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Improved Face Recognition Technique using Sift

Mr. Amit Kr. Gautam, Ms. Twisha
[1]*(Assistant Professor, Cluster Innovation Centre,University Of Delhi, India)*
[2]*(Assistant Professor,Cluster Innovation Centre,University Of Delhi, India)*

ABSTRACT:*Face recognition presents a challenging problem in the field of image analysis and computer vision. In the presented work we have proposed a novel approach for face recognition using Scale-invariant feature transform. We have the standard ORL (Olivetti Research Laboratories) Database. It contains 20 subject having 10 different orientation and expression. The database is divided into two parts, training and testing database. The SIFT features are generated for every training image and the features called key points is calculated, then k nearest neighbor's classifier is used for the matching scheme for test data . The recognition results demonstrate its robust performance under different expression conditions, Pose variation, illumination changes and partial occlusion. The Equal error rate can be calculated by FAR and FRR and the recognition rate show the robustness of the proposed method.*

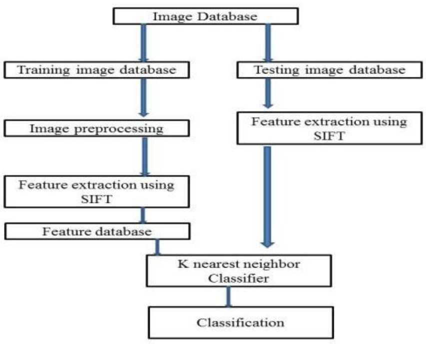
Keywords *: Scale invariant feature transform k nearest neighbors, Equal error rate and Recognition rate.*

I. INTRODUCTION

Face recognition is a task so common to humans. General People does not even notice the extensive number of times it is performed every day. For a Human it is a usual task which is done normally every day. Although research in automated face recognition has been conducted since 1960's, it is difficult problem in the area of computer vision which has recently caught the attention of the scientific community. Many face analysis and face modeling techniques have progressed significantly in the last decade [1].However, the reliability of face recognition schemes still poses a great challenge to the scientific community. There are many variations in the facial images that are considered for face recognition. These are due to changes in light intensity conditions, change in pose direction, different face expression and aging effect etc. Face recognition has recently received a blooming attention and interest from the scientific community as well as from the general public. The general public has the interest mostly due to the unusual events like terrorist attack around the world, so this becomes our need for useful security systems. There are various application areas in which face recognition can be used eg. In Security system, In video Surveillance system, General identity verification and "Smart Card" applications, gender classification [2], expression recognition [3]. In this work, we have focused on the problem of face recognition and have derived a novel way for recognizing faces using Scale-invariant feature transform.We have the standard ORL Database it is divided in two parts. The first part is training image and Second part is to test the image. The SIFT features are generated for every training image and then k nearest neighbors classifier is used for the matching scheme. The recognition results demonstrate its robust performance under different expression conditions, Pose variation, illumination changes and partial occlusion. For all the experiments conducted the ORL (Olivetti Research Laboratories) database has been used.

II. PROPOSED FACE RECOGNITION SYSTEM

Fig.1 shows the functional model of proposed technique. The entire face recognition system used in this work consists of 3 steps:



1) Image preprocessing- Image preprocessing commonly comprises of a series of sequential operations including image enhancement or normalization, geometric correction, Contrast adjustment, Histogram Equalization, removal of noise etc. It is done before applying the feature extraction techniques. Using the above mentioned techniques, we alter the image pixel values permanently and use this improved data for later analyses.

2) Feature extraction- This form of dimensionality reductionsimplifies the amount

of resources required to describe a large set of data accurately. Image features can refer to the global properties of an image like average gray level, shape of intensity histogram etc. or the local properties of the image like shape of contours, elements composing textured region etc.
In this work, the features are extracted from images using Scale invariant Feature transform (SIFT) methods.

Figure 1: Block Diagram of Proposed face recognition system

III. THEORY OF SIFT

Algorithms like PCA (principal component analysis), linear discriminant and 2D principal component analysis (2D PCA)[4] are used for extracting face information but all these algorithms are mostly sensitive to light, expression and pose, etc. So, to overcome these problems, SIFT [5] was introduced for feature extraction. This method has advantages like scale invariance, rotation invariance, affine invariance (translation and reflection) and has strong robustness for occlusion problem and noise.
SIFT mainly includes four steps:
Detection of extreme value in space scale: In SIFT, scale transformation is done by Gaussian convolution and the description ($L(x,y,\sigma)$) of input image ($I(x,y)$) in different scale can be expressed by the
$$L(x,y,\sigma) = G(x,y,\sigma) * I(x,y) \ldots\ldots\ldots\ldots\ldots 1$$
Where σ is scale factor (in this paper the scale is 5) and Gaussian convolution kernel $G(x,y,\sigma)$ is given as
$$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2} \ldots\ldots\ldots\ldots\ldots\ldots 2$$
After the convolution, the calculated image is a Gaussian image. L(x,y,σ), fig.1 is the spatial scale images. The image I(x ,y) zoom with σ, and the smoothness of the image would change with the change of σ, and then a series of scale image could be obtained.
According to those scale images, the extreme point (key-points (interest points) - face's key-points mainly includes eyes, nose and mouth) will be detected.
Filtering out key-points: The location of key-point is considered to filter out the key-points which are sensitive to noise or have no edge effect. So for that Taylor quadratic expansion, DoG (x,y,σ) can delete the extreme points which have lower contrast, and the value of Hessian vector and the ratio of determinant can reduce the edge effect.
$$\mathrm{DoG} = (\mathrm{G}(x,y,k\sigma) - \mathrm{G}(x,y,\sigma)) * \mathrm{I}(x,y) = \mathrm{L}(x,y,k\sigma) - \mathrm{L}(x,y,\sigma) \ldots\ldots\ldots 3$$
Direction of the key-point: After the position and scale of the key-point is determined, the next step is key-point's direction, which can ensure the feature's rotation invariance.
Module value: (gradient magnitude)
$$\mathrm{m}(x,y) = \sqrt{(\mathrm{L}(x+1,y) - \mathrm{L}(x-1,y))^2 + (\mathrm{L}(x,y+1) - \mathrm{L}(x,y-1))^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4$$
Phase: (orientation)
$$\Theta(x,y) = \arctan\left[\frac{L(x,y+1)-L(x,y-1)}{L(x+1,y)-L(x-1,y)}\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots 5$$
Steps for calculating direction of key-points are as follows:
Choose a neighborhood M by the center of the key-point.
Calculate the directions of points in M by phase equation.
Obtain the direction distribution, and draw the statistical histogram.
The direction of key-point is the maximal component in the statistical histogram.
Since the result of phase eq is a real number, we divide the real interval ($[0,2\pi]$) into 36 portions by $\pi/18$ so as to be convenient in obtaining the direction distribution, then the direction statistical histogram contains 36 phases, and the statistical rule is principle of proximity
Feature description of the key-points: The position, scale and direction of key-point can only ensure the 2D geometric invariance, but can't ensure the lightness and view transformation invariance. So SIFT introduces feature description to solve those problems. The step is as follows:

Select 16×16 pixel fields M in the neighborhood of key-point, and divide M into 16 subfields by 4×4.
According to module eq and phase eq, calculate the amplitude and direction in every subfield, and then the direction distribution in the ranges of [0, 45, 90, 135, 180, 225, 270, 315] could be obtained.
According to the direction statistical histogram of subfields, 8 direction descriptions will be calculated by the amplitude and Gaussian function.
The feature description is obtained by connecting the direction descriptions of all subfields; the total of the direction descriptions is 16, so the length of the feature description is 128=16×8.

In order to ensure the illumination invariance, the feature description should be normalized.

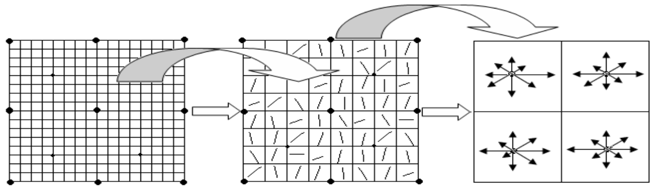


Figure 2: Feature description of key-points: (a) Neighborhood (b) Direction (c) Feature

KNearestneighbor (KNN) classifier In pattern recognition and classification, the k-nearest neighbor algorithm (k-NN) [6], is an algorithm for classifying data objects based on closest training examples in the feature space. The KNN is a type of instance based or lazy learning, where the function is only approximated locally and all computations are postponed till classification. The k-nearest neighbor algorithm is simplest among all machine learning algorithms: an object is classified by a majority vote of its neighboring data, and the test object is assigned to the class which is most common amongst its k nearest neighbors (k is a small positive integer). If ‘k’ is chosen to be 1, then the test object is simply assigned to the class to which its nearest neighbor belongs.

Although there is no explicit need for training in this algorithm, the neighbors can be regarded as training examples and are chosen from a set of objects for which the correct classification is known. The k-nearest neighbor algorithm is affected by the local structure of the data. The nearest neighbor rules effectively compute the decision boundary in an implicit way.The training examples can be regarded as vectors in a multidimensional feature space, each belonging to a class. So, in the training phase of the algorithm, it is required to only store the feature vectors of the training samples along with their class.

In the classification phase, k is a constant decided by the user and a test vector (can also be called query or a test point) is classified by assigning it the label which is most common among the k training data nearest to that particular test point.Euclidean distance is most commonly used as the distance measure; however this only applies to the continuous variables. For other types of classification like text classification, other measures such as the overlap metric (or Hamming distance) can also be used. The accuracy of the k nearest neighbor algorithm can be improved significantly by using special algorithms such as Large Margin Nearest Neighbor or Neighborhood components analysis.

The concept of ‘majority voting’ for classification has one drawback. If more examples in the training sample belong to one class, it tends to dominate the prediction of test sample, since their chances of being present in the k nearest neighbors is high owing to their large numbers. So the training examples have to be chosen very carefully. This problem can also be overcome by taking into consideration the distance from the test vector to each of the k nearest neighbors.

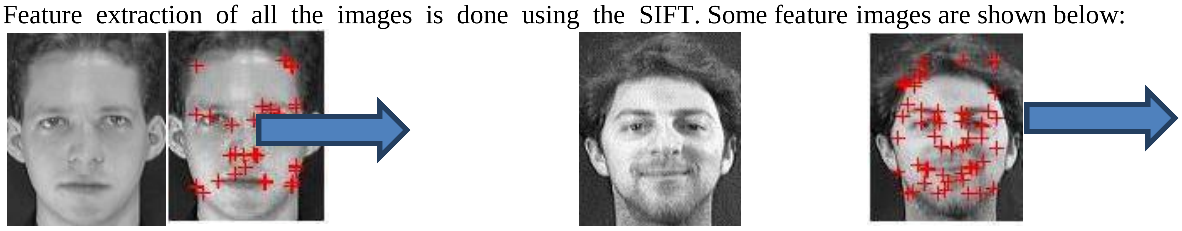
Choosing the value of ‘k’ also depends on the data. Larger values of ‘k’ help in reducing the effect of noise by averaging it out. But it makes the boundaries between the classes less distinct. There are various techniques for selecting the optimum value of ‘k’ like cross validation. The special case when the value of ‘k’ is ‘1’, i.e. the testing example is assigned the class to which its nearest neighbor belongs, is called the nearest neighbor algorithm.

IV. EXPERIMENTAL RESULTS

Scale invariant Feature transform is used for the purpose of feature extraction. The standard ORL database is used for conducting all the experiments. It consists of images of 20 subjects of size 92 x 112. There are variations in facial expression (open/closed eyes, smiling/non-smiling.), facial details (glasses/no glasses) and scale (variation of up to about 10 %). All the images were taken against a dark homogenous background with the subjects in an upright, frontal position, with tolerance for some tilting and rotation of up to about 20 degrees, and two orientations for testing.

Feature extraction

Feature extraction of all the images is done using the SIFT. Some feature images are shown below:



Result:
Matching with pose image ⁄illumination or intensity variation ⁄ Partial Occlusion

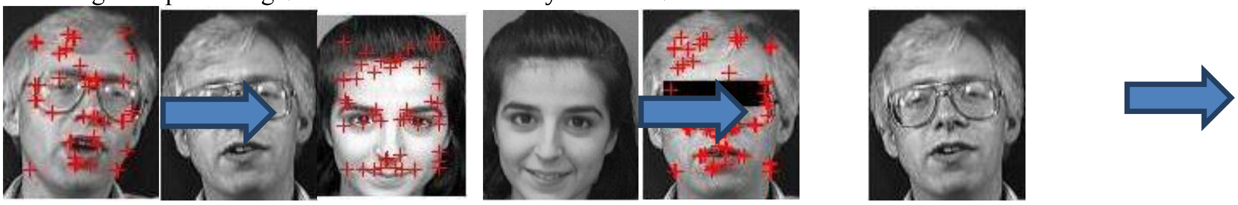


Figure 4: Matching result for different variation

Performancemeasures:Recognition systems result in two types of errors: a False Acceptance (FA), which occurs when the system accepts an impostor face, or a False Rejection (FR), which occurs when the system refuses a true face. The performance is generally measured in terms of False Acceptance Rate (FAR) and False Rejection Rate (FRR), defined as:

$$FAR = \frac{\text{number of False acceptance}}{numberofimpstorfacepresentations} \qquad FRR = \frac{\text{number of False rejection}}{\text{number of true face presentat ions}}$$

To aid the interpretation of performance, the two error measures are often combined using Equal Error Rate (EER)[7], when FAR=FRR on a particular database.
Figure 5 shows the Relation of False Acceptance Rate (FAR), False Rejection Rate (FRR) with the distribution of clients, imposters in a verification scheme. A) Shows the imposters and client populations in terms of the score (high score meaning high likelihood of belonging to the client population). B) The associated FAR and FRR, the Equal Error Rate (EER) is where the FAR and FRR curve meets and gives the threshold value for the best separability of the imposter and client classes. We can observe that the values of FAR and FRR intersects at point, defined as Equal error rate.

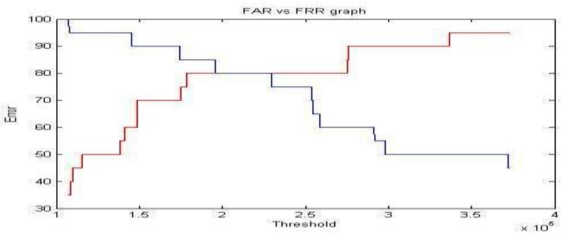


Figure 5: Experimental curve of FAR vs

METHOD	FISHER FACE	HANKAN'S	SIFT+SVM	PROPOSED METHOD
EER	4.58	2.61	2.58	0.80

Table 1: EER on ORL Database

Table 1 summarizes a comparative analysis on the ORL database our proposed method has minimum EER this show the robustness of the technique against face expression, illumination changes, pose changes and partial occlusion.Table 3 shows the Recognition rate in different algorithm.Table 2 shows the RT% (Recognition rate) in [8] various algorithm. It is seen that this proposed method give better result than previous work.

Table 2: The rate of recognition in different algorithm

METHOD	PCA	ICA	FISHER	2D_PCA	SIFT	PROPOSED METHOD
RT%	92.1	91.6	92.8	92.5	96.3	97.91

V. CONCLUSION

In the presented work, a novel method for face recognition using SIFT (Scale invariant Fourier transform) has been proposed. This method is invariant to pose, expression, illumination and partial occlusion. In our result we have observed the Equal error rate is 0.80 that should be below 0.89, obtained by using SIFT [5] with SVM [7].the Recognition rate is found 97.91% that show Robustness of this method. It shows all the matching between training images and test images. We have done the matching technique by using k nearest neighbors' classifier. The method is applied on ORL Database. We found that Face Recognition using SIFT technique is robust and invariant to pose, expression, illumination and partial occlusion. we can apply this method on aging effect and analyses the result.

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