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Multi Feature Face Identification Using Hash Table & Binary Tree Classifier

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Abstract: Face identification has recently attracted significant attention due to its application in biometrics and surveillance. Face Identification under uncontrolled environment is a key challenge for practical face identification systems. The use of efficient and discriminative face descriptors is crucial for this. Most of the existing approaches use just one feature for describing the face. Here combination of gradient orientation histogram and local binary pattern (LBP) features gives robust and efficient face recognition rate than either alone. They are implemented in the sense that, gradient orientation histogram captures shape and Local Binary Patterns (LBP) captures texture information. The proposed system uses a two stage classification approach, a higher level classification using hash table and a low level classification using binary tree. Combination of hash table and binary tree improves scalability and reduces recognition time especially when the gallery size is large.

Keywords: face identification; gradient orientation histogram; local binary pattern; shape; texture; hash classifier; binary tree classifier

I. INTRODUCTION

In recent years biometric based method have come out as the most promising option for recognizing individuals. Face identification has several advantages over other biometrics methods such as its convenience and social acceptability. Almost all other biometric technologies require some voluntary actions from the user. That is the user has to stand in front of a camera in a fixed position for retina or iris identification and user needs to place his/her hand on a hand rest for palm print or finger print identification. But face identification can be done passively without any active participation from the part of the user because face image is acquired from a distance by a camera. Face recognition has received large attention over last few years because of its large applications in various fields such as in security, surveillance, general identity verification etc.

Two face recognition scenarios are face verification and face identification. Face verification is a one to one matching process that compares an input face image against a template face image whose identity is being claimed. There is no need to check every images in the database but the system needs to check only the claimed identity. There are only two possible results: the person is recognized and person is not recognized.

Face identification is a one to many matching process that compares an unknown face image against a gallery of known people to determine the identity of the unknown face. Identification is more complex than verification. Identification can be subdivided into two: closed set identification and open set identification. In closed set identification, we want to identify a person and we know that the person is in the reference database or gallery. In open set identification we don't know in advance whether the person to be identified is in the gallery. Open set identification is more complex than closed set identification.

The result of the closed set and open set identification can be interpreted differently. In the case of close set identification, if there is no match in the result then we can understand that the system has made a mistake. But in the case of open set problem we don't know whether the person is not in the database or whether the system made a mistake. Real world identification applications are open set identification rather than closed set identification.

The first step in the facial recognition is the capturing of the face image (probe image) using a camera. The capturing of the face image can be done with or without the knowledge of the person. This is one of the most attractive property of facial recognition technology. Then extracting the features from the image to create template and then compared with those in the reference database (gallery).

When designing a face recognition system, there are some design issues to be taken into account. At first the execution speed of the system shows the ability to handle large amount of data and the possibility of online service. Some of the previous method could accurately identify the human faces by using complex algorithm which requires more time to work even in a small database. It is necessary to handle large amount of data and to speed up the existing algorithm.

Face identification under uncontrolled conditions is another important issue. Face identification under well controlled conditions provide high recognition rate. But the recognition rate significantly decreases when the identification is performed under uncontrolled conditions such as lighting, pose and facial expression changes. There are numerous commercial face identification systems are available. Current systems perform well under relatively controlled environment. Therefore, the goal of the ongoing research is to increase the robustness of the identification system under different factors.

The success of the face identification depends on feature representation and the classification method. The proposed system focuses on both feature representation and classification stage. The feature representation of a face is a critical aspect in face identification. Even the best classifiers cannot produce good result, if the feature representation step does not perform well. Good representation reduces intra person dissimilarity while maximize difference between persons. Most of the current identification systems use only one feature descriptor. But the use of single feature cannot capture all of the classification information of the images. So combination of different low level feature descriptors is used in this paper for the effective representation of face. This paper shows that face identification performance can be significantly improved by combining three feature extraction methods: local row average feature, gradient orientation histogram and Local Binary Pattern.

Our proposed face identification system focuses on the robustness under uncontrolled acquired images and scalability in large galleries. Also this method results high performance even though only single sample per subject is available. To make the method scalable to large gallery size, here used both hash table and binary tree classifier. Hash table is used for higher level classification and binary tree is used for lower level classification. By using hash table and binary tree a significant number of comparisons can be reduced. This helps to speed up the recognition rate.

II. LITERATURE SURVEY

The early works on face identification was based on geometric approach in which it finds the geometric relationships between facial landmarks for capture and extracts facial features. This method is highly dependent on the detection of the facial landmarks and stability of these relationships during the pose variations. This is a major limitation of the geometric approach. This approach was followed by photometric approach in which the face was treated as a general pattern. This approach is based on the photometric characteristics of the image.

One of the most thoroughly investigated approaches to face identification is eigen face method. It is also known as principal component, eigen picture, eigen vector etc. Principal component analysis is used in [16] to efficiently represent the face. PCA converts two dimensional image into one dimensional vector. This one dimensional vector is then decomposed into uncorrelated principal components also called as eigen faces. Eigen pictures are obtained from the eigen functions of averaged covariance of ensemble of faces. Sirovich and Kirby [15] used this eigen face method for face recognition. This method defines a feature space that reduces the dimensionality of original data space. Then this dimensionality reduce data space is used for the face recognition. PCA works well only if the probe image is similar to the gallery images in terms of pose, scale and illumination. Large computation and poor discrimination within the class are major limitations of PCA method.

Linear Discriminant Analysis (LDA) [10] uses the same statistical principles as PCA. Based on a set of training images of known people, LDA classifies the faces of unknown peoples. For that, this technique finds the underlying vector of facial feature space which maximizes the variance between the classes and minimizes the variance within the classes. To do this the database should contain numerous examples of face images for each person in the training set. The database should contain different frontal views of the persons with minor variations in view angle. The database must also include different lighting conditions, different facial expressions and background. If there is an increase in the number of varying samples of the same person, then there is a large variance between the classes and the system become more accurate. PCA and LDA work well only if the probe image is relative similar to the gallery images in terms of size, illumination, pose.

Elastic Bunch Graph Matching (EBGM) [12] addresses many non linear characteristics such as pose, illumination, and expressions. Linear methods such as PCA and LDA cannot handle these non linear characteristics. EBGM places Gabor filters (small blocks of numbers) over small areas of the face image. Then multiplying and adding the blocks with the pixel values. It will generate numbers (named as jets) at various parts of the image. Gabor filters remove variability of the image due to changes in lighting and contrast. Also they are robust to small shifts and deformations.

Neural network technique is another approach for face identification. The attractiveness of using neural network may be due to its nonlinearity in the network [9] used probabilistic decision based neural network (PDNN). PDNN does not have a fully connected network topology. It divides the network into small subnets. Each subnet is used for recognize one person in the database. The training of PDNN consists of two stages. In the first stage each subnet is trained by its own face image. In the second stage subnets are trained by some faces from other classes. Only misclassified patterns are used in the second phase. One limitation of this method is that computing expense is more when number of individuals or classes increases.

Edge information is an important object representation feature which is insensitive to illumination variations to a certain extent. Edge map is widely used in various pattern recognition. But it has been avoided in face identification except the work reported in [8]. Here used edge map to measure the similarity between the face images. An accuracy of 92 percentage is achieved by this method. Line Edge Map (LEM) approach proposed by Guo and Li in [6]. They used lines from the face edge map as features. This method is a combination of geometric feature matching and template matching. Line edge map method possess the advantage of feature based method, such as illumination invariance and low memory requirement. It also possess the advantage of template method such as high recognition performance. But LEM is more sensitive to large facial expression changes.

Support vector machine (SVM) technique is an effective method for general purpose pattern recognition [13]. When giving a set of points belonging to two classes, SVM finds a hyper plane which separates largest possible fraction of points of the same class on the same side. At the same time maximizing the distance to the hyper plane from either class. This hyper plane reduces the risk of misclassifying the samples in the training set and also unseen example of the test set. [7] used SVM with binary tree structure for solving the face recognition problem. After the feature extraction, SVM is used to learn the discrimination function between each pair. For recognition, the disjoint set enters to the system. They used binary tree structure for recognize the test samples. Potential drawback of SVM is that it is only directly applicable for two class problems. For reducing the multi class task to binary problems, algorithms must be applied.

Recently local matching approaches have shown good results in face identification [12]. Local matching method first locate several local facial features. Then classify the faces by comparing and combining the corresponding local statistics. The advantage of local representation is that only some parts of the representation is corrupted by the local changes on the face. For example wearing sunglasses affect only the local features near the eyes. However it is possible to recognize the person using the feature derived from nose and mouth.

Illumination compensation is a major problem in face identification. Gabor features and local binary patterns are illumination invariant features. However these features are insufficient to overcome large illumination variations. In recent years, Gabor filters have been widely used for face recognition [11],[4],[2]. This is because the Gabor filter is thought to be similar in perception in the human visual system. It exhibits desirable characteristics of spatial localization, orientation selectivity etc.

In [5] Ahonen and Hadid proposed a novel approach to face recognition using Local Binary Pattern(LBP). Here both shape and texture information are used to represent the face image. In this method the face image is divided into several regions. LBP feature distributions are extracted from each region and concatenated. This results an enhanced feature vector and it is used as face descriptors. Under different lighting conditions this approach achieved best performance. LBP based method is robust to facial expression, illumination, aging etc. The drawback of this approach is the length of the feature vector used for face representation. It slows down the recognition speed.

Tan and Triggs [1] combined Gabor wavelet and Local Binary Pattern for getting better performance than either alone under uncontrolled lighting conditions. They argue that robust recognition requires combination of different features which give different kinds of appearance information. LBP capture small appearance details and Gabor filter captures facial shape over a broad range of scales. Both features are high dimensional. Therefore PCA is used for dimensionality reduction prior to normalization and integration. This method is scalable to large number of samples and easy to extend to additional features.

III. Proposed System

The main purpose of the proposed technique is the accurate and fast face identification. This technique considers both shape and texture information to represent the face. The proposed system uses two stages of classification, a higher level classification as well as low level classification. Hash table is being used as a higher level classifier where the hash indices are determined after extracting the local row average of an image. Similarly a binary tree is being used a low level classifier along with sophisticated feature extraction methods. Combination of hash table and binary tree improves scalability when the gallery size is large and reduces the computational cost of matching probe images to a great extent.

Here the proposed method is explained in two steps. At first, here describe the feature extraction process and then describe classification process.

A. Feature Extraction

Feature extraction is an important step in the face identification process. Feature extraction process extract significant information from an image. Efficient and discriminative feature descriptors are required for the successful face identification under uncontrolled environment. This paper combines two local features which are gradient orientation histogram and Local Binary Pattern(LBP).

***Gradient Orientation Histogram*:** Gradient orientation histogram capture edge or gradient structure that represent local shape. This feature has been introduced by Navaneed Dalal and Bill Triggs [3]. Gradient orientation histogram counts the number of gradient orientation of pixels in a localized portion of an image. Local object appearance and shape can be described by the distribution of local edge direction or intensity gradients. This is the basic idea behind the gradient orientation method. Any changes to image illumination do not affect the gradients. Any blurring process will cause changes in the gradient magnitude. But the blurring process will not affect the gradient direction. The direction will be similar. Further, histogram will be a better idea, to make it invariant to small positional changes.

For the implementation of these descriptors, divide the image into cells which are small connected region. Then for each cell, obtaining a histogram of gradient direction or edge orientation of the pixels within the cell. Then the descriptor is represented by the combination of these histograms. That is for each pixel's orientation, the corresponding orientation bin is calculated. Then the orientation magnitude is voted to this bin. That is each sample added to the histogram is weighted by its gradient magnitude. The accuracy can be improved by block normalization. This is achieved by calculating the intensity across a larger region of the image, called a block. Then this value is used for normalize all cells within the block. Better invariance to change in illumination or shadowing can be achieved by using this normalization. According to Dalal and Triggs, there is a controllable degree of invariance to local geometric and photometric transformations since the gradient descriptor operates on localized cells. That is it provides invariance to translations and rotations smaller than local spatial or orientation bin size.

Local Binary Pattern (LBP): LBP gives the local spatial structure of an image. Local binary pattern performs binary comparison of pixel intensities between the centre pixel and the surrounding pixel. The LBP descriptor was introduced by Ojala et al [14]. It was proved as a powerful method for texture description. In this work LBP is used to determine the local features in face.

At first the image is divided into a number of blocks. Each block is as a matrix of type 3x3. Then for each block, the system comparing the centre pixel value with the pixel values in the neighborhood. A value of 1 is given if the value of neighboring pixels are greater than or equal to the value of centre pixel. Otherwise a value of 0 is given. In this way the binary number of each block is obtained. LBP code of the centre pixel is obtained by converting the binary code into decimal. This is obtained by summing the corresponding threshold values weighted by a binomial factor. In this way the image is represented with the LBP code. After labeling the image with the LBP code, find the histogram of labeled image. The 256 bin histogram of the labels contains the density of each label. This 256 bin histogram is used as a texture descriptor.

Local binary pattern features can be derived very fast. Even though LBP is a low-dimensional feature space, it retain discriminative facial information. Face image is a composition of micro pattern which can be effectively represented by LBP histogram. LBP histogram gives information about the local micro patterns such as spots, edges, corners and flat areas over the entire image. So LBP histogram is used to describe the image characteristics. Local binary pattern is an excellent choice for representing finer details of facial texture.

B. Hash Classifier

As a high level classifier, a hash table is being used in this paper which can significantly reduce the number of gallery images to be searched for finding the match. This will be quiet evident as the gallery size becomes huge. In this proposed system, each hash index is mapped to a binary tree, which is the low level classifier. More information about the tree classifier is mentioned in the section B. The proposed system can perform the hash table look up in O(1) to retrieve the tree data. This is achieved due to the fact that the proposed system groups images having similar hash indices and store it as a tree data modal against the hash index. So there will be only one tree against a hash index and always perform hash table in a single look up. In order to calculate the hash index of images, local row average features are extracted first. In this method the information is obtained by averaging the row intensity of pixels in a block. That is, here dividing the image into equal sized non overlapping blocks. Then local row average of each block is extracted for feature vector generation. A norm of this feature vector is calculated next, which is then subjected to some mathematical operations until we get the hash index. The steps for finding hash index are given below.

- Calculate the local row average of an image which is a row vector.
- Find the norm of the local row average feature. Usually this value is above 1000 for our images.

- Calculate the quotient and remainder by dividing the norm value with 1000.
- If reminder is greater than 800 then hash index is calculated by rounding up the quotient value, else round down.

Thus the hash index is obtained which has a certain level of tolerance and hence even though the images of same person are taken under different conditions, it would map to same hash index.

All the face images which are mapped to a same hash index will be grouped together and are represented by a binary tree modal. This binary tree will be stored as the hash value for the hash index obtained. Thus we can partition the entire gallery into manageable groups of images and thereby reducing the number of comparisons required in identification phase.

When an input image is given for face identification, a hash index of the input image needs to be calculated from the local row average feature. For finding a match hash index of both the input and trained image must be the same. Once the hash index is calculated, a look up will be performed on the trained data model to get the associated tree with this hash index. The tree will be then traversed for getting an exact match. The proposed system ensures that it does a hash table look up in O(1), which is the best for a hash table. This will aid the proposed method in achieving a faster look up compared to the traditional methods.

C. Binary Tree Classifier

In the proposed system, a binary tree classifier is used as a low level classifier where the feature vectors are stored that represents the face images. Binary tree classifier can give the best search complexity of O(log n) and in a worst case scenario, it will be O(n). Using a tree classifier significantly reduce the search time during identification phase. Tree creation begins after we have performed the high level classification. Now we have a collection of images mapped to a single hash index. The next step is to create a tree with this image collection and store it as the hash table value corresponding to the hash index.

The Fig. 1 illustrates an overall picture of the data modal where hash index 2 is mapped to a tree whose leaf nodes represent the actual image.

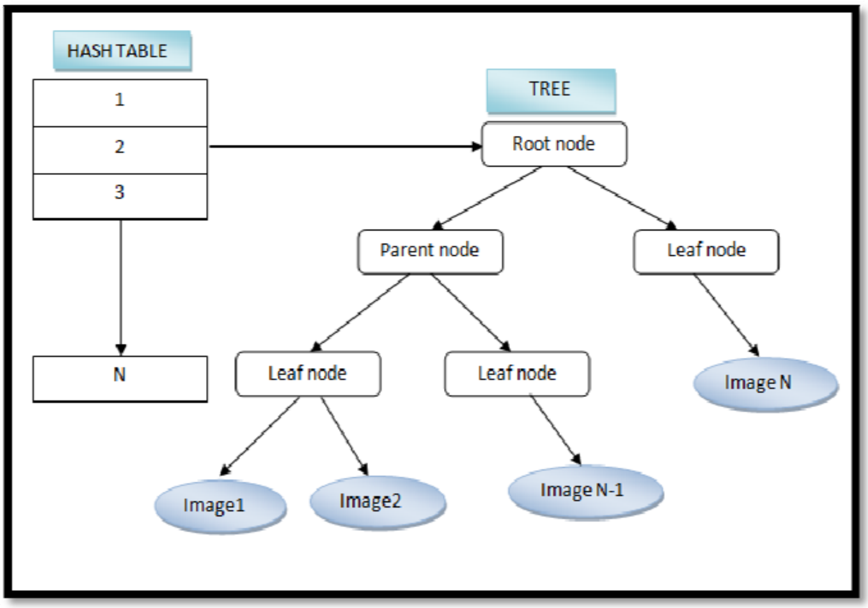

Fig 1. Overall picture of data modal

To create a binary tree, we need to have a splitting mechanism which allows us to split the collection of images into 2 group recursively until we reach a state where only two images are left under a node. We make this node as the leaf node and store the extracted feature vector of each image as a representation of the image. The splitting procedure that is used in our proposed system is K- means clustering algorithm. As an example, consider we have 'N' images (feature vectors) to form the tree. We will start at root level and the tree creation algorithm is given below.

- Apply K-means on feature vector matrix and get group of each image

- Collect the images which are in group1 and create a left child.
- Collect the images which are in group2 and create a right child.
- Set the centroid obtained in step1 as the centroid for the current node.
- Create left sub tree recursively using steps 1 to 3 until leaf nodes are obtained.
- Create right sub tree recursively using steps 1 to 3 until leaf nodes are obtained.
- Store the feature vectors of images under the leaf nodes.

When a probe image is supplied for identification, we will calculate the hash index of the probe image and locate the correct binary tree. The next step involves tree traversal and identifies the matching leaf node. The traversal algorithm which starts from root node is given below.

- Calculate the feature vector of the probe image.
- Find the norm (minimum distance) of the centroids of group1 and 2 in the current node with respect to the feature vector of the probe image.
- If the minimum norm with respect to group1, move to the left child node else to the right child node.
- Traverse until we reach a leaf node.
- If the leaf node contains 2 feature vectors, again take the norm of the feature vectors with respect to the feature vector of the probe image.
- The feature vector having minimum norm with respect to that of the probe image represents the matching image.

Tree traversal is significantly faster than one against all searching and thus over a large gallery size, we can minimize the search time significantly. As we are using hash table and tree together, image identification process should finish much quickly over the traditional approach. Also as the data model is scalable, it increases the overall scalability and we can represent large gallery size with this model.

IV. Experimental Results

This section evaluates the different aspects of our proposed method through various experiments. For checking the system's performance three different face data bases- Faces 94 database, Grimace database and FERET database are used. Faces 94 database contains very minor variation in head turn, tilt, slant and also minor variation in face position. Images in this database have considerable expression changes and there are no lighting variations.

The main characteristic of Grimace database is that it contains large expression variation. In acquisition stage of Grimace database, 20 images per person were taken using a fixed camera. During the acquisition time, person moves his/her head and makes large expression changes. Also it has fair amount of translation in face position and considerable variation in head turn, tilt and slant though there is only little lighting variations.

FERET (Facial Recognition Technology) contains large number of subjects in gallery and probe sets. This database contains images with different illumination, aging effects, pose and facial expression variations. In this paper, we are not using cropped and aligned facial samples because this process makes difficulty in directly applying the method to general images.

This experiment has been conducted in such a way that, it would demonstrate the impact of feature descriptors and classifiers separately. At first the impact of feature descriptor combination(facial expression, pose, lighting and presence of noise) in this method is explained and later the impact of classifiers are explained.

A. Impact of Combination of Feature Descriptors

Identification under uncontrolled environment is a key challenge for practical face identification systems. The use of efficient and discriminative feature descriptors is crucial for this. Most of the existing approaches use just one feature for describing the face. Here we argue that, the combination of different features results in robust and efficient recognition.

Different features can represent different characteristics of our face. This paper shows that combining two local face representations, gradient orientation histogram and local binary pattern(LBP), gives considerably better recognition rate than using either alone.

For gradient orientation histogram feature, here use a cell size of 16X16 pixels and block size of 2X2 cells. For LBP feature, here we use a block size of 3X3. The final length of the concatenated feature vector is 1456. This feature vector is used to describe the face and given to the final classification stage. When using gradient orientation histogram feature alone in feature extraction process, recognition accuracy is only 93% in faces 94 database. When local binary pattern alone is used, recognition accuracy was 95.5% . But when using both gradient orientation histogram and local binary pattern, recognition accuracy became 98%. This is when there is only single controlled training sample per individual and multiple uncontrolled probe.

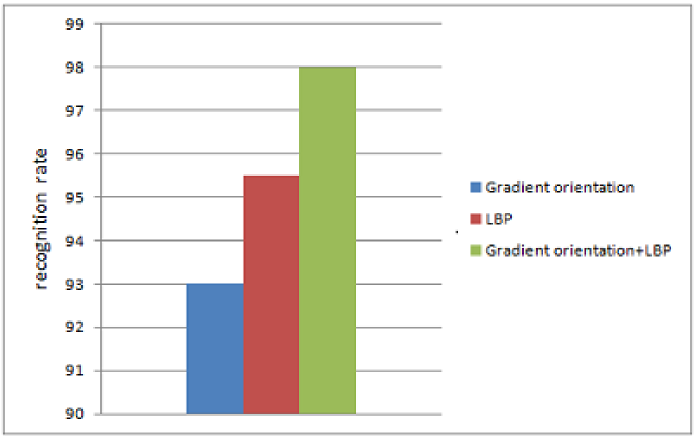

Fig. 2 Recognition result on faces 94 database

In the case of Grimace database, when gradient orientation histogram alone is used, recognition accuracy was 94%. When local binary pattern alone is used, recognition accuracy was 96% but using both features together increased the recognition rate to 98%. Result is shown in Fig. 3

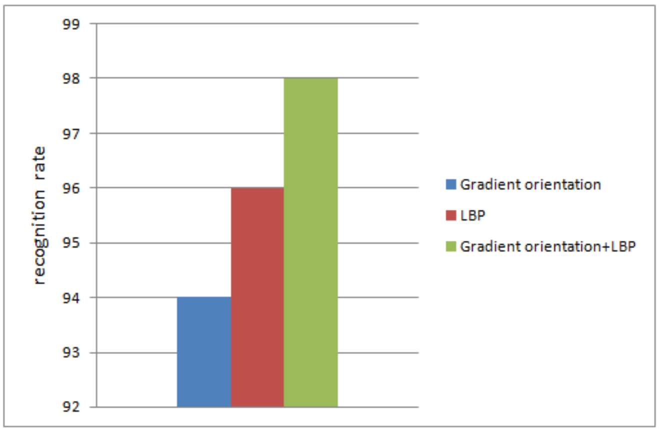

Fig. 3 Recognition result on faces 94 database

The above two tests shows that combining two features gives considerably better performance than either alone. Even though there was only single training image per sample, proposed system give best recognition rate. As the number of training sample per individual increases, the proposed method gives outstanding accuracy.

The proposed system gives high recognition rate under large facial expression changes. The feature descriptors used in this method are invariant to large expression variations. Most of the previous methods work by including samples with different facial expressions in the training data sets. The face images with similar expression often have higher identification accuracy.

But these methods require large number of training data. The proposed system uses robust and efficient facial descriptors to reduce the effect by facial expression variations without the need of training every types of facial expression. Experimental results show that proposed method has reliable recognition rate even with a single training sample. Fig 4 shows the result of large facial expression variation in Grimace database. It shows that large facial expression variations do not affect the recognition accuracy.

One of the most difficult tasks in face identification is identifying persons with different pose. That is probe face is having a different pose as compared to the one in the gallery. Our proposed method handles pose variations for face identification. This is accomplished by the feature descriptors which contain sufficient discriminative information to identify the person across changes in pose.

Fig.5 shows the recognition of face under pose changes. This shows the result from FERET image database.

Fig. 5 Identification of person having pose variations

The proposed system is invariant to moderate level of illumination variation. There is no pre-processing steps are used in this method for illumination normalization. Even though there is no pre-processing, the features used in this project are good enough to handle moderate level of illumination variations. FERET data sets are taken under different illumination conditions. The performance of the proposed system under varying illumination condition of FERET image is shown in the Fig. 6. The result also shows that the proposed system gives good result even when the images are under different focuses.

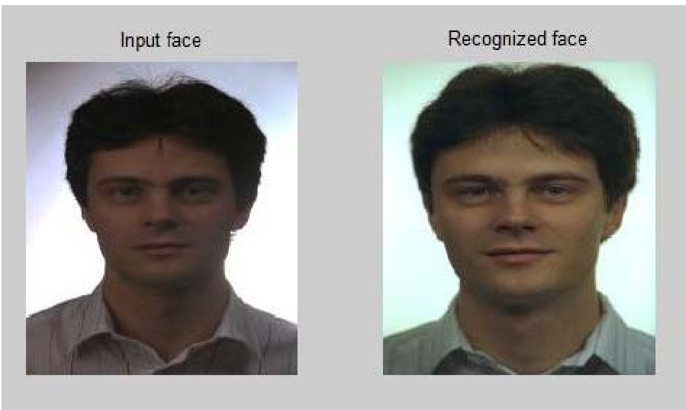

Fig. 6 Identification of person under different lighting conditions

The performance of the proposed system is evaluated by adding noise to the test image. Here both salt and pepper noise and additive white Gaussian noise with various intensities are included in the experiment. The system gives better performance up to a certain level of noise density. Fig. 7 shows the result of the system under the presence of additive white Gaussian noise.

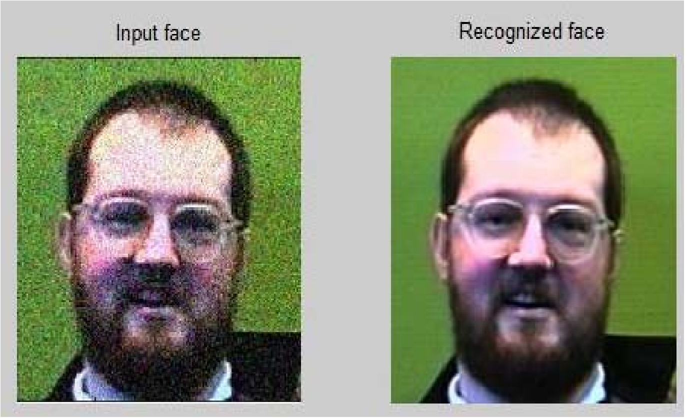

Fig. 7 Identification of person under the presence of additive white Gaussian noise

Fig. 8 shows the result of the system under the presence of salt and pepper noise. Increasing the salt and pepper noise level does not have significant effect in the performance till intensity 0.2. The proposed method has reliable recognition rate even with a single training sample per person.

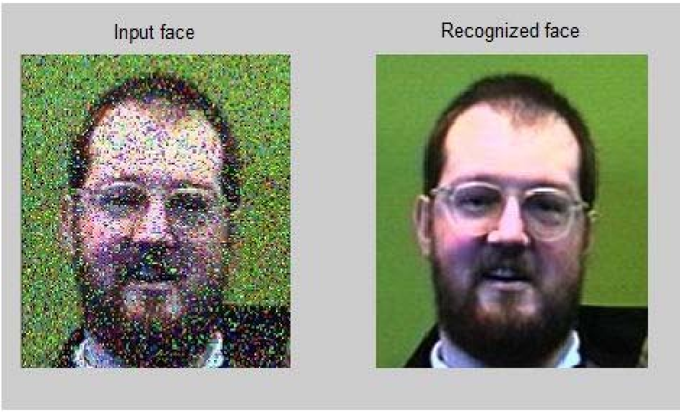

Fig. 8 Identification of person under the presence of salt and pepper noise

B. Evaluation of Classifiers

This section evaluates the performance of hash table and binary tree classifier used in the proposed system. The combined use of hash table and binary tree improves scalability especially when the gallery size is large and reduces the computational cost to a great extent. Aim of this experiment is to show that, the combination of these data structures gives a clear speed up for performing the evaluation of the probe set, without decreasing the recognition rate.

An experiment has been done to prove that the proposed method of using hash table and binary tree is better over using a binary tree alone. The experiment is conducted on gallery sizes of 25, 50, 75 and 100 images. The idea was to train the images first and then give a probe image to notice the time taken for identification. The details of the test environment are given below.

Processor : Intel(R) Core(TM) i3CPU

Installed memory (RAM) : 4.00GB (3.67 GB usable)

System type : 64 bit Operating system

TABLE I
Comparison of Proposed Method with Binary Tree

	Binary Tree	Proposed System
Gallery size	Time(ms)	Time(ms)
25	482.31	494.649
50	493.043	499.922
75	560.276	503.548
100	534.117	491.104

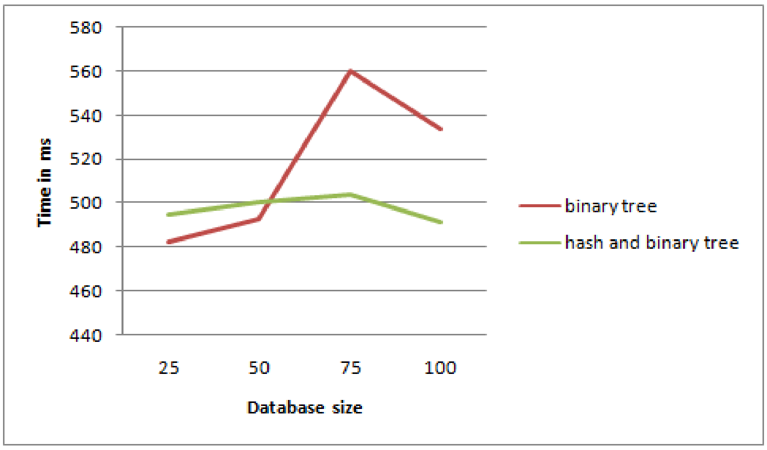

Fig.9 Comparison of proposed method with binary tree

The result obtained is given in the Table 1 and a graph of the same is plotted to show the trend. X axis represnts database scale and Y axis represents time in milliseconds. When the gallery size is very small i.e. 25, our proposed method is bit behind the binary tree alone method. However, as the gallery size increases, our proposed method wins over the binary tree alone method.

When the gallery size is very small, with our proposed method, there is an over head involved, i.e. of finding the hash index and more over there will be only fewer groups and images will be clustered. However, as the gallery sizes up, this overhead can be countered by the grouping mechanism and we need to search only in a particular group rather than searching on the entire gallery. In live scenarios, there will be over tens of millions of data in the gallery and our proposed method will definitely have an advantage over the traditional binary tree alone modal.

V. Conclusion

This paper investigated the benefits of combining two of the most successful feature sets in feature extraction stage and combining two data structures in classification stage. Two local features, gradient orientation histogram and local binary pattern gives considerably better performance than either alone. Because of these features, the proposed identification system is robust against large facial expression changes, pose, noise and illumination variations. Combination of hash table and binary tree gives the advantage of handle large database and reduce the computational cost. The combination of these data structures gives a clear speed up for performing the evaluation of the probe set, without decreasing the recognition rate. The proposed system gives high performance even though only single sample per subject is available. The proposed system focuses not only the accuracy but also the scalability. The proposed system can be used in the areas in which fast and accurate recognition are required

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