Illumination Invariant Face Recognition under Various Facial Expressions and Occlusions

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Abstract. This paper presents a new approach that increases face recognition performance using various facial expressions in the presence of illumination variations and occlusions. The new approaches use PCA and LDA with the combination of the preprocessing techniques of histogram equalization and mean-and-variance normalization in order to nullify the effect of illumination changes and any occlusions present which are known to significantly degrade recognition performance. To be consistent with the research of others, our work has been tested on the JAFFE database and its performance has been compared with traditional PCA and LDA.

Keywords: face recognition, facial expressions, face occlusion, illumination, PCA, LDA.

1 Introduction

Face recognition has been extensively studied in recent years. However, it is still an unsolved problem under varying conditions such as different facial expressions, illumination variations and partial occlusions. Researchers studying in this field [1-5] are trying to find robust techniques which recognize faces with different facial expressions, partial occlusions and illumination variations.

A facial expression results from one or more motions of the muscles of the face. These movements can depict sadness, anger, happiness, fear, disgust or surprise on the face of an individual. From the perspective of facial recognition, a facial expression can be considered to consist of deformation of facial components and their spatial relation, or changes in pigmentation of the face [6]. On the other hand, a person may have a medical operation on his/her face and a region on the face can be occluded by a band. These occlusions may randomly appear in any region of the face with different sizes or any specific area of the face such as one of the eyes, both left and right eyes, nose and mouth may also be occluded. In addition to these difficulties, there may be some illumination variations on the facial images in which the faces become darker or brighter according to some uncontrolled environmental conditions.

Each of these difficulties was studied separately to find robust face recognition methods which are not affected by illumination variations, occlusions and facial expressions. In [7], an occlusion robust face recognition scheme with dynamic similarity features was proposed which randomly crops different size patches on the test images.

They used FERET database for the experiments. The patches were small squares which were placed on the cropped face randomly. The proposed method which was a generalization of KDA algorithm was robust to random occlusions to some extent.

In [8], the authors performed experiments on AR database to recognize faces under different conditions such as using partially occluded faces with sunglasses and scarf, and using synthetic occlusion patterns (occlusions on local patches of the facial images). In this context, their S-LNMF based recognition algorithm is better than the other algorithms on real occlusions (sunglass and scarf occlusions) and it performs very well on synthetic occlusions.

Another technique was proposed in [9] which uses Lophoscopic PCA. The authors used six subsets of images in the training set which correspond to the whole face, and the masking of the left eye, right eye, both eyes, nose and mouth respectively. Then they combined these subjects using different combination strategies. They demonstrated that Lophoscopic PCA performs better than PCA approach. They created and used UPC database in their experiments.

On the other hand, [10] presents another scheme for face recognition in the presence of expression and/or illumination variation. Their wavelet-based face recognition scheme demonstrated an improved accuracy compared to PCA. They used JAFFE and ORL databases.

In this study, we considered all the difficulties faced in solving the face recognition problem in the presence of illumination variations, facial expressions and occlusions. These three difficulties were not considered altogether in the same study before and therefore, a new approach is proposed to reduce the effect of these difficulties on the face recognition problem using PCA-based and LDA-based approaches with the combination of the preprocessing techniques histogram equalization (HE) and mean-and-variance normalization (MVN) on the JAFFE database. Various experiments were performed to test the recognition performance of the proposed normalized approaches (nPCA and nLDA) under different illumination variations, six different facial expressions and specific and random occlusions on the facial images.

The rest of the paper is organized as follows. Section 2 presents the details of the proposed approaches. In Section 3, the experimental results for nPCA, nLDA, PCA and LDA approaches with different scenarios on the JAFFE database are demonstrated. Finally, Section 4 presents the conclusions.

2 Our Work

As we have aforementioned, in order to reduce the effect of illumination variations, facial expressions and occlusions altogether for the solution of the face recognition problem, we proposed a new approach using PCA- and LDA-based methods. The new approaches use PCA and LDA with the combination of the preprocessing techniques histogram equalization (HE) and mean-and-variance normalization (MVN). Both HE and MVN normalization are used to improve the face recognition performance since feature normalization techniques are able to largely reduce the actual mismatch between training and testing conditions [11]. In this study, the JAFFE database is used with various occlusion types applied to specific and random regions on the human face. An example subject from JAFFE database [12] with neutral face image

and the six facial expressions (happy, disgust, fear, surprise, sad, angry) are demonstrated in Fig. 1. Specific occlusions include the regions on the face such as the left eye, right eye, both eyes, nose and mouth as shown in Fig. 2. Random occlusions are arbitrarily chosen patches with different size (dimension) and position on the facial image. Fig. 3 is a demonstration of random occlusions with five different size patches randomly placed on the cropped facial images.

Fig. 1. An example subject from JAFFE database with neutral expression and six facial expressions (angry, happy, sad, surprise, disgust, fear)

The aim of this study is to eliminate the effect of illumination variations and occlusions on facial images that has different facial expressions. The difficulty of face recognition under different facial expressions is known. In addition to this, occlusions are added on the corresponding facial images which include the following facial expressions: happiness, disgust, fear, surprise, sadness, anger.

Fig. 2. Specific occlusions on both eyes, left eye, right eye, nose and mouth region on the face

In this study, we first reduce the effect of illumination variation using histogram equalization (HE) and mean-and-variance normalization (MVN) [11] as a preprocessing technique. Then, in order to reduce the effect of facial expressions and occlusions on the face recognition performance, we applied PCA- and LDA-based normalized approaches (nPCA and nLDA) on the cropped facial images. In all recognition experiments, Euclidean distance measure was used for classification. Different scenarios on how to apply occlusions on the facial images were studied. The first scenario puts the occlusions on the neutral training images and the remaining six facial expressions for each person were tested using both normalized and traditional approaches. Then, occlusions were applied on the test images which were demonstrating one of the six facial expressions. The final scenario, which is a new scheme, is to apply occlusions on both test and training images in order to improve the recognition performance. The experimental results on these scenarios are demonstrated in the next section with different occlusion types.

Fig. 3. Random occlusions with five different size patches randomly placed on the cropped facial images (10x10, 20x20, 30x30, 40x40, 50x50 patches)

3 Experimental Results

Recognition performance of the new approach is measured using the JAFFE database. We performed 3 sets of experiments on the JAFFE database to compare the face recognition performance of the new PCA-based and LDA-based approaches (nPCA and nLDA) and the traditional PCA and LDA.

Japanese Female Facial expression Database (JAFFE) contains 213 images of 10 Japanese female facial expressions with 3 or 4 examples of each of the 6 basic facial expressions (happy, sad, surprise, anger, disgust, fear) and a neutral face. Original 256x256 images were cropped automatically by aligning the eyes at the same position and the images were rescaled down to 116x180. In each experimental set, 2 neutral images of each subject from the database is chosen and used as training images. Two sample images from the remaining 6 facial expressions of each subject are chosen to test the recognition performance of the methods used in the experiments.

In the first set of experiments the effect of illumination is studied on the face recognition problem under different facial expressions. We brighten and darken the test images by 5, 10, 15, 20, 25 percent and evaluate the recognition performance of PCA, LDA, nPCA and nLDA methods. The results of the brightening and darkening operations are demonstrated in Table 1 and Table 2. It is clear that nPCA performs better compared to the original PCA but LDA performs better than nLDA whenever the images become brighter. Darkening the images reduces the performance of PCA significantly whereas nPCA performs well in this situation. On the other hand, LDA and nLDA records a slight drop in performance whenever we darken the images.

In general, nPCA is not sensitive up to 25% illumination (either brightening or darkening) whereas PCA is sensitive to these variations. For brightening, LDA is not sensitive up to 20% whereas nLDA is sensitive to this type of changes. However they (LDA and nLDA) are both sensitive to darkening since we see a slight drop in their performance.

The second set of experiments evaluate the recognition performance of the methods under specific occlusions on both eyes, left eye, right eye, nose and mouth regions of the facial images. The experiments in this set are performed in 3 scenarios such that the specific occlusions are placed on the training images, on the test images, and on both of them. The results are presented in Table 3 through Table 5 for PCA, nPCA, LDA and nLDA.

The recognition performance of all the methods in Table 3 indicates that specific occlusions applied on the training images only do not affect the recognition performance in the presence of facial expressions on the test images.

Table 1. Recognition Rates (%) under brightened test images

Brightening Percentage	PCA	nPCA	LDA	nLDA
0	80.83	85	88.33	88.33
5	76.66	85	88.33	84.16
10	59.16	85	88.33	84.16
15	34.16	85	88.33	84.16
20	25	85	88.33	84.16
25	20.83	85	87.5	85

Table 2. Recognition Rates (%) under darkened test images

Darkening Percentage	PCA	nPCA	LDA	nLDA
0	80.83	85	88.33	88.33
5	67.5	84.16	87.5	85
10	40.83	84.16	85.83	82.5
15	24.16	84.16	83.33	81.66
20	18.33	85	80	80
25	11.66	85	74.16	80

The recognition performance over the facial expressions and occlusions on the test images of LDA and nLDA are similar and these methods are not very sensitive to specific occlusions. However, PCA and nPCA are both sensitive to specific occlusions and facial expressions over the test images with nPCA performing better than PCA as shown in Table 4.

On the other hand, whenever we apply occlusion on both training and test images, we realize from Table 5 that LDA and nLDA perform similarly and they are not very sensitive to occlusions in this scenario. PCA and nPCA are also not sensitive but nPCA is slightly better than PCA over the specific occlusion on both the training and test images.

Table 3. Recognition Rates (%) with Specific Occlusions on Training Images

Occlusion Region	PCA	nPCA	LDA	nLDA
None	80.83	85	88.33	88.33
Both eyes	80.83	83.33	84.17	85
Left eye	80	82.5	79.17	87.5
Right eye	80.83	84.17	66.67	80.83
Nose	77.5	84.17	57.5	84.17
Mouth	79.17	84.17	72.5	82.5

Table 4. Recognition Rates (%) with Specific Occlusions on Test Images

Occlusion Region	PCA	nPCA	LDA	nLDA
None	80.83	85	88.33	88.33
Both eyes	30	58.33	83.33	82.5
Left eye	59.17	75	80	82.5
Right eye	72.5	73.33	88.33	82.5
Nose	40.83	55.83	71.67	73.33
Mouth	37.5	71.67	65.83	80.33

Table 5. Recognition Rates (%) with Specific Occlusions on both Training and Test Images

Occlusion Region	PCA	nPCA	LDA	nLDA
None	80.83	85	88.33	88.33
Both eyes	80.83	83.33	84.16	85.83
Left eye	80	83.33	85.83	88.33
Right eye	80.83	84.16	78.33	86.66
Nose	77.5	82.5	80.83	87.5
Mouth	79.16	84.16	88.33	87.5

In general if we have specific occlusions on the training images, all the methods behave similarly and they are not affected much by these occlusions. However, putting specific occlusions on the test images does not affect the performance of LDA and nLDA while a performance decrease occurs for PCA and nPCA with PCA showing the greater degree of sensitivity. For the case of occlusions on both training and test images, the recognition performance for PCA and nPCA are not affected that much, nevertheless, nPCA performs better than PCA.

The effect of random occlusion is evaluated using 3 scenarios by applying patches of various sizes (dimensions) at arbitrary positions on the facial images. The dimensions of the patches are 10x10, 20x20, 30x30, 40x40 and 50x50. The third set of experiments is performed by repeating each experiment 3 times and then taking the

Table 6. Recognition Rates (%) with Random Occlusions on Training Images

Patch Dimension	PCA	nPCA	LDA	nLDA
None	80.83	85	88.33	88.33
10x10	80.83	84.72	83.61	87.77
20x20	80.83	79.17	82.5	86.67
30x30	64.97	62.77	65.55	65
40x40	41.66	33.05	46.38	53.05
50x50	41.66	20.81	46.94	47.22

Table 7. Recognition Rates (%) with Random Occlusions on Test Images

Patch Dimension	PCA	nPCA	LDA	nLDA
None	80.83	85	88.33	88.33
10x10	76.94	84.72	88.33	87.22
20x20	74.17	83.33	86.67	84.17
30x30	70.27	79.72	84.72	82.22
40x40	58.33	76.94	83.05	81.11
50x50	43.32	73.05	85.27	72.22

Table 8. Recognition Rates (%) with Random Occlusions on both Training and Test Images

Patch Dimension	PCA	nPCA	LDA	nLDA
None	80.83	85	88.33	88.33
10x10	78.87	85	86.22	84.17
20x20	74.58	67.78	73.13	78.12
30x30	58.05	55.64	51.04	62.92
40x40	35.55	29.44	26.25	32.5
50x50	23.75	17.44	25	28.75

average of these 3 runs. The experimental results demonstrated in Table 6 through Table 8 are the average recognition rates of the 3 runs.

As shown in the above tables, whenever random occlusions are placed on the training images, we see that all methods are sensitive to this type of occlusion with nLDA only slightly outperforming LDA as the patch size increases. Meanwhile PCA performs better than nPCA as the patch size increases.

On the other hand whenever we have random occlusions on the test images, the situation is reversed. LDA performs better than nLDA as the patch size increases while nPCA performs better than PCA. In general, all methods are sensitive to random occlusions applied on the test images. For the final scenario in which occlusions are applied on both training and test images, all the methods show a greater degree of sensitivity than other scenarios, there is a sharp decrease in performance as the patch sizes increases. In that case, PCA and nLDA show slightly better performances than nPCA and LDA respectively.

4 Conclusions

This paper has presented a new approach that increases face recognition performance over the traditional approaches (PCA and LDA) using facial expressions in the presence of illumination variations and occlusions. The results obtained has shown that nPCA gives a better performance over PCA in all the scenarios considered with the exception of when there is a random occlusion on both training and test images. For LDA-based approaches when there is a specific occlusion on a training set or when

specific occlusions are present on both training and test set, nLDA should be preferred to LDA. Also when random occlusions are present on training images or on both training and test images, nLDA outperforms LDA. Either LDA or nLDA could be used in situations when the test images are darker than training images or with specific occlusions on test images. However LDA outperforms our approach as illumination increases or with the presence of random occlusions only on the test images.

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