Extended Set of DCT-TPLBP and DCT-FPLBP for Face Recognition

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***Abstract*—**In this paper, we describe an application for face recognition. Many studies have used local descriptors to characterize a face, the performance of these local descriptors remain low by global descriptors (working on the entire image). The application of local descriptors (cutting image into blocks) must be able to store both the advantages of global and local methods in the Discrete Cosine Transform (DCT) domain. This system uses neural network techniques. The letter method provides a good compromise between the two approaches in terms of simplifying of calculation and classifying performance. Finally, we compare our results with those obtained from other local and global conventional approaches.

***Keywords*—**Face detection, face recognition, discrete cosine transform (DCT), FPLBP, TPLBP, NN.

I. Introduction

During the past two decades, face recognition has received great attention and tremendous progress. Currently, it has become the most successful application of image analysis [1].

In general, face recognition technique can be divided into two groups, based on the face representation:

- Feature-based it uses geometric facial features (mouth, eyes, brows, etc...) and geometric relationships between them [4].
- Appearance-based which uses holistic texture features and is applied to either whole face or specific region in a face image [17].

The aim of this paper is to reduce the complexity of calculation generated by FPLBP and TPLBP because the response time is very important in this case. One solution is to use the DCT coefficient vector of the image instead of using the same vector image itself. In this paper, we are focusing on the choice of descriptors and the definition of a method of recognizing block that would be combined in our study to Neural Network for classification [1]. For this reason, we propose dividing the face image into regular blocks and calculate each block descriptors. This block method, which will be described subsequently as semi-local method, will be compared to the global and local methods. For this comparison, we consider different sizes of learning and various disturbances applied to the images database. The rest of this paper is organized as follows. In Section II, we present the state of face recognition technique. In Section III, we present the techniques: Four-Patch (FPLBP), Three-Patch (TPLBP), DCT-FPLBP and DCT-TPLBP. In Section IV, we describe the steps of proposed approach. Section V describes the architecture of neural network used for classification. Section VI represents the results and discussions and the last section we conclude the paper and gives future works.

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II. State of Face Recognition Technique

Being studied for 30 years, the face recognition literature is vast. The conventional algorithms such as: the eigenfaces, the Fisherfaces and analysis by [2], [3] produce good results in the controlled environments. However, the results fall drastically in the face of variability such as quality, installation and lighting. Therefore, new solutions are developed. In [4], the researchers used the combination of ICA and NN for face recognition and claimed that ICA and NN combination was better than PCA and NN. It also states that ICA is feature extraction technique which may be considered as generalization of PCA. It is a known fact that PCA tries to obtain a representation of the inputs based on uncorrelated variables, whereas, ICA provides a representation based on statistical independent variables on Yale or AR database.

Here we present only the most representative methods. In general, the methods of face recognition can be divided into two groups: global methods and local methods.

A. Global Methods

Global methods are based on well-known statistical analysis techniques [1]. It is not necessary to look at some characteristic points of the face (as the centers of the eyes, nostrils, and the center of the mouth...) to normalize the images [9]. In these methods, face images (as can be shown by matrices of pixel values) are processed as a whole and are generally transformed into vectors, which are easier to handle. The main advantage of global methods is that they are relatively quick to implement and that the basic calculations are of average complexity. However, they are very sensitive to variations in illumination, placement and facial expression. In global methods, the most popular technique is the Principal Component Analysis (PCA) [9].

The idea is to find a linear transformation into a space of reduced size that maximizes the variance of the projection of the original samples. In 1996, the approach of the Principal Component Analysis (PCA) has been extended to non-linear version by the introduction of functions to nonlinear kernels, called "Kernel Principal Component Analysis" (KPCA)[10]. There are other techniques such as Linear Discriminant

Analysis (LDA) or Independent Component Analysis (ICA) [11], [12]. [5]. It uses the criterion of reduction which is based on the concept of separability of data per class. This method been applied to faces in 1996 [13].

B. Local Methods

Local methods are based on first detects the points of interest and then features located on these points of interest are extracted. The oldest in face recognition methods fall into this category [14], [15].

All of these methods are based on the extraction of specific geometric characteristics such as the width of the head, the distance between the eyes [16], [17].This data is then used by classifiers to recognize individuals. These two methods have the following disadvantages:

1- Geometric characteristics are difficult to remove in some cases since the spot the accurate detection of characteristic points is not easy, especially in the case of occlusions or variations (pose, expression) faces are present.
2- The purely geometrical characteristics are not enough to truly represent a face while other useful information such as the values of the gray levels of the image is completely open.

III. Descriptors

In all methods of face recognition, the extraction of characteristics step is important. The choice of local characteristics has several advantages over the overall characteristics. It is for this reason that the newer systems rely on local facial features [6]. Here we present two of the most successful in the context of face recognition using local characteristics, namely, three-patch Local Binary Patterns and four-patch Local binary Patterns. For each type of feature, there are several ways to use them [7]. We present in the following the principal base of this descriptors.

A. Three-Patch LBP Codes

As its name implies, the Three-Patch LBP (TPLBP) code is produced by comparing the values of three patches to produce a single bit value in the code assigned to each pixel [7]. For each pixel in the image, we consider the w patch centered on the pixel, and S additional patches distributed uniformly in a ring of radius r around it (Fig. 1). For a parameter α, we take pairs of patches, α- patches apart along the circle, and compare their values with those of the central patch. The value of a single bit is set according to which of the two patches is more similar to the central patch. The resulting code has S bits per pixel. Specifically, we produce the Three-Patch LBP by applying the following formula to each pixel:

$$TPLBP_{r,S,w,\alpha}(P) = \sum_{i}^{S} f(d(C_i, C_p) - d(C_{i+\alpha \bmod S}, C_p))2^i$$

This section reports the performance of a feature as three-patch LBP and four-patch LBP extensions. Prior to matching the face have been normalized by using an affine transformation [13].

The Three-Patch LBP (TPLBP) and Four-Patch LBP (FPLBP) are illustrated in Figs. 1 and 2. Interestingly, the different descriptors show only modest performance differences between TPLBP and FPLBP.

For future directions, we present our methodology of fusion score of two approaches face recognition are: TPLBP with other approaches.

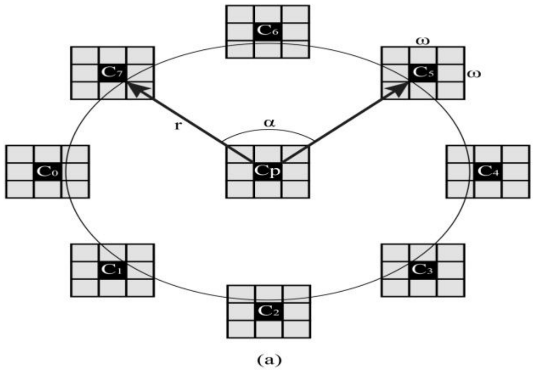

Fig. 1 (a) The Three-Patch LBP code with α= 2 and S =8.

$$TPLBP_{r,8,3,2}(p) = f\left(d(C_0,C_p) - d(C_2,C_p)\right)2^0 + f\left(d(C_1,C_p) - d(C_3,C_p)\right)2^1 + f\left(d(C_2,C_p) - d(C_4,C_p)\right)2^2 + f\left(d(C_3,C_p) - d(C_5,C_p)\right)2^3 + f\left(d(C_4,C_p) - d(C_6,C_p)\right)2^4 + f\left(d(C_5,C_p) - d(C_7,C_p)\right)2^5 + f\left(d(C_6,C_p) - d(C_0,C_p)\right)2^6 + f\left(d(C_7,C_p) - d(C_1,C_p)\right)2^7$$

Fig. 1 (b) The TPLBP code computed with parameters S= 8, w = 3, and α= 2

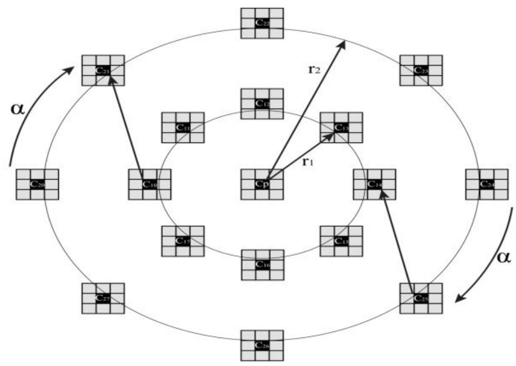

Fig. 2 (a) The Four-Patch LBP code

$$FPLBP_{r1,r2,8,3,1}(p) = f(d(C_{10},C_{21}) - d(C_{14},C_{25}))2^0 + f(d(C_{11},C_{22}) - d(C_{15},C_{26}))2^1 + f(d(C_{12},C_{23}) - d(C_{16},C_{27}))2^2 + f(d(C_{13},C_{24}) - d(C_{17},C_{28}))2^3$$

Fig. 2 (b) The FPLBP code computed with parameters S = 8, w = 3, and α = 1

B. Four-Patch LBP Codes

For every pixel in the image, we look at two rings of radi r_1 and r_2 centered on the pixel, and S patches of size w spread out evenly on each ring (Fig. 3). To produce the Four-Patch LBP (FPLBP) codes, we compare two center symmetric patches in the inner ring with two center symmetric patches in the outer ring positioned α patches away along the circle (say, clockwise). One bit in each pixels code is set according to which of the two pairs being compared is more similar [9]. Thus, for S patches along each circle we have S/2 center symmetric pairs which are the length of the binary codes produced. The formal definition of the FPLBP code is:

$$FPLBP_{r,S,w,\alpha}(P) = \sum_{i=1}^{\frac{S}{2}} f(d(C_{1i}, C_{2,i+\alpha \bmod S}) - d(C_{1,i+\alpha+\frac{S}{2}}, C_{2,i+\frac{S}{2}+\alpha \bmod S}))2^{i} \tag{2}$$

C. The FPLBP and TPLBP in the Field DCT

The computational complexity caused by the FPLBP and TPLBP, particularly when the image resolution and the size of the learning sample are too large, that researchers thought to integrate a step that could reduce the computation time to reach a true system of Face Recognition, because the response time is very important in this case. A solution is to use the coefficient vector 2D-DCT [14] of the image instead of using the vector image itself (Fig. 3).

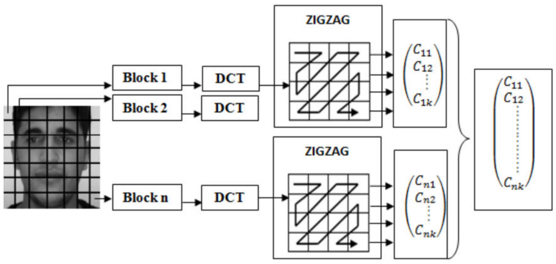

Fig. 3 Feature extraction in DCT-TPLBP and DCT-FPLBP

IV. The Proposed Approach

In this section, we present our methodology for face recognition approaches namely: the DCT-TPLBP and DCT-FPLBP. Fig. 4 shows the diagram of the proposed method. This method contains the following steps:

- Modeling of the faces based approaches by: DCT-TP LBP, and DCT-FPLBP.
- Calculating distance vectors DCT-TPLBP and DCT-FPLBP, for all M faces of the data base faces.
- Standardization of distance vectors.

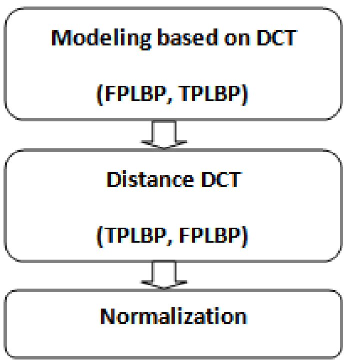

Fig. 4 Diagram of the proposed method

V. Classification with Neural Network (NN)

Classification into a recognition system includes two tasks: learning, recognition and decision. At this point, the features of the previous step are used to identify a text segment and assign it to a reference model.

A Neural Network (NN) consists of a set of interconnected neural then giving rise to networks with varying structures. For our application, we use the layers structure (Multi-Layer Perceptron: MLP). Such structure (see Fig. 5) disseminates information from the input layer, composed by the neural receiving primitive information to the output layer, which contains the final neurons transmitting output information processed by the entire network, while traversing a or more intermediate layers, called hidden layers. The network is well established a nonlinear system that combines, input feature vectors and the outline of face of the output layer.

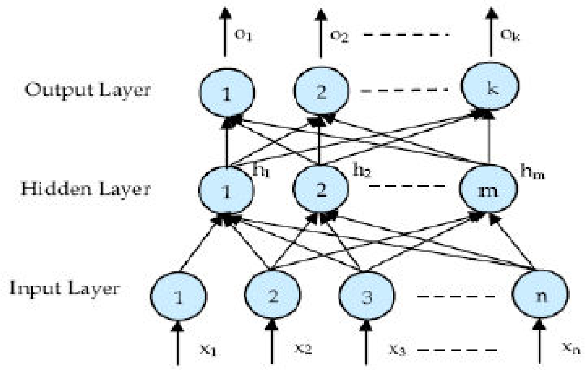

Fig. 5 Multilayer neural network

VI. Results and Discussions

All simulations have been realized on a core i3 with 2, 53 GHZ 2, 53 GHZ and a RAM 3GB. The face database Olivetti Research Laboratory (ORL) is used for testing. It contains 400 images of 40 individuals, for each person we have 10 images with size 112x92 pixels. For some individuals, the images are captured at different times. The facial expression and the facial appearance vary too. Five images of the same person in the ORL database are shown in Fig. 6.

Fig. 6 Five images of the same person in the ORL database

In this simulation, we randomly selected five persons for learning, and the rest of image for testing. Thus, the total number of training image and testing is 200 for both. We calculate learning recognition rates of each method: TPLBP, FPLBP, DCT-TPLBP and DCT-FPLBP.

In Table I, we represent the recognition rate using the methods: TPLBP, FPLBP, DCT-TPLBP and DCT-FPLBP. We note that the DCT methods give better performance.

In Table II, we represent the times of learning and identification (number of image of learning and identification is 200), times are calculated with the developed software in Matlab. We note that DCT significantly reduces the learning time and identification.

Table III, displays the recognition rate of the DCT method for different sizes of the training set and different sizes of imagettes.

It is necessary to note that the recognition rate depend on the size of the training set of the DCT method.

TABLE I
BEST METHODS RECOGNITION RATE: TPLBP, FPLBP, DCT-TPLBP AND DCT-FPLBP IN %

Distance	TPLBP	DCT-TPLBP	FPLBP	DCT-FPLBP
L1	93.02	94.23	95.5	97.2
L2	93.78	95.1	96.4	98.1

TABLE II
LEARNING TIME AND IDENTIFICATION

Time	TPLBP	DCT-TPLBP	FPLBP	DCT-FPLBP
Learning	120 s	10 s	80 s	5 s
Identification	4.8 s	0.8 s	1.7 s	0.5 s

TABLE III
RECOGNITION RATE OF THE DCT METHOD FOR DIFFERENT SIZES OF THE TRAINING SET AND DIFFERENT SIZES OF IMAGES

Size of the training set	25%	50%	75%
Imagette 8x8	83.20	89.7	93.4
Imagette 16x16	85.12	90.1	94.62
Imagette 32x32	87.1	91.4	95.3
Imagette 64x64	90.2	93.5	97.4

VII. CONCLUSION

In this paper, we have discussed a new procedure for face recognition. The systems represent a comparison of four different approaches. The major advantage of DCT is that it basically enables to reduce redundant information and can be used as a step of extracting image features. This makes the suggested technique more suitable for real time applications. The simulation results in the "specific" and "independent" case which showed that DCT-FPLBP converge is better than the DCT-TPLBP. In the future, we may test the robustness of the DCT on the other faces database.

REFERENCES

[1] V. N. Vapnik, "The Nature of Statistical Learning Theory", 2nd ed., Springer-Verlag New York Inc., 314 pages, 2000.
[2] S. Z. Li, A. K. Jain, Handbook of Face Recognition. Springer, 2005.
[3] P.N. Belhumeur, J.P. Hespanha and D.J. Kriegman, Eigenfaces vs fisherfaces: Recognition using class specific linear projection. IEEE Trans. on Pattern Analysis and Machine Intelligence (PAMI), 19(7):711–720, Juillet 1997.
[4] A. Mellakh, A. Chaari., S. Guerfi& all., 2D Face Recognition in the IV2 Evaluation Campaign. Conf. on Advanced Concepts for Intelligent Vision Systems (ACIVS), Bordeaux, France, Octobre 2009.
[5] X. Zhang and Y. Jia, Face Recognition Based on Steerable Feature and Random Subspace LDA. Inter. workshop on Analysis and Modelling of Faces and Gestures (AMFG), 3723(2):170-183, Pekin, Chine, Octobre 2005.
[6] M. El Aroussi, M. El Hassouni, S. Ghouzali, M. Rziza1 and D. Aboutajdine, Novel face recognition approach based on steerable pyramid feature extraction. IEEE Inter. Conf. On Image Processing (ICIP), 4165 – 4168, Caire, Egypte, Novembre 2009.
[7] Y. Su, S.G. Shan, X.L. Chen, and W. Gao, Hierarchical ensemble of global and local classifers for face recognition. Journal of IEEE Trans. on Image Processing, IEEE, 18(8): 1885-1896, Juin 2009.
[8] W. Zuo, K. Wang, D. Zhang and H Zhang, Combination of two novel LDA-based methods for face recognition. Journal of Neurocomputing, Elsevier, 70 (4-6): 735-742, 2007.
[9] M. Turk and A. Pentland. Face recognition using eigenfaces. In Proc. Intl. Conf. On Computer Vision and Pattern Recognition, 1991.
[10] B Scholkopf, Asmola, and KR Muller. Nonlinear component analysis as a kernel eigenvalue problem. Technical Report No 44, December 1996.
[11] M. Bartlett, J. Movellan, and T. Sejnowski. Face recognition by independent component analysis. IEEE Transactions on Neural Networks, Vol. 13, No. 6, pp. 1450-1464, 2002.
[12] Daniel L. Swets and John (Juyang) Weng. Using discriminant eigenfeatures for image retrieval. IEEE Transactions on Pattern Analysis and Machine Intelligence,18(8) :831-836, 1996.
[13] W. Chen, M. J. Er and S. Wu, PCA and LDA in DCT domain, Pattern Recognition Letters, Volume 26,Issue 15, 2005, pp. 2474 2482.
[14] Michael David Kelly. Visual identification of people by computer. PhD thesis, Stanford,CA, USA, 1971.
[15] KANADE, T. 1973. Computer recognition of human faces. Birkhauser, Basel, Switzerland, and Stuttgart, Germany.
[16] Brunelli, R., and Poggio, T., Face Recognition: Features versus Template, IEEE Trans. Pattern Anal. Machine Intell., vol. 15, pp.1042-1052, 1993.
[17] D. H. Hubel and T. N. Wiesel, Functional architec- ture of macaque monkey visual cortex, Proc. Royal Soc. B (London), vol. 198, pp.1-59, 1978.