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RESEARCH ARTICLE

Comparison of HGPP, PCA, LDA, ICA and SVM

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ABSTRACT

Here, we are comparing the performance of five algorithms of the face recognition i.e. HGPP, PCA, LDA, ICA and SVM. The basis of the comparison is the rate of accuracy of face recognition. These algorithms are employed on the ATT database and IFD database. We find that HGPP has the highest rate of accuracy of recognition when it is applied on the ATT database whereas LDA outperforms the all other algorithms when it is applied to IFD database.

Keywords : Face Recognition, HGPP, PCA, LDA, PCA, GPP, GGPP and LGPP.

1. INTRODUCTION

Today, we have a variety of biometric techniques like fingerprints, iris scans, and speech recognition etc. but among of them face recognition is still most common technique which is in use. It is only due to the fact that it does not require aid or consent from the test subject and easy to install in airports, multiplexers and other places to recognize individuals among the crowd. But face recognition is not perfect and suffers due to various conditions like scale variance, Orientation variance, Illumination variance, Background variance, Emotions variance, Noise variance, etc[15]. Due to these challenges, researchers are very keen to find out the rate of accuracy for face recognition. So they are always trying to evaluate the best algorithm for face recognition. Various comparisons had been performed by the researchers[1], [3], [4], [5], [10], [11], [16]. Here we are also compare five algorithms like PCA[17], LDA[19], ICA[2], SVM[7], and HGPP[20] on the basis of rate of accuracy of face recognition. The brief description of all above said algorithms are given below :

2. FACE RECOGNITION ALGORITHMS

2.1. Principal Component Analysis (PCA)

It is an oldest method of face recognition which is based on the Karhunen-Loeve Transform (KLT) (also known

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as Hotelling Transform and Eigenvector Transform), works on dimensionality reduction in face recognition. Turk and Pentland used PCA exclusively for face recognition[17]. PCA computes a set of subspace basis vectors for a database of face images. These basis vectors are representation of an images which is correspond to a face – like structures named Eigenfaces. The projection of images in this compressed subspace allows for easy comparison of images with the images from the database.

The approach to face recognition involves the following initialization operations[17]:

- Acquire an initial set of N face images (training images).
- Calculate the eigenface from the training set keeping only the M images that correspond to the highest eigenvalues. These M images define the "facespace". As new faces are encountered, the "eigenfaces" can be updated or recalculated accordingly.
- Calculate the corresponding distribution in M dimensional weight space for each known individual by projecting their face images onto the "face space".
- Calculate a set of weights projecting the input image to the M "eigenfaces".
- Determine whether the image is a face or not by checking the closeness of the image to the "face space".
- If it is close enough, classify, the weight pattern as either a known person or as an unknown based on the Euclidean distance measured.
- If it is close enough then cite the recognition successful and provide relevant information about the recognized face from the database which contains information about the faces.

Mathematically, it can be explained as given below.

Assume (x_1, x_2, x_3,……, x_m) is a set of M train set from N face images arranged as column vector.

Average face of set can be defined as:

$$\boldsymbol{\Psi} = \left(\frac{1}{M}\right) \sum_{n=1}^{M} (\mathrm{x_n}) \qquad \dots (1)$$

Each face differs from the average by vector

$$\boldsymbol{\Phi_i} = \boldsymbol{x_i} - \boldsymbol{\Psi} \qquad \dots (2)$$

When applied to PCA, this large set of vectors seeks a set of M orthogonal vectors U_n, which describes the distribution of data.

The K[th] vector $\mathbf{U_k}$ is chosen such that

$$\boldsymbol{\lambda_k} = \left(\frac{1}{M}\right) \sum_{n=1}^{M} [[(\mathbf{U_k})^T * \boldsymbol{\Phi_n}]^2 \qquad \dots (3)$$

is maximum, applied to

$$(\mathbf{U_k})^T \mathrm{U_k} = \delta_{lk} = f(x) = \begin{cases} 1, if\ l = k \\ 0, otherwise \end{cases} \quad \dots (4)$$

The vector U_k and scalar $\boldsymbol{\lambda_k}$ are the eigenvectors and eigenvalues respectively of the covariance matrix

$$\boldsymbol{C} = (\tfrac{1}{M}) \sum_{n=1}^{M} (\boldsymbol{\Phi_n})\,(\boldsymbol{\Phi_n})^T \quad \dots (5)$$

$$= AA^T \ .$$

Where the matrix A = [$\mathbf{\Phi_1}, \mathbf{\Phi_2}$ **……..**$\mathbf{\Phi_M}$].

2.2. Linear Discriminant Analysis (LDA)

LDA also known as Fisher's Discriminant Analysis, is another dimensionality reduction technique. It is an example of a class specific method i.e. LDA maximizes the between – class scattering matrix measure while minimizes the within – class scatter matrix measure, which make it more reliable for classification. The ratio of the between – class scatter and within – class scatter must be high[19].

Basic steps for LDA[4], [10], [11], [16]:

Calculate within - class scatter matrix S_W:

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

Where X_i^j is the i[th] sample of class j is, μ_j is the mean of class j, C is the number of classes, N_j is the number of samples in class j.

Calculate between-class scatter matrix S_B :

$$S_B = \sum_{j=1}^{C} (\mu_j - \mu)\,(\mu_j - \mu)^T \quad \dots (7)$$

where μ represents the mean of the classes.

Calculate the eigenvectors of the projection matrix

$$W = eig(S_W^{-1} S_B) \quad \dots (8)$$

Each and every test image is projected to the same subspaces and compared by the training images.

2.3. Independent Component Analysis (ICA)

Generalization View of the PCA is known as ICA. It minimizes the second order and higher order dependencies in the input and determines a set of statistically independent variables or basis vectors. Here we are using architecture I which finds statistically independent basis images[2].

Basic steps for ICA[10]:

Collect X_i of n dimensional data set X, i = 1, 2, 3… M.

Mean correct all the points: calculate mean M_X and substract it from each data point, $X_i - M_X$

Calculate the covariance matrix :

$$C = (X_i - M_X)(X_i - M_X)^T \quad \dots (9)$$

The ICA of X factorizes the covariance matrix into the following form: $\mathrm{C} = \mathrm{F}\Delta\mathrm{F}^{\mathrm{T}}$ where $\boldsymbol{\Delta}$ is a diagonal real positive matrix.

F transforms the original data X into Z such that the components of the new data Z are independent: X = FZ.

2.4. Support Vector Machines (SVMs)

The Support Vector Machine is based on VC theory of statistical learning. It is implement structural risk minimization[17]. Initially, it was proposed as per a binary classifier. It computes the support vectors through determining a hyperplane. Support Vectors maximize the distance or margin between the hyperplane and the closest points.

Assume a set of N points and $X_i \in \boldsymbol{R^n}$, i=1, 2, 3…N. Each point belongs to one of the two classes i.e. $\boldsymbol{Y}_i \in \{-1,1\}$. Here optimal separating hyperplane (OHS) can be defined as

$$(x) = \sum_{i=1}^{l} \alpha_i Y_i \boldsymbol{X}_i . \boldsymbol{X} + b \quad \dots (10)$$

The coefficients α_i and b are the solution of a quadratic equation[7]. Sign of f(x) decides the 'Classification' of a new point data in the above equation.

In the case of multi-class classification the distance between hyperplane and a data set can be defined as:

$$d(x) = \frac{\sum_{i=1}^{l} \alpha_i \boldsymbol{Y}_i \boldsymbol{X}_i . \boldsymbol{X} + \boldsymbol{b}}{\|\sum_{i=1}^{l} \alpha_i \boldsymbol{Y}_i \boldsymbol{X}_i\|} \quad \dots (11)$$

Larger |d| shows the more reliable classification.

2.5. Histogram Of Gabor Phase Patterns (HGPP)

HGPP is the combination of spatial histogram and Gabor phase information. Gabor phase information is of two types. These are known as Global Gabor phase pattern (GGPP) and Local Gabor phase pattern (LGPP). Both of the Gabor phase patterns are based on quadrant-bit codes of Gabor real and imaginary parts ($P_{u,v}^{Re}(Z), P_{u,v}^{Im}(Z)$). Quadrant–bit codes proposed by Daugman for iris recognition[6]. Here GGPP encodes orientation information at each scale whereas LGPP encodes the local neighborhood variations at each orientation and scale. Finally, both of the GPP's are combined with spatial histograms to model the original object image.

Gabor wavelet is well known algorithm for the face recognition. Conventionally, the magnitude of the Gabor coefficients are considered as valuable for face recognition and phase of the Gabor coefficients are considered useless and always discarded. But use of the spatial histograms, encodes the Gabor phases through Local binary Pattern (LBP) and provides the better recognition rate comparable with that of magnitude based methods. It shows that combination of Gabor phase and magnitudes provides the higher classification accuracy. These observation paid more attention towards the Gabor phases for face recognition.

So, Gabor Wavelet can be defined as[9]:

$$\Psi_{u,v}(Z) = \frac{\|k_{u,v}\|^2}{\sigma} e^{\left(\frac{-\|k_{u,v}\|^2 \|Z\|^2}{2\sigma^2}\right)} \left[e^{ik_{u,v}Z} - e^{\frac{-\sigma^2}{2}}\right] \qquad \ldots (12)$$

Where $\overrightarrow{k_{u,v}} = \begin{pmatrix} k_{jx} \\ k_{jy} \end{pmatrix} = \begin{pmatrix} k_v \cos\emptyset_u \\ k_v \sin\emptyset_u \end{pmatrix}$, $k_v = \frac{f_{max}}{2^{v/2}}$, $\emptyset_u = u\left(\frac{\pi}{8}\right)$, $v = 0, \ldots, v_{max} - 1$,

$v = 0, \ldots, u_{max} - 1, v\ is\ the\ frequency$ and $u\ is\ the\ orientation\ with\ v_{max} = 5$, and $u_{max} = 8, \sigma = 2\pi$.

Here, in the R.H.S the term in the square bracket determines the oscillatory part of the kernel and the second term compensates for the magnitude of the DC value. σ determines the ratio of the Gaussian window width to the wavelength[9].

Now, the Gabor transformation of a given image can be defined as:

$$G_{u,v}(Z) = I(Z) * \Psi_{u,v}(Z) \qquad \ldots (13)$$

$G_{u,v}(Z)$ is the convolution of corresponding to the Gabor kernel at scale v and orientation u. Again, the Gabor wavelet coefficient $G_{u,v}(Z)$ can be rewritten as a complex number.

$$G_{u,v}(z) = A_{u,v}(Z) \,.\exp\left(i\theta_{u,v}(Z)\right) \qquad \ldots (14)$$

Here,$A_{u,v}(Z)$ is the magnitude and $\theta_{u,v}(Z)$ is the phase of the Gabor wavelets. Magnitude varies slowly whereas phase varies with some rate with respect to spatial position. The rotation of the phases takes different values of the image but it represents almost the same value features. This causes severe problem in the face matching, that is the reason people used to make use of only the magnitude for face classification.

But Daugman's approach demodulated the Gabor phase with phase – quadrant demodulation coding. He used this coding for Iris recognition[6]. This coding assigns the each pixel into two bits$\left(P_{u,v}^{Re}(Z), P_{u,v}^{Im}(Z)\right)$. It is also known as quadrant bit coding (QBC). QBC is relatively stable. It actually quantifies the Gabor features.

$$P_{u,v}^{Re}(Z) = \begin{Bmatrix} 0, if\ Re\left(G_{u,v}(Z)\right) > 0 \\ 1, if\ Re\left(G_{u,v}(Z)\right) \leq 0 \end{Bmatrix} \qquad \ldots (15)$$

$$P_{u,v}^{Im}(Z) = \begin{Bmatrix} 0, if\ Im\left(G_{u,v}(Z)\right) > 0 \\ 1, if\ Im\left(G_{u,v}(Z)\right) \leq 0 \end{Bmatrix} \qquad \ldots (16)$$

Above these equations encoded by Daugman and named as Daugman's encoding method, are followed as:

$$P_{u,v}^{Re}(Z) = \begin{Bmatrix} 0, if\ Re\ \theta_{u,v}(Z) \in \{I, IV\} \\ 1, if\ Re\ \theta_{u,v}(Z) \in \{II, III\} \end{Bmatrix} \quad \ldots (17)$$

$$P_{u,v}^{Im}(Z) = \begin{Bmatrix} 0, if\ Im\ \theta_{u,v}(Z) \in \{I, II\} \\ 1, if\ Im\ \theta_{u,v}(Z) \in \{III, IV\} \end{Bmatrix} \quad \ldots (18)$$

$\theta_{u,v}(Z)$ defines the Gabor phase angle for the pixel at the spatial position Z. It transforms the same feature ("00") for the phase angle in $(0°, 90°)$ and so on.

From here, the GGPP algorithm computes one binary string for each pixel by concatenating the real or imaginary bit codes for different orientations for a given frequency at a given position. Now $GGPP_v(Z_0)$ formulates the values of GGPP at the frequency v and at the position (Z_0), which is shown as follows :

$$GGPP_v^{Re}(Z_0) = P_{0,v}^{Re}(Z_0), P_{1,v}^{Re}(Z_0), \ldots., P_{k,v}^{Re}(Z_0)] \quad \ldots (19)$$

$$GGPP_v^{Im}(Z_0) = [P_{0,v}^{Im}(Z_0), P_{1,v}^{RIm}(Z_0), \ldots., P_{k,v}^{Im}(Z_0)] \quad \ldots (20)$$

There are total eight orientations which can represent 0-255 different orientation modes.

Further, we can encode the local variations for each pixel, denoted as LGPP. This scheme encodes the sign difference of the central pixel from its neighbors. This shows the spots and flat area in the any given images. It can be computed using local XOR pattern or LXP operator. It can formulate as given below:

$$LGPP_{u,v}^{Re}(Z_0) = P_{u,v}^{Re}(Z_0)\ XOR\ P_{u,v}^{Re}(Z_1), P_{u,v}^{Re}(Z_0)\ XOR\ P_{u,v}^{Re}(Z_2)$$

$$,\ldots.., P_{u,v}^{Re}\ (Z_0) XOR P_{u,v}^{Re}(Z_8)] \ldots (21)$$

$$LGPP_{u,v}^{Im}(Z_0) = P_{u,v}^{Im}(Z_0)\ XOR\ P_{u,v}^{Im}(Z_1), P_{u,v}^{Im}\ (Z_0)\ XOR\ P_{u,v}^{Im}(Z_2)$$

$$\ldots., P_{u,v}^{Im}\ (Z_0)\ XOR\ P_{u,v}^{Im}(Z_8)] \ldots (22)$$

Here $Z_1, Z_2, Z_3, \ldots., Z_8$ are the eight neighbors around Z_0 and XOR denotes the bit exclusive or operator.

Above process to encode the both GPP's provide 90 images (five real GGPP's, five imaginary GGPP's, 40 real LGPP's and 40 imaginary LGPP's) with the same size as the original face images. These images are in the form of micro – pattern and look like the images with rich structural textures. Histogram serves as a good description tool for above said micro – pattern and structural textures. In order to preserve the spatial information in the histogram features, both the GPP's are spatially subdivided into the non-overlapping rectangular region. Further spatial histogram can extract easily from non – overlapping rectangular regions. Then all of these histograms are concatenated into a single extended histogram features. It is also named as Joint local – histogram features (JLHF). It works on all frequencies and orientations.

The HGPP can be defined as:

$$\text{HGPP} = (H_{GGPP}^{Re}, H_{GGPP}^{Im}, H_{LGPP}^{Re}, H_{LGPP}^{Im}) \quad \ldots (23)$$

Where $H_{GGPP}^{Re} and H_{GGPP}^{Im}$ are the sub-region histograms of the real and imaginary part of GGPP whereas

H_{LGPP}^{Re} and H_{LGPP}^{Im} are the sub region histograms of the real and imaginary part of LGPP. Both can formulate as given below:

$$H_{GGPP}^{Re}=(H_{GGPP}^{Re}(v,l): v=0,\ldots.,4; l=1,\ldots.,L) \quad \ldots(24)$$

$$H_{GGPP}^{Im}=(H_{GGPP}^{Im}(v,l): v=0,\ldots.,4; l=1,\ldots.,L) \quad \ldots(25)$$

$$H_{LGPP}^{Re}=(H_{LGPP}^{Re}(v,l): u=0,\ldots.7;\ v=0,\ldots.,4; l=1,\ldots.,L) \quad \ldots(26)$$

$$H_{LGPP}^{Im}=(H_{LGPP}^{Im}(v,l): u=0,\ldots.7;\ v=0,\ldots.,4; l=1,\ldots.,L) \quad \ldots(27)$$

Where L is the number of sub-regions divided for the histogram computation.

3. RESEARCH METHODOLOGY

We used ATT and IFD database for comparison of different face recognition algorithms such as PCA, LDA, ICA, SVM and HGPP. Based on algorithm, we extract different features from a training set. Using these feature we trained the classifier. We extract features from testing set and find the accuracy of the algorithm.

4. DATA ANALYSIS

We used ATT and IFD databases for training and testing different algorithms. We took 40 persons images from ATT and IFD database. 5 images of each person are used for training and 5 images of each person are used for testing algorithms. From Fig. 3 it is observed that all algorithms give better result on ATT database then IFD database. HGPP give best result on ATT database and LDA give best result on IFD database.

5. EXPERIMENTAL RESULTS

Here, two face databases have been employed for comparison of performance. These are - 1. ATT face database and 2. Indian face database (IFD). These two databases have been chosen because the ATT contains images with very small changes in orientation of images for each subject involved, whereas the IFD contains a set of 10 images for each subject where each image is oriented in a different angle compared to another.

CSU Face Identification Evaluation system is used to provide the pre-processed databases which are converted to JPEG format and resizes them to smaller size to speed up computation. A few images of both databases are shown below :

Fig.1: Images of a Subject from the ATT Database

Fig.2: Images of a Subject from the IFD Database

The evaluation is carried out using the Face Recognition Evaluator. It is an open source MATLAB interface. Comparison is done on the basis of rate of recognition accuracy. Comparative results obtained by testing the five i.e. PCA, LDA, ICA, SVM and HGPP algorithms on both the IFD and the ATT databases.

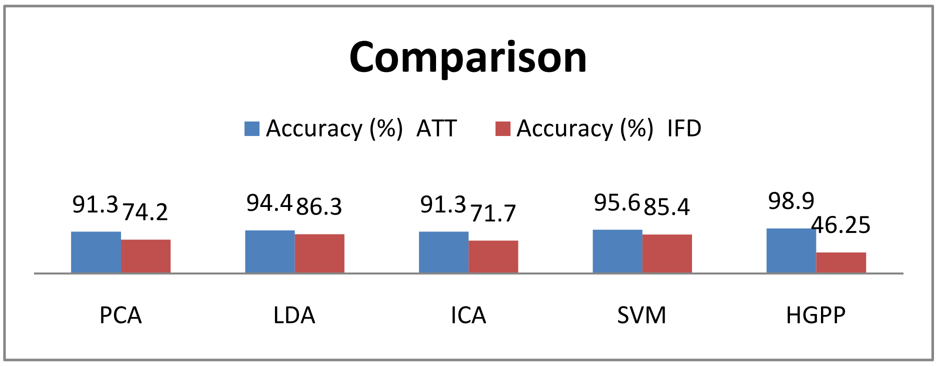

Fig. 3: Comparative Study of Five Algorithms On The Basis Of Recognition Accuracy

6. PERFORMANCE ANALYSIS

Above analysis shows the performance of the five algorithms on the database of the ATT and IFD. Following points we have observed in this experiment.

- It is observed that recognition rate of the ATT database is higher as compare to IFD database. This observation is due to the nature of images contain in the IFD database. In this database, each subject is portrayed with highly varying orientation angles. It also shows that each image has rich background region than the ATT database.
- It is observed that HGPP has 98.9% rate of accuracy of recognition. LDA and SVM have the almost same rate of accuracy of recognition, which outperform the PCA and ICA.
- It is observed that when five algorithms employed on IFD database then LDA outperform all remaining four algorithms. LDA has highest rate of accuracy of recognition i.e. 86.3%. Although LDA has the highest rate but it is marginally higher than SVM i.e. 85.4%. PCA and ICA the moderate rate of accuracy of recognition i.e. 74.2% and 71.7**%** respectively. HGPP has the lowest rate of accuracy of recognition i.e. 46.25%. It shows that HGPP is effective but suffers from the local variations.

7. CONCLUSION

Here, we have employed five algorithms of face recognition i.e. PCA, LDA, ICA, SVM and HGPP. The performance was calculated in terms of the recognition accuracy. It is observed that recognition rate of the ATT database is higher as compare to IFD database. This observation is due to the nature of images encompassed in the IFD. It is observed that HGPP has 98.99% rate of accuracy of recognition for ATT. It is observed that when five algorithms employed on IFD database then LDA outperform all remaining four algorithms. LDA has highest rate of accuracy of recognition i.e. 86.3%. HGPP is effective but suffers from the local variations that's it has the lowest rate of accuracy when HGPP employed on IFD database.

8. FUTURE SCOPE

Lot of work can be done in field of face recognition such as most of the algorithms give good result on Frontal Face recognition but at different angles they do not give good result. To recognize a face at an angle we have to give some 3D face recognition algorithm. We can club other modality with face recognition algorithm for best results example face- iris, face-fingerprint, face-iris-fingerprint. Face recognition algorithm rate can be improved by first detecting the face from image and then crop the detected face and process it for recognition.

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