

# Comparison of face Recognition Algorithms on Dummy Faces

Aruni Singh, Sanjay Kumar Singh, Shrikant Tiwari

Department of Computer Engineering, IT-BHU, Varanasi-India

arunisingh@rocketmail.com

sks.cse@itbhu.ac.in

shrikant.rs.cse@itbhu.ac.in

## **ABSTRACT**

*In the age of rising crime face recognition is enormously important in the contexts of computer vision, psychology, surveillance, fraud detection, pattern recognition, neural network, content based video processing, etc. Face is a non intrusive strong biometrics for identification and hence criminals always try to hide their facial organs by different artificial means such as plastic surgery, disguise and dummy. The availability of a comprehensive face database is crucial to test the performance of these face recognition algorithms. However, while existing publicly-available face databases contain face images with a wide variety of poses, illumination, gestures and face occlusions but there is no dummy face database is available in public domain. The contributions of this research paper are: i) Preparation of dummy face database of 110 subjects ii) Comparison of some texture based, feature based and holistic face recognition algorithms on that dummy face database, iii) Critical analysis of these types of algorithms on dummy face database.*

## **KEYWORDS**

*Face recognition, dummy face, dummy face database and biometrics.*

## **1. INTRODUCTION**

Over a last decade face recognition has become increasingly important in the direction of computer vision, pattern recognition, surveillance, fraud detection, psychology, neural network, content based video processing, etc. Rapid development of face recognition is due to combination of the factors such as active development of algorithms, availability of large facial database and method of evaluating the performance of recognition algorithms [9,11]. Hence Facial Recognition Technology (FRT) has emerged as an attractive solution to address many contemporary requirements for identification [6,16] and verification of identity claims. This paper highlights the potential and limitations of the technology, noting those tasks for which it seems ready for deployment, those areas where performance obstacles may be overcome by future technological developments and its concern with efficacy extends to ethical considerations [1,2,7,8]. For the development of FRT face image database is needed. Several researchers have developed so many real face databases [10] with a lot of covariates. They have designed and tested many algorithms for recognition and identification of human faces and demonstrated the performance of the algorithms but the performance of face recognition algorithms on dummy and fake faces are not reported in the literature. Since face is non-intrusive physiological biometrics [12] for the verification of identity claim therefore in the age of increasing crime, criminals always pay more attention to hide or tamper their facial organs by using so many artificial techniques such as

plastic surgery, disguise, mask and dummy faces. Preliminary researches have also been attempted on plastic surgery and disguised face recognition or identification by [27, 28, 29].

The main purpose behind spoofing and hiding the original identity by using the masks, disguise or by means of plastic surgery is just to hide the real identity for the purposes of shifting the liability from real to imaginarily face which really does not exist or to adopt the identity of others[30]. This type of situation creates a lot of problems before the courts of law in the administration of criminal justice. Sometimes even such persons (whose mask face has been used by some other person at the time of committing the offence) may be punished who has not committed the offence. Accordingly innocent persons shall be liable for the act of others and thus it will abort the policy or philosophy of criminal justice. This type of spoofing the real face will also attract the amendment of the procedural law and law of evidence. In this paper we have tried to address the comparison of holistic based, texture based and feature based face recognition algorithms on dummy or fake faces.

This paper has eight sections: section 2 explains the database description and preprocessing while section 3 consists experimental work and brief description about the algorithms used to identify dummy face. Section 4 contains experimental protocol and section 5 explains experimental results at different scenario while section 6 and section 7 are experimental analysis and future scope respectively. Lastly section 8 contains conclusion.

## 2. DATABASE DESCRIPTION

It is necessary to quote here that these dummy face images do not follow the strictly controlled benchmark protocol of database acquisition because these images are situated at various real public places where any controlling constraints can't be imposed on acquisition. Due to this we have created our own protocol for data acquisition and prepared a comprehensive database of 110 dummy faces.

We have captured outdoor photographs of 110 subjects (65 females and 45 males) with 10 images per subject from different positions for pose variation as shown in figure 1. For the data acquisition 12.2 megapixels, 5x optical image stabilized camera has been used and images have been captured at a distance nearly 24 cm. from dummy in an uncontrolled environment. We have set the camera at the approximated angles shown in the figure 2. Angles between the posses are maintained by  $\theta = x/r$  radians, where  $x$  is the arc size and  $r$  is approximated distance of camera from dummy face. Thus the captured images are natural images without imposition of any constraints neither on the targeted subjects nor their surroundings. It took more than 10 months of time for database acquisition of dummy faces.



Figure 1: Pose variation of captured dummy face images

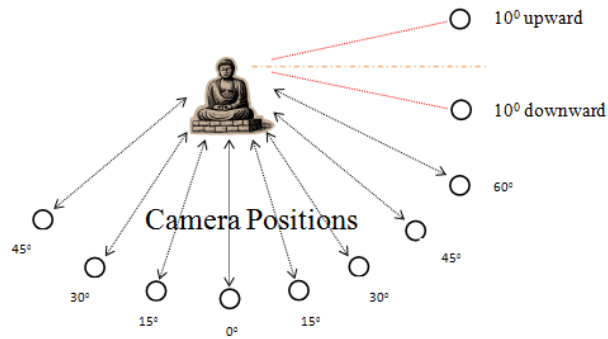


Figure 2: Camera positions for the pose variation

Data acquisition of dummy face is itself a challenging task because unlike real face images we don't have any control over the pose, expression, illumination and occlusion. Thus we have taken the photographs which are originally available in the public places or market as shown in figure 3.

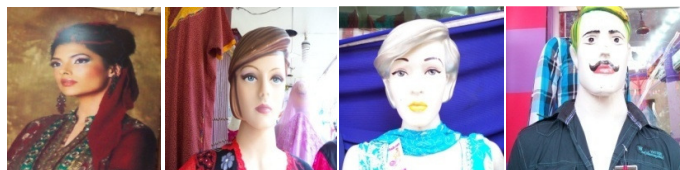


Figure 3: Original Dummy Faces

Further, these images do not follow the standard protocol of face database acquisition. Therefore, our own protocol for data acquisition has been created.

## 2.1 Pre-processing

For the testing of various algorithms preprocessing is required because the images of the subjects are taken in uncontrolled environment. For this purpose we have done pre-processing steps shown in figure 4. The images have been rotated up to certain degree so that the face image could be aligned and then cropped out only dummy faces from the dynamic scenes ousting the background. Finally all cropped dummy face image have normalized to set all the subjects at normal gray level illumination [4] and of same size.

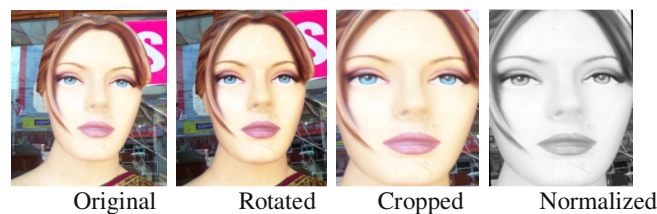


Figure 4: Preprocessed Images

Illumination covariate together with pose is a real challenge in face recognition. Dummy face images are captured during day time in outdoor environment, but are affected by change in weather condition. The shadow of dummy faces is due to extreme light which diminishes certain

facial features also. Moreover, extreme lighting can also produce too bright images, which can affect the automatic recognition process [24].

In last decade *Face Modeling, Normalization and Preprocessing*, and *Invariant Features Extraction* approaches have been addressed to resolve the illumination problem up to the certain level [25]. In this research *normalization and preprocessing* approach has been attempted for illumination compensation because the algorithm of this category doesn't requires any training and modelling steps.

**Illumination Plane Subtraction with Histogram Equalization:** The illumination plane  $dummyP(x, y)$  of an image  $dummy(x, y)$  corresponds to the best-fit plane from the image intensities.  $dummyP(x, y)$  is a linear approximation of  $dummy(x, y)$  given by:

$$dummyP(x, y) = a \cdot x + b \cdot y + c \quad (1)$$

where coefficients  $a$ ,  $b$  and  $c$  are described in multiple linear regression rely on the independence of model terms. When terms are correlated and column of design matrix  $N$  have an approximate linear dependence, the matrix  $(N^T N)^{-1}$  becomes close to singular and estimated as:

$$p = (N^T N)^{-1} N^T x \quad (2)$$

which becomes highly sensitive to random errors in the observed response  $x$ , producing a large variance. Thus the situation of *multicollinearity* can arise. For example, when data are collected without an experimental design. Now  $p \in \beta^3$  containing the plane parameters ( $a$ ,  $b$  and  $c$ ) and  $x \in \beta^n$  is  $I(x, y)$  in vector form ( $n$  is a number of pixels). So,  $N \in \beta^{n \times 3}$  is a matrix containing the pixel coordinate: the first column contains horizontal coordinates, second column vertical coordinates and third column has all values fixed to 1 because images are 2D images.

After estimating  $dummyP(x, y)$  resultant image  $dummyR(x, y)$  is obtained as-

$$dummyR(x, y) = dummy(x, y) - dummyP(x, y) \quad (3)$$

This mechanism abbreviates the shadows due to extreme light angles and then histogram equalization is applied for the brightness compensation [26] of the images as shown in the figure 5 and figure 6.

In figure 5 it is clearly visible that if the illumination in gray scale image is high, normalization [27] process reduces the illumination. Similarly in figure 6 the normalization process improves the illumination.



Figure 5: (a) Original dummy image (b) Gray scale dummy image (c) Dummy image after normalization: Illumination reduces



Figure 6: (a) Original dummy image (b) Gray scale dummy image (c) Dummy image after normalization: Illumination improves

### 3. EXPERIMENTAL WORK

For the dummy face datasets, we have evaluated the three types of face recognition algorithms: Holistic Performance Based, Local Feature Based and Texture Based. PCA, LDA, iSVM, LBP and SIFT. The previous three algorithms show the holistic performance [5], LBP is texture based algorithm and SIFT is feature based algorithm. A brief description of all the five algorithms is given below.

#### 3.1. Principal Component Analysis (PCA)

Principal Component Analysis commonly uses the eigenfaces [13,15] in which the probe and gallery images must be the same size as well as normalized to line up the eyes and mouth of the subjects whining the images. Approach is then used to reduce the dimension of data by the means of image compression basics [17] and provides most effective low dimensional structure of facial pattern. This reduction drops the unuseful information and decomposes the face structure into orthogonal (uncorrelated) components known as eigenfaces. Each face image is represented as weighted sum feature vector of eigenfaces which are stored in 1-D array. A probe image is compared against the gallery image by measuring the distance between their respective feature vectors then matching result has been disclosed. The main advantage of this technique is that it can reduce the data needed to identify the individual to 1/1000<sup>th</sup> of the data presented [18].

The basis vector are computed from the set of training images  $I$ . The average image in  $I$  is computed and subtracted from the training images, creating set of data samples

$$i_1, i_2, \dots, \dots, i_n \in I - \bar{I} \quad (4)$$

These data samples are arrange in a matrix represented as

$$X = \begin{bmatrix} \begin{bmatrix} \vdots \\ i_1 \\ \vdots \end{bmatrix} & \dots & \begin{bmatrix} \vdots \\ i_n \\ \vdots \end{bmatrix} \end{bmatrix} \quad (5)$$

$XX^T$  is then the sample covariance matrix for the training images and the principal components of the covariance matrix are computed by solving  $R^T(XX^T)R = \Lambda$  where  $\Lambda$  the diagonal matrix of eigenvalues is and  $R$  is the matrix of orthonormal eigenvectors. Geometrically,  $R$  is a rotation matrix that rotates the original coordinate system onto the eigenvectors, where the eigenvector associated with the largest eigenvalue is the axis of maximum variance, the eigenvector associated with the second largest eigenvalue is the orthogonal axis with the second largest variance, etc. Typically, only the  $N$  eigenvectors associated with the largest eigenvalues are used to define the subspace, where  $N$  is the desired subspace dimensionality.

In eigenspace terminology, each face image is projected by the top significant eigenvectors to obtain weights which are the best linearly weight the eigenfaces into a representation of the

original image. Knowing the weights of the training images and a new test face image, a nearest neighbour approach determines the identity of the face.

### 3.2. Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis is a statistical approach for classifying samples of unknown classes based on training samples with known classes[14]. This technique aims to maximum between-class (across users) variance and minimum within class (within user) variance. In these techniques a block represents a class, and there are a large variations between blocks but little variations within classes.

It searches for those vectors in underlying space that best discriminate among classes (rather than those that best describe the data). More formally given a number of independent features relative to which the data is described. LDA creates a linear combination of these which yields the largest mean difference between desired classes. Mathematically two measures are defined (i) One is called *within-class* scatter matrix which is given by-

$$S_w = \sum_{j=1}^c \sum_{i=1}^{N_j} (X_i^j - \mu_j)(X_i^j - \mu_j)^T \quad (6)$$

Where  $X_i^j$  is the  $i^{\text{th}}$  sample of class  $j$ ,  $\mu_j$  is mean of class  $j$ ,  $c$  is number of classes, and  $N_j$  is number of samples in class  $j$ , and (ii) Other is called between class scatter matrix

$$S_b = \sum_{j=1}^c (\mu_j - \mu)(\mu_j - \mu)^T \quad (7)$$

Where  $\mu$  represents the mean of all classes. The goal is to maximize the between class measure while minimizing the within class measure. To do this we maximize ratio  $\frac{\det |S_b|}{\det |S_w|}$  to prove that if

$S_w$  is non-singular matrix then this ratio is maximized when the column vectors of the projection matrix,  $W$ , are eigenvectors of  $S_w^{-1}S_b$ . It is noted that - (i) there are at most  $c-1$  non zero generalised eigenvectors, and so an upper bound of  $f$  is  $c-1$  and (ii) require at least  $c+t$  samples to guarantee that  $S_w$  does not become singular. To solve this proposes the use of an intermediate space[23]. In both cases this intermediate space is chosen to be the PCA space. Thus the original  $t$ -dimensional space is projected onto an intermediate  $g$ -dimension space using PCA and then final  $f$ -dimension space LDA.

### 3.3. Improved Support Vector Machine (iSVM)

Support Vector Machine (SVM) is very popular binary classifier as methods for learning from examples in science and engineering. The performance of SVM is based on the structure of the Riemannian geometry induced by the kernel function. Amari in 1999 proposes a method of modifying a Gaussian kernel to improve the performance of a SVM. The idea is to enlarge the spatial resolution around the margin by a conformal mapping, such that the separability between classes is increased [21]. Due to the encouraging results with modifying kernel, this study proposes a novel facial expression recognition approach based on improved SVM (iSVM) by modifying kernels. We have tested this algorithm on our novel dummy database and encouraging result is demonstrated in the figures below.

A nonlinear SVM maps each sample of input space  $R$  into a feature space  $F$  through a nonlinear mapping  $\phi$ . The mapping  $\phi$  defines an embedding of  $S$  into  $F$  as a curved sub manifold. Denote  $\phi(x)$  the mapped samples of  $x$  in the feature space, a small vector  $dx$  is mapped to:

$$\varphi(dx) = \nabla\varphi \cdot dx = \sum_i \frac{\partial}{\partial x^i} \varphi(x) dx^i \tag{8}$$

The squared length of  $\varphi(dx)$  is written as:  $ds^2 = |\varphi(dx)|^2 = \sum_{i,j} g_{ij}(x) dx^i dx^j$  (9)

Where  $g_{ij}(x) = \left(\frac{\partial}{\partial x^{(i)}} \varphi(x)\right) \cdot \left(\frac{\partial}{\partial x^{(j)}} \varphi(x)\right) = \frac{\partial}{\partial x^{(i)}} \cdot \frac{\partial}{\partial x^{(j)}} \cdot K(x, x')|_{x'=x}$  (10)

In the feature space F, we can increase the margin (or the distances  $ds$ ) between classes to improve the performance of the SVM. Taking equation (9) into account, this leads us to increase the Riemannian metric tensor  $g_{ij}(x)$  around the boundary and to reduce it around other samples. In view of (7), we can modify the kernel K such that  $g_{ij}(x)$  is enlarged around the boundary [21].

### 3.4. Local Binary Pattern (LBP)

The LBP operator is a powerful texture descriptor [26]. The square matrix of pixels are considered to generate the labels. The binary number sequence after thresholding is considered as resultant labels. The histogram of labels are used as texture descriptor. figure 7 illustrates the preparation of LBP operator.

A histogram of labelled dummy face image  $dumm_l(x, y)$  is defined as

$$H_i = \sum_{x,y} I\{dumm_l(x, y) = i\}, i = 1, 2, \dots, (n - 1) \tag{11}$$

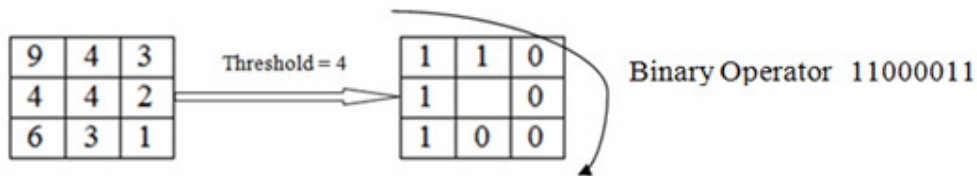


Figure 7: Preparation of LBP operator

In this LBP operator produces  $n$  different labels and

$$\begin{aligned} \text{If } dumm_l(x, y) = i \text{ then } I\{dumm_l(x, y) = i\} &= 1 \\ dumm_l(x, y) \neq i \text{ then } I\{dumm_l(x, y) = i\} &= 0 \end{aligned}$$

The spatial information about whole dummy face image is obtained by dividing into regions as in figure 8.

$$R_0, R_1, R_2, \dots, R_{k-1} \text{ where } k \text{ is number of regions}$$

Spatially enhanced histogram is

$$H_{x,y} = \sum_{x,y} I\{dumm_l = i\} I\{(x, y) \in R_j\}, i = 0, 1, \dots, n - i \text{ and } j = 0, 1, \dots, m - 1 \tag{12}$$

After this process, obtained histogram  $H_{x,y}$  contains complete information of whole dummy face image of about local face macula, spots, surface flat areas, edges, and all about textures. This technique is very rich in class information almost containing one training sample per class. Due to this reason here nearest neighbour classifier is used for classification.

For the measurement of dissimilarity among the images histogram intersection, log-likelihood and Chi-square distance are evaluated. And when image is divided into several reasons then it is

very much crucial to judge that some reasons containing important cues such as eyes, lips and chin etc. Evaluate those reasons with applying weighted chi-square statics.

$$\chi_{\omega}^2(S, M) = \sum_{i,j} \omega_j \frac{(S_{i,j} - M_{i,j})^2}{S_{i,j} + M_{i,j}} \quad (13)$$

in this  $\omega_j$  is the weight for the image reason  $j$ .

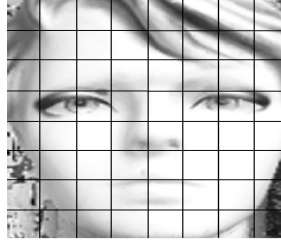


figure 8: Dummy face image divided into 8x8 window reasons

### 3.5. Scale Invariant Feature Transformation (SIFT)

In SIFT, features are extracted from images for matching between different pose of same subject [20]. These features are invariant to scale and orientation. Steps to find out these features [19] are –

**Step I- Scale Space extrema Detection:** Computation of locations for our potential interests by selecting maxima and minima of a set of Difference of Gaussian (DOG) filters applied at different scales all over the image. The scale space of dummy face image is defined as function  $L(x, y, \sigma)$  is obtained by convolving by Gaussian  $G(x, y, \sigma)$  with input dummy face image  $dumm(x, y, \sigma)$ :

$$L(x, y, \sigma) = G(x, y, \sigma) * dumm(x, y, \sigma) \quad (14)$$

Where

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2} \quad (15)$$

$\sigma$  is standard detection of Gaussian  $G(x, y, \sigma)$ . The difference of Gaussian function  $G(x, y, \sigma)$  is computed as the difference of Gaussian of two scale that are separated by two scale by a factor  $k$ :

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * dumm(x, y) = L(x, y, k\sigma) - L(x, y, \sigma) \quad (16)$$

Local maxima and minima of  $D(x, y, \sigma)$  are computed on comparison of sample point and its eight neighbors in current dummy face image as well as nine neighbors in scale above and below. These selected points are local maxima and minima or candidate points.

**Step II-Removal of unlike points:** In this calculation the low contrast points and poorly localized points are removed by evaluating the value of  $|D(x, y, \sigma)|$  at each candidate



points. These candidate points are below the threshold value, points are discarded else selected.

**Step III-Orientation assignment:** Build a histogram of gradient orientation  $\theta(x, y)$  weighted by gradient magnitude –

$$m(x, y) = \sqrt{((L(x + 1, y) - L(x - 1, y))^2 + (L(x, y + 1) - L(x, y - 1))^2)} \quad (17)$$

$$\theta(x, y) = \tanh (L(x, y + 1) - L(x, y - 1) / (L(x + 1, y) - L(x - 1, y))) \quad (18)$$

**Step IV-Key point descriptor evaluation:** Finally, a local feature descriptor is computed at each key point. This descriptor is based on the local image gradient, transformed according to the orientation of the key point to provide orientation invariance. Every feature is a vector of dimension 128 distinctively identifying the neighborhood around the key point.

Each keypoint descriptor is extracted from probe dummy face image and matched independently with stored keypoint descriptor of gallery dummy face image and best match is evaluated by nearest neighbor technique.

#### 4. EXPERIMENTAL PROTOCOL

For our experiment we have taken 10 preprocessed images of each 110 subjects and compressed those images using Gaussian Pyramid [3]. After compression we have prepared the images in the form of Gaussian levels. Level 1 contains images of 100x100 pixels, Level 2 contains images of 50x50 pixels, Level 3 contains images of 25x25 pixels, Level 4 contains images of 13x13 pixels and Level 5 contains images of 7x7 pixels.

Both open and closed universe environment for our experiments have been used. In closed universe, every probe images are available in the gallery while in open universe some probe images are not available in the gallery. Both logic [9] reflect very important aspect and report different performance statistics.

#### 5. EXPERIMENTAL RESULTS

For our experiment we have taken 110 subjects and involved 10 photographs of each subject in following four scenarios and results are shown in the tables as well as in the figures accordingly.

- (i) For 6 images of each subject as Gallery and 4 images as probe in open universe environment the result or algorithms are shown in Table 1 and figure 9.

60/40 % Gallery/Probe	Level 1	Level 2	Level 3	Level 4	Level 5
PCA	71.5	72	71	71	51
LDA	76.5	73	75	72.5	48.5
iSVM	79	79	79	78.5	63.5
LBP	78.6	78	78	77.2	60

SIFT	81	80	80	78	61
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Table 1: Identification accuracy table in open universe environment

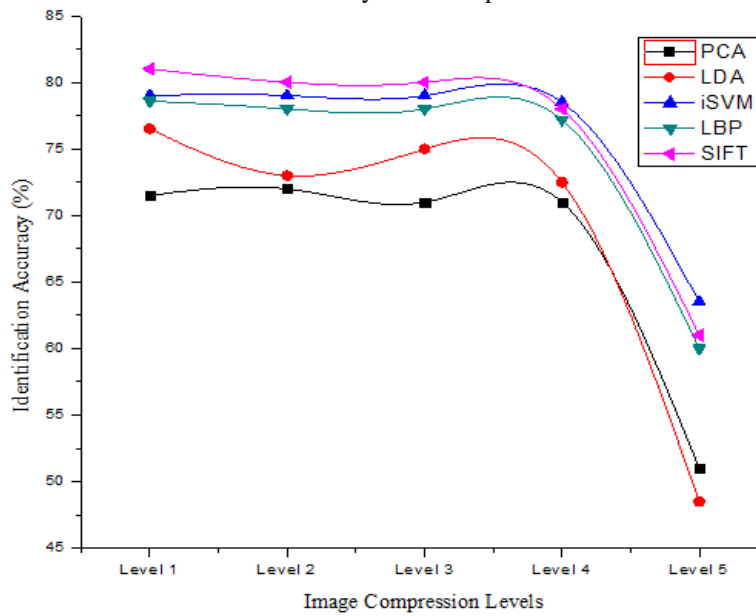


Figure 9: Identification accuracy graph in open universe environment

- (ii) For 8 images of each subject as Gallery and 2 images as probe in open universe environment the results of algorithms are shown in Table 2 and Figure 10.

80/20 % Gallery/Probe	Level 1	Level 2	Level 3	Level 4	Level 5
PCA	75	75	79	83	56
LDA	77	77	83	82	58
iSVM	84	84	85	83	66
LBP	81.3	81	82.5	79	61
SIFT	83	83	82	80	70

Table 2: Identification accuracy table in open universe environment

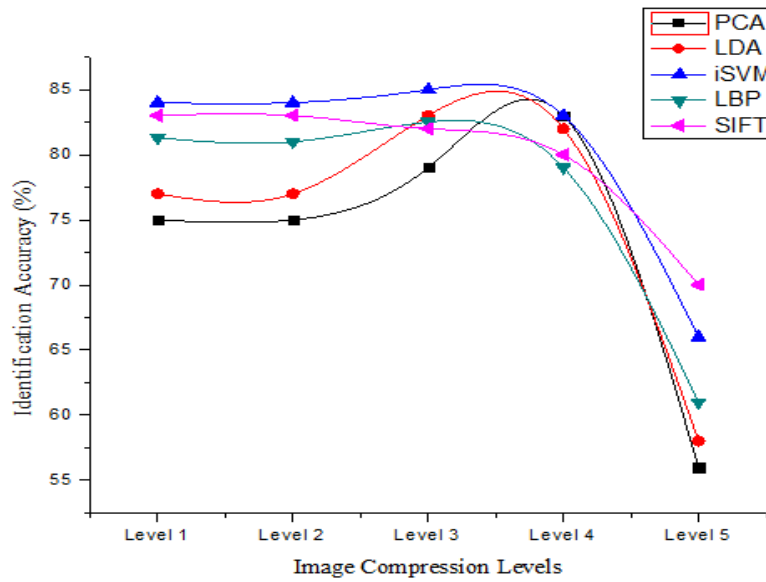


Figure 10: Identification accuracy graph in open universe environment

- (iii) For 6 images of each subject as Gallery and 4 images as probe in close universe environment the results of algorithms are shown in Table 3 and Figure 11.

60/40 % Gallery/Probe	Level 1	Level 2	Level 3	Level 4	Level 5
PCA	86.5	86.5	87.5	86.5	76.5
LDA	89.5	89	88	89.5	78.5
iSVM	91	93	92	86.5	79.5
LBP	90	90	88.5	88	79
SIFT	90	91	90	84	80

Table 3: Identification accuracy in close universe environment

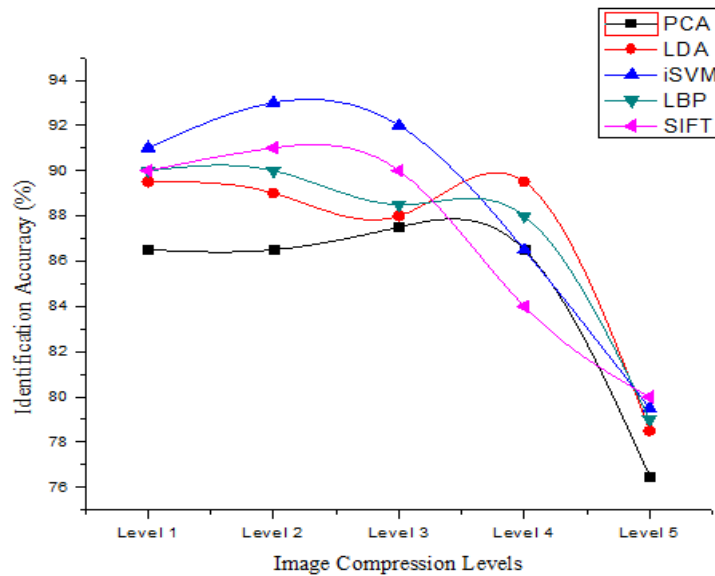


Figure 11: Identification accuracy graph in close universe environment

- (iv) For 8 images of each subject as Gallery and 2 images as probe in close universe environment the results of algorithms are shown in Table 4 and figure 12.

80/20 % Gallery/Probe	Level 1	Level 2	Level 3	Level 4	Level 5
PCA	90	91	91	88	78
LDA	93	92	93	94	84
iSVM	95	95	94	95	82
LBP	94.5	94	93	90	80
SIFT	94	95	94	93	80

Table 4 Identification accuracy table in close universe environment

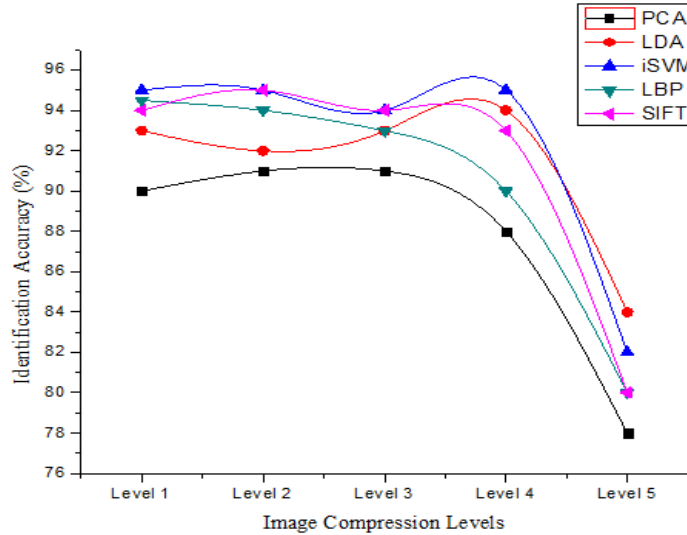


Figure 12: Identification accuracy graph in close universe environment

The results show that the relative performance of some algorithms is dependent on training conditions (data, protocol) as well as environmental changes. Over the last decade the development of biometric technologies has been greatly promoted by important research techniques.

## 6. EXPERIMENTAL ANALYSIS

The result shows that the performance varies significantly and iSVM approach has the best performance in level 1 to 4.

- PCA improves the accuracy in with increasing in Gaussian levels because eigenfaces encodes illumination variations.
- LDA is infeasible in large system. In our result the database size is not very large therefore the performance of LDA is in second position after iSVM.
- It is clearly visible that the performance of LBP is better than PCA and LDA because for the dummy face image there are no change in the texture.
- The performance of identification of SIET is very close to iSVM because SIFT works on local feature as a descriptor and in dummy face image. There are no any change in local feature of dummy face because images have been taken in
- As we compress the images there is loss of some of its important features and therefore in higher level of compression accuracy decreases.
- When we increase the number of gallery images the algorithms gives the better results.

## 7. FUTURE SCOPE

The approach described in this paper is initially successful and encouraging in face recognition of dummy faces but more research is to be done in the following domain:

- Size of database is to be increased with illumination variation, pose variation, distance variation, date-variation, expression variation and occlusion variation conditions must be considered while capturing the dummy face of the subjects.
- Our current study reports observed changes due to covariates; however the analysis does not attempt to explain the cause of the effect in detail. Answering the underline cause of the affects will assist in designing more robust face recognition algorithms and then based on their values the most effective algorithm would perform the matching. Alternatively the weighting of an algorithm response would change based on estimated covariates.
- In this respect the evaluation of other types of algorithms are to be done.
- Design and development of new algorithms to distinguish between real and dummy faces.

## 8. CONCLUSION

There are so many challenges to develop a comprehensive dummy face database and one of the most fundamental problem in data acquisition is the ability to take consistent, high-quality, repeatable dummy images. In order to compare the performance of some face recognition algorithms on dummy faces we have prepared as well as presented a novel dummy database and tested the matching accuracy of PCA, LDA, iSVM, LBP and SIFT face recognition algorithms.

The detailed identification results are presented and result demonstrate the factors which affect the identification accuracy are image quality, gallery and probe distribution and uncontrolled image environment. In holistic based algorithms PCA has range of accuracy from (51-72)%, LDA (48.50-76.50)%, iSVM (63.5-79)% while texture based algorithm LBP shows the identification accuracy (60-94.5)% and feature based algorithm SIFT demonstrates the accuracy range (61-94)% at various image compression levels in open universe environment and close universe. When we increase the gallery size the identification accuracy of each algorithms increases. In this paper, we present a methodology for creating such database preparation and demonstrate the percentage identification accuracy.

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## Authors

Shrikant Tiwari passed his M.Tech. degree in Computer Science and Technology from University of Mysore, India, in 2009. Currently pursuing Ph.D. degree at the Institute of Technology, B.H.U., Varanasi, India. His research interests include Biometrics, Image Processing and Pattern Recognition.



Sanjay K. Singh is Associate Professor in Department of Computer Engineering at Institute of Technology, B.H.U., India. He is currently doing research in Biometrics.



Aruni Singh, Assistant Professor in the Department of Computer Sc. & Engineering, KNIT, Sultanpur, India. His research interests include computational intelligence, biometrics, machine learning. Currently pursuing Ph.D. at the Institute of Technology, Banaras Hindu University, Varanasi, India.

