Article

A Comparative Study of Face Recognition Algorithms under Occlusion

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Abstract

Face recognition algorithms are used to automatically recognize human faces. It has got a wide variety of applications in many areas such as Surveillance, access, security, advertisement, healthcare, and etc. Many big tech companies have already adopted this technology and it has been proved as promising convenient biometric technology. In this paper, we are comparing the face recognition algorithms performance against the datasets that are reflecting considerable occlusion (the hidden part of the face, the face parts could be hidden with scarf, glasses, hair or any other object). We selected two publicly available datasets, the first one is the face disguise dataset that reflects major occlusion and the second one that is Specs on Faces (SoF) dataset that reflects partial occlusion. After the data collection, we run the data preprocessing techniques in which we removed the existing noise to the datasets and organized them into different sets. Afterward, we applied feature extraction algorithms and then we fed them into classifiers to get algorithm's performance. At the end of the experiments, we observed that the Local Binary Pattern Histogram (LBPH) algorithm outperforms the other two algorithms by securing 33.444% accuracy against the dataset with major occlusion and 98.504% accuracy against the dataset with partial occlusion, and Linear Discriminant Analysis (LDA) secured the second position against the dataset with major occlusion but third position against the dataset with partial occlusion.

Keywords: *Face Recognition; PCA; LDA; LBPH; Specs on Faces; Occlusion; Face Disguise Dataset*

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Introduction

Machines are getting trained with a set of human face images and corresponding labels or names, then a test or probe image is sent for the verification or identification. In the process of verification or identification, a person gets identified or verified by using the stored database of faces. The trained model returns the label associated with the probe image. Features such as race, gender, facial expression, pose variation, and age could be used to limit the search space. The process of auto face recognition contains three subtasks that are face detection, feature extraction, and identification or verification [2].

The significance of face recognition technology in solving real-world problems has attracted researchers' attention from different fields of study. Researchers from computer vision, computer graphics, pattern recognition, image processing, psychology, and other areas have contributed to solving the problem of face recognition by machine [1]. Face recognition can be effectively used in many daily life systems, it's already integrated into different systems such as criminal identification, digital photo album organization, image tagging, surveillance, etc. Also, face recognition has got many advantages over other biometric approaches. Some of the advantages are as follows: intrusiveness (subject physical contact is not needed), subject identification from a distance, consent (subject permission is not required, especially in surveillance). Besides that, face recognition has got some shortcomings such as big template size, distinctiveness and even some of the features may repeat for different subjects, accuracy, and stability [13].

Challenges of the face datasets, affect the accuracy of face recognition algorithms. A dataset may reflect different challenges or only one challenge. The dataset challenges that could pose variation are, facial expression, occlusion, illumination, aging, etc. Some algorithms may result comparatively well against datasets reflecting the pose variation while some other may obtain good results against datasets reflecting the partial occlusion or facial expression challenge or factor [3]. Occlusion, either partial or major are the factors that affect the face recognition algorithm's accuracy, so what classic face recognition algorithm should be considered against the datasets reflecting this factor [17] [18]? To deal this situation and tackle the problem, we arranged a comparative study of three 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 occlusion that are Specs on Faces (SoF) dataset [16] and Face Disguise Dataset of faces [15].

Paper organization is as follows: section 2 covers the related work, section 3 addresses the methodology, the Experiments results have explored in section 4 and section 5 covers Conclusion and future work

2. Related Work

Feature extraction is the most important step of any face recognition system which takes place after face detection. It is the process of extracting related and discarding irrelevant information from a face image. These features must be appropriate for the next step of identifying or verifying the subject with a satisfactory error rate. The feature extraction process should be effective in terms of memory usage and computational speed and at the same time, the features space should be optimized for the classification step.

There are three sub-steps in the feature extraction process that are: dimensionality reduction, feature extraction, and feature selection. These steps may edge each other such that dimensionality reduction could be achieved as a result of the feature extraction [4]. Figure 1 shows a generic approach to the face recognition.

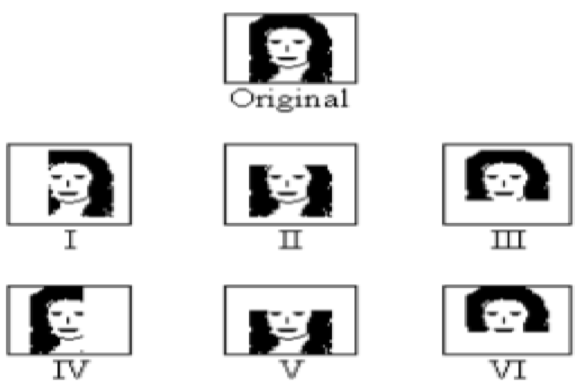

Figure 1: *Generic approach to face recognition [4].*

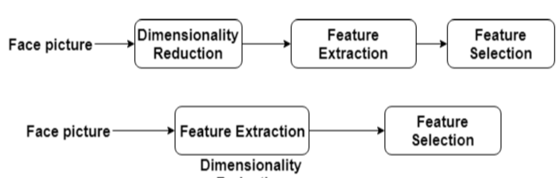

Figure 2: *Left, right, up, and down occlusion [19].*

The term "classic algorithms" is used for the algorithms which work with 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]. They have used the Yale dataset of faces and AT&T-ORL database of faces. Both of the datasets reflect partial occlusion as subjects with wearing glasses. The number of images in each dataset varies as there are 400 images for 40 subjects in the AT&T-ORL dataset and 165 images for 15 subjects in Yale face dataset. During the experiments, it was observed that the histogram algorithm outperformed PCA and PCA with KNN. The histogram has topped the list with 99.75% and PCA with KNN and PCA have obtained 95.5% and 94.25% accuracy respectively; while, against Yale face database, the accuracy of the histogram is lower than PCA with KNN.

A comparative study of PCA and LDA methods conducted by [11] using the Yale face database. As shown in Table 1, LDA has outperformed the PCA for the whole set of the dataset while results vary for the different trials they have conducted under different face challenges. To test the accuracy under partial occlusion, they have considered a subset of images with glasses and without glasses. Under partial occlusion, LDA has got 93.33%, while PCA has scored 83.33%. The obtained results show that LDA is more robust under partial occlusion factor, and the results also confirm that LDA is more robust for facial expression as compared to PCA.

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 (%)
Glass Non Glass	30	25	28	83.33	93.33
Illumination condition	45	25	22	55.55	48.88
Facial expression	90	70	70	77.77	81.21
All images	165	120	123	72.72	74.47

Table 1: *Accuracy of facial recognition algorithms against Partial occlusion [11].*

In a study of relative performance evaluation, various types of experiments have done against six types of sub-datasets that were formed from one original dataset. Figure 2. shows the partial occlusion from left, right, up and down [19]. For the experiments they have used 25 and 50 images, the following scores have been observed after the experiment(.)

Method	No. of Training Faces	Case I Percentage	Case II Percentage	Case III Percentage	Case IV Percentage	Case V Percentage	Case VI Percentage
PCA	25	96	60	100	100	32	100
	50	33	37	90	58	21	71
LDA	25	0	0	0	20	0	0
	50	4	1	7	0	1	1
ICA	25	28	24	4	20	20	20
	50	10	20	2	10	20	10

Table 2: *Experiment results with partial occlusion [19]***.**

A PCA based face recognition technique called Lophoscopic PCA has been presented that tries to tackle the problem of partially occluded faces or strong facial expression variations. The result of the experiments shows that the performance of PCA can be increased using this technique. However, the major drawback of the new algorithm is the computational cost that is six times higher than the traditional PCA algorithm. The Lophoscopic LDA technique has been developed which is currently being implemented to enable the whole approach more robust against the illumination conditions [12].

Comparing SURF (Speed-Up Robust Features) based feature extraction and recognition method with SIFT (Scale Invariant Feature Transform) [14] for the experiments, authors have used two datasets of faces that are the AR-Face database and CMU-PIE database. The AR-Face dataset contains images of 126 subjects which are 70 males and 56 females. The photos were taken in a two-week time in two different terms, in each term. They took 13 images of a person with some partial occlusion on faces and with different variations in pose and lighting. The CMU-PIE database contains 41368 images of 68 people each person with 13 invariant poses under 43 different lighting conditions and with 4 variant facial expressions. Only AR face dataset has been used for evaluating the partial occlusion, and the results of the experiments are given in table 3. It has been observed that the U-SIFT descriptor has secured the best average result.

Descriptor	Error Rates [%]					
	AR1scarf	*AR1sun*	*ARneutral*	*AR2scarf*	*AR2sun*	Avg.
SURF-64	2.72	30.00	0.00	4.54	47.27	16.90
U-SURF-64	4.54	23.63	0.00	4.54	47.27	15.99
SURF-128	1.81	23.63	0.00	3.63	40.90	13.99
U-SURF-128	1.81	**20.00**	0.00	3.63	41.81	13.45
SIFT	1.81	24.54	0.00	2.72	44.54	14.72
U-SIFT	**1.81**	20.90	**0.00**	**1.81**	**38.18**	**12.54**
U-SURF-128+R	1.81	19.09	0.00	3.63	43.63	13.63
U-SIFT+R	2.72	**14.54**	0.00	**0.90**	35.45	10.72
U-SURF-128+U-SIFT+R	**0.90**	16.36	**0.00**	2.72	**32.72**	**10.54**
DCT [[illegible]], baseline	8.2	61.8	7.3	16.4	62.7	31.28
DCT [[illegible]], realigned	2.7	1.8	0.0	6.4	4.5	3.08

Table 3: *Error rates for the AR-Face dataset with partially occluded faces using different descriptors, 1024grid-based extractors and grid-based matching constraints [14].*

3. Methodology

The objective of this experimental work is to find out the accuracy of face recognition algorithms. As a result, we have considered different facial recognition algorithms against the datasets reflecting major occlusion on faces. Figure 2 shows the working pipeline of methodology

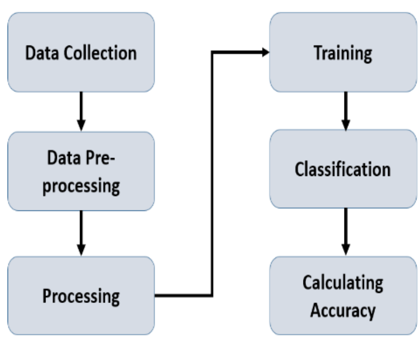

Figure 3: *Methodology.*

A. Data Collection

Since we are finding out the accuracy of algorithms against the occlusion challenge, the dataset of interest is the dataset which reflects considerable occlusion, for this purpose, we have worked on publicly available datasets that are Specs on Faces (SoF) dataset, and Face Disguise dataset of faces. The Specs on Faces (SoF) dataset of faces contains 42,592 images of 112 people (66 males and 46 females) with partial occlusion and illumination conditions. Out of 112 subjects we have chosen only 81 subjects for the experiments and for each subject we have chosen 6 different images under different partial occlusion. Figure 3 shows a sample of the dataset.

Figure 4: *Sample images of Specs on Faces [16].*

The Face Disguise Dataset contains 2000 images recorded with male and female subjects aged from 18 years to 30 years. The dataset was collected from 8 different backgrounds and 10 different occlusions. For occlusion, they have used scarf, beard, and glasses, cap (hat) and combined as cap and scarf. We have chosen 10 images of each subject under glasses, beard, and scarf. Figure 4 shows a sample of dataset images.

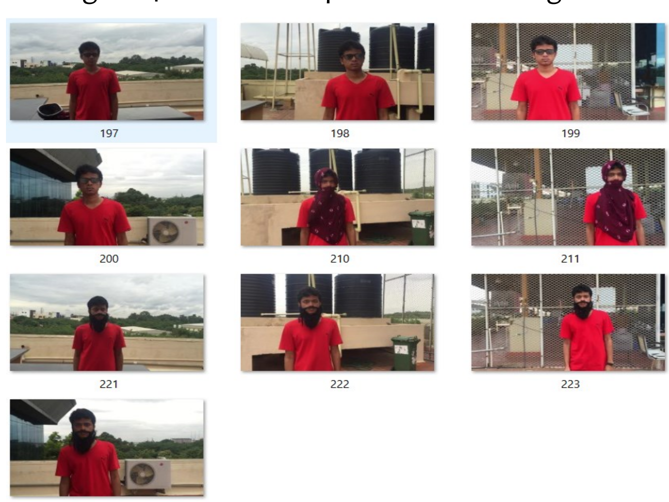

Figure 5: *Sample images Face Disguise Dataset [15].*

B. Data Pre-processing

We proceeded with the data pre-processing. For better data organization we have placed each subject into a different directory and then we have retrieved them in python as Numpy arrays, as we were interested in only faces so we have used some built-in methods to crop images into face area or to the region of interest.

C. Processing

Now as we got the faces out of images by removing the background. It is time to extract the features from the faces. For this, we have considered three face recognition algorithms that are PCA, LDA, and LBPH. At the end of each algorithm, we have some features which will be used for the classification in the upcoming step.

D. Training and Classification

Features have been extracted in the previous step now it is time to feed them into a model and provide probe images for the classification. (In)here for training and classification, the k-fold cross validation method has been used as the data of each dataset has been divided into 10 folds. In each iteration, and the model has been trained with 9 folds and tested with one-fold. The testing fold swapped in each iteration with one of the training folds. It means that in the first iteration the first 9 folds were used for the training and the 10th fold used for the testing. For the second iteration, the first 8 folds and the 10th used for the training and the 9th fold used for the testing. In the third iteration the first 7 folds and fold 9th and 10th used for the training and fold 8 used for the testing. This procedure is continued until 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 6: *K-fold cross validation configuration.*

E. Calculating Accuracy

At the end of each fold, the program counts the true positive rates and false positive rates, then in the end of last fold, it summed up the true positive rates as a total. The total is divided by the overall number of samples to find out the accuracy. The standard deviation has been calculated in the same way.

4. Experiments

We have used python 3.6 as a programming language on the top of the Windows operating system. Python supports machine learning and computer vision libraries, such as OpenCV, Keras, Tensorflow, Scikit-learn, etc. In order to run the experiments and find out accuracy of face recognition algorithms, we have used OpenCV 3.4 (Open Computer Vision) along with some other general-purpose libraries like OS (used for read/write operations), Numpy which 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, recognition, tracking camera movement, etc. In this work, we have used some pre-defined functions REPRESENTING A CERTAIN ALGORITHM'S functionality such as eigenface Recognizer_create () for PCA, fisher Face Recognizer_create() for LDA, and LBPH Face Recognizer_ create() for LBP Histogram algorithm. It also offers many functions for image pre-processing such as color conversion, removing image noise, cropping, deformation, and many others. We usually do the pre-processing after images collection, which helps to avoid errors.

The experiments results conducted against the face disguise dataset show that the LBPH algorithm is robust to occlusion. Even though LBPH is not obtaining a very good percentage of accuracy but still good as compare to the other two algorithms. As discussed earlier the face disguise dataset reflects major occlusion even in some images with scarfs the nose and mouth are hidden. Table 5 shows the accuracy and standard deviation obtained during experiments.

S.No	Algorithm	Accuracy ± Std
1	LBPH	33.444 ± 0.031
2	LDA	23.411 ± 0.054
3	PCA	22.073 ± 0.067

Table 4: *Accuracy and Standard Deviation against face disguise dataset of faces.*

Table 6 contains the result of the experiments against Specs on Faces (SoF) dataset of faces, LBPH has outperformed PCA and LDA algorithms, PCA secured 2nd position by obtaining 98.290% of accuracy. As discussed earlier the SoF dataset of faces doesn't reflect a great amount of occlusion but a part of the face is hidden with glasses.

S.No	Algorithm	Accuracy ± Std
1	LBPH	98.504 ± 0.0138
2	LDA	90.384 ± 0.053
3	PCA	98.290 ± 0.016

Table 5*: Accuracy and Standard Deviation of PCA, LDA and LBP against SoF dataset of faces.*

5. Conclusion and Future Work

In the first round of experiments, all three algorithms have been running against face disguise dataset that reflects major occlusion, the LBPH algorithm outperformed the other two by obtaining 33.444% of accuracy. LDA secured the second position by obtaining 23.411% of accuracy and PCA remained last in the list by obtaining 22.073% of accuracy. In the second round of experiments, that were against SoF dataset reflect partial occlusion and again LBPH algorithm outperformed the other two by obtaining 98.504% of accuracy, PCA secured the second position by obtaining 98.290% of accuracy and LDA remained last in the list by obtaining 90.384% of accuracy. To conclude the discussion, we can say that the LBPH algorithm is performing comparatively well against the dataset that reflects partial and major occlusion. The deep learning structures have not been considered in this study; these structures may produce interesting results against the dataset that reflects occlusion.

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