and reduced using PCA have proved to be successful in recognizing disguised face images. This method can be further extended to recognize the face images altered due to aging.

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