



Enhanced Face Recognition System with Combined SIFT and T-test Methods

Neethu Krishnan S¹, Sonia George²

Student, Computer Science and Engineering, Lourdes Matha College of Science and Technology, Trivandrum, India¹

Assistant Professor, Dept of CSE, Lourdes Matha College of Science and Technology, Trivandrum, India²

Abstract: Face recognition has attracted much attention because of its wide applications. However, face recognition is still an unsolved problem as human face is not a rigid object and it can be transformed easily under large intra-class facial variations such as pose, illumination, expression and small inter-class difference. In some cases the difference of face image of same person could be larger than those from different one. Therefore, how to represent the intrinsic attributes of a human face effectively becomes much more important to increase the accuracy of face recognition systems. Proposed system uses person-specific SIFT features and a simple non-statistical matching strategy to solve face recognition problems and also uses t-test algorithm for feature selection. First, Region of interest is deduced from the face image using object detector which has advantage over Haar cascade object detection which is effective only on frontal image. In the feature extraction step, Scale Invariant Feature Transform (SIFT) is applied. In contrast to Gabor features, SIFT features are invariant to image scaling, rotation and also partially invariant to illumination. Then the dimension of the feature space is reduced by defining features over regions of interest that are selected by t-test feature selection with feature correlation weighting. T-test is done based on high probability feature index with common features from different class is given low probability value and also high probability value for discriminant features that is enlarge the variation between the classes and minimize the similarity. In image classification, matching strategy is used. If the matching value is high the image is recognized. Experimental results demonstrate that the proposed algorithm yield superior performance with much lower dimensionality as compared to performance on the original data or on data transformed with other dimensionality-reduction approaches.

Keywords: Scale Invariant Feature Transform, T-test.

I. INTRODUCTION

In today's networked world, the way of crime is becoming easier than before. For this reason network security is becoming a major concern in various fields in the society. We all know that bank and computer system uses PIN, password, key and cards for identification and security clearances. Identity verification (authentication) in computer system has been based on something that one has (key, magnetic or chip cards) or one knows (PIN, password). When credit and ATM cards are lost or stolen, an unauthorized user can use the card with easily guessed PIN and passwords. Recent cases of identity theft have heightened the need for technology to prove authenticity. Therefore, in order to achieve reliable verification and identification we should use something that uniquely characterizes the identity of the person. One such technology that we use nowadays is Biometrics. The term Biometrics is derived from the Greek words bio (life) and metric (to measure). A Biometric is the unique measurable characteristics of a human being that can be used to automatically recognize an individual and verifies the individual's identity based on biometric identifiers. Biometric identifiers are often categorized as physiological versus behavioural characteristics. Physiological characteristics are derived directly from the human body. Examples include fingerprint, palm veins,

Face recognition, DNA, palm print, hand geometry, iris recognition and retina. Behavioural characteristics are related to the pattern of behaviour of a person, includes keystroke, gait, voice and signature. Physiological characteristics generally provide higher recognition accuracy than behavioral features. While behavioral characteristics can change from day to day because of stress, illness, or mood, physiological characteristics almost always remain unchanged, unless a serious injury occurs.

Facial Recognition Technology (FRT) has emerged as an attractive solution to address the identification and verification of identity claims. The face recognition have application in various field such as information security, smart cards, access and border control in e-government, e-health and e-commerce service, criminal identification, law enforcement and surveillance purposes such as search for wanted criminals and suspected terrorist.

Face recognition is chosen over other biometric such as iris, fingerprint due to number of reasons. 1) It requires no interaction on behalf of the user. 2) It is fast and accurate 3) It allows for high enrolment and verification rates. 4) It does not require an expert to interpret the comparison result. 5) It is the only biometric that allows to



perform passive identification.6) It is easy to use, embed and also inexpensive compared to iris and fingerprint technology.7).It is also non intrusive.

The most popular approaches to face recognition are based on either: 1) the location and shape of facial attributes, such as the eyes, eyebrows, nose, lips, and chin and their spatial relationships or 2) the overall (global)analysis of the face image that represents a face as a weighted combination of a number of canonical faces.

The face recognition procedure is divided mainly into three steps: Face Detection, Feature Extraction, and Face Recognition. The input of a face recognition system is always an image or video stream. The output is an identification or verification of the subject or subjects that appear in the image or video.

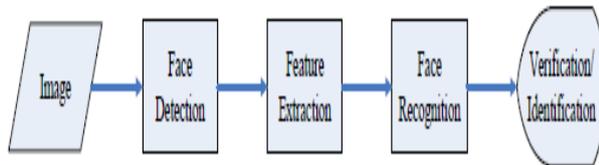


Fig.1 Configuration of a general face recognition structure

Face Detection

Face detection is defined as the process of extracting faces from scenes. The main function of this step is to determine (1) whether human faces appear in a given image, and (2) where these faces are located at. The expected outputs of this step are patches containing each face in the input image. Also some pre-processing could also be done to adapt the input image to the algorithm prerequisites.

Feature Extraction

Feature extraction process can be defined as the procedure of extracting relevant information from a face image or patches. Feature extraction involves several steps - dimensionality reduction, feature extraction and feature selection. A feature selection algorithm selects the best subset of the input feature set. It discards non-relevant features.

Face Recognition/Image classification:

Once the features are extracted and selected, the next step is to classify the image. For each person, several images are taken and their features are extracted and stored in the database. Then when an input face image comes in, we perform face detection and feature extraction, and compare its feature to each face class stored in the database. There are two general applications of face recognition, one is called identification and another one is called verification. Face identification means given a face image, we want the system to tell who he / she is .while in face verification, given a face image and a guess of the identification, we want the system to tell true or false about the guess.

II. RELATED WORKS

The main feature extraction approaches are subspace holistic features and local appearance features. Holistic subspace analysis represents the global appearance of a human face with its projections on the subspace This method performs well under controlled condition and achieves high recognition rate. But misalignment of face images may cause significant degradation of recognition performance. Typical holistic features include principal component analysis (PCA) [1], linear discriminate analysis (LDA) [2], independent component analysis (ICA) [3]etc.

Using the statistical Local Feature Analysis (LFA) technique, a set of feature points is extracted from each face image. Local feature analysis has achieved better performance in different face recognition tasks which is characterized by the following reasons: 1) local features can characterize the facial details for personal identification; 2) there are some local features designed with illumination robust property such as LBP.3) statistical histograms of local features are used as facial descriptors, being robust against partial variations of local features; 4) local methods provide more flexibility for recognizing faces with partial occlusions.

Two representative methods of local feature analysis in face biometrics are Gabor wavelets [4] and Local Binary Patterns (LBP) [5]. Gabor wavelets can extract the local features of facial regions on multiple channels of frequencies and orientations. Gabor features are discriminative and robust to illumination and expression changes and it can explore the neighbouring relationship in spatial, frequency and orientation domain. Gabor transformation has high computational cost and storage space because Gabor transformation of an input image needs to be implemented in multiple scale and orientation.

The general shortcoming of the Gabor wavelet is high dimensionality of the feature vector. LBP is basically a fine-scale descriptor, which captures small texture details, in contrast to Gabor features, which encode facial shape and appearance over a range of scales. The process of extracting LBP features is much faster than that of Gabor-based features. Various feature analysis methods are used in face recognition are mentioned below..

A. Local Binary Pattern

Local binary pattern is a means of summarizing local grey level structure. The LBP operator takes a local neighborhood around each pixel, thresholds the pixels of the neighborhood at the value of the central pixel and uses the resulting binary-valued image patch as a local image descriptor. LBP features are completely invariant to monotonic grey scale transformation. Therefore LBP is simple and effective way to represent face image because of its robustness with respect to facial expression, aging and alignment. But the LBP achieved poor performance against illumination problem and also sensitive to noise.



B. Local Ternary Pattern

LBP threshold exactly at the value of the central pixel i_c they tend to be sensitive to noise, particularly in near-uniform image regions such as cheeks and foreheads. So a generalization of LBP called local ternary patterns (LTP) is introduced that is more discriminant and less sensitive to noise in uniform regions[6].

LTP extends LBP to 3-valued codes, LTP, in which gray-levels in a zone of width $\pm t$ around i_c are quantized to zero, ones above this are quantized to +1 and ones below it to -1, Even though LTP codes are more resistant to noise, they are no longer strictly invariant to gray-level transformations.

Patterns of Oriented Edge Magnitudes

One of the shortcomings of Gabor filter is that it is computationally expensive. So Patterns of Oriented Edge Magnitudes (POEM), a descriptor for face recognition that balances the three concerns 1) distinctiveness; 2) robustness; and 3) computationally inexpensive cost [7]. It involves applying idea of self-similarity calculation from the LBP based structure on the distribution of local edge through different orientations. The resulting features are referred as POEM. To calculate the POEM codes for one pixel, the intensity values in the calculation of conventional LBP are replaced by gradient magnitudes, which are calculated by accumulating a local histogram of gradient directions over all pixels within a spatial patch.

POEM characterizes not only local object appearance and shape but also the relationships between this information in neighboring regions. It captures both local information and more global structure. Using gradient magnitudes, instead of pixel intensity values, for the construction makes POEM robust to lighting variance.

Spatial histogram can be used to model the encoded POEM features and refer this algorithm to as the POEM Histogram Sequence (POEM-HS). Although POEM-HS has significantly speeded up the face recognition process when compared to similarly high performing descriptors its dimension is still relatively high. To tackle the problem, we apply the PCA dimensionality reduction technique, followed by a whitening process, on POEM-HS named WPCA-POEM. The POEM-HS descriptor has less computational complexity compared to Gabor feature extraction. Both algorithms have several desirable features: robust to lighting, pose, and expression variations, and is fast to compute when compared to many of the competing descriptors.

C. Gabor Volume Based LBP on Three Orthogonal Planes (GV-LBP-TOP)

Both LBP and Gabor representations are rich in information and computationally efficient, and their complementary nature makes them good candidates for fusion. First, the multi scale and multi orientation representations are derived by convolving the face image

with a Gabor filter bank and formulated as a third-order volume. Second, LBP operator is applied on the three orthogonal planes (XY, XT, and YT) of Gabor volume, respectively, named GV-LBP-TOP[8] and then combines the description codes together to represent faces. The codes from three planes are different and, hence, may supply complementary information helpful for face recognition. After that, three histograms corresponding to GV-LBP-XY, GV-LBP-XT, and GV-LBP-YT codes are computed.

D. Effective GV-LBP

The aforementioned GV-LBP-TOP is of high computational complexity. To address this problem, we propose an effective formulation of GV-LBP (E-GV-LBP) which encodes the information in spatial, frequency and Orientation domains simultaneously and reduces the computational cost.

III. EXISTING SYSTEM

Gabor Ordinal Measures (GOM) is an efficient method for face recognition. The basic idea of GOM is to integrate distinctiveness of Gabor features and robustness of this kind of ordinal measures as a promising solution to jointly handle inter-person similarity and intra-person variations in face images. GOM is a type of Ordinal measure (OM), which is defined as the relative ordering information of multiple variables. There are two types of ordinal measures: intensity level and feature level. Intensity level ordinal measure may be the qualitative relationship between the average intensity values of two image regions. Feature level ordinal measure is the qualitative information computed on the image features, e.g. Gabor features.

In the proposal, different kinds of ordinal measures are derived from magnitude, phase, real, and imaginary components of Gabor images, respectively, and then are jointly encoded as visual primitives in local regions. The statistical distributions of these visual primitives in face image blocks are concatenated into a feature vector and linear discriminant analysis is further used to obtain a compact and discriminative feature representation. Finally, a two-stage cascade learning method and a greedy block selection method are used to train a strong classifier for face recognition.

A. Haar Cascade Face Detection

Object Detection using Haar feature-based cascade classifiers is an effective object detection method proposed by Paul Viola and Michael Jones. It is a machine learning based approach where a cascade function is trained from a lot of positive and negative images. It is then used to detect objects in other images. Initially, the algorithm needs a lot of positive images (images of faces) and negative images (images without faces) to train the classifier. Then Haar features are extracted.

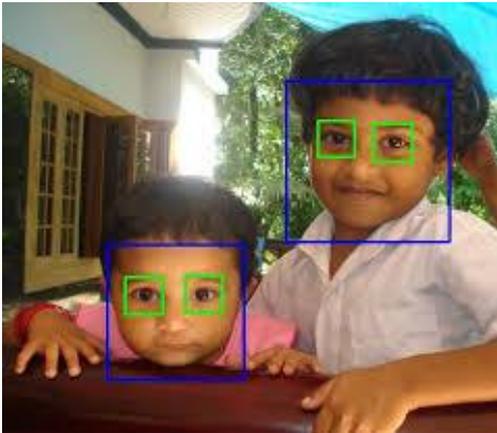


Fig.1.Haar cascade face detection

Working with only image intensities, (RGB pixel values) in every single pixel in the image, made feature calculation rather computationally expensive. This problem was addressed by the so-called Haar-like features, developed by Viola and Jones. The Haar-like feature considers neighbouring rectangular regions at a specific location in a detection window, sums up the pixel intensities in each region and calculates the difference between these sums. This difference is then used to categorize subsections of an image. The sums of pixel values over rectangular regions are calculated rapidly using integral images. An example of this would be the detection of human faces. One example of a Haar-like feature for face detection is a set of two neighboring rectangular areas above the eye and cheek regions, shown in Fig.1. The advantage of Haar like feature is its calculation speed and works well for representing fine scale textures. But Haar features are not strong, so a large number of features are needed for object detection. So OpenCV classifier contains a pertained classifier for faces, eyes, smile etc is used to collect large number of haar features.

A. Gabor filter

The kernels of 2-D Gabor wavelets are similar to the receptive fields of simple cells in the mammalian visual cortex, exhibiting desirable characteristics of spatial locality and orientation selectivity. Therefore Gabor filters are used to characterize discriminant texture pattern of face images. In our implementation of GOM, a family of 2D Gabor filters composed by five frequencies and eight orientations is performed on every pixel of a face image, which can be formulated as

$$\psi_{\mu,v}(z) = \frac{\|k_{\mu,v}\|^2}{\sigma^2} e^{\left(-\frac{\|k_{\mu,v}\|^2 \|z\|^2}{2\sigma^2}\right)} \left[e^{ik_{\mu,v}z} - e^{-\frac{\sigma^2}{2}} \right]$$

where $\mu \in \{0, \dots, 7\}$ and $v \in \{0, \dots, 4\}$ determine the orientation and scale of the Gabor filters and $z = (x, y)$ represents the spatial position. The wave vector $k_{\mu,v}$

$= k_v e^{i\phi_{\mu}}$ has a magnitude $k_v = k_{max}/\lambda^v$, where λ is the frequency ratio between filters and $\phi_{\mu} = \pi\mu/8$. The response of a face image $I(x, y)$ to a Gabor filter $\psi_{\mu,v}(z)$ is obtained by the convolution:

$$G_{\mu,v}(x, y) = I(x, y) * \psi_{\mu,v}(z).$$

B. Greedy Selection Algorithm.

A greedy algorithm is an algorithm that follows the problem solving heuristic, which always makes the choice that looks best at that moment. That is, it makes a locally optimal choice in the hope that this choice will lead to a globally optimal solution. Greedy methods are iterative procedures that perform forward greedy feature selection steps and optional backward greedy removal steps. It iteratively evaluates a candidate subset of features, then modifies the subset and evaluates if the new subset is an improvement over the old. Evaluation of the subsets requires a scoring metric that grades a subset of features. Exhaustive search is generally impractical, so stopping point is defined; the subset of features with the highest score discovered up to that point is selected as the satisfactory feature subset.

In general, greedy algorithms have five components:

- A candidate set, from which a solution is created
- A selection function, which chooses the best candidate to be added to the solution
- A feasibility function, that is used to determine if a candidate can be used to contribute to a solution
- An objective function, which assigns a value to a solution, or a partial solution, and
- A solution function, which will indicate when we have discovered a complete solution.

IV. STEPS INVOLVED IN GOM

The GOM face recognition mainly involves five different steps. 1). Preprocessing, 2). Face detection using Haar cascade classifier, 3). Feature extraction using Gabor filter and histogram distribution on resulting gabor magnitude and phase images, 4). Dimensionality reduction by Greedy block selection method, 5). image classification by two stage cascade classifier.

There are mainly two phases: testing and training phase. Before querying the face recognition system with test image training should be done on an offline basis.

In the training phase, training is performed on all the images stored in the database. This training procedure includes preprocessing of true images, Face detection is to detect the face region in image, Gabor feature extraction is performed on the detected face and Feature selection using greedy block selection. Then the resulting relevant features are stored in a storage medium in order to perform comparison with test image features at the image classification step.

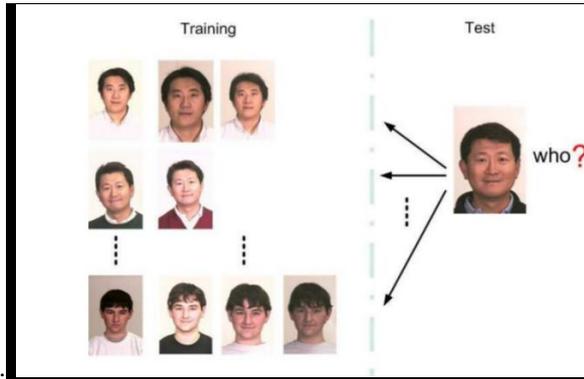


Fig.2 .Matching of the test image against a set of true images

All of these steps are also performed with test image .At the image classification step, matching between the test image and train image is performed, shown in fig.2 and the decision is made whether the test image is matched with any one of the train image of Particular class. The FR system is implemented as Graphical User Interface. The test image can be already registered or scaled, rotated or blurred version of the true image. Also it can be the image that is not registered. Each of the steps is detailed below.

A. Preprocessing

The image should be resized into 256x256 formats. To increase the luminance contrast enhancement is done, which increases the contrast of the image by mapping the values of the input intensity values to new values. Contrast enhancement of color image is done by transforming an image into a color space that has image component. One such color space is L*a.b (L-luminance component and a and b are color components). Color transformation function converts RGB to L*a.b by using transformation structure. Then work with luminosity layer of the image. After performing enhancement L*a.b color space is converted back into RGB color space. Lab is suitable for digital image manipulation than RGB color space.

B. Face detection using Haar cascade classifier

Haar cascade face detector/classifier find whether the face is present in the input image and also locate where it is located at ,shown in Fig.4.It uses OpenCV classifier data to detect the face. The detector computes the integral images, facilitates the summation of pixel (performed in constant time) instead of filter size .Then one of the detected objects is chosen.



Fig.4. Face detection using Haar cascade classifier

C. Feature extraction using Gabor filter

First, to reduce the processing complexity RGB image of 256x256 is resized into 120x120 format .Then to deal with illumination problem color space conversion is done by converting detected face image of RGB format to YCbCr format.(Y-intensity component and Cb and Cr are color components) shown in fig.5.



Fig.5. YCbCr image

Then Gabor filter of size 15x15 is convolved separately with each component of YCbCr(shown in fig.6) by taking Inverse Fourier Transform of element wise product of Fourier Transform of the image and filter. As a result Gabor magnitude and phase images are created. Then these magnitude and phase images are further divided into 15x15 blocks and for each and every block histogram features are generated .In the final step, histogram distribution of each and every blocks of both Gabor magnitude and phase images are concatenated to form a single vector .

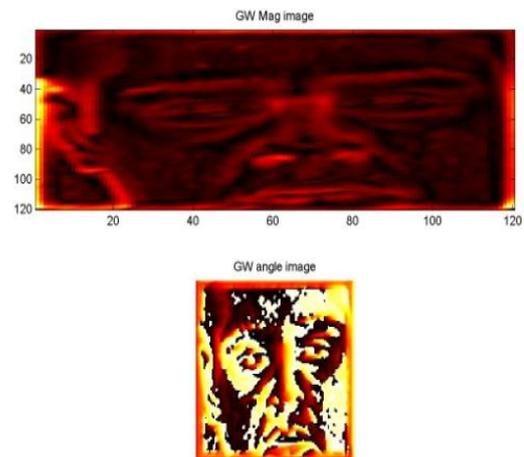


Fig.6.Gabor magnitude and phase images of Y component

D. Feature selection using greedy block selection algorithm.

One of the problems of the Gabor filter is the high dimensionality of the feature vector. Only subset of features should be used for best classification. So there is a need for feature selection to reduce the dimensionality of feature vector. A simple greedy block selection method is used in the training phase in order to select a subset of discriminative blocks with a minimum empirical error. The iterative algorithm selects best value in each of its iterations and stored in a variable. The best value is updated in each iteration, shown in fig 7.

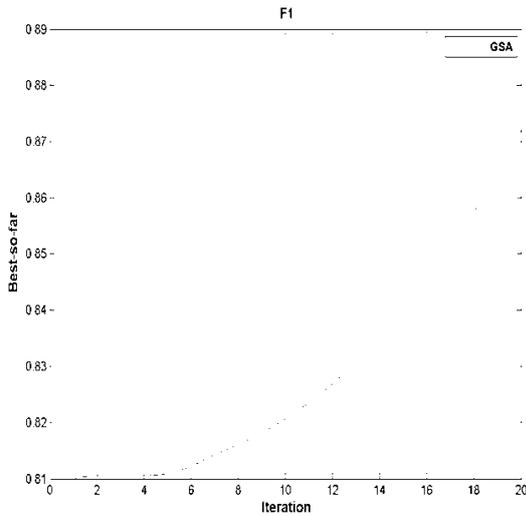


Fig.7.Selection of best value using GSA



Fig.9.Image classifications: Matching of test images with true images.

E. Image classification

The objective of face image classification is to measure the dissimilarity between two feature vectors of GOM. A number of issues should be considered in face image classification. Firstly, it is desirable to correct possible intra-class variations of GOM features in feature matching step. Secondly, the effectiveness of GOM varies from block to block for face recognition and it is necessary to select only the most effective GOM feature blocks for feature matching. Such a block selection can improve both accuracy and efficiency of face recognition. Thirdly, a smart matching strategy is needed to handle “easy” and “hard” samples separately in face recognition. Therefore, image classification is done by using two-stage cascade classifier which is shown in Fig.8.

Both trained feature sets and test image feature tests are multiplied by the weight, best value computed by GSA. Then the pair wise Euclidean distance between test image and every training data is computed. If the pair wise distance (minimum distance) is less than 100, then the test image is recognized.

V. PROPOSED SYSTEM

Face recognition techniques have always been a very challenging task for researches because of its difficulties and limitations. Although there exists various feature extraction methods for face representation and recognition, some of the face recognition problems are remains unsolved. One problem of face recognition is the fact that different faces could seem very similar (inter class similarity). Therefore a discrimination task is needed to recognize people with similar appearance. On the other hand, when we analyze the face of the same person , many characteristics may have changed due to intra person differences such as changes in illumination, variation in facial expressions, occlusion ,pose ,aging, presence of accessories (glasses, beards, etc.) and also the rotation of a face may change many facial characteristics. Therefore how to extract robust and discriminate features which makes the inter-person faces compact and enlarge the margin among different persons become a critical and difficult problem in face recognition. Feature extraction is one of the most important steps in the process of face recognition in order to overcome these problems.

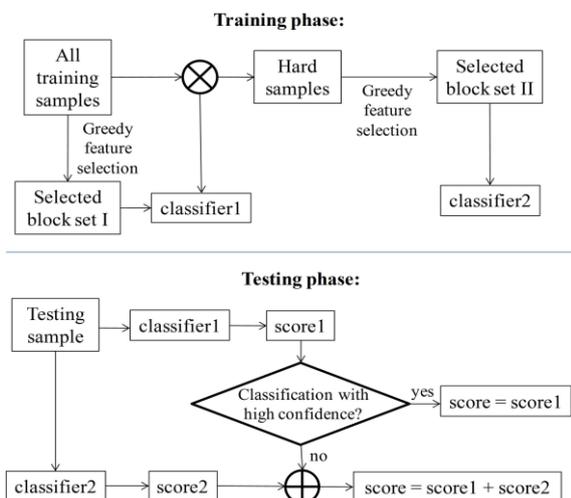


Fig.8. Flowchart of two-stage cascade classifier learning.

Based on the literature Gabor Ordinal Measures is chosen as best one, it has some disadvantages. Gabor filters are not much robust to illumination, pose variations, scaling and rotation. Therefore, for the same person the features extracted from the test image should be different from the features already extracted during training stage. So at the image classification stage there is a chance of misclassification of the test image even though it is already enrolled in the database. Another problem is the high computational complexity of Gabor filter. Gabor transformation has high computational cost and storage space because Gabor transformation of an input image needs to be implemented in five different scales and eight different orientations. Also Greedy block selection has high time complexity.



Haar based face detection have disadvantages. It is effective only on frontal images of faces and takes high computation time to detect face in an image. It can hardly cope with 45° face rotation both around the vertical and horizontal axis and also sensitive to lighting conditions.

To overcome the problems of Gabor Ordinal Measures a Face representation and recognition system with the combination of SIFT feature extraction method and T-test for feature selection is proposed here, named SIFT-T-test. Here, face detection is done by MATLAB function `vision.CascadeObjectDetector`.

A) Scale Invariant Feature Transform

The Scale-Invariant Feature Transform (SIFT) bundles a feature detector and a feature descriptor. The detector extracts from an image a number of frames (attributed regions) in a way which is consistent with (some) variations of the illumination, viewpoint and other viewing conditions. SIFT is mainly used in feature extraction, for object classification applications. The features extracted by SIFT are invariant to image scaling, rotation and partially invariant to the change of projection and illumination.

Therefore, the SIFT based method is insensitive to the scaling, rotation, projective and illumination factors. The SIFT based method firstly searches over all scales and image locations by using a difference-of-Gaussian function to identify potential interest points. Then an elaborated model is used to determine finer location and scale at each candidate location and key points are selected based on the stability. Then one or more orientations are assigned to each key point location based on local image gradient directions. Finally, the local image gradients are evaluated at the selected scale in the region around each key point.

B) T-test Algorithm

The dimension of the voxel intensities feature space is reduced by defining features over regions of interest that are selected by t- test feature selection with feature correlation weighting. T-test is done based on high probability feature index with common features from different class is given low probability value and also high probability value for discriminant features that is enlarge the variation between the classes and minimize the similarity.

The most common type of t-test is often used to assess whether the means of two classes are statistically different from each other by calculating a ratio between the difference of two class means and the variability of the two classes. The t-test has been used to rank features for microarray data and for mass spectrometry data. These uses of t-test are limited to two-class problems. For multi-class problems, Tibshirani et al calculated a t-statistics value for each gene of each class by evaluating the

difference between the mean of one class and the mean of all the classes, where the difference is standardized by the within-class standard deviation.

$$t_{ic} = \frac{\bar{x}_{ic} - \bar{x}_i}{M_c \cdot (S_i + S_0)}$$

$$S_i^2 = \frac{1}{N - C} \sum_{c=1}^C \sum_{j \in c} (x_{ij} - \bar{x}_{ic})^2$$

$$M_c = \sqrt{1/n_c + 1/N}$$

Here t_c is the t-statistics value for the i-th gene (feature) of the c-th class; \bar{x}_{ic} is the mean of the i-th feature in the c-th class, and \bar{x}_i is the mean of the i-th feature for all classes; x_{ij} refers to the i-th feature of the j-th sample; N is the number of all the samples in the C classes and n_c is the number of samples in class c; S_i is the within-class standard deviation and S_0 is set to be the median value of S_i for all the features.

$$t_i = \max \left\{ \frac{|\bar{x}_{ic} - \bar{x}_i|}{M_c S_i}, c = 1, 2, \dots, C \right\}$$

C) Confusion matrix

In the field of machine learning and specifically the problem of statistical classification, a confusion matrix, also known as an error matrix. It is a specific table layout that allows visualization of the performance of an algorithm, Each column of the matrix represents the instances in a predicted class while each row represents the instances in an actual class,. The name stems from the fact that it makes it easy to see if the system is confusing two classes (i.e. commonly mislabeling one as another).

It is a table with two rows and two columns that reports the number of false positives, false negatives, true positives, and true negatives. This allows more detailed analysis than mere proportion of correct guesses (accuracy).

Performance of FR systems is commonly evaluated using the data in the matrix. The fig.10. Shows the confusion matrix for a two class classifier.

The entries in the confusion matrix have the following meaning in the context of our study:

- a is the number of correct predictions that an instance is negative,
- b is the number of incorrect predictions that an instance is positive,
- c is the number of incorrect of predictions that an instance negative, and
- d is the number of correct predictions that an instance is positive.



		Predicted	
		Negative	Positive
Actual	Negative	a	b
	Positive	c	d

Fig .10.confusion matrix for a two class classifier

Several standard terms have been defined for the 2 class matrix:

- The accuracy(AC) is the proportion of the total number of predictions that were correct. It is determined using the equation:

$$AC = \frac{a+d}{a+b+c+d} \dots\dots(1)$$

- The recallor true positive rate (TP) is the proportion of positive cases that were correctly identified, as calculated using the equation:

$$TP = \frac{d}{c+d} \dots\dots(2)$$

- The false positive rate(FP) is the proportion of negatives cases that were incorrectly classified as positive, as calculated using the equation:

$$FP = \frac{b}{a+b} (3)$$

- The true negative rate(TN) is defined as the proportion of negatives cases that were classified correctly, as calculated using the equation:

$$TN = \frac{a}{a+b} \dots\dots(4)$$

- The false negative rate(FN) is the proportion of positives cases that were incorrectly classified as negative, as calculated using the equation:

$$FN = \frac{c}{c+d} \dots\dots(5)$$

- Finally, precision(P) is the proportion of the predicted positive cases that were correct, as calculated using the equation:

$$P = \frac{d}{b+d} \dots\dots(6)$$

VI. STEPS INVOLVED IN SIFT-T-TEST

The proposed system is implemented four steps:

1. Face detection using vision.cascadeObjectdetector.
 2. Feature Extraction using SIFT.
 3. Feature selection usingT-test.
 4. Image classification using SIFT matching strategy..
- Face detection, Feature extraction and feature selection is done on both training and testing phase. But Image classification is done only in testing phase. Before implementing these modules first the user has to select Test image

A. Face detection using Object detector.

The system detects the Region of Interest from the image by creating an face detector using vision.cascade Objectdetector. Then step function is used to detect the face region and ROI is displayed using insertObjectAnnotation.

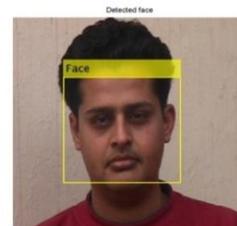


Fig.11. Detected face



Fig.12. Cropped face

B. Feature Extraction

This module includes extracting features using sift which is included from VL FEAT tool box. SIFT is applied along three components of RGB image. Before applying SIFT image should be converted into single precision.

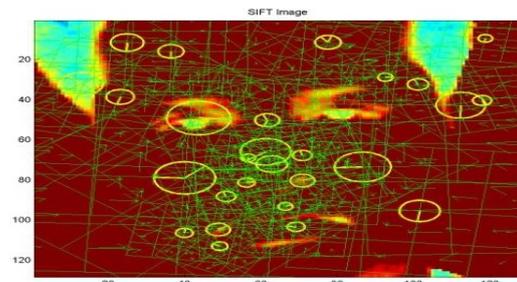


Fig.13.SIFT feature extracted from R component

C. Feature selection

T-test is used to select the important sift feature

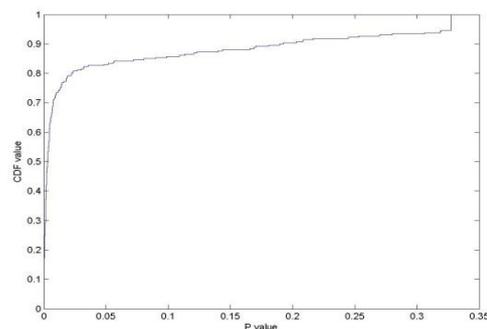


Fig.14.CDF



D. Image classification:

This module performs the matching between test and trained feature in order to detect whether the test image is matched with trained image that are already stored in database



Fig.15. Image classifications

VII. PERFORMANCE EVALUATION

The proposed system outperforms the existing Gabor based FR methods in terms of accuracy and time complexity. The comparison of the existing and proposed algorithms are given in the table.

Table 1 comparison of the existing and proposed algorithms

Algorithm	Time complexity	Accuracy	Recognatio Rate
GOM	High	Average	Average
FR using SIFT and T-test	Reduced	Inceased Accuracy	High

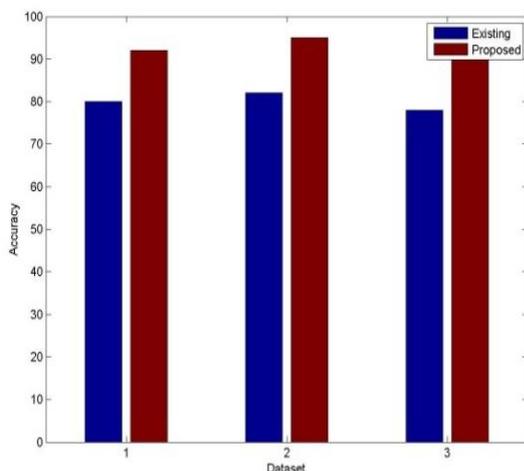


Fig.16. Comparison based in accuracy

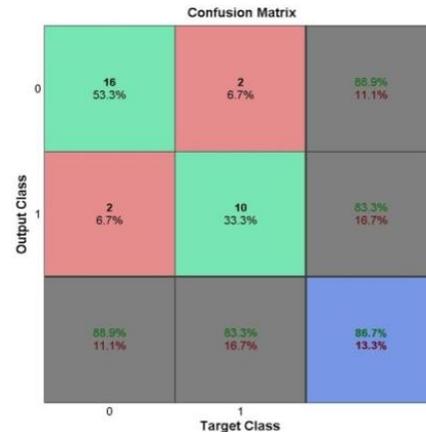


Fig.17. Confusion matrix for existing GOM method

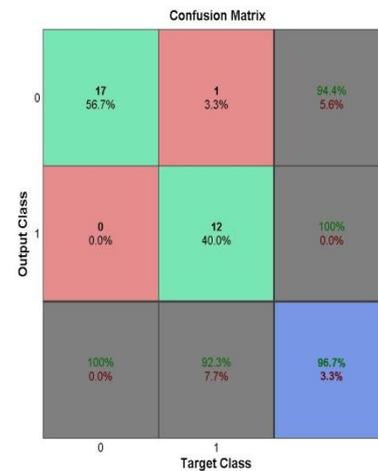


Fig. Confusion matrix for proposed SIFT-T-test method

From the performance analysis, it is inferred that misclassification error can be minimized. So that high accuracy is achieved.

VII. CONCLUSION

Face recognition techniques have always been a very challenging task for researchers because of its difficulties and limitations. Face recognition system, is widely used in various applications such as security, access control, surveillance, law enforcement and face identification. One problem of face recognition is the fact that different faces could seem very similar (inter class similarity). Therefore a discrimination task is needed to recognize people with similar appearance. On the other hand, when we analyze the same face, many characteristics may have changed (intra person differences) due to changes in illumination, variability in facial expressions, occlusion, pose, aging, the presence of accessories (glasses, beards, etc.) and also the rotation of a face may change many facial characteristics. Therefore how to extract robust and discriminate features which makes the inter-person faces compact and enlarge the margin among different persons become a critical and difficult problem in face recognition. In the literature



review, compared to other FR methods gom is chosen as a good one .But it a have disadvantages. Gabor filters are sensitive to illumination, pose variations, scaling and rotation. Therefore, for the same person the features extracted from the test image should be different from the features already extracted during training stage. So at the image classification stage there is a chance of misclassifying the eventhough the test image is already enrolled in the database. Another problem is the high computational complexity of gabor filter. Because Gabor filtering is usually applied at five different scales and eight different orientations.

Therefore a new FR system combined with SIFT feature extraction and T-test algorithm is introduced. SIFT features are nvariant to pose variation, scaling, rotation and illumination. Also T-test algorithm is used to select the important features, thereby reducing the dimensionality of the feature space. Experimental results demonstrate that the proposed algorithm yield superior performance over GOM interms of accuracy.

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