LOCAL VECTOR PATTERN IN HIGH-ORDER DERIVATIVE SPACE FOR FACE RECOGNITION

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ABSTRACT

In this paper, a novel local pattern descriptor generated by the proposed local vector pattern (LVP) in high-order derivative space is presented for face recognition. The proposed vector representation of the referenced pixel is generated to provide the one-dimensional structure of micropatterns. To effectively extract more detailed discriminative information in a given sub-region, the vector of LVP is refined by varying local derivative directions from the n^{th}-order LVP in $(n-1)^{th}$-order derivative space. The proposed LVP is compared with the existing local pattern descriptors including local binary pattern (LBP), local derivative pattern (LDP), and local tetra pattern (LTrP) to evaluate the performances from input grayscale face images. Extensive experiments conducting on benchmark face image databases, FERET and Extended Yale B, demonstrate that the proposed LVP in high-order derivative space indeed performs much better than LBP, LDP and LTrP for face recognition.

Index Terms— Local pattern descriptors, local vector pattern (LVP), comparative space transform (CST), face recognition

1. INTRODUCTION

Recently, face recognition attracts extensive attention in real-world applications [1], [2]. It is well known that face feature description significantly affects the face recognition performance. It has been admitted that the three critical issues for developing a good face descriptor are: (1) maximize the margin between inter-person, (2) minimize the correlation between intra-person, and (3) can be extracted with low computational cost from original input data. However, a good recognition result can not be anticipated by using unsatisfactory face features, even though adopting the optimum classifier. The existing face descriptions attempt to incorporate and balance the above criteria to produce more prominent recognition results.

Primarily, the desirable components of well-recognized face features in face recognition system are comprised mainly of local pattern descriptors [3], [4], Eigenface [5], Fisherface [6], and manifold-based learning methods [7], [8]. These methods are inclined to effectively extract the representation and discriminate classes from original input images. In particular, the importance of local pattern descriptors has been well recognized in face recognition society because they can successfully and effectively represent the spatial structure information of an input image to generate distinguishing local features, such as local binary pattern (LBP) [9], [10] which has been successfully applied to facial application for achieving good recognition results permitted with computational simplicity as well as low-dimensional space requirements. Murala *et al*. proposed the local tetra pattern (LTrP) to extend the two distinct values to four distinct values by using the two high-order derivative direction patterns for generating more effective information [11].

In this paper, we propose a novel pattern descriptor, called local vector pattern (LVP), for use in face recognition. We mainly aim at enhancing the proposed method with respect to the two problems (high redundancy and feature length increasing) from LTrP [11]. To resolve these two problems, we develop a novel vector representation to represent the one-dimensional direction and structure information of the face texture. Moreover, we develop a novel coding scheme, comparative space transform (CST), in LVP encoding to encode a pairwise direction of vector. Furthermore, the proposed CST uses a designed dynamic linear decision function to suppress the slight noise influence, such as intensity change in a flat surface. In our work, the LVP can also be applied in various high-order derivative spaces to refine the vector representation for obtaining a more compact and discriminative local pattern descriptor.

The rest of this paper is organized as follows. The proposed local vector pattern (LVP) and coding scheme (comparative space transform, CST) are presented in Section II. The extension of LVP in high-order derivative space is addressed in Section III. Experimental results conducted on FERET [12] and Extended Yale B [13], [14] databases in the comparison study are demonstrated in Section IV. Finally, conclusions are given in Section V.

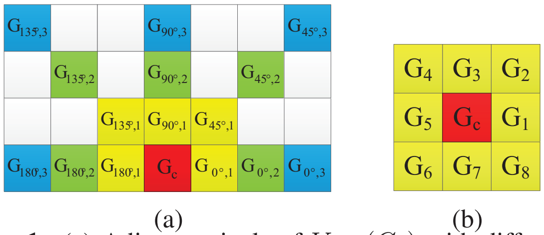

Fig. 1. (a) Adjacent pixels of $V_{\beta,D}(G_c)$ with different distances along each direction. (b) The 8-neighborhood surrounding G_c.

2. THE PROPOSED LOCAL PATTERN DESCRIPTOR

The proposed Local Vector Pattern (LVP) generates the micropatterns encoded through the pairwise directions of vector by using an effective coding scheme called Comparative Space Transform (CST) for successfully extracting distinctive information. In addition to the proposed LVP and CST, the histogram intersection method adopted in existing local pattern descriptors for evaluating the similarity between the spatial histograms of two distributions extracted from the LVP is also addressed.

2.1. Local Vector Pattern

The proposed local vector pattern (LVP) is designed to represent the one-dimensional direction and structure information of local texture by calculating the values between the referenced pixel and the adjacent pixels with diverse distances from different directions. The detail description is presented as follows.

Given a local sub-region I, the direction value of a vector is denoted as $V_{\beta,D}(G_c)$ as illustrated in Fig. 1(a). Let G_c denote the referenced pixel marked with red in I, β be the index angle of the variation direction, and D be the distance between the referenced pixel and its adjacent pixels along the β direction. For illustration purpose, the distance $D = 1$ is marked with yellow, $D = 2$ is marked with green, and $D = 3$ is marked with blue. The direction value of a vector at the referenced pixel G_c can be defined as

$$V_{\beta,D}(G_c) = (I(G_{\beta,D}) - I(G_c)). \tag{1}$$

The LVP in β direction of vector at G_c, $LVP_\beta(G_c)$, is encoded as

$$LVP_\beta(G_c) = \sum_{p=1}^{P} f(V_{\gamma,D}(G_p),V_{\gamma,D}(G_c))\times 2^{p-1}|_{\gamma\in\{\beta,\beta+45^\circ\},P=8} \tag{2}$$

where $f(\cdot,\cdot)$ represents the proposed CST which can be formally defined as

$$f(V_{\gamma,D}(G_p),V_{\gamma,D}(G_c))\,|_{\gamma\in\{\beta,\beta+45^\circ\}} = \begin{cases} 1,\text{if } V_{\beta+45^\circ,D}(G_{p,R}) - \left(\frac{V_{\beta+45^\circ,D}(G_c)}{V_{\beta,D}(G_c)}\times V_{\beta,D}(G_{p,R})\right) \geq 0 \\ 0,\text{else.} \end{cases} \tag{3}$$

Finally, the LVP at referenced pixel G_c, $LVP(G_c)$, is defined as the concatenation of the four 8-bit binary patterns LVPs.

$$LVP(G_c) = \{LVP_\beta(G_c)|\beta = 0^\circ, 45^\circ, 90^\circ, 135^\circ\}. \tag{4}$$

2.2. Coding Scheme - Comparative Space Transform

In our proposed coding scheme, Comparative Space Transform (CST), the LVPs generate the binary code by using CST that design the weight vectors of dynamic linear decision function to separate the neighborhoods with the pairwise direction of vector in the two-dimensional distribution. Thus, the basic weight vectors of dynamic linear decision function can be designed as the following form

$$w(G_c) = \left(1, -\frac{V_{\beta+45^\circ,D}(G_c)}{V_{\beta,D}(G_c)}\right)^T \tag{5}$$

where the first component of weight vectors w is assigned to "1" that represents the original $(\beta + 45^\circ)$-direction value of neighborhood pixel G_p, the second component of weight vectors w which is the transform ratio calculated by using the pairwise direction of vector of the referenced pixel G_c is used to transform the β-direction value of neighborhood pixel G_p to comparative space $(\beta + 45^\circ)$-direction.

Therefore, the pairwise direction values of one of the surrounding neighborhoods can be formed as

$$x(G_p) = (V_{\beta+45^\circ,D}(G_p), V_{\beta,D}(G_p))^T \tag{6}$$

where x called the augmented pattern represents the pairwise direction values of vector of neighborhood pixels G_p.

Since the binary code can be considered as a two-class case by using dynamic linear decision function to calculate the CST values of the neighborhoods for encoding a bit string via the sign function, we refer the context of w and x in (5) and (6) to formulate the dynamic linear decision function as

$$CST(G_p) = w(G_c)^T \cdot x(G_p). \tag{7}$$

Note that the context of w, x and CST can be reformed depending on the pairwise direction values of vector of the referenced and its neighborhoods to dynamic linear decision function for generating the various discriminative features of LVPs.

2.3. Measurement of Similarity

In out work, the spatial histogram is adopted for modeling the distribution of the proposed LVP in a given local sub-region. Given an image I in β direction of vector, the micropatterns of LVP_β are categorized into various parts corresponding to the sub-region M_i which is denoted by spatially dividing the given image into regular sub-regions $M_1, \ldots, M_L$, where L represents the amount of sub-regions. Therefore, the spatial histograms $H_{LVP}(i, \beta)$ can be defined as

$$H_{LVP}(i, \beta) = \{H_{LVP_\beta}(M_i) | i = 1, 2, \ldots, L; \\ \beta = 0°, 45°, 90°, 135°\} \quad (8)$$

where $H_{LVP_\beta}(M_i)$ is the LVP spatial histogram in β direction of vector which is extracted from the local sub-region M_i, and H_{LVP} is acquired as the concatenation of the $H_{LVP_\beta}(M_i)$.

3. EXTENDING LOCAL VECTOR PATTERN TO HIGH-ORDER DERIVATIVE SPACE

The existing local pattern descriptors, local binray pattern (LBP), local derivative pattern (LDP) [15] and local tetra pattern (LTrP), extract local features using various high-order derivative directions from grayscale images. In this paper, the vector of LVP is further refined for extracting more detailed discriminative features in high-order derivative space with the proposed CST coding scheme.

Given a local sub-region I, the vector is refined with the first-order derivative along 0°, 45°, 90° and 135° directions, denoted as $\widehat{V}^1_{\beta,\alpha}(G_c)$ where $\alpha = 0°, 45°, 90°, 135°$, to calculate the second-order LVP in the first-order derivative space. Let G_c be a referenced pixel in I. The four first-order derivative directions of vector at G_c can be defined as

$$\widehat{V}^1_{\beta,0°}(G_c) = V_{\beta,D}(G_1) - V_{\beta,D}(G_c) \quad (9)$$

$$\widehat{V}^1_{\beta,45°}(G_c) = V_{\beta,D}(G_2) - V_{\beta,D}(G_c) \quad (10)$$

$$\widehat{V}^1_{\beta,90°}(G_c) = V_{\beta,D}(G_3) - V_{\beta,D}(G_c) \quad (11)$$

$$\widehat{V}^1_{\beta,135°}(G_c) = V_{\beta,D}(G_4) - V_{\beta,D}(G_c) \quad (12)$$

where G_1, G_2, G_3 and G_4 are the derivative pixels of the referenced pixel G_c in 0°, 45°, 90° , and 135° directions, respectively as shown in Fig. 1(b).

Similar to the second-order LVP in the first-order derivative space, the vectors can be refined with the second-order derivative along 0°, 45°, 90° and 135° directions, denoted as $\widehat{V}^2_{\beta,\alpha}(G_c)$ where $\alpha = 0°, 45°, 90°, 135°$, which is defined as

$$\widehat{V}^2_{\beta,0°}(G_c) = \widehat{V}^1_{\beta,0°}(G_1) - \widehat{V}^1_{\beta,0°}(G_c) \quad (13)$$

$$\widehat{V}^2_{\beta,45°}(G_c) = \widehat{V}^1_{\beta,45°}(G_2) - \widehat{V}^1_{\beta,45°}(G_c) \quad (14)$$

$$\widehat{V}^2_{\beta,90°}(G_c) = \widehat{V}^1_{\beta,90°}(G_3) - \widehat{V}^1_{\beta,90°}(G_c) \quad (15)$$

$$\widehat{V}^2_{\beta,135°}(G_c) = \widehat{V}^1_{\beta,135°}(G_4) - \widehat{V}^1_{\beta,135°}(G_c). \quad (16)$$

In a general formulation, the n^{th}-order LVP in the $(n-1)^{th}$-order derivative space can be defined by refining the vector with the $(n-1)^{th}$-order derivative along 0°, 45°, 90° and 135° directions as

$$LVP^n_{\beta,\alpha}(G_c) = \\ \sum_{p=1}^{P} f\Big(\widehat{V}^{n-1}_{\gamma,\alpha}(G_p), \widehat{V}^{n-1}_{\gamma,\alpha}(G_c)\Big) \times 2^{p-1}|_{\gamma \in \{\beta, \beta+45°\}, P=8} \quad (17)$$

where $\widehat{V}^{n-1}_{\beta,\alpha}(G_c)$ is the refined vector with the $(n-1)^{th}$-order derivative in β direction of vector and α derivative direction at G_c.

The n^{th}-order LVP in $(n-1)^{th}$-order derivative space is defined as

$$LVP^n(G_c) \\ = \{LVP^n_{\beta,\alpha}(G_c) | \beta = 0°, 45°, 90°, 135°; \\ \alpha = 0°, 45°, 90°, 135°\}. \quad (18)$$

Similar to the first-order LVP in the zero-order derivative space, the spatial histogram of the n^{th}-order LVP in the $(n-1)^{th}$-order derivative space $\widehat{H}_{LVP}(i, \beta, \alpha)$ is defined as

$$\widehat{H}_{LVP}(i, \beta, \alpha) \\ = \{\widehat{H}_{LVP_{\beta,\alpha}}(M_i) | i = 1, 2, \ldots, L; \\ \beta = 0°, 45°, 90°, 135°; \\ \alpha = 0°, 45°, 90°, 135°\} \quad (19)$$

where $\widehat{H}_{LVP_{\beta,\alpha}}(i, \beta, \alpha)$ is the high-order LVP spatial histogram in β direction of vector and α derivative direction which is extracted from the local sub-region M_i.

The merits of our proposed LVP comparing with the other local pattern descriptors can be summarized as follows:

1. The LVP reduces the feature length better than the LTrP by using the proposed coding scheme CST with pairwise direction of vector which is used to encode the LVP.

2. The n^{th}-order LVP adopts both one-dimensional and two-dimensional direction information to extract the local patterns, whereas both n^{th}-order LDP and n^{th}-order LTrP only use one-dimensional direction information. Hence, the n^{th}-order LVP provides more detailed discriminative features than the n^{th}-order LDP and n^{th}-order LTrP.

4. EXPERIMENTAL RESULTS

In this section, various experiments were conducted to demonstrate the performance of the proposed and comparative methods. In our experiments, two publicly available face databases, FERET [12], and Extended Yale B [13], [14]

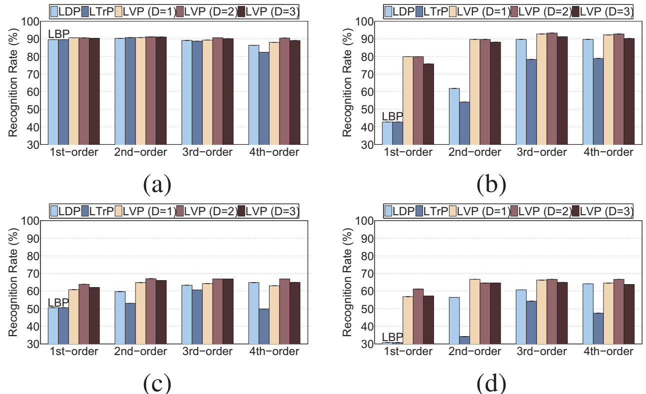

Fig. 2. Comparative recognition accuracies between different orders of LBP, LDP, LTrP and LVP on the FERET data sets. (a) Result conducting on *Fb*, (b) result conducting on *Fc*, (c) result conducting on *DupI*, (d) result conducting on *DupII*.

databases, are used. All the original facial images were normalized and cropped to 64×64 except that the Extended Yale B database was normalized to 96×84 based on the location of the two eyes. Moreover, each image is partitioned with 4 $\times$ 4 sub-regions and uses the uniform quantization method to reduce the number of histogram bins in each sub-region from 256 to 8.

4.1. Results on FERET Database

In this experiment, the FERET [12] face database is used to evaluate the comparative performances between the proposed LVP and the other methods for face recognition. The FERET database provides the evaluation protocol as gallery (*Fa*) and probe sets (*Fb*, *Fc*, *DupI* and *DupII*) that are used to evaluate the performance of the above methods. For each probe image, the framework selects the nearest image by measuring the similarity computed using histogram intersection.

The LVP generates a complete binary code of micropatterns by using various pairwise directions of vector which is computed based on the parameter D, and then we test the parameter D to evaluate the performance of the proposed method. Experimental results illustrated in Fig. 2 demonstrates that the recognition rate is significantly affected by parameter D. In LVP, the performance drops when parameter $D = 3$ in different orders of derivative space. It is due to the fact that the correlation of vector decreases when the value of parameter D increases. In addition, the feature length of the first-order LVP is 4 times of the LBP, and the feature length of the LVP is 4 and 16/13 times of the LDP and the LTrP in high-order derivative space respectively. Although the feature length of the LVP is slightly higher, the performance is significantly improved in terms of recognition rate comparing with the other methods. Moreover, the LVP exhibits better performance than the other methods even under the same order derivative space. To be more precise, the LVP can extract more detailed discriminative information than the other comparative methods.

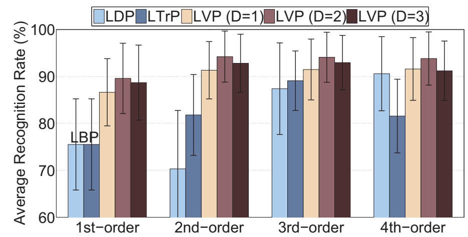

Fig. 3. Comparative average recognition accuracies between the different orders of LBP, LDP, LTrP and LVP on the Extended Yale B database.

4.2. Results on Extended Yale B Database

In our experiments, the Extended Yale B face database is also used to demonstrate the comparative performances between the proposed LVP and the other methods under severe illumination variations. The experimental database contains 2,432 frontal facial images of 38 subjects with 64 different illumination variations. Each image from the subject in the database is used as the gallery set and the others as the probe set. Then, we perform 64 run of tests for each method with 1-NN classifier. The experimental results reporting the comparative average recognition rates and standard deviations of the LVP and the other methods are illustrated in Fig. 3. Apparently, the LVP significantly improves the performance of face recognition than the other existing methods even under severe illumination variations.

5. CONCLUSIONS

In this paper, a novel local pattern descriptor is devised and investigated for generating effective and powerful representation for face recognition. First of all, we develop a novel vector representation, Local Vector Pattern (LVP), to represent the one-dimensional direction and structure information of the face texture. Moreover, a novel coding scheme, Comparative Space Transform (CST), in LVP encoding is proposed to encode a pairwise direction of vector for reducing the feature length and high redundancy resulting from LTrP. The proposed LVP can also be applied in various high-order derivative spaces to refine the vector representation for obtaining a more compact and discriminative local pattern descriptor. The measurement of similarity that performs histogram intersection is adopted to evaluate the performance with two public face databases including FERET and Extended Yale B databases. Experimental results demonstrate that the proposed method outperforms several state-of-the-art local pattern descriptors in face recognition.

6. REFERENCES

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