

Biometric Face Recognition System using SURF Based Approach

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF
Bachelor of Technology

in
Computer Science And Engineering

By

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**Under the Supervision of
Prof. R. Baliar Singh**



COMPUTER SCIENCE AND ENGINEERING
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Ved Prakash Sonker

&

Mahendra Behera



CERTIFICATE

This is to certify that the thesis entitled, “BIOMETRIC FACE RECOGNITION SYSTEM USING SURF BASED APPROACH” submitted by Ved Prakash Sonker And Mahendra Behera in partial fulfillment of the requirements for the award of Bachelor of Technology Degree in Computer Science And Engineering at National Institute of Technology, Rourkela is an authentic work carried out by him under my supervision and guidance. To the best of my knowledge, the matter embodied in this Project review report has not been submitted to any other university/ institute for award of any Degree or Diploma.

Date: 14th MAY 2012

(Prof. R. Baliar Singh)

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ABSTRACT

Face recognition can be viewed as the problem of robustly identifying an image of a human face, given some database of known faces [6]. We propose a novel, SURF based approach to the problem of face recognition. Although the results are not gratifying our proposed approach loosens the burden of creating the sub spaces as is done in PCA, LDA and the most recent Bayesian approach. Also, during the experiments even though we used an unturned program for the proposed approach, it outperforms the basic PCA and LDA based approaches in terms of consistency.

This article presents a scale-invariant and novel rotation detector and descriptor known as SURF (Speeded-Up Robust Features). SURF outperforms previously defined schemes with respect to repeatability as well as distinctiveness and robustness. It's computing and comparing can be much faster. This is done by relying on integral images for image convolutions; by making the strengths of the leading existing detectors and descriptors (specifically, using a Hessian matrix-based measure for the detector, and a distribution-based descriptor); and by simplifying these methods to the essential. Its result is a combination of novel detection, description, and finding match steps. The paper contains an overview of the detector and descriptor and then finds out the effects of the most important parameters. The article is concluded with SURF's application to two challenging. Yet it converse goals i.e. camera calibration which is a special case of image registration and recognition of objects. Our experiments show that SURF is very useful in vast areas of computer vision.

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INTRODUCTION

1. Introduction

1.1 What is biometrics?

Biometrics is a subject that deals with the methods of recognizing humans uniquely based upon one or more intrinsic physical or behavioral traits [11]. In computer science, it is mainly used as a form of identity access management and access control. Based upon the traits, it is divided into two main classes.

Physical: These are the traits that are related to the structure of the body. Examples include fingerprint, face recognition, DNA, Palm print, hand geometry, Iris recognition etc.

Behavioral: Also coined by some researchers as behaviometrics, these traits are related to the behavior of the person. Examples include typing rhythm, gait, voice etc. Generally a biometric system can operate in one of the following two modes.

Identification: This includes a one to one comparison of the unknown captured biometric, with all the stored templates to identify or reject him as one of the person in the stored templates.

Verification: This process includes a one to one comparison of the captured biometric, with a stored template to verify whether the individual is who he claims to be. It can be done in conjunction with a smart card, username or ID number.

1.2 Why face identification is required?

The development of automatic visual surveillance system is a popular research topic in computer vision. Not only for surveillance but it can also be used to design systems for automated payroll, visual sensors, machine learning etc.

The main task of the proposed face recognition system is recognition which in general case means to determine whether or not a given probe image is present in the gallery. Although recognition is our main problem, in the experiments, we consider identification which is a

general experimental proof of recognition. Identification involves determining the best possible match for a given probe (Forced choice experiment) and hence it may give false positives. In order to overcome this we use ranking [8], with the help of which, we can project identification as the problem of recognition in the Cumulative Match Curve (CMC).

1.3 Challenges in Face recognition

The major challenges in face recognition are the possibilities of when a face recognition system might fail. These include

1. Illumination variation
2. Change in the expression
3. Change in Camera angle
4. Head pose
5. Size of the scaled face image
6. Growth of facial hair due to age or duplicated hair attached to fool the system
7. Speed, robustness and reliability of the system

Our system overcomes majority of these problems using the SURF based features, which are easier to calculate and are both rotation and scale invariant.

LITRATURE REVIEW

2.LITRATURE REVIEW

Computer vision has several applications. One of the tasks is to find point correspondences between two same scenes or object. Image registration, camera calibrations are just a few. Besides these, object recognition, and image retrieval are also included. There are three main steps to search for discrete image point correspondences. 'Interest points' are chosen first. These are found at distinctive locations in the image. Those areas are corners, blobs, and T-junctions. Repeatability is the most important property of an interesting point detector. It is nothing but the reliability of a detector to find out the same physical interest points under different viewing conditions. Next, the neighborhood of every interest point is a feature vector. This descriptor is distinctive and at the same time robust to noise. It is also robust to detection displacements and geometric and photometric deformations. Finally, matching is done between the descriptor vectors of different images. The matching is based on a distance between the vectors. It is either the Mahalanobis or Euclidean distance. All descriptors have dimensions. It has a direct impaction on the time this takes for matching. Fewer dimensions are desirable for fast matching. However, lower dimensional feature vectors are less distinctive. And their high-dimensional feature vectors are more distinctive.

Our focus is to develop a detector and a descriptor. If we compare to the state-of-the-art, are fast to compute while not sacrificing performance. In order to succeed, one has to give a balance between the requirements as stated above. It is like simplifying the detection scheme while keeping it accurate, and reducing the descriptor's size while keeping it sufficiently distinctive.

There are several detectors and descriptors have already been found in the literature (e.g. [12,13,14]). Also, detailed comparisons and evaluations taking the benchmark of datasets have been performed [28, 30, 31]. Our fast detector and descriptor is called SURF and was introduced in [4]. It is built on the insights gained from this previous work. In our experiments taking these benchmark datasets, SURF's detector and descriptor are faster. But the detector is more repeatable and the descriptor is more distinctive. We focus on scale and in-plane rotation-independent detectors and descriptors. It is a good compromise between feature complexity and robustness to commonly occurring photometric deformations. Skew, anisotropic scaling are assumed to be second order effects that are covered too little extent by the descriptor. Note that the descriptor can be extended towards affine-invariant regions using affine normalization of the ellipse (cf. [12]), although this impacts on the computation time. Extending the detector, on the other hand, is less straightforward. As far as the photometric deformations are concerned, we assume a simple linear model with an offset (bias) and contrast change (scale factor). Neither detector nor descriptor use color information. Followings are its structures. In Section 2, we give a review over previous work in interest point detection and description. In Section 3, we describe the method applied to detect interest point very fast and robust. The input image is analyzed at different scales in order to give independent of scale change. The detected interest points are given with a rotation as well as scale-invariant description in Section 4. Furthermore, a simple and efficient first-line indexing technique, based on how the interest point with its surrounding, is proposed. In Section 5, some of the available parameters and their effects are discussed, including the benefits of an upright version (not invariant to image rotation). We also investigate how SURF's performance is important in two application scenarios. The case of image registration is first considered. It is the problem of camera calibration for 3Dreconstruction. SURF's application to an object recognition experiment is the second step. Both applications highlight SURF's benefits. The benefits are in terms of speed and robustness. It is opposed to other strategies. Section 6 shows the conclusion of this article.

RELATED WORK

3. Related Work

3.1 PCA

PCA is a standard technique that is used to approximate the original data with lower dimensional feature vectors. The basic approach [1] is to compute the eigenvectors of the covariance matrix, and approximate the original data by a linear combination of leading eigenvectors. These leading Eigen vectors are also called as Eigen faces because these are the principal components of the set of faces.

Although PCA is the basis for a lot of techniques that are available today, it has several limitations

1. An Eigen feature, [3] however may represent aspects of the image which are unrelated to recognition such as illumination direction. Hence, an increase or decrease in number of Eigen vectors that are used does not necessarily lead to an improved success rate.
2. Changes in expression may lead to a large variation in the Eigen vectors of the same subject.
3. Camera angle and head pose, which may lead to rotation also reduce the performance of this method drastically.

This paper includes two variations of PCA, PCA Euclidean and PCA MahCosine based upon the method used in distance measurement for the purpose of testing.

3.2 LDA

This algorithm uses Fisher's Linear Discriminants for classification. LDA mainly tries to produce linear transformations that emphasize difference between classes while reducing difference within classes. The goal is to form a subspace that is linearly separable between classes. LDA takes care of scatter in between classes more using the Most Discriminating features [3] while PCA takes care of scatter within classes using the Most Expressive features. Although LDA is developed as a better alternative to PCA, when there are a small number of subjects within each class, PCA outperforms LDA.

In this paper, we have included two methods of LDA, of which, both perform PCA, first to reduce the number of feature vectors and then perform LDA.

1. LDA soft, which is a soft distance measure, essentially the L2 norm with each axis weighted by the associated generalized Eigen value used to find the Fisher basis vectors.
2. LDA Euclidean which uses the general Euclidean measure as distance metric

3.3 Other Approaches

There are a lot of other approaches proposed in the recent years such as the Bayesian Intrapersonal/ Extra personal Classifier developed by Moghaddam and Pentland [4], Elastic Bunch Graph Matching algorithm and many others. But since these algorithms are much in development stages and are not considered standard by most of the researchers, we have excluded these algorithms from our tests.

PROPOSED APPROACH

4. Proposed Approach

4.1 Preprocessing

Before applying SURF, we have preprocessed the images taken from the color FERET database that are used for testing purpose as stated in the documentation of color FERET database [5].

Face detection - Eye Center Coordinates

In order to do the face detection, and normalize the images as explained in the next section the eye center coordinates of both the eyes are need to be determined. We constructed a haar classifier based program to perform the eye detection and use that data to calculate the eye center coordinates. Out of the 2722 images tested, it gave false positives for 631 images. For those images, we used GIMP photo manager, to manually hand mark the eye center coordinates.

Face Normalization

For normalization, we used the CSU face evaluation system by supplying the eye center coordinates calculated as discussed in the previous section. The normalization schedule is as follows [7]

1. Integer to float conversion -It converts 256 gray levels into floating point equivalents.
2. Geometric normalization – It lines up human chosen eye coordinates.
3. Masking – It crops the image using an elliptical mask and image borders in such a way that only the face from forehead to chin and cheek to cheek is visible to us.
4. Histogram equalization – It equalizes the histogram of the unmasked part of the image.
5. Pixel normalization – It scales the pixel values to have a mean of zero and a standard deviation of one.

This completes the process of normalization and it gives images in three formats-

1. NRM
2. SFI
3. PGM

Of these the images in PGM (Portable Grey Map) are viewable. An example of the original image and its normalized PGM image are shown in figure -1. NRM format is the legacy format in old NIST normalization code. The 1996 FERET evaluations used this format. But the algorithms prepared using CSU Face Evaluation System use images in the SFI(Structured Field Introducers) format which is created at CSU as a floating point variant of PGM(Portable Grey Map). It is similar to the NRM, only with an additional header. After the calculation of normalized images, we used SURF approach for feature extraction as explained in the sub sequent sections.

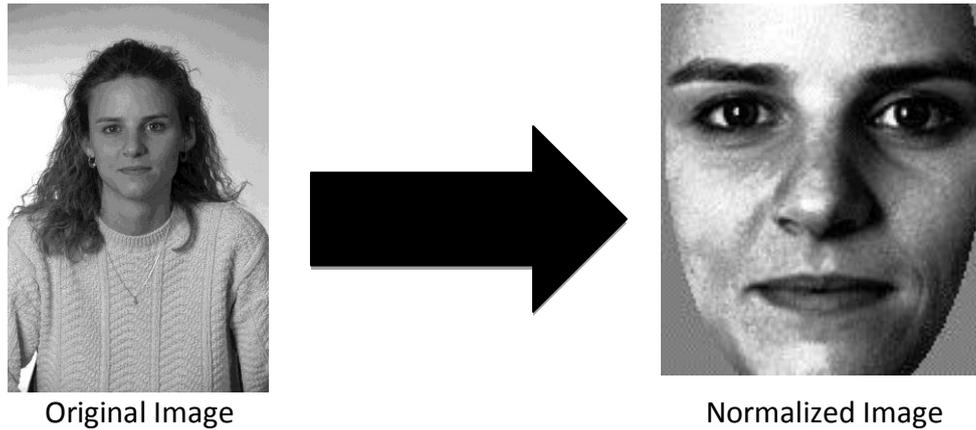


Figure - 1

SURF (Speeded-up Robust Features)

5 Feature Extraction - SURF (Speeded-up Robust Features)

SURF is an approach generally used to construct a robust image detector and descriptor that can be used in computer vision tasks like object recognition and 3D reconstruction [9]. SURF is based on approximated 2D Haar wavelet responses and makes better use of integral images.

It utilizes an integer approximation to the determinant of Hessian blob detector, which can be computed extremely fast with the use of integral image. For features, it uses the sum of Haar wavelet responses around the point of interest. Again these can be computed with the aid of integral image.

Interest point detection

We are using Hessian matrix approximation to find out the interesting points. So it is obvious to use integral images as given by Viola and Jones [11]. It makes computation time very less. Integral images fit in the more general framework of box lets. It is proposed by Simard et al. [8].

5.1 Integral images

Here we used to make the article more self-contained, we briefly discuss how and what the integral images are. They allow for fast computation of box type convolution filters. At location $\mathbf{x} = (x, y)$ \mathbf{T} . It represents the sum of all pixels in the input image I bounded by a rectangular region formed by the origin and x . The length and breadth of the rectangle will be like this.

If the point X having coordinate (x, y) . And

Length= x ;

Breadth= y ;

Here the top-left corner is taken as the origin and along right wards it is taken as X-axis and along top-down wards it is taken as Y-axis.

$$I_{\Sigma}(x, y) = \sum_{i=0}^{i \leq x} \sum_{j=0}^{j \leq y} I(x, y)$$

Where $0 < i < x$ and $0 < j < y$;

Once the integral image has been computed, it takes three additions to calculate the sum of the intensities over any upright, rectangular area (see Fig. 1). Hence, the calculation time is independent of its size. This is important in our approach, as we use big filter sizes.

Hessian matrix-based interest points

We can claim our base depending on Hessian matrix detector because its performance is good in accuracy. Mostly speaking, blob-like structures are detected. These are the locations having maximum determinant value. In opposite to the Hessian-Laplace detector by Mikolajczyk and Schmid [6], we focus on the determinant of the Hessian. It is also for the scale selection, as done by Lindeberg [9].

Let us say a point $x=(x, y)$ in an image I , the Hessian matrix in x at scale r is defined as follows-

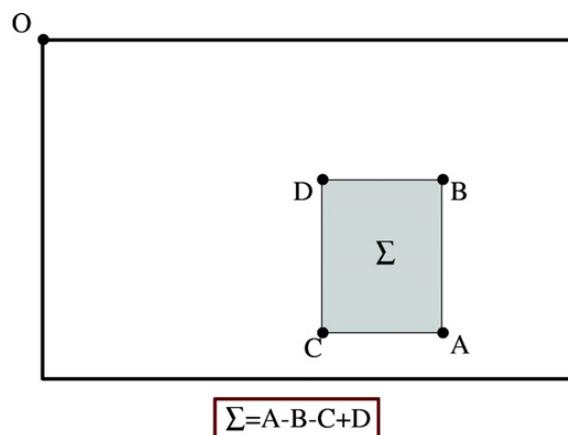


Fig.1. Using integral images, it takes only three additions and four memory accesses to calculate the sum of intensities inside a rectangular region of any size.

The SURF detector is based up on the determinant of the Hessian matrix. In order to utilize the use of the Hessian, [9] we considered a continuous function of two variables in such a way that the value of the function at (x, y) is given by $f(x, y)$. The Hessian matrix, H , is the matrix of partial derivatives of the function f .

$$H(f(x, y)) = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial x \partial y} & \frac{\partial^2 f}{\partial y^2} \end{bmatrix}$$

The determinant of this matrix is known as the discriminant and is calculated by:

$$\det(H) = \frac{\partial^2 f}{\partial x^2} \frac{\partial^2 f}{\partial y^2} - \left(\frac{\partial^2 f}{\partial x \partial y} \right)^2$$

The values of the discriminants are used to classify the maximum and minimum value of the function by the second order derivative test. Since the determinant is the product of eigenvalues of the Hessian, so we can classify the points based on the sign of the result. If the determinant is negative then the eigenvalues have different signs and hence the point is not a local extreme; if it is positive then either both eigenvalues are positive or both are negative and in either case the point is classified as an extreme.

First we replace the function values $f(x, y)$ by the image pixel intensities $I(x, y)$. Next we need a method to calculate the second order partial derivatives of the images. We can calculate the derivatives by convolution with an appropriate kernel. In case of SURF the second order scale normalized Gaussian is the chosen filter as it allows for analysis over the scales as well as the space.[10]

We can now calculate the Hessian matrix H , as function of both space $X = (x,y)$ and scale σ .

$$H(\mathbf{x}, \sigma) = \begin{bmatrix} L_{xx}(\mathbf{x}, \sigma) & L_{xy}(\mathbf{x}, \sigma) \\ L_{xy}(\mathbf{x}, \sigma) & L_{yy}(\mathbf{x}, \sigma) \end{bmatrix},$$

Here $L_{xx}(x, \sigma)$ is the convolution of second order derivative $\frac{\partial^2 g(\sigma)}{\partial x^2}$ with the image at point $X = (x,y)$ and similarly for $L_{xy}(x, \sigma)$ and $L_{yy}(x,\sigma)$.

The weights applied to the rectangular region are kept simple for computational efficiency.

Interest point description and matching

The SURF descriptor describes how the pixel intensities are distributed within a scale dependent neighborhood of each interest point detected by the Fast-Hessian. This approach is similar to that of SIFT but integral images used in conjunction with filters known as Haar wavelets are used in order to increase robustness and decrease computation time. Haar wavelets are simple filters which can be used to find gradients in the x and y directions.

5.2 Detector – descriptor Scheme:

This can be decomposed into three parts -

1. Fixing a reproducible orientation based on information from a circular region around the interest point.
2. Construct a square region aligned to the selected orientation and extract the SURF descriptor from it.

3. Finally features are matched between the two images.

Orientation Assignment

In order to achieve invariance to image rotation each detected interest point is assigned a reproducible orientation as given in OpenSURF Library[10]. Extraction of the descriptor components is performed relative to this direction so it is important that this direction is found to be repeatable under varying conditions. To determine the orientation, Haar wavelet responses of size 4σ are calculated for a set pixel within a radius of 6σ of the detected point, where σ refers to the scale at which the point was detected. The specific set of pixels is determined by sampling those from within the circle using a step size of σ .

Representation of Scale space

Interest points are necessary to be found at different scales, not least because the search of correspondences often requires their comparison in images where they are seen at different scales. Scale spaces are usually implemented just like a pyramid of image. The images are constantly smoothed with a Gaussian and then sub-sampled in order to achieve a strong pyramid. Lowe [4] subtracts these pyramid layers.

The main reason is to get the DoG (Difference of Gaussians) images where we can find edges and blobs. As we are using box filters as well as integral images, we do not need to apply again and again the same filter to the output of a previously filtered layer. But instead of this we can apply box filters of any size at exactly the same speed directly and even in parallel (although the latter is not exploited here).

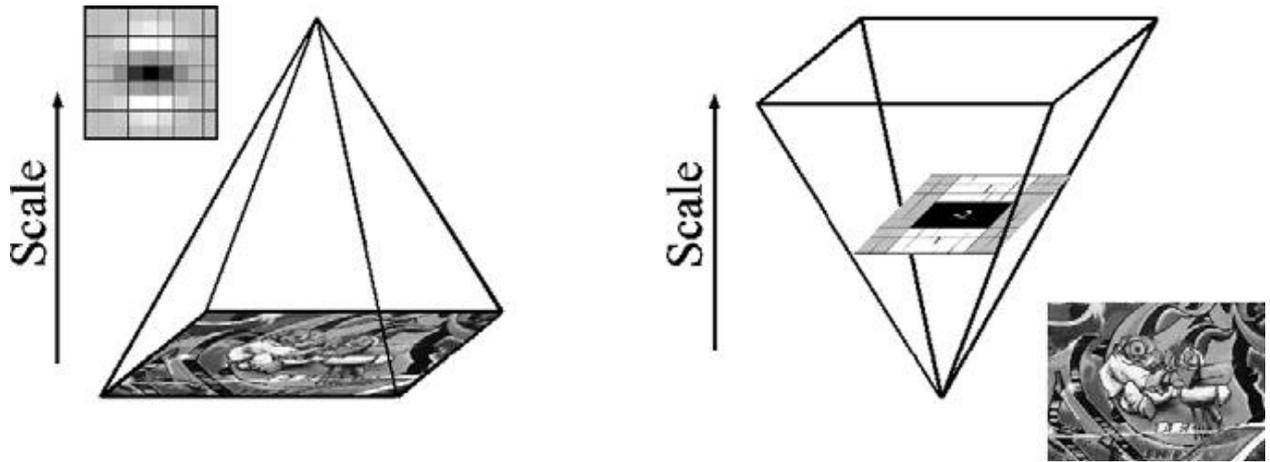


Fig.2. Rather than using repetitively reducing the image size (left), the use of integral images allows the up-scaling of the filter at constant cost (right).

Descriptor Component

The first step in extracting the SURF descriptor is to construct a square window around the interest point. This window contains the pixels which will form entries in the descriptor vector and is of size 20σ , again where σ refers to the detected scale. Furthermore the window is oriented along the direction found in orientation assignment such that all subsequent calculations are relative to this direction.

The descriptor window is divided into 4×4 regular sub-regions. Within each of these sub-regions Haar wavelets of size 2σ are calculated for 25 regularly distributed sample points. If we refer to the x and y wavelet responses by dx and dy respectively then for these 25 sample points (i.e. each sub-region) we collect, [9].

$$v_{subregion} = [\sum dx, \sum dy, \sum |dx|, \sum |dy|]$$

Therefore each sub-region contributes four values to the descriptor vector leading to an overall vector of length $4 \times 4 \times 4 = 64$. The resulting SURF descriptor is invariant to rotation, scale, brightness and, after reduction to unit length.

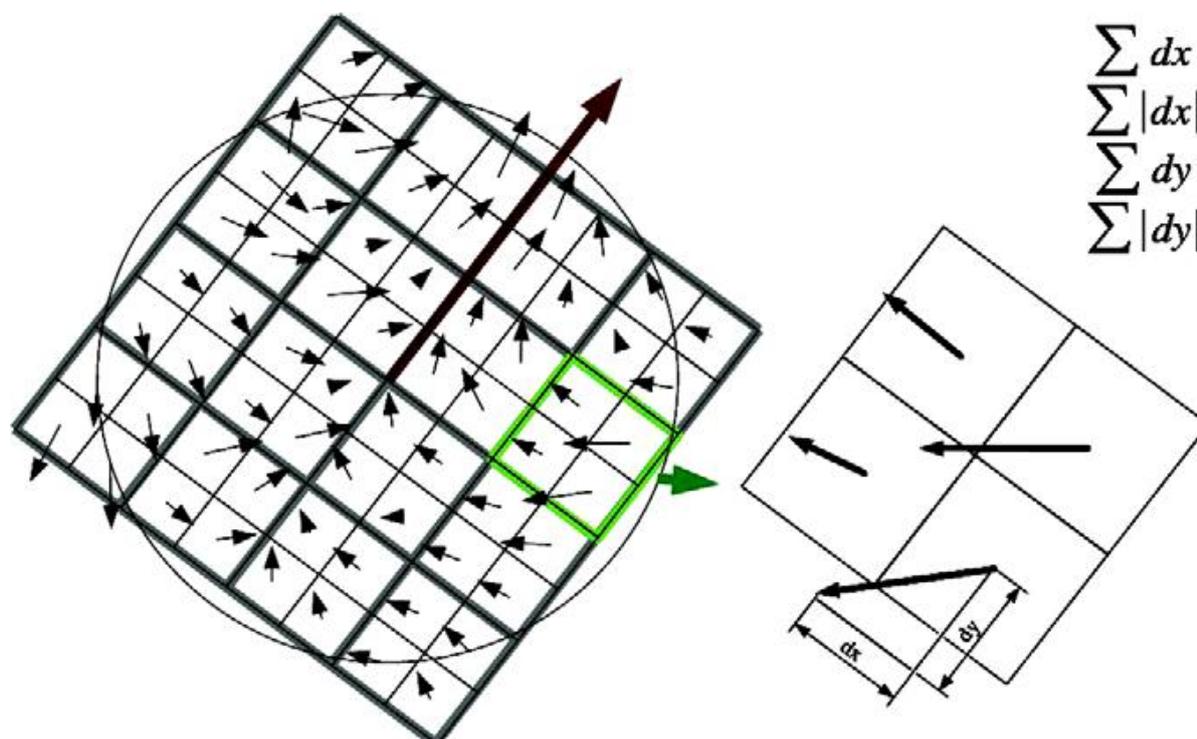


Fig. 3. To build the descriptor, an oriented quadratic grid with 4×4 . square sub-regions is laid over the interest point.

Feature Matching

For fast indexing during the matching stage, the sign of the trace of Hessian matrix for the underlying interest point is included. If the contrast between two interest point is different, the candidate is not considered a valuable match.

5.3 Storing feature vectors We need to store the vectors of key points and descriptors related to each and every image of the testing color FERET data set. We used the above SURF based

method to construct an algorithm. Then we constructed a program based on that algorithm to extract these features in the form of vectors and store them in plain text files.

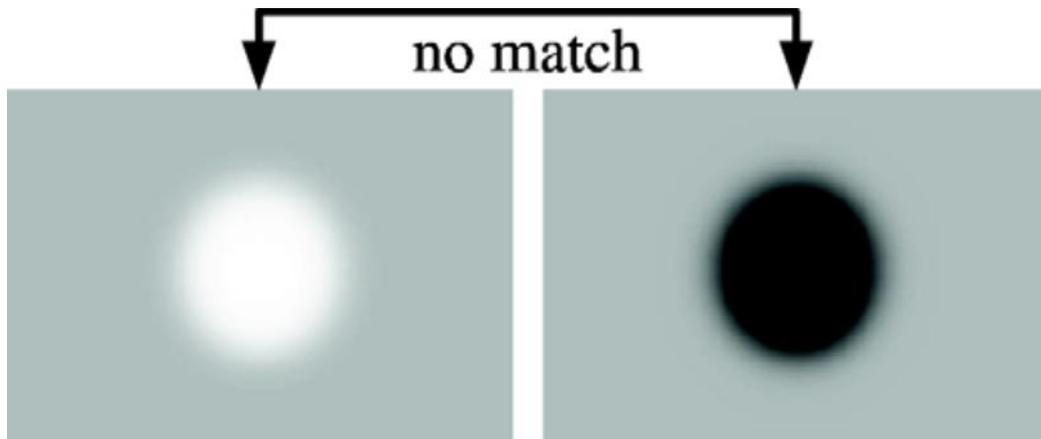


Fig.4. If the contrast between two interest points is different (dark on light background vs. light on dark background), the candidate is not considered a valuable match.

5.4 Retrieving of feature vectors and calculation of results

We constructed an algorithm and then a program using it, to retrieve the feature vectors stored, as shown in the previous section. Then we used a special procedure to perform the face recognition as described below

1. We assume that we have been given a probe image and a set of gallery images
2. Then we proceed by finding the nearest neighbors of the probe image within the gallery image set
3. Now we will consider a parameter called recognition rank [8]. As per this concept, the rank is the number of nearest neighbors we take into consideration, while calculating the results. That is, if the rank is five, we take only five nearest neighbors of the probe image within the gallery set and if it contains an image of the same subject as the probe, we consider that a hit, if not, we consider that a miss

4. In this way, we extend the above procedure to all the probe images and calculate their recognition performance
5. Finally based upon the recognition rank and the hit rate, we plot the algorithm as a function of Hit rate vs. Recognition rank using special type of curves called Cumulative Match Curves (CMC)

The Cumulative Match Curves obtained finally are as shown in Figure -4 and Figure-5

6. Experiment

6.1 Arrangements for the experiments

Database

The CSU Face Evaluation system is modified a little to use the gallery and probe sets that are mentioned in the documentation of color FERET database [5]. The following table illustrates the counts of different types of images and the explanation about them can be found in the subsequent sections.

Type	Number of images
fa set	994
fb set	992
dup-1 set	736
dup-2 set	228

Gallery

Gallery contains the set of known individuals for a given algorithm. All the images of fa set (994 images) are taken as gallery. This set contains images taken in the first session and contains one image per subject and hence is apt for the gallery.

Probe

Probe set contains the set of individuals which need to be identified within the given gallery set. As mentioned in the documentation of the color FERET database [5], there are three probe sets that need to be identifies as mentioned below

Probe-1 (FB probe)

The Probe-1 set contains all the images from the fb set (992 images) which is used as a first probe set. This set contains images taken at a session immediately after the first session, but with a change in the expression pertaining to the face.

Probe-2 (Dup-1 Probe)

This Probe-2 set contains all the images from the dup-1 set (736 images) which is used as a second probe set. This set contains images, taken at a later session other than the sessions of fa and fb sets. This may span from one day to two – three years.

Probe-3 (Dup-2 Probe)

The Probe-3 set contains all the images from the dup-2 set (228 images) which are used as a third and final probe set. This set contains the images, taken at a later session other than the sessions of fa and fb sets but fall within the range of one and half years (540 days approx.). Hence this set is a subset of Dup-1 probe set.

6.2 Environment

We conducted the experiments in the following environment

Operating System	Ubuntu 10.10
------------------	--------------

Libraries used	OpenCV
Programming Language	ANSI C, Shell Scripting
Processor	2 GHZ Dual Core
RAM	2 GB
Database	FERET color testing dataset
Compiler	GCC
Other Softwares/Packages	CSU Face Evaluation System, GIMP

7. Setup of the algorithm and Results

The CSU face identification evaluation system is used to test the performance of the proposed algorithm with that of the existing algorithms. The system follows the procedure of the FERET test for semi-automatic face recognition algorithms [7] with slight modifications. Although the original FERET tests were performed on the grey FERET database [2] , we tweaked the system a little to perform the tests on color FERET database in order to be more near with the real world scenario. But we followed the rules that are needed to be followed when doing the experiments on color FERET database [5] as stated in the documentation of the color FERET database. Also since the CSU Face Evaluation system only works with grey scale images, we used the program “Image Magick” to convert the colored images in JPEG format to grey scale images in PGM format and supplied to the system.

The algorithms of PCA and LDA that are tested are the standard algorithms provided as part of the CSU face evaluation system. All use the normalized images that are obtained from the preprocessing of images from the standard color FERET testing datasets as mentioned in the previous section.

The SURF based algorithm that we developed also uses the normalized images as part of the anomaly. We can say that the SURF based method outperformed all the other methods in extracting features and distance calculation in terms of speed. The Cumulative Match curves

of only our SURF based approach are shown in Figure-6 and the Cumulative Match Curves of SURF vs. the standard algorithms is shown in Figure-8.

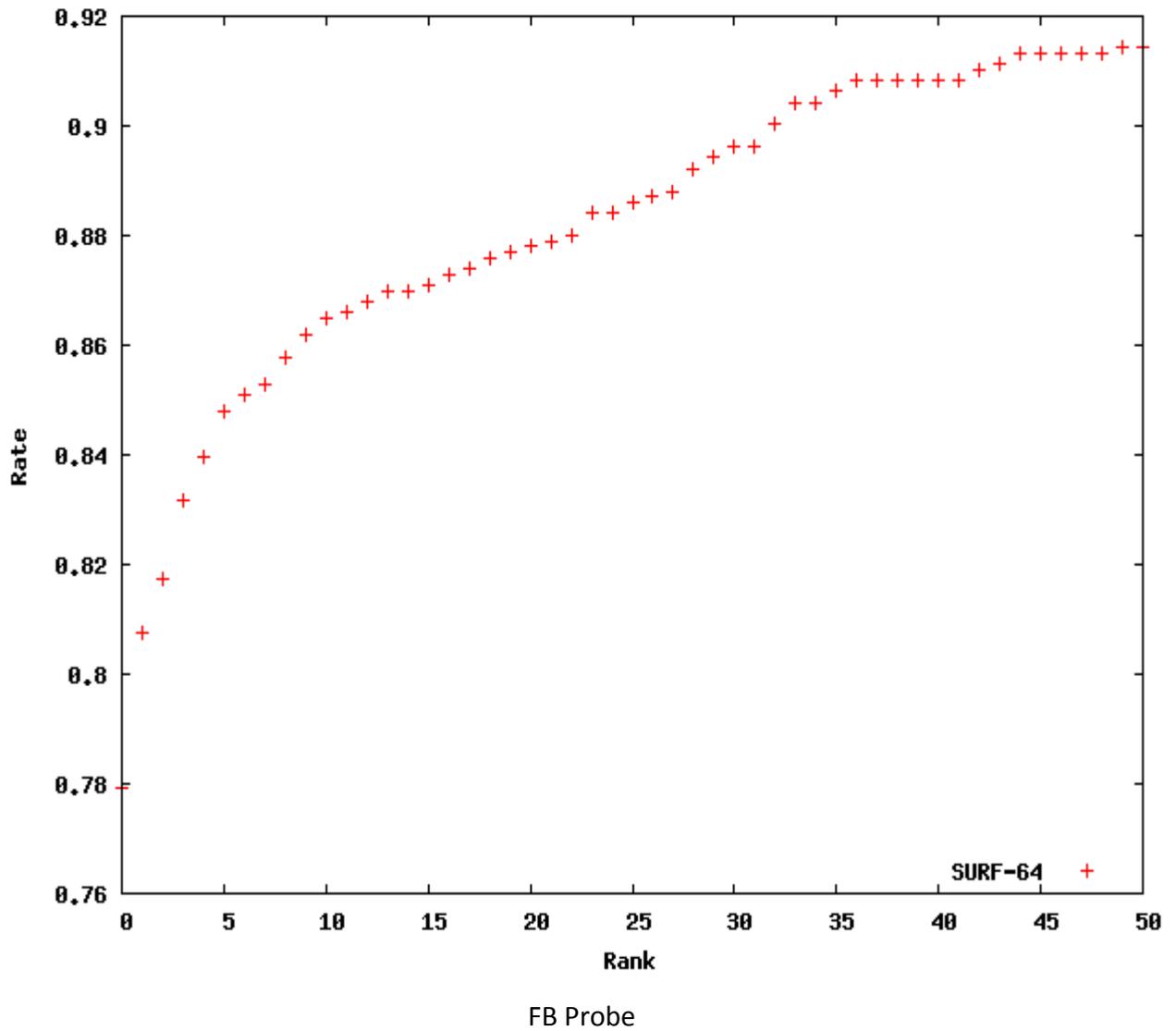
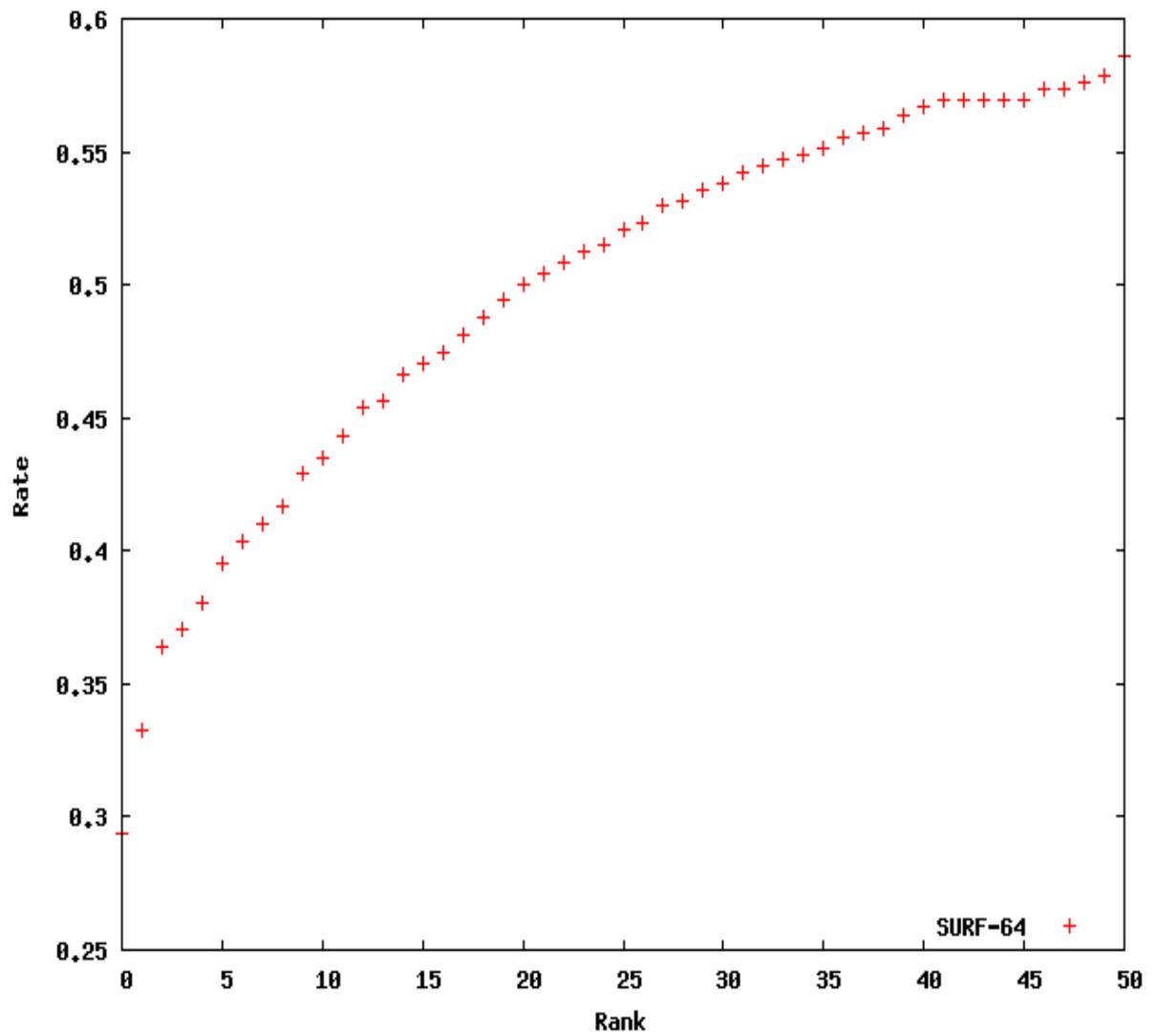


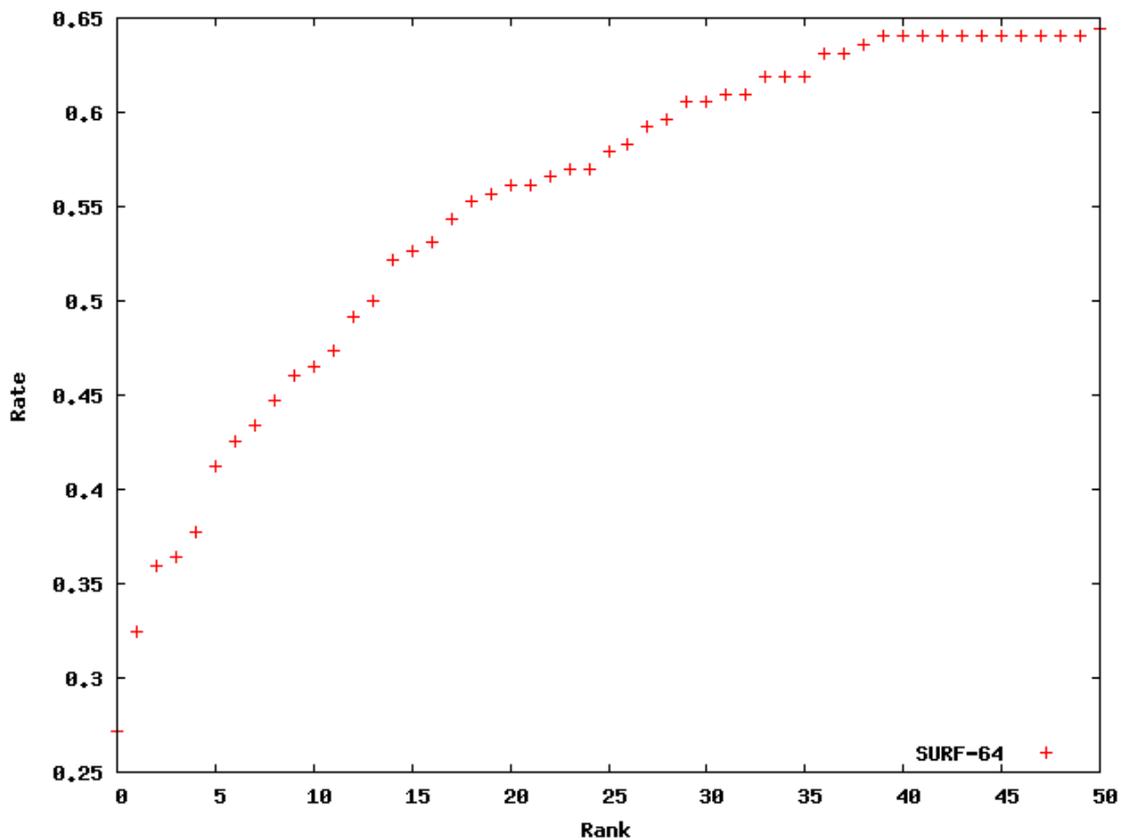
Fig.5. Graphs showing the Recognition rank vs Hit rate for SURF based face recognition algorithm for FB probe set.



Dup-1 Probe

Fig. 6. Graphs showing the Recognition rank vs Hit rate for SURF based face recognition algorithm

for Dup-1 probe set.



Dup-2 Probe

Fig.7. Graphs showing the Recognition rank vs Hit rate for SURF based face recognition algorithm

Since there is not much time left with us, we made the program, but we hadn't tuned it as the research people have tuned the corresponding PCA and LDA. Although this shows a decrease in performance of our proposed SURF based approach, it gives the consistent performance as is evident from the Cumulative Match Curves of Figure-7.

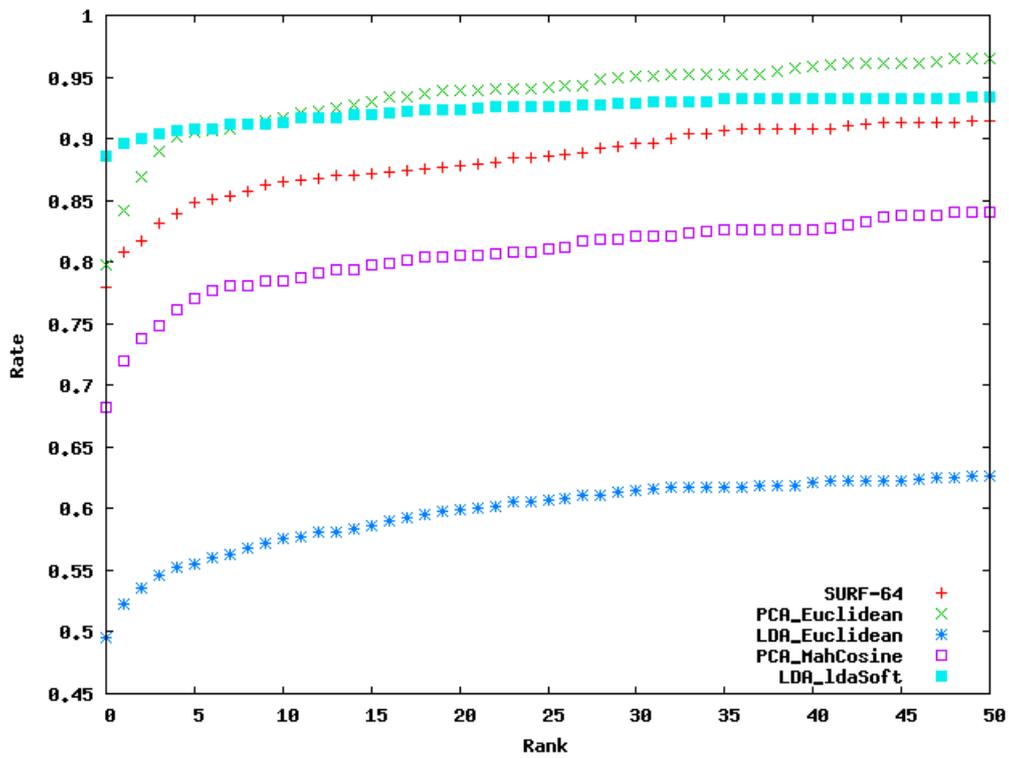
In figure-6, we have included a table showing the hit rate and penetration rate at different recognition ranks for the FB probe set to provide an overview of the performance of SURF based face recognition system. The hit rate and Penetration rate are calculated as shown in the following equations

Hit rate at a Recognition Rank

$$= \frac{\text{Number of Gallery Images correctly detected at the recognition rank}}{\text{Total number of Gallery Images}}$$

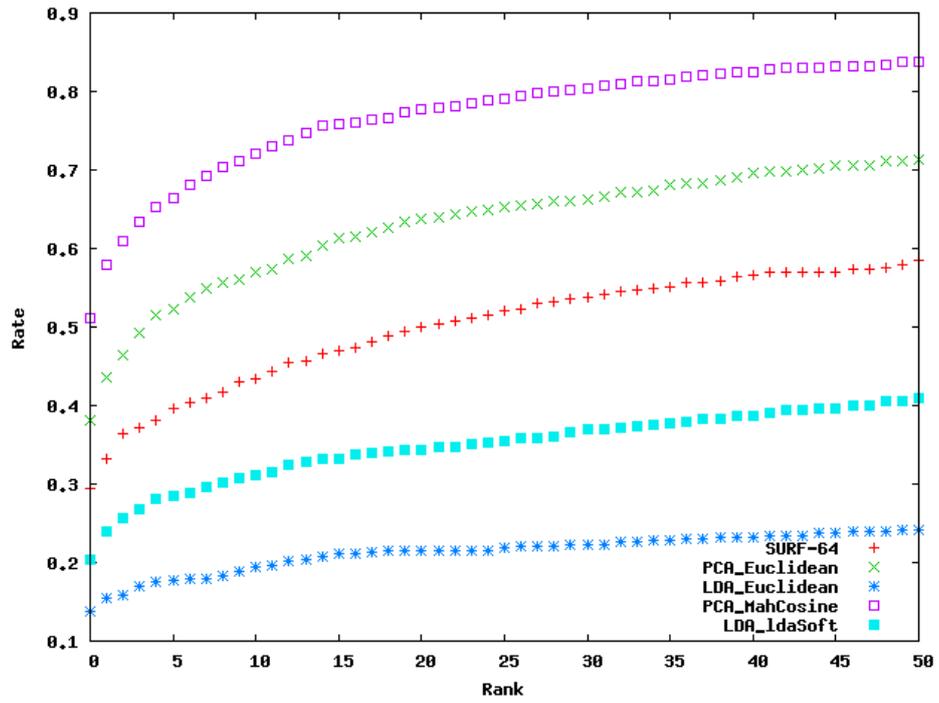
Penetration rate at a Recognition Rank

$$= \frac{\text{Recognition rank}}{\text{Number of Gallery Images correctly detected at the recognition rank}}$$

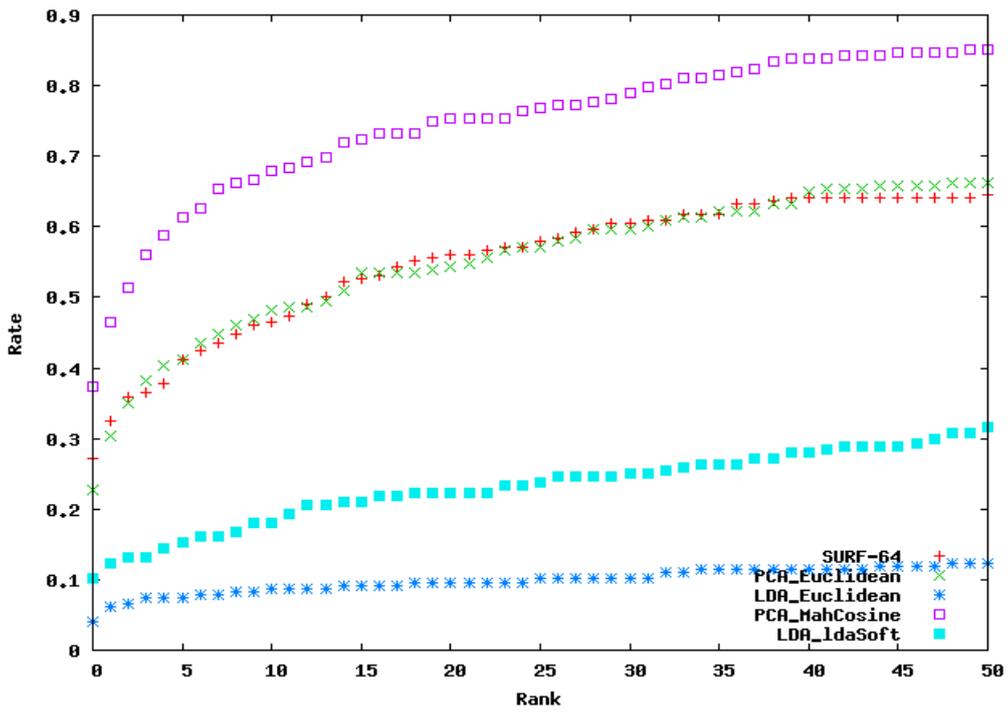


FB Probe

Fig.8. Graphs showing the Recognition rank vs. Hit rate for SURF based face recognition algorithm in comparison with other standard algorithms for FB probe set.



Dup-1 Probe



Dup-2 Probe

8. Discussion and Future work

It should be noted that we did not use the original programs that were framed during the discovery of the PCA and LDA algorithms, but the refined programs at CSU for testing purpose. As is noted in the CSU face evaluation paper [7], there is a lot of significant improvement of the four algorithms that are tested along with the SURF and their performance is so high, when compared to the original programs tested during FERET tests. This suggests that tuning plays a very important role and our proposed approach, if tuned will definitely outperform other approaches.

Rank	Hit rate	Penetration rate
1	0.779234	0.001248
50	0.914315	0.055126
100	0.939516	0.107296
150	0.954637	0.158394
200	0.963710	0.209205

Figure - 9: Performance of SURF algorithm on FB
Probe set

We are planning to make a real time system based on this SURF based approach for face recognition and put it into test with the available systems. Also this work can be extended to work with all the feature variables that we could get from a descriptor (we used 64, but it is possible to get 128 variables of each descriptor are possible), so that the system becomes more robust and if possible, perform the FERET tests again and produce the results in another paper.

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