ATLANTIS PRESS
*Advances in Computer Science Research, volume 80*
International Conference on Computer Science, Electronics and Communication Engineering (CSECE 2018)

# Face Recognition Based on LBP(2D)$^2$PCA+SVM

Yanmei Jiang, Wei Wei, Xue Liu and Ying Shi
LMIB and School of Mathematics and Systems Science Beihang University Beijing, China

***Abstract*—In this work, we present a novel approach of face recognition which considers local binary pattern (LBP), principal component analysis (PCA) and support vector machine (SVM) algorithms, which is named as LBP(2D)$^2$PCA+SVM. This method firstly extracts facial texture features, then uses (2D)$^2$PCA algorithm to reduce its dimensions, and finally employs SVM algorithm to classify and recognize the images. Our consideration is that LBP algorithm has a characteristic of rotation invariance, which is robust to illumination change and pose variation; (2D)$^2$PCA is an improvement of PCA, using this method the image can reach the maximum degree of dimension reduction; SVM has the advantages of global optimization, simple structure, strong generalization ability and so on. By synthesizing the advantages of the algorithms, our proposed LBP(2D)$^2$PCA +SVM algorithm performs higher recognition rate than other algorithms, and the effective combination of different strategies can greatly help us to improve the recognition rate.**

***Keywords*—face recognition; (2D)$^2$PCA; LBP; SVM**

## I. INTRODUCTION

Face recognition is an important biometric identification technology, detects the human face image and compares the face images from a static image or video image in the database, and finds matching face process in order to achieve the purpose of identification and appraisal [1]. Face recognition is important in both theory and application. On one hand, it can deepen persons' understanding of human visual system. On the other hand, it can meet the requirements of artificial intelligence in practical applications [2]. To improve the efficiency, many researchers have developed the method of the geometric characteristics, the method of template matching, the method of characteristics of face, hidden Markov model [3], neural network [4], the method of elastic graph matching and so on. At present, most mainstream face recognition algorithms are based on statistical characteristics, such as principal component analysis [5] and linear discriminant analysis [6]. The basic idea of these methods is to use the algebraic tools to reduce the face image to a linear subspace, and then performs classification and identification. The two-dimensional principal component analysis (2DPCA) [8] was proposed for face representation and recognition. The main idea behind 2DPCA is that it is based on 2D matrices as opposed to the standard PCA [7], which is based on 1D vectors. By simultaneously considering the row and column directions, Daoqiang ZHANG, Zhi-Hua ZHOU developed the two-directional 2DPCA, i.e. (2D)$^2$PCA [9]. The (2D)$^2$PCA algorithm reduces the dimension of the image feature matrix from two directions, and the computation time and memory space are reduced. The availability of numerous commercial face recognition systems attests to the significant progress in the research field. Despite these achievements have achieved, face recognition continues to be an active topic in computer vision research. The current system works well in a relatively controlled environment, but it tends to be affected when different factors (such as posture, lighting, etc.) change. Timo Ahonen, Abdenour Hadid, Matti Pietikainen et al. presented a new approach for face recognition with local binary pattern (LBP) [10]. The goal of the research is to increase the robustness of the systems against different factors. Support Vector Machines (SVMs) have been recently proposed by Vapnik and his co-workers as a very effective method for general purpose pattern recognition.

On the basis of previous work, we introduce a new approach LBP(2D)$^2$PCA+SVM which adopts the LBP algorithm to extract the face image texture information, reduces the influence of illumination change of face image, then uses (2D)$^2$PCA dimension reduction to decrease the computer storage cost and save time for subsequent classification recognition, and finally utilizes support vector machine for classification and identification. The experimental results show that this method combines the advantage of the main component analysis, the robustness of LBP algorithm, the efficiency of support vector machine's classification ability, which improves the face recognition rate.

## II. ALGORITHM DESCRIPTION

As the local binary pattern has illumination invariant and the advantage of rotation invariance, and can effectively describe the image of the local characteristics, we make use of the local binary pattern for feature extraction [11, 12]. The process is stated as follows.

LBP operator is used to calculate the LBP value of each pixel in the image, and the LBP value is used to replace the gray value of corresponding pixel, and get a new image $f_{LPB}(x,y)$. Then we calculate the histogram of the image $f_{LPB}(x,y)$:

$$H = (H_0, H_1, \dots, H_{n-1}),$$

Where $H_i = \sum_{x,y} I\{f_{LPB}(x,y) = i\} \;\; i = 0,1,\dots,n-1,$

$$I\{A\} = \begin{cases} 1 & A \text{ true} \\ 0 & A \text{ false} \end{cases}.$$

Then we show an example which deals with images using the LBP algorithm, and the image size of ORL face library [15] is 92x112, and the face image and LBP image are obtained respectively, and their histograms are given.

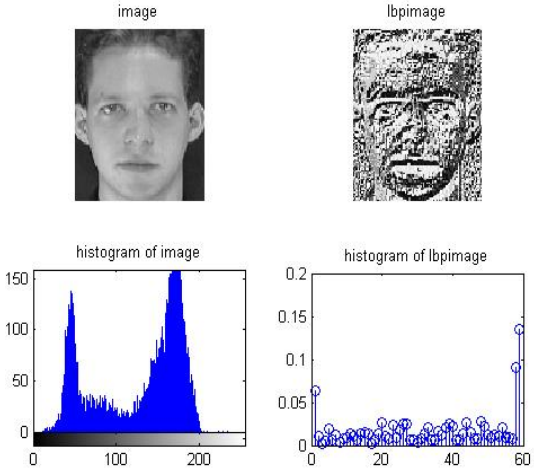


FIGURE I. THE LEFT TOP IS THE ORIGINAL IMAGE WITH THE LEFT BOTTOM ITS HISTOGRAM, AND THE RIGHT TOP IS THE CORRESPONDING LBP IMAGE WITH THE RIGHT BOTTOM ITS HISTOGRAM.

In order to present spatial location information of the small image pattern, we perform the image block to divide the image into several non-overlapping rectangle areas $R_0$, $R_1$, …, $R_{m-1}$, then calculate the histograms of each block area:

$$H_{i,j} = \sum_{(x,y)\in R_j} I\{f_{LPB}(x,y) = i\},$$

$$i = 0,1,\dots,n-1;\ \ j = 0,1,\dots,m-1.$$

For example, we divide the above image into 16 subdomain, and their histograms are given.

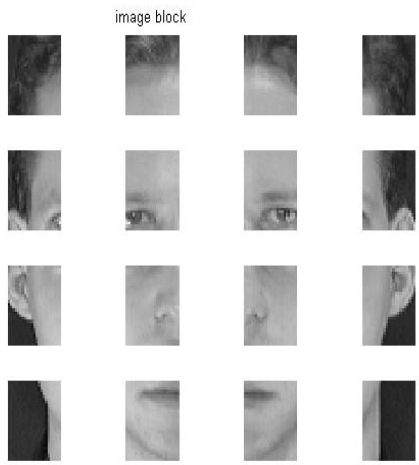


FIGURE II. THE BLOCK IMAGE OF FOUR ROWS AND FOUR COLUMNS.

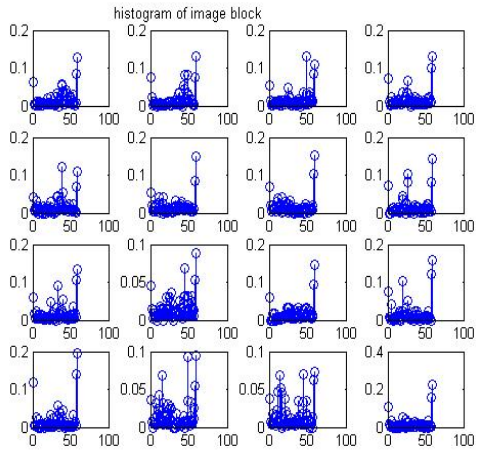


FIGURE III. HISTOGRAMS OF BLOCK IMAGE OF FOUR ROWS AND FOUR COLUMNS.

Because the $(2D)^2$PCA algorithm lowers down the dimension of the image feature matrix from two directions, the computation time and memory space are saved, and we use $(2D)^2$PCA algorithm for feature reduction. The process is as follows.

The characteristic vector of the face image is generated by connecting these histogram of image blocks,

$$H = (H_{0,0},\dots,H_{0,m-1},\dots,H_{n-1,0},\dots,H_{n-1,m-1}).$$

The characteristic vector can be rearranged, and the rearrangement is expressed by $H'$,

$$H' = \begin{bmatrix} H_{0,0} & H_{0,1} & \dots & H_{0,m-1} \\ H_{1,0} & H_{1,1} & \dots & H_{1,m-1} \\ \vdots & \vdots & \vdots & \vdots \\ H_{n-1,0} & \dots & \dots & H_{n-1,m-1} \end{bmatrix}.$$

By the $(2D)^2$PCA algorithm, the row and column of the matrix are reduced in two directions. Then the covariance matrix in the direction of the row is obtained:

$$G_t = \sum_{p=1}^{n} (H'^p - \overline{H}'^p)^T (H'^p - \overline{H}'^p).$$

Similarly, in the direction of column, the covariance matrix can be expressed as:

$$G_t{}' = \sum_{p=1}^{n} (H'^p - \overline{H}'^p)^T (H'^p - \overline{H}'^p).$$

The eigenvalues and eigenvectors of the covariance matrix are calculated. The eigenvectors corresponding to the eigenvalues of about 90% rate of contribution are selected as the optimal projection matrix. Therefore, by this way we can gain the row direction of projection matrix $X$ and column

direction of projection matrix $Z$, and the image matrix $A$ of size $m \times n$ can be projected onto $X$ and $Z$ respectively. The projection of $A$ on $X$ and $Z$ is denoted by a matrix $C$ with size $q \times d$ : $C=Z^TAX$ in face recognition, and matrix $C$ is called the characteristic matrix.

Because the support vector machine [13] has the advantages of global optimal, simple structure and strong promotion ability, we can use support vector machine to solve the multi-classification problem of face recognition.

The SVM have been recently proposed by Vapnik and his co-workers [14] as a very effective method for general purpose pattern recognition. Intuitively, given a set of points belonging to two classes, a SVM finds the hyperplane that separates the largest possible fraction of points of the same class on the same side, while maximizing the distance from either class to the hyperplane. According to Vapnik [14], this hyperplane is called Optimal Separating Hyperplane (OSH) which minimizes the risk of misclassifying not only the examples in the training set but also the unseen examples of the test set.

We put the corresponding labels on the feature matrix, select a part of the data as a training set with the rest as a test set, and then use the test set to predict identification and recognition rate.

The main steps of general facial recognition process include: face detection, feature extraction, feature dimensionality reduction and classification and recognition. Our LBP(2D)$^2$PCA+SVM algorithm flow is as follows:

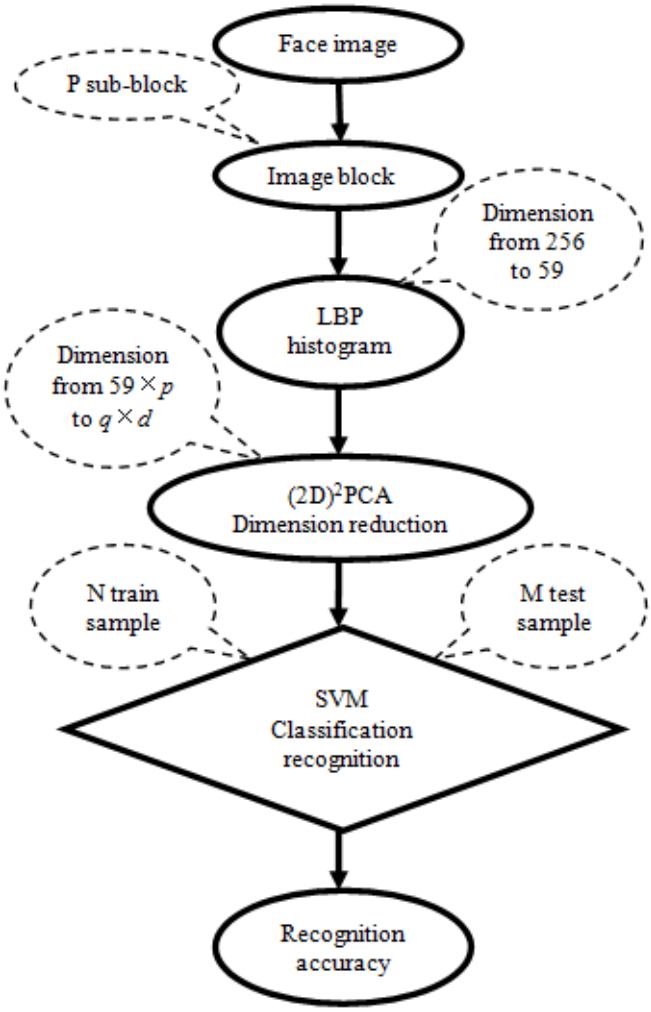


FIGURE IV. THE LBP(2D)$^2$PCA+SVM ALGORITHM FLOW.

## III. EXPERIMENTAL RESULTS AND ANALYSIS

We program the algorithm into MATLAB language and conduct experiments in MATALB2014A platform. In order to verify the superiority of the LBP(2D)$^2$PCA+SVM algorithm in face recognition, use ORL face image database for face recognition rate experiment.

The ORL databases[15] contains 400 images of 40 people with a 92x112 grayscale image, and each person is collected with 10 different images. All images have similar dark background, and different images are from the same person at different times, different illumination and different head posture, facial expression and facial details under sub-Saturn hemisphere, but the above several changes usually will not appear in the same 10 images at the same time.

In the experiments, we use 1-8 training samples separately to fulfill recognition process of LBP(2D)$^2$PCA +SVM algorithm and other algorithms. The face recognition rate data and line graph are gained with different algorithms in different training samples.

FIGURE I. THE TABLE IS THE FACE RECOGNITION RATE FOR DIFFERENT ALGORITHMS

| Train sample | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| SVM | 51 | 64 | 71 | 77 | 76 | 82 | 84 | 84 |
| PCASVM | 48 | 63 | 74 | 80 | 83 | 91 | 90 | 93 |
| PCA2DSVM | 70 | 70 | 75 | 81 | 84 | 94 | 94 | 95 |
| PCA2D2SVM | 63 | 78 | 83 | 87 | 89 | 92 | 95 | 95 |
| LBPSVM | 59 | 67 | 69 | 77 | 82 | 85 | 92 | 93 |
| LBPPCASVM | 46 | 58 | 58 | 67 | 75 | 79 | 85 | 86 |
| LBP4X4PCA2D2SVM | 54 | 62 | 79 | 93 | 98 | 99 | 98 | 96 |
| LBP8X4PCA2D2SVM | 61 | 78 | 82 | 92 | 93 | 98 | 97 | 96 |

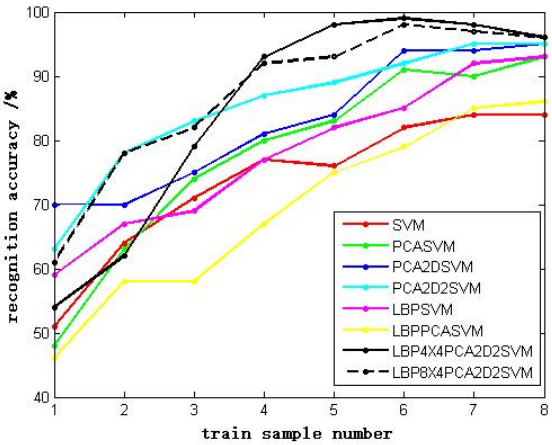


FIGURE V. THIS DIAGRAM SHOWS THE LINE DRAWING OF DIFFERENT ALGORITHMS UNDER DIFFERENT TRAINING SAMPLES.

By the experiment results, the LBP(2D)$^2$PCA+SVM algorithm includes the principal component analysis (PCA) dimensionality reduction effect and the local binary pattern texture illumination invariant and rotation invariance, and the fast and efficient classification of support vector machine (SVM) algorithm. Therefore, it has a good effect on face recognition. When the number of training samples is low, the recognition effect is not very good which compared with other algorithms. When the number of training samples is large, the recognition effect is obvious. When the training sample is over half, the recognition rate was over 95%. When the training sample is six, the recognition rate is up to 99%. The LBP(2D)$^2$PCA+SVM algorithm uses the statistical characteristics of the face information effectively, and has the light robustness and rotation invariance of LBP algorithm to extract image texture information of the face effectively. In changes of the light, attitude and expression, the recognition rate has improved obviously, so the overall recognition rate has improved.

## IV. CONCLUSION

In this article, we mainly studied the face recognition method LBP(2D)$^2$PCA+SVM. First, the face image is partitioned, then we calculate each sub-block face image texture image and their statistics histograms, and connect each sub-block histogram into a histogram vector. The blocks are too many, and the dimension of the histogram vector is too high, which make us use (2D)$^2$PCA algorithm for the histogram dimension reduction. Finally, the algorithm of support vector machine is used to classify the test images. The method takes the advantages of dimension maximization reduction of the principal component analysis (PCA) and combines it with the rotation invariance of LBP operator and merits of illumination invariance. Therefore, it can effectively utilize the statistical features of face images and make full use of the texture features of face images, thus reduces the influence of light changes on face recognition and improves the recognition rate. Comparing the LBP(2D)$^2$PCA+SVM algorithm with other algorithm, we conduct our algorithm is better for face recognition.

## ACKNOWLEDGMENT

This work was supported by the Major Program of National Natural Science Foundation of China (11290141), National Natural Science Foundation of China (11401017, 11571028 and 11671025) and Fundamental Research of Civil Aircraft No. MJ-F-2012-04.

## REFERENCES

[1] Zhou Ji-Liu, Zhang Ye. Research advances on the theory of face recognition [J]. Journal of Computer-Aided Design & Computer Graphics. 1999, 11(2): 180-184.

[2] A.K. Jain, R.P.W. Duin, J. Mao, Statistical pattern recognition: a review, IEEE Trans. Pattern Anal. Mach. In tell. 22 (1) (2000) 4–37.

[3] Samaria F. Face Recognition Using Hidden Markov Models [D]. PhD Thesis. Cambridge, University of Cambridge, 1994.

[4] Lawrence S, Giles C L, Tsoi A C, et al. Face recognition: A convolutional neural network approach[R]. IEEE Trans. PAMI, 1997, 8: 98-113.

[5] I.T. Jolliffe, Principal Component Analysis, Springer, New York, 1986.

[6] W.J.Krzanowski, P.Jonathan, W.V Mc Carthy, and M.R. Thomas. Discriminant analysis with singular covariance matrices: methods and applications to spectroscopic data. Applied Statistics, 44: 101–115, 1995.

[7] Agarwal M, Jain N, Kumar M, et al. Face recognition Using Principle Component Analysis, Eigen face and Neural Network [C]. Signal Acquisition and Processing, 2010: 310-314.

[8] J. Yang, D. Zhang, A.F. Frangi, J.Y. Yang, two-dimensional PCA: a new approach to appearance based face representation and recognition, IEEE Trans. Pattern Anal. Mach. In tell. 26 (1) (2004)131–137.

[9] Daoqiang Zhang, Zhi-Hua Zhou. (2D)$^2$PCA: Two-directional two-dimensional PCA for efficient face representation and recognition [J]. Neuro, computing, 2005, 69(1/3): 224-231.

[10] Timo Ahonen, Abdenour Hadid, Matti Pietikainen et al. Face Recognition with Local Binary Patterns[C]. //8th European Conference on Computer Vision (ECCV 2004), part I.2004: 469-481.

[11] Ojala, Pietikăinen, Măenpăă, Multiresolution gray-scale and rotation invariant texture classification with local binary patterns[C]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2002, 24, 971-987.

[12] Timo Ahonen, Abdenour Hadid, Matti Pietikainen et al. et al. Face Description with Local Binary Patterns: Application to Face Recognition[J].IEEE Transactions on Pattern Analysis and Machine Intelligence, 2006,28(12): 2037-2041.

[13] G. Guodong, S. Li, and C. Kapluk. Face recognition by support vector machines. In Proc. IEEE International Conference on Automatic Face and Gesture Recognition, pages196–201, 2000.

[14] V. N. Vapnik. Statistical learning theory. John Wiley & Sons, New York, 1998.

[15] http://cobweb.ecn.purdue.edu/~aleix/aleix_face_DB.html