Research Journal of Applied Sciences 11 (10): 948-952, 2016
ISSN: 1815-932X

An Efficient SVD's Principle Components for Face Recognition

W. Al-Hameed
Department of Computer Science, Information Technology College, Basra, Iraq

Abstract: By using the direct relationship between the Principle Component Analysis (PCA) and Singular Value Decomposition (SVD), it can draw the important landmarks that represent the basic components of the data, tried to create preference in terms of rates of discrimination within the SVD decomposition matrices themselves. Experimentally, it have been found out that high percentage of similarity between SVD and PCA when applied on the same dataset of images in terms of results. As result, the advantage of the direct relationship between PCA and SVD has been exploited and using SVD's principle components as features for recognition stage. Least Square Support Vector Machine(LSSVM) has been applied to recognize faces.

Key words: Percentage of similarity, SVD, PCA, direct relationship, LSSVM

INTRODUCTION

During recent decades, faces recognition has become a vast area to research. However and through the experiments, there are some disadvantages of this application of which is not accurate just like any other biometrics , needs to the large amount of the storage also good quality images are required (in terms of lighting and position, etc.).

Most of the researches on the issue of faces recognition are concerned which means of discrimination or classification methods and how to find the best values for the tuning parameters with less interesting to the main factor for the success which is how draw the best features that describe the sample correctly, for examples, The research (Faruqe and Hasan, 2009) addressed the issue of face recognition which used PCA as an analytic tool to extract attributes and used SVM as a means of classification show that Polynomial and Radial Basis Function (RBF) SVMs achieves superior than Linear SVM and the later superior the Multi-Layer Perceptron (MLP) Classification criterion.

The researcher (Bellakhdhar *et al*., 2013) tried the improvements in both sides, they used Gabor filter, the characteristics included the presence of both magnitude and the phase of Gabor in a single vector while using SVM for recognition. Despite good performance of the Gabor in providing us with geometric properties, the complexity of calculations cost is large especially in some applications when there is huge amount of samples in the dataset.

The researcher Zhao *et al*. (2012) use both analysis tool SVD and FFT then compare their decomposition matrix. The researcher checks the quality and relevance of the information carried by the S matrix results from SVD decomposition and verified by calculating the cosine criteria to obtain the angle between the matrix S and the amplitude spectrum and phase matrixes results when applying Fast Fourier Transform (FFT) on the image to see how they close each other. However, the author did not clarify the importance of this information or experiences evidenced by means of classification or distinction available.

The research Xu and Lee (2014) suppose an integrated algorithm for recognition depending on the specific characteristics of each of the WT, 2D PCA and SVM. In the first WT transform used for decomposing the original images into high and low frequencies, retaining the low frequency which preserve the primary information while high frequency were neglected. PCA used for feature extraction. SVM used for classification stage. However, By the author the 2D PCA accuracy rate is limited.

From the first indications of the relationship between PCA and SVD was by the reseacher Huang (2013), who pointed that the PCA and SVD are very similar.

Definitions of the three known transforms SVD, Karhunen-Loeve Transform (KLT) and PCA were given by author in (Gerbrands, 1981) and verify their relationships. He state through multivariate analysis that these three transforms are very similar when a specific estimate of the column matrix covariance is used.

There are not a lot of practical applications that exploit the relationship between PCA and SVD. The researcher in (Dash *et al*., 2014) noted that using PCA's singular value decomposition method made a significant reduction in the ratio of compression against increasing in the number of principle components.

For exploitation of this useful property in another significant application which is face recognition, so that, the objective of this research is to find the best features though apply SVD and used their decomposition matrixes as principle components (singular vectors) by taking the advantage of the direct relationship between the two analysis tools PCA and SVD specially where the principle components are result from covariance matrix.

MATERIALS AND METHODS

Singular value decomposition: It is can be view the Singular Value Decomposition (SVD) through the three points (Baker, 2005): the first, it's a way to convert the correlated variables into a set of uncorrelated elements that present a better relationship between the original data elements, on the other hand it is a way to identify and ordering the dimensions along the data points that reveal most discrepancy, of a third party it is the best way to iron approximation of data points using fewer dimensions. This can have a look on it's as a method for data reduction. The $R(i\times j)$ matrix, with i<j can be written as (Hogben, 2006):

$$R = U\Sigma V^T \tag{1}$$

Where:

U	=	Orthogonal (ix I) matrix
Σ	=	Diagonal matrix (ix j) of singular values
V^T	=	Orthogonal (jxj) matricx

$$U^TU = V^TV = I \tag{2}$$

SVD property is to provide the approximation matrix to the original matrix by retaining only the best vectors after setting small singular values to zero and this is useful in image processing for reducing the noise and compression (Richards, 1999).

The Background theory of LSSVM: The researchers (Gestel *et al*., 2004) (Suykens and Vandewalle, 1999) reformulate the standard SVM of Vapnik to dispose the problem of quadratic programming by the adding a new factor that is least squares in cost function. This addition is never costly only solving a set of linear equations, this will provide a very important preserve in two terms of complexity and computation. The decision function for a two class problem is:

$$d(x_i) = w^T\varnothing(x_i) + b \;\text{ for } i = 1...m.......... \tag{3}$$

where, w is the l-dimensional vector, $\varnothing(x)$ is the mapping function that maps m- dimensional feature vector x into the feature space, b is the bias term.

- If d(x) >0, X is classified into class1
- If d(x)<0,x is classified into class2

The LSSVM objective function is formulated as:

$$\min j(w,e) = \frac{1}{2}w^TW + Y\sum_{t=1}^{M} e_i^2 \tag{4}$$

Subject to the constraint:

$$y_{\downarrow}i(w^{\uparrow}T) = \varphi(x =_{\downarrow} i) + b) = 1 - e_{\downarrow}i = 1,......M,...... \tag{5}$$

where, (Xi, yi) (i=1,................m), are training input-output pair. ${}^{e}k$ is a variable that allows some of a tolerance error of misclassification when the distributions of the data set is overlapped. ϒis a regularization parameter trade off between minimization the errors of training and minimizes the complexity of the model. y_i, is the output of the classifier. So, if d(x)>0, the input pattern belongs to Class 1 and the output y_i=+1. If d(x)<0 the input pattern belongs to Class 2 and the output y_i= -1 (Hameed, 2014).

Face recognition using the most principle components: The proposed system to recognize faces depends on the best principle components features obtained from calculating SVD on the face image. This study describes the two experiments:

Experiment (1) Principle components without simulate the PCA method:

- Normalization (each image has been subtracted from the mean image)
- Apply SVD directly for each image, decomposing it into three matrixes
- Convert The Diagonal matrix (singular values) into vector
- Store the ID singular values vector in 2D matrix ${}^{A}(M\times N)$ (M, represent the number of images, N is the singular values vector for each image)
- k-cross validation to prepare the training and testing sets
- Attach label for each training sample
- LSSVM for Matching process

Experiment (2) Principle components of SVD method:

- Normalization (each image has been subtracted from the mean image)
- Convert each face image into ID vector, store in 2D matrix ${}^{A}(M\times N)$. Each column represent one image .
- Calculates Covariance matrix $W(M\times M) = {}^{A}(M\times N)\,{}^{AT}(N\times M)$
- Apply SVD technique to decompose the matrix W into singular values ${}^{U}(M\times M)$ and ${}^{V}(M\times M)$. and singular vectors ${}^{U}(M\times M)$ and ${}^{V}(M\times M)$
- Construct a sub-vector space using singular vectors as inputs features to the recognition tool

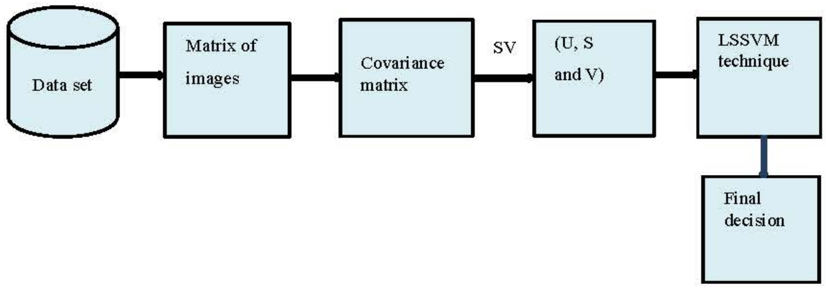

Fig. 1: The proposed face recognition system

Fig. 2: Some typical original face images. (a) test image and (b-e) train images

- k-cross validation to prepare the training and testing sets
- Attach label for each training sample
- LSSVM (Fig. 1)

RESULTS AND DISCUSION

In order to evaluate the performance of the proposed system, Using IMM Database faces of individuals has been implemented. It is divided into training data and the test data using k-cross validation, where every time the share randomly of training a total of 70% o1f the images while 30% have been used for the testing process. It was used 20 class. 120 images, six for each person with a different positions and lighting conditions. The success rate (in percentage) for recognition is summarized using different principle components.

It is known that SVD decompose the image into three 2D matrix V,S and U.the first test implemented without using covariance matrix, singular values S is preserved as features used for matching after converting the 2D matrix into one dimensional vector thus we get the 2D matrix, the number of columns represents singular values of the images, the number of rows represents the number of images.

The second test, SVD is implemented on the covariance matrix and using singular vectors U and V as features. The results of test is compared with already known PCA technique when eigenvectors used as a features. In both cases the vectors is arranged according to singular values which ordered from large to small and neglect the smallest values, that decrease the corresponding number of eigenvectors and singular vectors respectively.

For recognition, LSSVM. Multi-classification issues formulated as a binary classification using One verses One technique been used . It is Known that LSSVM is a supervised learning, label term is attached correspond to each sample in the input matrix.

To avoid over fitting, cross validation is used to evaluate fitting. k-cross validation achieves a compromise between computational requirements and reliability in evaluation of the error.

Record information of training process was kept including the most important fields containing bias b values and a set of support vectors which will be used later in the classification equation for classifying test x_j images in the testing process (11).

Table 1: Face recognition rates using different principle components

	Singular Vectors U (SVD's) principle components	Singular values (S) from SVD	Singular Vectors V (SVD's) principle components	Eigen vectors (E) from PCA
LSSVM for recognition (%)	89	83	89	89

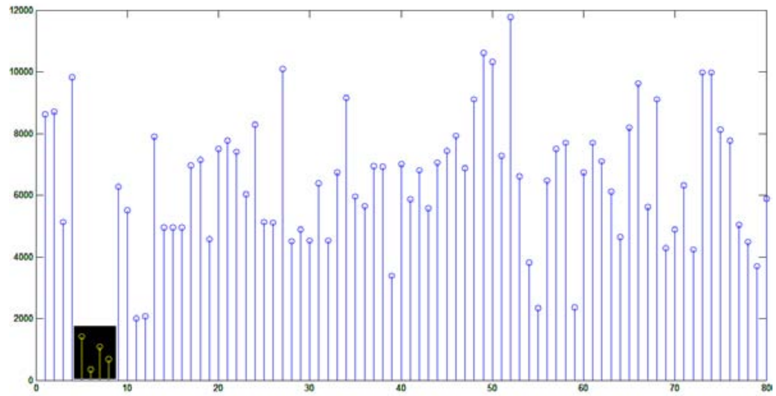

Fig. 3: Distances indicate the amount of closeness from test image using V singulars vectors

$$y_j = \sum_{i}^{N} a_i y_i K(x_1 . x_j) + b \qquad (6)$$

where, (x_i, x_j) is kernel function (RBF). It was observed from the experimental term that we can use alternatively any of the PCA or SVD to extract the most principle components and obtain the same effect as when using column matrix covariance.

This is clear in the (Table 1) and clear through the (Fig. 2) which shows the system's ability to discriminate people faces. For example the test image discriminated properly when the training images that the person belonged to achieved less distances (Shaded in black) using singulars vectors shown in (Fig. 3).

CONCLUSION

In this research we tried to focus on the task to distinguish the faces of people through the process of analyzing the SVD tool And note the importance of the relationship with PCA and the resulting characteristics for face recognition application using LSSVM evident by encouraging our results. In one experiments many singular vectors that correspond to rest of the vectors corresponding to zero values. Other experiment singular values vector has been used as a features.

The outcomes of this research firstly reduce the size of the decomposing matrixes from different size to the equal size. The second reduction represented by discard the small values of singular values that lead to discard the corresponding singulars vectors.

REFERENCES

Baker, K., 2005. Singular Value Decomposition Tutorial. Ohio State University, Columbus, Ohio,.

Bellakhdhar, F., K. Loukil and M. Abid, 2013. Face recognition approach using Gabor Wavelets, PCA and SVM. Intl. J. Comput. Sci. Issues, 10: 201-207.

Dash, P., M. Nayak and G.P. Das, 2014. Principal component analysis using singular value decomposition for image compression. Intl. J. Comput. Appl., Vol.93,

Faruqe, M.O. and M.A.M. Hasan, 2009. Face recognition using PCA and SVM. Proceedings of the 3rd International Conference on Anti-Counterfeiting, Security and Identification in Communication, Aug. 20-22, Hong Kong, pp: 97-101.

Gerbrands, J.J., 1981. On the relationships between SVD, KLT and PCA. Pattern Recognit., 14: 375-381.

Gestel, T.V., J.A.K. Suykens, B. Baesens, S. Viaene and J. Vanthienen et al., 2004. Benchmarking least squares support vector machine classifiers. Mach. Learn., 54: 5-32.

Hameed, W.A., 2014. Defect detection of radiography image with annotation using LSSVM_GSC techniques. Masters Thesis, Babylon University, Hillah, Iraq.

Hogben, L., 2006. Handbook of Linear Algebra. CRC Press, Boca Raton, Florida,.

Huang, T.S., 2013. Picture Processing and Digital Filtering. Springer Science and Business Media, Berlin, Germany,.

Richards, J.A., 1999. Remote Sensing Digital Image Analysis. 4th Edn., Springer-Verlag, Berlin.

Suykens, J.A.K. and J. Vandewalle, 1999. Least squares support vector machine classifiers. Neural Process. Lett., 9: 293-300.

Xu, W. and E.J. Lee, 2014. Face recognition using wavelets transform and 2D PCA by SVM classifier. Intl. J. Multimedia Ubiquitous Eng., 9: 281-290.

Zhao, L., H. Wanbao and C. Lihong. 2012. Face recognition feature comparison based SVD and FFT. J. Signal Inf. Proc., 3: 259-262.