ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 2, Issue 1, January 2014

BLUR AND ILLUMINATION ROBUST FACE RECOGNITION USING BAYES CLASSIFIER

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Abstract-Human face recognition by computer systems has become a major field of interest. Face recognition algorithms are used in a wide range of applications like security control, video retrieving, Biometric signal processing, human computer interface, image database management, etc. It is difficult to develop a complete robust face detector due to various light operating conditions, different face sizes and face orientations, background and skin colors. This paper, proposes a face recognition method for locate the problem of unconstrained face recognition from remotely acquired images. The main factors to affect this system is challenging are image degradation due to blur, appearance variations due to illumination and pose. In this paper, using a blur-robust algorithm based on PCA with Euclidian(K-NN) Classifier, is a non-parametric method for classification and regression, which predicts objects' "values" or class memberships based on the Nth closest sampled examples in the feature space. In Future of the work propose a blur-robust algorithm based on Eigen Face with Bayes classifier whose main step involves a simple probabilistic classifier based on applying Bayes' theorem with strong independence assumptions. Finally to compare both the face recognition methods and prove that the proposed method is better by overcoming the disadvantages of existing method. A computer simulation using MATLAB/SIMULINK confirms the predicted results.

1. INTRODUCTION

1.1 FACE RECOGNITION

.The recognition of faces is very important for many applications: video The face is considered a good biometric for many reasons: the acquisition process is non intrusive and does not require collaboration of the subject to be recognised.. On the other hand, many problems arise, because of the variability of many parameters: face expression, pose, scale, lighting, and other environmental parameters. For this reason, the applications which involve face recognition can be subdivided in two fields:

1) Face verification
2) Face identification

The aim of the system is to verify the matching between the claimed identity and the given biometric. This kind of applications is typical for internet transactions, driver's licenses and access to limited areas..

1.2 PROCESS OF FACE RECOGNITION

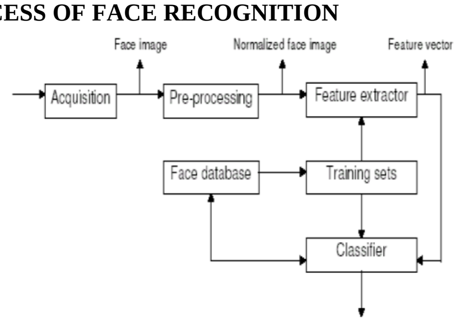

Figure 1.1 Facial Recognition System

Facial recognition system usually consist of four steps, as shown in Figure 1.1 face detection (localization), face preprocessing (face alignment /normalization, light correction and etc.), feature extraction and feature matching.

The aim of face detection is localization of the face in an image. In the case of video input, it can be an advantage to track the face in between multiple frames, to reduce computational time and preserve the identity of a face (person) between frames. Methods used for face detection includes: Shape templates, neural networks and Active Appearance Model. The aim of the face preprocessing step is to normalize the coarse face detection, Depending of the application, face preprocessing includes: Alignment (translation, rotation, scaling) and light normalization/correlation. The aim of feature extraction is to extract a compact set of interpersonal discriminating geometrical or/and photometrical features of the face. Methods for feature extraction include: PCA, LDA and Locality Preserving Projections. Feature matching is the actual recognition process. The feature vector obtained from the feature extraction is matched to classes (persons) of facial images already enrolled in a database.

1.2.1 FACE RECOGNITION APPROACHES

The image based face recognition has classified into Appearance-based face recognition and Model-based face recognition show in figure 2. Appearance based face recognition further classified into linear and non-linear analysis. The Classical linear appearance-based analysis – Principal Component Analysis (PCA), Incremental Component Analysis (ICA) and Linear Discriminate Analysis

ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526

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INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 2, Issue 1, January 2014

(LDA) each has its own basis vectors of a high dimensional face image space.

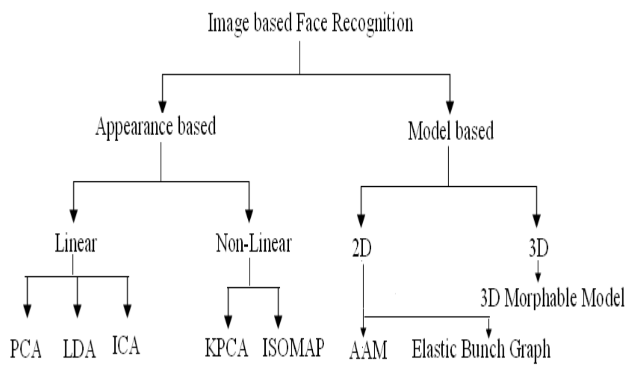

Figure 1.2 Classification of Face Recognition

The Classical linear appearance-based analysis – Principal Component Analysis (PCA), Incremental Component Analysis (ICA) and Linear Discriminate Analysis (LDA) each has its own basis vectors of a high dimensional face image space.

1.2.2 HUMAN RECOGNITION

Biometric identification is the technique of automatically identifying or verifying an individual by a physical characteristic or personal trait. The term "automatically" means the biometric identification system must identify or verify a human characteristic or trait quickly with little or no intervention from the user. Biometric technology was developed for use in high-level security systems and law enforcement markets. The key element of biometric .One of the newest biometric technologies, automatic facial recognition, is based on this phenomenon. Facial recognition is the most successful form of human surveillance. Inorder to improve human efficiency face recognition technology is being used.

1.3 PERFORMANCE EVALUATION METRICS

Pose changes affect the authentication process, because it introduces projective deformation and self-occlusion. Even if methods dealing with up to 32_ head rotation exist, that methods do not solve the problem considering that security cameras can create viewing angles that are outside of this range when positioned..

Another important factor is the time delay, because the face changes over time, in a nonlinear way over long periods. In general this problem is harder to solve with respect to the others and not much has been done especially for age variations.The two standard biometric measures to indicate the identifying power are

- False Rejection Rate (FRR)
- False Acceptance Rate(FAR)
-

1.3 SPARSE REPRESENTATION

The technique, called sparse representation issued to provide new solution, to use computer program to classify human identity using frontal face images, i.e., the well-known problem of face recognition.

The basic idea is to cast recognition as a *sparse representation* problem, in which compressed sensing and L1 minimization Uses as a new mathematical tools This leads to highly robust, scalable algorithms for face recognition based on linear or convex programming. This algorithm produce effective striking results, by accurately recognizing large databases despite severe corruption and occlusion. The theory of sparse representation gives us a computationally tractable method to compute the sparse solution.

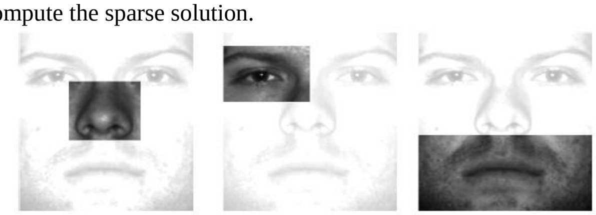

Fig.1.3 Illustration of the three partial features.

In the statistical signal processing field, the problem of algorithmic computing sparse linear representations with respect to an over complete dictionary of base elements or signal atoms has seen a recent surge of interest . The discriminative nature of sparse representation to perform classification. Instead of using the well-defined dictionaries, the test sample are represented in an over complete dictionary whose base elements are the training samples themselves.

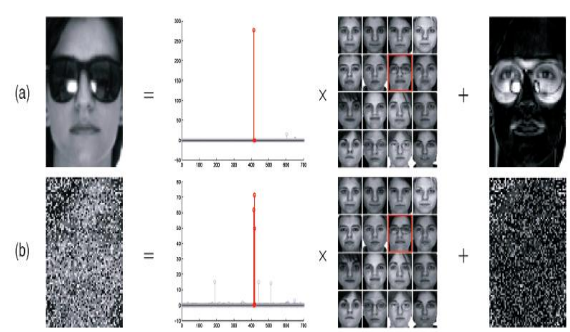

Fig.1.3.1 Overview of our approach.

The proposed classifier can be considered a generalization of popular classifiers such as nearest neighbor (NN) and nearest subspace (NS) (i.e., minimum distance to the subspace spanned all training samples from each object class). NN classifies the test sample based on the best representation in terms of a single training sample, whereas NS classifies based on the best linear representation in terms of all the training samples in each class..

The theory of sparse representation and compressed sensing yields new insights into two crucial issues in automatic face recognition: the role of feature extraction and the difficulty due to occlusion.

1.4 FEATURE EXTRACTION

Feature extraction is one of the most widely employed methods for reducing the data dimensionality. The two major categories of dimensionality reduction techniques. The first

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ISSN (Print) 2321 – 5526
INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 2, Issue 1, January 2014

category utilizes an unsupervised setting, with Principal Component Analysis being one of the most well-known methods. The second category employs the supervised setting, with Linear Discriminant Analysis being one of the most well-known methods.

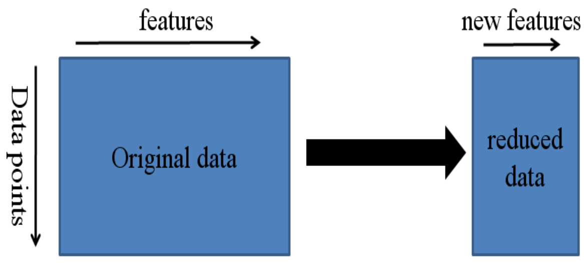

Fig.1.4 Feature extraction

An enormous volume of literature has been devoted to investigate various data-dependent feature transformations for projecting the high-dimensional test image into lowerdimensionalfeaturespaces: examplesincludeEigenfaces, Fisherfaces, Laplacianfaces, and a host of variants. Even random features contain enough information to recover the sparse representation and hence correctly classify any types of test image, in which the critical is that the dimension of the feature space is sufficiently large and that the sparse representation is correctly computed.

2. PROPOSED SYSTEM

2.1 THE PRINCIPAL COMPONENT ANALYSIS (PCA)

The Principal Component Analysis (PCA) is one of the most successful techniques that have been used in image recognition and compression. PCA is a statistical method under the broad title of *factor analysis*. The purpose of PCA is to reduce the large dimensionality of the data space (observed variables) to the smaller intrinsic dimensionality of feature space (independent Variables), which are needed to describe the data economically.

2.1.1 COMPUTATION

Once the eigenfaces have been computed, several types of decision can be made depending on the application. What we call face recognition is a broad term which may be further specified to one of following tasks:

• Identification where the labels of individuals must be obtained.

• Recognition of a person, where it must be decided if the individual has already been seen,

• Categorization where the face must be assigned to a certain class.

The system computes its distance from all the stored faces. However, two issues should be carefully considered:

1. What if the image presented to the system is not a face?

2. What if the face presented to the system has not already?

learned, i.e., not stored as a known face?

The first defect is easily avoided since the first eigenface is a good face filter which can test whether each image is highly correlated with itself. Low correlation images are rejected Or both issues are altogether addressed by categorizing following four different regions:

1. Near face space and near stored face =⇒ known faces

2. Near face space but not near a known face =⇒ unknown faces

3. Distant from face space and near a face class =⇒ non-faces

4. Distant from face space and not near a known class =⇒ non-

Faces

An experiment with a subset of 12 subject's images, database, has been performed to ensure how well the eigenface system can identify each individual's face. Please note that this experiment is not exhaustive for the database. The system has been implemented by MATLAB. 10 subjects are selected as training set and other 2 subjects are the part of test set, which should be classified as unknown faces. There are 5 additional test images, each of which is the known face. I also appended 2 non-face images to test whether it can detect them correctly. The experiment told me that the identification of known faces is quite good, which is comparable to the case of larger dimensions of *M*. That it, we can express the face image data in much smaller dimensions with the help of some prominent basis vectors, which in fact reflect maximum variability.

2.2 DIRECT RECOGNITION OF BLURRED FACES (DRBF):

Here first review the convolution model for blur. Next, show that the set of all images obtained by blurring a given image is convex and finally we present our algorithm for recognizing blurred faces.

2.2.1 Convolution Model for Blur

A pixel in a blurred image is a weighted average of the pixel's neighborhood in the original sharp image. Thus, blur is modeled as a convolution operation between the original image and a blur filter kernel which represents the weights. Blur kernels also satisfy the following properties- their coefficients are non-negative ≥ 0, and sum up to 1()The blur kernel may possess additional structure depending on the type of blur (such as circular-symmetry for out-of focus blurs), and these structures could be exploited during recognition.

2.2.2 Set of All Blurred Images

We want to characterize the set of all images obtained by blurring a given image I. To do this we re-write (3.1) in a matrix-vector form. Let h ∈R(2k+1)2 be the vector obtained by concatenating the columns of H, i.e., h = H(:) in MATLAB notation, and similarly ib = Ib(:) ∈ RN be the representation of Ib in

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ISSN (Print) 2321 – 5526

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 2, Issue 1, January 2014

the vector form, where N is the number of pixels in the blurred image.

We have the following result about the set B.

Proposition 2.1: The set of all images B obtained by blurring an image I is a convex set. Moreover, this convex set is given by the convex hull of the columns of matrix A, where the columns of A are various shifted versions of I as determined by the blur kernel.

Proof: Let i1 and i2 be elements from the set B. Then there exists h1 and h2, with both satisfying the conditions $h \geq 0$and $h1 = 1$, such that i1 = Ah1 and i2 = Ah2. To show that the set B is convex we need to show that for any λ satisfying$0 \leq \lambda \leq 1$, $i3 = \lambda i1 + (1 - \lambda)i2$ is an element of B. Now

$$
\begin{aligned}
i3 &= \lambda i1 + (1 - \lambda)\, i2 \\
&= A\,(\lambda h1 + (1 - \lambda)\, h2) \\
&= Ah3.
\end{aligned}
$$

Note that h3 satisfies both the non-negativity and sum conditions and hence i3 is an element of B. This, by definition, is the convex hull of the columns of A.

2.2.3 Geometric Face Recognition algorithm:

We first present the basic version of our blur-robust face recognition algorithm. Let I j , j = 1, 2, . . . , M be the set of M sharp gallery images. From the analysis above, every gallery image I j has an associated convex set of blurred images Bj .Given the probe image Ib, we find its distance from the set Bj , which is the minimum distance between Ib and the points in the set Bj

This is a convex quadratic program which can be solved efficiently. For $ib \in RN$ and $h \in RK$, the computational complexity is O(NK2). We compute r j for each j = 1, 2. . . M and assign Ib the identity of the gallery image with the minimum r j . If there are multiple gallery images per class (person), we can use the k-nearest neighbor rule, i.e. we arrange the r j s in ascending order and find the class which appears the most in the first k instances. In this algorithm we can also incorporate additional information about the type of blur.

The most commonly occurring blur types are the out of-focus, motion and the atmospheric blurs. The out-offocusand the atmospheric blurs are circularly-symmetric, i.e. the coefficients of H at the same radius are equal; whereas the motion blur is symmetric about the origin, i.e. $H(i, j) = H(-i,-j)$.

2.2.4 Making the Algorithm Robust to Outliers and Misalignment:

By making some minor modifications to the basic algorithm, we can make it robust to outliers and small pixel misalignments between the gallery and probe images. It is well known in face recognition literature that different regions in the face have different amounts of information. Also learn the weight W, a diagonal matrix, using a training database.

2.3 INCORPORATING THE ILLUMINATION MODEL:

The facial images of a person under different illumination conditions can look very different, and hence for any recognition algorithm to work in practice, it must account for these variations. First, we discuss the low-dimensional subspace model for handling appearance variations due to illumination. Next, we use this model along with the convolution model to define the set of images of a face under all possible lighting conditions and blur. We then propose a recognition algorithm based on minimizing the distance of the probe image from such sets.

2.3.1 Low-Dimensional Linear Model for Illumination Variations:

It has been that when an object is convex and Lambertian, the set of all images of the object under different illumination conditions can be approximately represented using a nine-dimensional subspace. Though the human face is not exactly convex or Lambertian, it is often approximated a one; and hence the nine-dimensional subspace model captures its variations due to illumination quite well The nine dimensional linear subspace corresponding to a face image I can be characterized by 9 basis images. In terms of these nine basis images Im,m = 1, 2, . . . , 9.

We use the average 3-D face normal from for n and we approximate the albedo ρ with a well-illuminated gallery image under diffuse lighting. In the absence of a well-illuminated gallery image, we could proceed by estimating the albedo from a poorly lit image using approaches.

2.3.2 Illumination-Robust Recognition of Blurred Faces (IRBF):

Corresponding to each sharp well-lit gallery image I j , j =1, 2, . . . , M, we obtain the nine basis images I j,m,m =1, 2, . . . , 9. Given the vector zed probe image ib, for each gallery image I j we find the optimal blur kernel hj and illumination coefficients αj,m, then transform (blur and re-illuminate) each of the gallery images I j using the computed blur kernel hj and the illumination coefficients αj,m. Next, we compute the LBP features from these transformed gallery images and compare it with those from the probe image Ib to find the closest match.

Each step is now a convex problem: the optimization over h for fixed αm reduces to the same problem asand the optimization of α given h is just a linear least squares problem. The complexity of the overall alternation algorithm is O (T (N + K3)) where T is the number of iterations in the alternation step, and O (N) is the complexity in the estimation of the illumination coefficients.

Again, we use the alternation procedure which reduces each step of the algorithm to a convexL1-norm problem. We formulate these L1-norm problems as Linear Programming (LP) problems. The complexity of the overall alternation algorithm is O(T (N3 + (K + N)3)).

3. RESULTS

3.1 INPUT IMAGE

The results are shown here. The fig3.1 shows the input image

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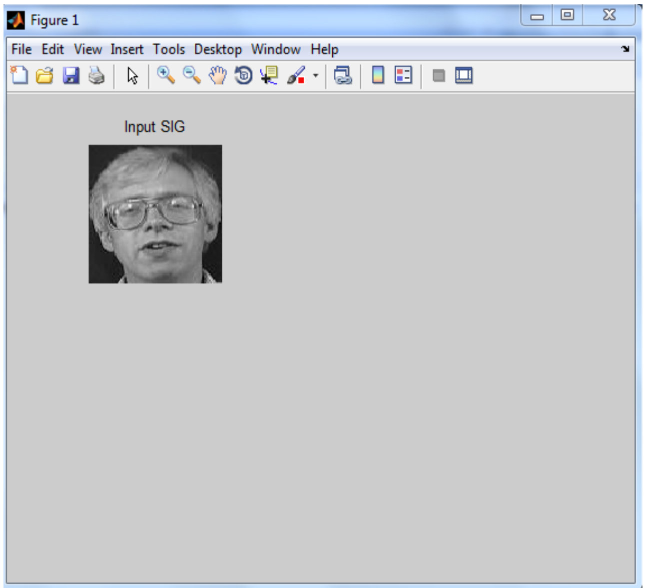

Fig 3.1 Input image

3.2 TRAINING SET

Fig. 3.2 which is given below shows the Training set of images. Training set contain number of images

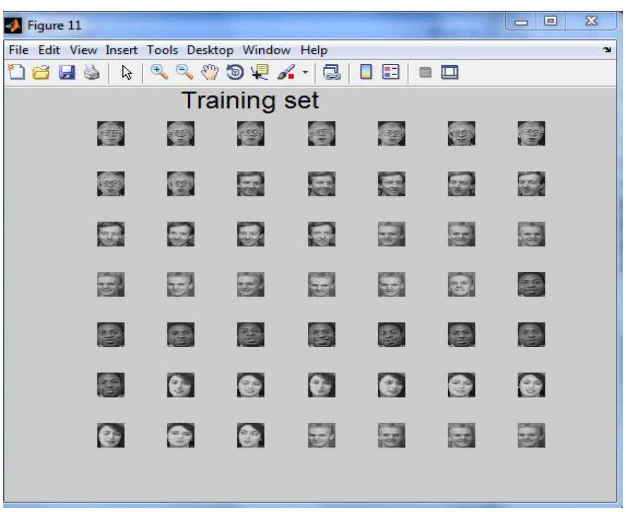

Fig. 3.2 Training Set

3.3 NORMALIZED TRAINING SET

Fig. 3.3 which is given below shows the Normalized Training set. Normalization is a process that changes the range of pixel intensity values. Normalization is sometimes called contrast stretching.

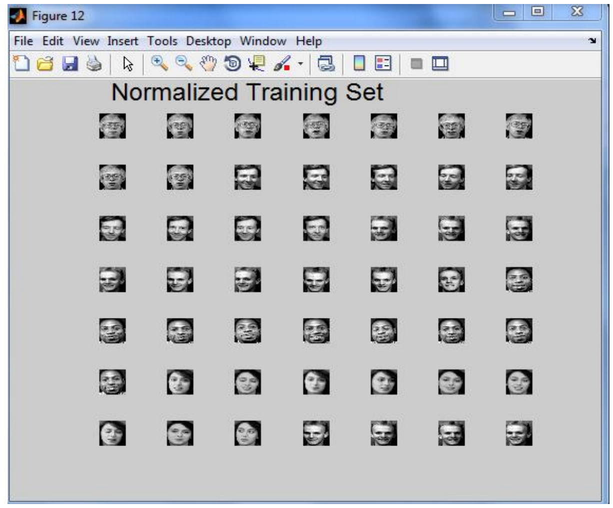

Fig. 3.3 Normalized Training set

3.4 MEAN IMAGE

Fig. 3.4 which is given below shows the Mean Image of an image. The mean image is represented as a column vector where each scalar is the mean of all corresponding pixels of the training images

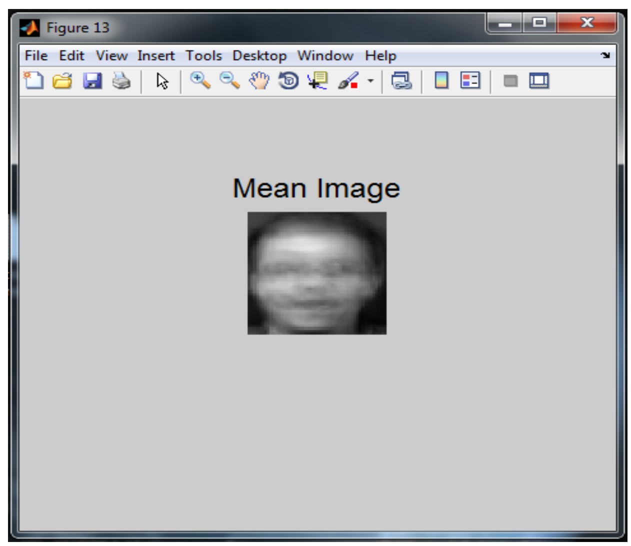

Fig.3.4Mean Image

3.5 EIGEN FACES

Fig. 3.5 which is given below shows the Eigen faces. Feature extraction is one of the most widely employed methods for reducing the data dimensionality.

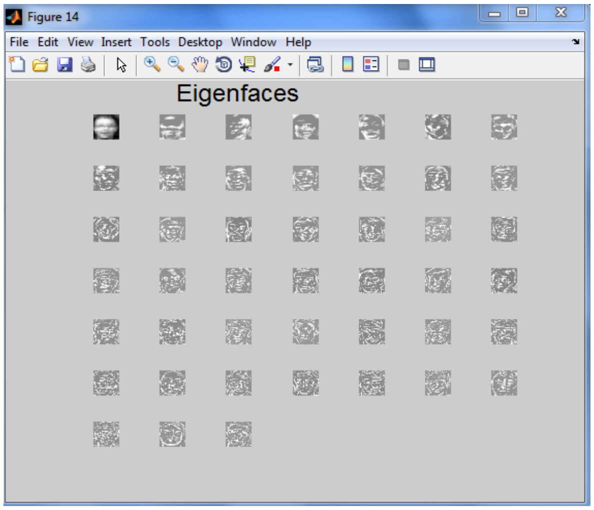

Fig. 3.5 Eigen Faces

5.6. FACE RECOGNITION OUTPUT

Fig. 5.6 shows the output window for the Robust Face Recognition using variations in Blur and Illumination.

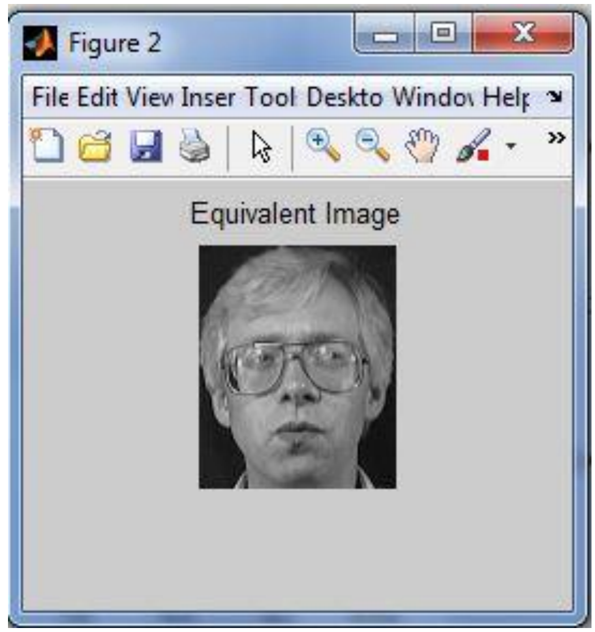

Fig.3.6. Face Recognition Output

4. CONCLUSION

Motivated by the problem of remote face recognition, we have addressed the problem of recognizing blurred and poorly illuminated faces. We have shown that the set of all images obtained by blurring a given image is a convex set given by the convex hull of shifted versions of the image. Based on this PCM with Euclidean classifier, we proposed a blur-robust face recognition algorithm DRBF. In this algorithm we can easily incorporate prior knowledge on the type of blur as constraints. Using the low-dimensional linear subspace model for illumination, we then showed that the set of all images obtained from a given image by blurring and changing its illumination conditions is a bi-convex set. Again, we proposed a blur and illumination robust algorithm IRBF. We also demonstrated the efficacy of our algorithms in tackling the challenging problem of face recognition in uncontrolled settings.

This algorithm is based on a generative model followed by nearest-neighbor classification between the query image and the gallery space, which makes it difficult to scale it to real life datasets with millions of images. This is a common issue with most algorithms based on generative models. Broadly speaking, only classifier-based methods have been shown to scale well to very large datasets; this is because the size of the gallery largely affects the training stage, the testing stage. The same algorithm can be implemented in Bayes classifier with Eigen face which is a simple probabilistic classifier based on applying Bayes' theorem with strong (naive) independence assumptions, which can be used as a future work to improve the performance of facial recognition systems.

ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 2, Issue 1, January 2014

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BIOGRAPHY

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