Sensitivity Analysis of Partitioning-based Face Recognition Algorithms on Occlusions

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Abstract: Holistic Principal Component Analysis (PCA) and holistic Independent Component Analysis (ICA) methods require long training times and large storage spaces for the recognition of facial images. These drawbacks can be avoided by using partitioning-based methods, namely partitioned PCA (pPCA) and partitioned ICA (pICA), which yield similar performance for pPCA and improved performance for pICA method compared to the holistic counterparts of these methods for the recognition of frontal facial images. This paper demonstrates the sensitivity analysis of pPCA and pICA methods on several types and sizes of occlusions for the recognition of facial images with similar facial expressions. The recognition rates for pPCA and pICA over occlusions are contrary to the recognition rates of these methods on occlusion-free facial images with different facial expressions.

Key-words: face recognition, PCA, ICA, multiple classier systems, classifier combination, face occlusion

1. Introduction

Face recognition is still an unsolved problem under varying conditions. The solutions to the face recognition problem are successful under controlled conditions such as controlled illumination, limited pose variations, specific facial expressions and limited face occlusions. Researchers studying in this field are trying to find robust techniques which recognize faces with occlusions, illumination variations and different facial expressions[1-6].

A number of experimental results for the face recognition problem under limited uncontrolled conditions exist but they do not exactly give a complete solution for this problem. Some researchers used facial images from their own databases which were created with limited number of individuals[1]. Others used several databases such as FERET, AR, AT&T to compare the recognition performance results of various methods[2-6]. However, there is no standardization of the number of facial images, type of facial images, type and size of occlusions, percentage of illumination changes on the faces that can be used in face recognition experiments.

In this study, the standard facial image database FERET is used with various occlusion types applied to different regions of human face such as the forehead, eyes, nose, mouth and chin. These regions are occluded horizontally on the facial images as if they are tied with thick rope or sticky tape. The main inspiration behind this study is that a person may have a medical operation on his/her face and any region in the face can be occluded by a band. In addition to these type of occlusions, the facial images are partially occluded with different percentages from their four edges as in real life the hard copy of a facial image may be burnt partially from top, bottom, left or right edges. The comparative performance analysis of partitioned PCA (pPCA) and partitioned ICA (pICA) methods are performed on the mentioned occlusion types to test the sensitivity of these techniques to partial occlusions.

The rest of the paper is organized as follows. Section 2 summarizes the previous work for the face recognition problem. pPCA and pICA methods are presented in Section 3. In Section 4, an overview of the partitioning method for face recognition is given. The experiments done for the sensitivity analysis of partitioned PCA and partitioned ICA on occlusions are demonstrated in Section 5. Finally, the conclusions and future work are presented in Section 6.

2. Previous Work

There is an extensive research on the face recognition problem over the last two decades. In the literature, a number of new techniques are investigated and proposed to find an exact solution for this problem. Among them, Kirby and Sirovich in 1990 [7] introduced Karhunen-Loeve procedure for the characterization of human faces, and then, Turk and Pentland [8] in 1991 generalized this procedure and proposed eigenface approach to extract features from the face. Eigenface approach is one of the most popular techniques for face recognition which is also known as Principal Component Analysis (PCA).

Another technique which is successfully applied on the face recognition problem is elastic bunch graph matching proposed by Lades et al. [9] in 1993. Swets and Weng [10] used Fisher's linear discriminant analysis (LDA) in 1996, and then, in 1997, Belhumeur et al. [11] popularized the use of fisherfaces for the recognition of facial images.

Independent component analysis (ICA) is also an appearance-based statistical method which was first introduced by Comon [12] in 1994 and then popularized by Hyvarinen and Oja [13] in 1997 for successful recognition of faces.

On the other hand, neural network approaches have been widely explored for feature representation and face recognition. Cottrell and Fleming [14] applied autoassociation and neural networks in 1990. Support vector machines (SVM) have been proposed as a new technique in 1995 by Vapnik [15]. In 1994, Samaria and Young [16] successfully used hidden markov models (HMM) in face recognition. Although all these algorithms have been used successfully for face recognition, each of them has its own advantages and disadvantages [17-20] that has to be considered before applying them in any recognition problem.

3. Partitioned PCA and Partitioned ICA

Principal Component Analysis (PCA) and Independent Component Analysis (ICA) are widely used appearance-based statistical approaches for the solution of face recognition problem. They are mainly dimensionality reduction algorithms which are used for feature extraction to train classifiers.

PCA projects images into a subspace in order to find the principal components that best describe data among classes [7,8]. ICA is a method for transforming an observed multidimensional random vector into its components that are statistically as independent from each other as possible [12,13].

Another name given to PCA is Eigenspace Projection or Karhunen-Loeve Transformation. PCA is used for compression and recognition problems. This method projects images into a subspace such that the first orthogonal dimension of this subspace captures the greatest amount of variance among the images and the last dimension of this subspace captures the least amount of variance among the images [7,8]. In this respect, the eigenvectors of the covariance matrix are computed which correspond to the directions of the principal components of the original data and their statistical significance is given by their corresponding eigenvalues.

ICA is an appearance-based statistical method which represents the data in terms of statistically independent variables. The goal is to minimize the statistical dependence between the basis vectors and ICA can be distinguished from other methods since it looks for components that are both statistically independent and nongaussian [12,13].

Appropriate feature extraction is an essential component of a successful face recognition algorithm [17-20]. For this purpose, statistical dimensionality reduction methods such as PCA and ICA are demonstrated to be successful in several academic studies and commercial applications [17-20]. The success and popularity of these algorithms are mainly due to their statistics–based ability of automatically deriving the features instead of relying on humans for their definitions. These algorithms are widely studied within individual and multiple classifier systems. In this study, partitioned PCA and partitioned ICA are implemented with a divide-and-conquer strategy for the solution of the face recognition problem.

The divide-and-conquer approach implemented over multiple classifier systems (MCSs) [21-23] is used to improve the computational efficiency and recognition performance of PCA and ICA methods on the face recognition problem. MCSs combine the output information provided by two or more classifiers.

In the implementation of the divide-and-conquer methodology for the face recognition problem, face images are divided horizontally into equal-width segments and PCA or ICA are used for each face segment as a feature extraction method. Consequently, a multiple classifier system is established based on a particular distance measure and finally the outputs of multiple classifiers are combined using well-known multiple classifier combination methods to recognize the whole face under occlusions.

4. Partitioning Method for Face Recognition

PCA and ICA methods require long training times and large storage spaces particularly for huge databases of facial images. The difficulties of these appearance-based face recognition algorithms are result of their holistic approach for feature extraction, which considers the features from all facial areas with equal importance. However, considering the horizontally localized characteristics and vertical symmetry of facial images, feature extraction from smaller segments may yield several advantages. Firstly, feature extraction from smaller facial segments is computationally simpler and results in faster recognition which is an important issue for large databases. Furthermore, using these features as the main components of a multiple classifier system emphasizes their contribution to the overall recognition performance.

The division process divides the face images into a number of segments and the features of each segment are extracted independent of each other using one of the appearance-based statistical methods. All the training and testing face images are cropped as shown in Fig.1(a). Cropping operation is applied in the same way for both the training and test images, so that all the images include only the head of a face after this operation. In other words, there is the forehead (without hairs) on top and the chin at the bottom of each face image (without the neck and shoulders).

After applying a dimensionality reduction algorithm on each segment of training and test images, Euclidean distance measure is used to find the distance between features of these image segments. For each test image, the distances between the test image and all the training images are compared. The training image that has the minimum distance to the test image is the image that mostly resembles to it. Consequently, a multiple classifier system is established and the outputs of individual classifiers are combined using a well-known multiple classifier combination method to recognize the whole face. For a better understanding of the theoretical gains achieved with the divide-and-conquer approach, the evaluation of computational and storage space efficiencies can be found in [19].

5. Experiments and Results

Partitioned PCA and partitioned ICA algorithms are tested on the standard FERET facial image database [24, 25] using several occlusion types and sizes. In these methods, the first *(n-1)* of the superior components are used, where *n* is the number of training face images which is 200. The training set includes 100 individuals' faces with 2 samples per person in all experiments. The test set includes 21 samples of facial images with similar facial expressions compared to the training images of individuals and different type and size of occlusions for each individual, totally 4200 facial test images.

In this study, the face images used are cropped so that they only include the head of the individuals. The face images were scaled down to 45x35 pixels from the original size of 384x256 pixels.

In the implementation of the divide-and-conquer approach, multiple classifiers are considered using the Borda Count classifier combination method. The output of each individual classifier is computed separately, followed by a multiple-classifier combination procedure which produces the final classifier or recognition output.

Two set of experiments are performed and their results are presented in Table1 and Table2. The recognition rates of both pPCA and pICA using 200 facial images for training and 200 facial images with similar facial expressions for test are 100%. In order to test the sensitivity of pPCA and pICA to occlusions, facial images with similar expressions on the training and test faces are used in the experimental datasets. The training images include the faces of individuals without any occlusion although the test images include faces of the same individuals with similar facial expressions and different size and type of occlusions.

In the first set of experiments, the facial images are occluded with different percentages (5%, 10%, 15%, 20%) from the four edges of facial images. As an example, 20% occlusions from the four edges of faces are shown in Fig.1(b)-(e).

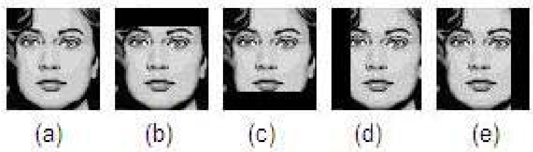

Fig. 1 Training and test images with occlusions from top, bottom, left and right edges

As shown in Fig.1, an original facial image is trained by pPCA and pICA and then 16 different variations of the training image (5%, 10%, 15%, 20% horizontal and vertical occlusions from the top, bottom, left and right edges of the image) are tested for comparing the robustness of pPCA and pICA over several occlusions. The recognition rates are demonstrated in Table 1 for several different occlusion types using pPCA and pICA.

Table1. Recognition Rates of pPCA and pICA with Several Type and Size of Occlusions (Recognition Rates of Occlusion-free pPCA and Occlusion-free pICA are both 100%)

Edge	Method	Recognition Rate(%) with Occlusion size			
		5%	**10%**	**15%**	**20%**
Top	pPCA	91	75	63	36
	pICA	96	96	91	86
Bottom	pPCA	98	88	67	46
	pICA	98	96	90	86
Left	pPCA	94	77	58	33
	pICA	99	97	96	86
Right	pPCA	93	78	55	43
	pICA	98	98	94	85

The graphical representation of the recognition rates for 5%, 10%, 15% and 20% occlusions on each edge of the face (top, bottom, left, right) are demonstrated in Fig.2 through Fig.5 respectively for both pPCA and pICA methods.

The recognition rates shown in the above table and the following figures show that whenever the occlusion size grows, pPCA recognition rates decrease drastically for top, bottom, left and right occlusions. Whenever there is a 5% occlusion in each edge of a facial image, the recognition rate of pPCA is between 91%-98% which means that it is almost robust to 5% occlusion. However, for 20% occlusions for all edges of a facial image, pPCA performance decreases to 33%-46% which means that it is significantly sensitive to more than

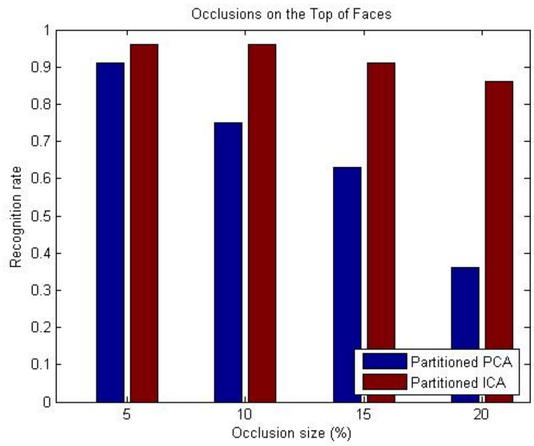

Fig. 2 Facial Recognition Performance with Occlusions on the Top of Faces

5% occlusions. In general, pPCA performance decreases approximately 60% which is a drastic decrease and shows the significant sensitivity of pPCA over occlusions.

On the other hand, the recognition rates of pICA slightly decrease whenever the occlusion size increases from 5% to 20% for all the edges of a facial image. 5% occlusion in all edges produces a recognition rate between 96%-99% which shows the robustness of pICA to 5% occlusions and it decreases slightly to 85%-86% recognition rate for 20% occlusion size in all edges of a facial image which is also a good performance over occlusions.

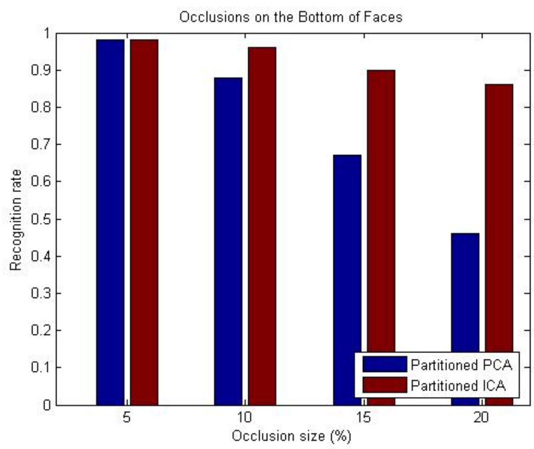

Fig. 3 Facial Recognition Performance with Occlusions on the Bottom of Faces

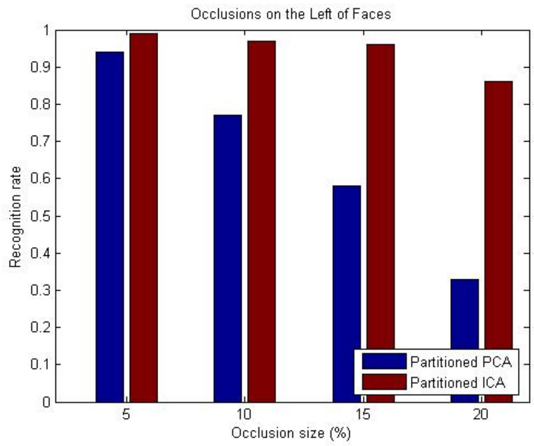

Fig. 4 Facial Recognition Performance with Occlusions on the Left of Faces

In general, pICA performance decreases approximately 10% whenever the occlusion size increases 15% which demonstrates the robustness of pICA method to different type and size of occlusions.

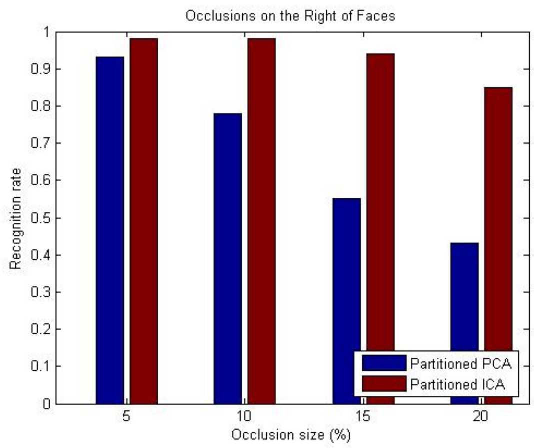

Fig. 5 Facial Recognition Performance with Occlusions on the Right of Faces

On the other hand, the recognition rates of pPCA show that pPCA is sensitive to occlusions. pPCA has the highest recognition rates for bottom occlusions, but still these results are not satisfactory for the robustness of pPCA over occlusions. pICA recognition rates are almost similar in all types of occlusions and it is seen that even for 15% occlusions, the recognition rates are at least 91% which shows the robustness of pICA to occlusions.

The experimental results for several occlusion sizes and types indicate that pPCA recognition rate drastically decreases (60% performance decrease for 15% occlusion size increase) while pICA recognition rate is slightly affected (10% performance decrease for 15% occlusion size increase). These results are interesting since pICA is better than pPCA in recognition performance under occlusions, however pPCA is better than pICA in the literature [19] for frontal facial image recognition without occlusions.

In the second set of experiments, various occlusion types are applied horizontally to different regions of human face such as forehead, eyes, nose, mouth and chin as shown in Fig. 6(b)-(f). Regional horizontal occlusions are experimented in this set of experiments for five different specific regions of a face. These regions are occluded horizontally on the facial images as if they are tied with thick rope or sticky tape. A person may have a medical operation on his/her face and any region in the face can be occluded by a band as shown in Fig.6(b)-(f).

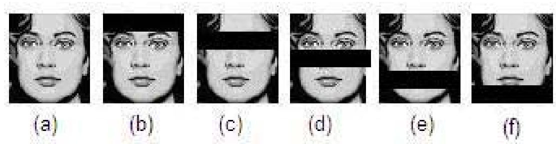

Fig. 6 Training and test images with horizontal occlusions at forehead, eyes, nose, mouth and chin regions

The recognition rates of pPCA and pICA under several regional occlusions are numerically shown in Table 2 and graphically represented in Fig. 7. Each specific region of the face is occluded horizontally and the recognition rates for both pPCA and pICA are demonstrated. For each specific region of a face, the recognition rates of pPCA and pICA are approximately 40% and 85% respectively. These results indicate that pPCA is significantly sensitive to specific regional occlusions on facial images, but pICA is slightly sensitive to specific regional occlusions on facial images.

Table2. Recognition Rates of pPCA and pICA with Occlusions on Specific Regions of Faces

Face Region Occluded	Recognition Rate(%)	
	pPCA	**pICA**
None (occlusion free)	100	100
Forehead	36	86
Eyes	45	83
Nose	47	85
Mouth	48	88
Chin	46	86

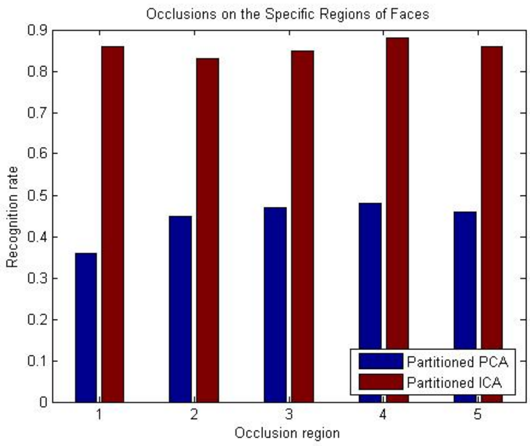

Fig. 7 Facial Recognition Performance with Occlusions on the Specific Regions of the Face as (1) forehead (2) eyes (3) nose (4) mouth (5) chin

In general, pICA is better than pPCA according to the results obtained from both set of experiments using facial images with similar facial expressions on the training and test faces and it can be stated that pPCA is very sensitive to occlusions while pICA is less sensitive to facial occlusions. These results are interesting since pICA is better than pPCA in recognition performance on facial images with similar facial expressions under occlusions, however, as demonstrated in [19], pPCA is better than pICA for frontal occlusion-free facial image recognition with different facial expressions.

6. Conclusions and Future Work

Sensitivity analysis of partitioning-based face recognition algorithms, pPCA and pICA, is performed over several types and sizes of occlusions for the recognition of facial images. The experimental results demonstrate that pICA is better than pPCA according to the results obtained from experiments using occluded images with similar facial expressions. It can also be stated that pPCA is very sensitive to occlusions while pICA is less sensitive to facial occlusions. These results are interesting since pICA is better than pPCA in recognition performance using occluded images with similar facial expressions, however pPCA is better than pICA for frontal occlusion-free facial image recognition with different facial expressions. Future work will investigate the robustness of pPCA, pICA and other partitioned appearance-based statistical methods such as partitioned LDA to occlusions over a larger number of facial images with similar and different facial expressions.

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