

A Comparative Study of Face Recognition Algorithms under Facial Expression and Illumination

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Abstract—Face recognition algorithms enable computational devices to automatically recognize human faces and have been adopted by many big tech companies. These algorithms have shown fairly acceptable performance in criminal identification, healthcare, advertisement, access and security, payments and other different areas. In this paper, we attempt comparatively to identify best algorithms in terms of accuracy when applied on datasets that have considerable facial expression and pose illumination challenges. We selected benchmark datasets and applied preprocessing techniques to suppress noise in the images. We then applied different algorithms for feature extraction and then feed these features to the classifier. Based on the conducted experiments, we observed that the Local Binary Pattern Histogram algorithm outperformed the other two selected algorithms by about 1% against Linear Discriminant Analysis (LDA) and about 9% against Principal Component Analysis (PCA). In addition, LDA outperformed the other two by obtaining about 99.532% of accuracy on JAFFE dataset.

Keywords—Face Recognition; PCA; LDA; LBPH; Yale Faces; Illumination; Facial Expression.

I. INTRODUCTION

In general, we can define face recognition by a machine as identification or verification of a person or persons in a test image or video using a stored database of faces. In order to narrow down the search, other available information, such as race, gender, facial expression, and age are used by the system. The face recognition model gets trained with the set of face images and corresponding identities. The trained model will return the identity associated with the trained faces by providing a test image. The problem of automatic face recognition involves three key subtasks: 1. Detection 2. Feature extraction and 3. Identification and verification [2].

The importance of face recognition to solve real-world problems has captured the attention of researchers from different areas. Researchers from computer vision, computer graphics, pattern recognition, image processing, psychology and from some other areas have contributed solving the problem of facial recognition [1]. It has numerous application, in day to day life, such as criminal identification, digital photo album organization, image tagging, surveillance, and etc. Moreover, it has many advantages over other biometric approaches that are intrusiveness (subject physical contact is not needed to present the biometric sample), subject identification

from a distance, consent (permission of the subject is not required in surveillance). Beside some advantages it has some limitation, such as large template size, distinctiveness which means that some feature may repeat for different subjects, accuracy, and stability [13].

The accuracy of facial recognition algorithms depends on the challenges of faces dataset. The datasets may reflect different challenges, such as pose variation, facial expression, occlusion, illumination, aging, and etc. Some algorithms may perform comparatively well against datasets having the facial expression while some other may produce good results against datasets having the partial occlusion or pose variation challenge or factor [3]. Facial expression and pose illumination are the factors that affect the face recognition algorithm's accuracy, so what classic face recognition algorithm should be considered against the datasets reflecting these two factors together or one of them alone[17][18]? To overcome these problems, we have arranged a comparative study to find and compare the accuracy of three classic face recognition algorithms that are PCA (Principal Component Analysis), LDA (Linear Discriminant Analysis), and LBPH (Local Binary Pattern Histogram) against two face datasets having considerable facial expression and pose illumination that are Yale dataset of faces [16] and JAFFE (Japanese Female Facial Expression) dataset of faces [15].

This paper is organized as follows: section 2 covers the related work; section 3 addresses the methodology; section 4 explores the Experiments results; section 5 covers Conclusion and future work; section 6 contains references; and section 7 contains acknowledgements.

II. RELATED WORK

The most important step for any facial recognition system is to extract features from a face image. This feature extraction practice can be defined as the procedure of extracting related information from a face image. This information must be valuable to the later step of identifying or verifying the subject with a satisfactory error rate. It should be effective in terms of computation speed and memory usage and should be optimized for the classification step.

Feature extraction includes several sub-steps i.e. dimensionality reduction, feature extraction, and feature selection. These steps may overlap such that dimensionality reduction could be achieved as a result of the feature extraction [4]. Figure 1 show a generic approach of face recognition.

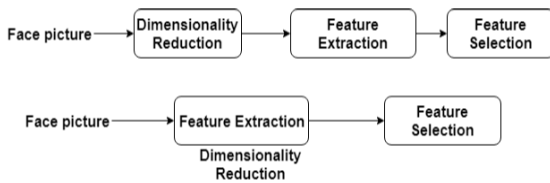


Figure 1. Generic approach to face recognition ([4]).

We have used the term “classic algorithms” for the algorithms that use some statistical approaches to solve the problem of facial recognition. The examples of classic algorithms are Principal Component Analysis [5], Linear Discriminant Analysis [6], Local Binary Pattern [7], Histograms of Oriented Gradients-Elastic Bunch Graph Matching [8], and Scale Invariant Feature Transform [9].

A comparative study of PCA, PCA with KNN (K Nearest Neighbor) classifier and histogram method for recognizing faces have been conducted by [10]. The databases that have been used in this work are AT&T-ORL database and Yale database. AT&T-ORL database has got 40 unique subjects each subject contains ten face images. Some subjects are varying in lighting and also in the facial expression, such as open/closed eyes, smiling/not smiling and some with partial occlusion by having glasses. The background of all images was the same and images were taken in an upright frontal position. In Yale face database, there are 15 subjects each subject has 11 images. During the experiments, it have been observed that the histogram outperformed PCA and PCA with KNN. Histogram has topped the list with 99.75% and PCA with KNN and PCA have obtained 95.5% and 94.25% of accuracy respectively; while, against Yale face database, the accuracy of histogram has been observed lower than PCA with KNN.

In a critical performance appraisal of four major classical facial recognition techniques i.e. I) Principal Component Analysis (PCA), II) Linear Discriminant Analysis (LDA), III) Discrete Cosine Transform (DCT), and IV) Independent Component Analysis (ICA), it has been observed that DCT is robust to facial expression variation. LDA has topped the list for the lighting effects, and PCA has topped the list for pose variation. The experimental results have been observed with three publicly available datasets i.e. ORL, Yale, and FERET datasets. The performance appraisal has been made based on variant facial expression, illumination, and poses [11]. To evaluate the performance under pose variation the authors have selected 200 images of twenty individual per individual 10 images from FERET database. The model has been trained with 100 images (five images per every twenty persons) and has been tested with 100 images (five images per every twenty persons). Table 1 shows the accuracy rate of all four algorithms against facial expression while Table 2 shows the accuracy rate under illumination.

Strategy	Results	
	Method	Recognition Rate %
Using first five images of each person for training and remaining six images of that person for testing	PCA	171/200 = 85.5
	LDA	177/200 = 88.5
	DCT	183/200 = 91.5
	ICA	175/200 = 87.5

Table 1. Accuracy of facial recognition algorithms against facial expression ([11]).

Strategy	Results	
	Method	Recognition Rate %
Using first five images of each person for training and remaining six images of that person for testing	PCA	74/90 = 82.22
	LDA	78/90 = 86.66
	DCT	69/90 = 76.66
	ICA	64/90 = 71.11

Table 2. Accuracy of facial recognition algorithms against Illumination ([11]).

Another comparative study of PCA and LDA methods conducted by [12] using Yale face database, which contains 165 images of 15 different persons with considerable variation in lighting, and facial expression. Each image size were 320x243 pixels. The results of the experiments are given in Table 3.

Category of images	Total No. of Test Images	No. of Face Recognized PCA	No. of Face Recognized LDA	Face Recognition Ratio in PCA (%)	Face Recognition Ratio in LDA (%)
Illumination Condition	45	25	22	55.55	48.88
Glass-Non Glass	30	25	28	83.33	93.33
Facial Expression	90	70	70	77.77	81.21
All Images	165	120	123	72.72	74.47

Table 3. The experiments results ([12])

To compare SURF (Speed-Up Robust Features) based feature extraction and recognition method with SIFT (Scale Invariant Feature Transform) [14] the authors have used two databases of faces that are the AR-Face database and CMU-PIE database. The AR-Face database contains frontal view face images of 126 persons 70 male and 56 female, the photos have been taken in two terms with a two-week time delay, in each term, they took 13 images of a person with different variations in pose and in lighting and with some partial occlusion on faces. The CMU-PIE database contains 41368 images of 68 persons each person with 13 invariant poses, under 43 different lighting condition and with 4 variant facial expressions. The authors have only used the frontal images subset under lighting for their experiments. For feature extraction, they have used a grid based local feature extraction method instead of an interest point detection based extraction. The result showed that surf descriptors are more robust to lighting, whereas, the SIFT descriptors are more robust to pose variation. Another method of facial recognition called HOG-EBGM (Histograms of Oriented Gradients-Elastic Bunch Graph Matching) has been proposed by [8]. They have used the histogram descriptor instead of Gabor feature to have better results. The experiments have been conducted against subsets of FERET database. During experiments, they have observed that the proposed method is more robust to illumination, rotation and small displacement. Table 4 contains the comparison of HOG-EBGM with other facial recognition algorithms.

FERET subsets	PCA Euclidean	PCA Mahalanobis Cosine	LDA	Bayesian MAP	Bayesian ML	Gabor-EBGM	HOG-EBGM
Fafb	74.3%	85.3%	72.1%	81.7%	81.7%	87.3%	95.5%
Fafc	5.6%	65.5%	41.8%	35.0%	34.5%	38.7%	81.9%
Dup1	33.8%	44.3%	41.3%	50.8%	51.5%	42.8%	60.1%
Dup2	14.1%	21.8%	15.4%	29.9%	31.2%	22.7%	55.6%

Table 4. Recognition rate for PCA Euclidean, PCA Mahalanobis Cosine, LDA, Bayesian MAP, Bayesian ML, Gabor-EBGM and HOG-EBGM using the FERET database ([8]).

III. METHODOLOGY

The research methodology for this work is experimental, we will be observing the accuracy of different facial recognition algorithms against various types of face databases. figure 2 illustrate the comprehensive pipeline of our methodology.

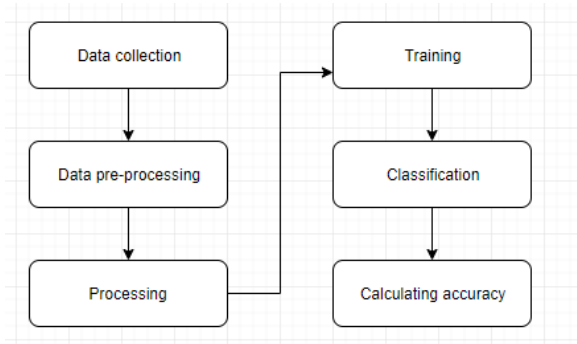


Figure 2. Methodology

A. Data Collection

Our dataset of interest were the datasets reflecting facial expression and illumination for this reason we have downloaded two publicly available dataset that are Yale face database and JAFFE (Japanese Female Facial Expression) face database. The Yale face dataset contains the images of 15 individual, it contains 11 images per person that make 165 images in total, all the images are in GIF format. Each image has been captured with different configuration, such as wink, surprised, sleepy, sad, right-light, normal, without glasses, left-light, happy, and center-light. The database is publicly available for non-commercial use [16]; a single subject sample is shown in figure 3.



Figure 3. Sample images of Yale face database ([16]).

The JAFFE database of faces contains 213 images of 10 individuals taken at Psychology Department in Kyushu University. The JAFFE database has got considerable facial expression, the photos have been taken under 6 basic facial expression with a neutral expression. Figure 4 shows the way images have been taken under different facial expression [15].



Figure 4. Sample images of JAFFE face database ([15]).

B. Data Pre-processing

After we have collected the data, in very first step, we have copied all the images of each subject to a separate directory and name them accordingly. Then we have retrieved them in Python for further processing. We have used some built-in function to detect faces in images and have converted them into numpy arrays. During face detection, the images have been cropped only to face area which is also known as Region of Interest (ROI).

C. Processing

After the pre-processing and converting images into Numpy arrays (matrices), it is time to apply some feature extraction algorithms to extract the useful feature. For the trials purpose, we have used 3 different algorithms for the feature extraction i.e. PCA, LDA and LBPH.

D. Training and Classification

For training and classification, we have used the k-fold cross validation method as such that we have divided all data of each dataset into 10 folds, where the model has been trained with 9 folds and tested with one fold. In each iteration, the testing fold was getting swapped with one of the training fold in decrementing order to have better estimation of accuracy. For example, the 165 images of the Yale face database have been divided into ten folds, now some fold will hold 16 and some other will hold 17 images. In first iteration, the first 9 folds which hold 148 images will go for the training and the 10th fold will go for the testing, while in 2nd iteration, the first 8 folds which holds 131 images plus the last fold which hold 17 images will go for the training, and the 9th fold will go for the testing. This procedure will continue till the end; figure 5 illustrates the configuration of k-fold cross validation.

Fold 0	Train	Train	Train	Train	Train	Train	Train	Train	Train	Test
Fold 1	Train	Train	Train	Train	Train	Train	Train	Train	Test	Train
Fold 2	Train	Train	Train	Train	Train	Train	Train	Test	Train	Train
Fold 3	Train	Train	Train	Train	Train	Train	Test	Train	Train	Train
Fold 4	Train	Train	Train	Train	Train	Test	Train	Train	Train	Train
Fold 5	Train	Train	Train	Train	Test	Train	Train	Train	Train	Train
Fold 6	Train	Train	Train	Test	Train	Train	Train	Train	Train	Train
Fold 7	Train	Train	Test	Train	Train	Train	Train	Train	Train	Train
Fold 8	Train	Test	Train	Train	Train	Train	Train	Train	Train	Train
Fold 9	Test	Train	Train	Train	Train	Train	Train	Train	Train	Train

Figure 5. K-fold cross validation configuration

E. Calculating Accuracy

The true positive rate and false positive rate have been counted at the end of each fold and has summed up at the end as a total; the total then have been divided by the total number of samples. The standard deviation has been calculated in the same way.

IV. EXPERIMENTS

The 64 bit version of python 3.6 has been used as a programming language on the top of Windows operating system. Python offers support for various types of computer vision and machine learning libraries, such as OpenCV, Keras, Tensorflow, Scikit-learn, and etc. For the problem of face recognition, we have used OpenCV 3.4 (Open Computer Vision) along with some other general purpose libraries like OS (used for read/write operations), numpy that is used for the complex arrays or matrices, pickle (Serialization purpose), Pillow, and some other. OpenCV offers hundreds of optimized algorithms that can be used for object identification, human action classification in a video, face detection and recognition, tracking camera movement, and etc. In this work, we have used some pre-defined functions representing a certain algorithm's functionality, such as `eigenFaceRecognizer_create()` for PCA, `fisherFaceRecognizer_create()` for LDA, and `LBPFaceRecognizer_create()` for LBP Histogram algorithm. It also offers many function for image pre-processing such as color conversion, removing image noise, cropping, deformation, and many other. We usually do the pre-processing after images collection, which helps to avoid errors.

The experiments results conducted against Yale face database shows that the LBPH algorithms is more robust to illumination and a little facial expression as compare to other two. Table 5 shows the accuracy and standard deviation obtained during experiments.

S.No	Algorithm	Mean accuracy $\pm$ Std
1	LBPH	84.242 $\pm$ 0.0562
2	LDA	83.636 $\pm$ 0.099
3	PCA	75.151 $\pm$ 0.083

Table 5. Accuracy and Standard Deviation against Yale Face Database

Table 6 contains the result of the experiments against JAFFE database of faces, LDA has outperformed PCA and LBPH algorithms for a database that is reflecting facial expression.

S.No	Algorithm	Mean accuracy $\pm$ Std
1	LBPH	98.598 $\pm$ 0.029
2	LDA	99.532 $\pm$ 0.0136
3	PCA	99.065 $\pm$ 0.027

Table 6. Accuracy and Standard Deviation of PCA, LDA and LBP against JAFFE Face Database.

V. CONCLUSION AND FUTURE WORK

The experiments have been carried out against the two datasets of faces reflecting considerable facial expression and illumination. From the conducted experiments, it have been observed that LBPH algorithm is more robust to illumination factor in general; while LDA has been proven more robust to facial expression factor. With this work, now it is clear that the classical facial recognition algorithm is not performing so well against illumination effects. So deep learning model needs to be tested against this challenge with various types of available face datasets.

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