World Academy of Science, Engineering and Technology
International Journal of Electronics and Communication Engineering
Vol:3, No:11, 2009

Local Steerable Pyramid Binary Pattern Sequence LSPBPS for face recognition method

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Abstract—In this paper the problem of face recognition under variable illumination conditions is considered. Most of the works in the literature exhibit good performance under strictly controlled acquisition conditions, but the performance drastically drop when changes in pose and illumination occur, so that recently number of approaches have been proposed to deal with such variability. The aim of this work is to introduce an efficient local appearance feature extraction method based steerable pyramid (SP) for face recognition. Local information is extracted from SP sub-bands using LBP(Local binary Pattern). The underlying statistics allow us to reduce the required amount of data to be stored. The experiments carried out on different face databases confirm the effectiveness of the proposed approach.

Keywords—Face recognition (FR), Steerable pyramid (SP), local Binary Pattern (LBP).

I. INTRODUCTION

IN the last two decades, several studies have proposed to deploy multi-resolution feature extraction algorithms in face recognition. Among multi-resolution algorithms, the most popular are Discrete Wavelet transform (DWT), Gabor wavelets [1], contourlet[2] and curvelet transforms [3], [4]. These approaches have proved to be very successful to capture more discriminant features of face images allowing to achieve good performance and robustness against various challenging conditions such as variations in pose, lighting and expression. Steerable pyramid is another muli-resolution transform similar to the two-dimensional DWT, but with interesting translation- and rotation-invariance properties [5]. Several studies have investigated the discriminating power of steerable pyramid-based features (SP) in various applications including: image denoising [6], textures classification [3], image processing [7], [8], [9] and face hallucination [17].

In this paper, we present a novel face recognition approach based on steerable pyramid (SP) decomposition. In order to capture multi-orientation information in face images better, a straightforward solution is calculating derivatives in different directions. Therefore, each face image is described by a subset of band filtered images containing steerable pyramid coefficients which characterize the face textures, followed by the local binary patterns (LBP) [14], [15] operator. The combination of SP and LBP further enhances the representation power of the spatial histogram greatly. Note that, to construct the final feature vectors, one does not need a training stage necessarily, which has naturally avoided the generalizability problem. For each SP sub-bands we apply uniform LBP. This is done by dividing each sub-band into small sub-blocks, from which we extract uniform LBP features . For recognition, χ square distance is used to measure the similarity of different LSPBP(Local Steerable Pyramid Binary Pattern) feature vectors and the nearest neighborhood is exploited for final classification. We design experiments specifically to investigate the improvement in robustness against illumination and facial expression changes. The main idea behind using the multi-resolution analysis is to obtain multiple evidences (sub-band) from the same face. Experimental results are presented using images from the ORL and the YALE databases. The efficiency of our approach is analyzed by comparing the results with those obtained using the well-known subspace reduction based methods PCA, LDA and BLDA (Boosted LDA [13]) and multi-resolution methods like wavelet, gabor, contourlet and curvelet.

The remainder of the paper is organized as follows. In Section 2, steerable pyramid transform and Local Binary Pattern (LBP) used in the study are explained. Section 3 describes the computation of the proposed LSPBPS face representation in detail, how to recognize faces based on LSPBPS are presented in Section 4, followed by the experimental part with rich comparisons with other approaches. Some brief conclusions are drawn in the last section with some discussion on future work.

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II. STEERABLE PYRAMID FACE REPRESENTATION

In signal processing, a signal can be decomposed into subbands, such as by wavelet transform. The wavelet transform is widely used in many applications including a retrieval system, since the pyramid structure of wavelets responds well to human visual system. However, one drawback of wavelets (orthogonal) is the lack of translation invariance especially in two-dimensional (2-D) signals [18]. To overcome this problem, the 'steerable' pyramid wavelet, a class of arbitrary orientation filters generated by linear combination of a set of basis filters, has been proposed [18]. A face image of a person contains similarity (approximation) information of the face as well as discriminatory (detail) information with respect to faces of all other persons. The discriminatory information is due to structural variations of the face which are acquired as intensity variations at different locations of the face. The location and degree of intensity variations in a face for an individual are unique features which discriminate one person from the rest of the population. Steerable pyramid (SP) decomposition can be used to split the features in a face image into

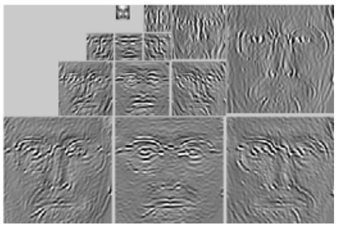

Fig. 1. Tree-stage & 4 orientation steerable pyramid transform.

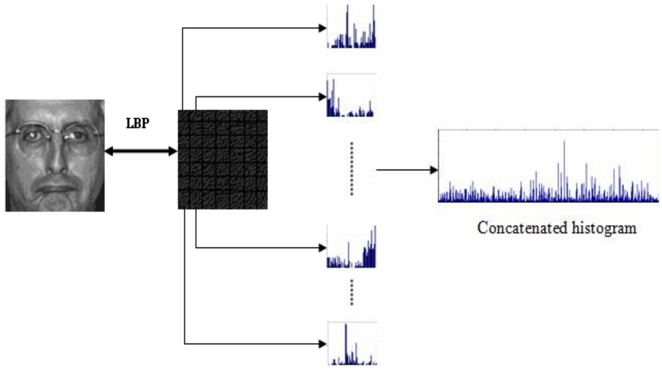

Fig. 2. Illustration of the procedure for LBP extraction.

different sub-bands at different levels, with 'approximations' and 'details'. Based on the theorem of steerable filter [9], the derivatives of an image in any direction can be interpolated by several basis derivative functions.

Figure 1, shows the analysis and synthesis representation of the steerable pyramid transform. A face image is decomposed into a steerable pyramid by four oriented third-order band-pass basis filters. In the first level, four sub-band images are obtained. In this figure, we can see that each oriented filter is most sensitive to the oriented information (e.g. edges) that is perpendicular to the direction of filter. The steerable pyramid combines facial images spatial multi-scale features with multi-orientation local features. These features are exactly perceptible by V1 area (the first visual area) of human visual cortex. Therefore it is reasonable that we choose steerable pyramid as local low-level features for face images. The S-P representation of a face image is derived by convolving the face image with the S-P filters. Let $f(x, y)$, be the face image, its convolution with a S-P filter $\psi_{\mu,\nu}(z)$ is defined as follows

$$G_{\psi f}(x, y, \mu, \nu) = f(x, y) * \psi_{\mu,\nu}(z) \quad (1)$$

where $*$ denotes the convolution operator, ν and μ is the number of scales and orientations respectively. Convolving the image with each of the $\nu times \mu$ SP filters can then generate the SP features

A. Local Binary Pattern

In order to enhance the information in the SP bands, we encode the magnitude values with LBP operator. The Local Binary Pattern (LBP), a relative new approach, was introduced in 1996 by Ojala et al. [16]. The LBP operator has been made into a really powerful measure of image texture, showing excellent results in terms of accuracy and computational complexity in many empirical studies. Moreover, LBP's are resistant to lighting effects in the sense that they are invariant to monotonic gray-level transformations, and they have been shown to have high discriminative power for texture classification. Formally, the LBP operator takes the form

$$LBP(x_c, y_c) = \sum_{n=0}^{7} 2^n s(i_n - i_c) \quad (2)$$

Where in this case n runs over the 8 neighbors of the central pixel c, i_c and i_n are the gray-level values at c and n, and $s(u)$ is 1 if $u \geq 0$ and 0 otherwise.

With uniform LBP, $\mathrm{LBP}^{u^2}_{P,R}$, it is possible to detect characteristic (local) textures in image, like spots, line ends, edges and corners [14], [15]. This is done by dividing an image into several small regions from which the features are extracted. These features consist of binary patterns that describe the surroundings of pixels in the regions of P sampling points on a circle of radius of R. The obtained features from the regions are then concatenated into a single feature histogram, which forms a representation of the image S-PBPS (Steerable Pyramid Binary Pattern sequence)(Fig.2). This model contains information on three different levels : (i) LBP code labels for the local histograms (pixel level), $(2i)$ local histograms (region level) and $(3i)$ a concatenated histogram which builds a global description of the face image (image level).

III. Proposed Method

A. Feature vectors

In this approach, a face image is modeled as a "histogram sequence" by the following procedure: (1) An input face image is normalized and transformed to obtain multiple S-P sub-bands by applying multi-scale and multi-orientation S-P filters; (2) Each sub-band is converted to Local S-P Binary Pattern (SPBP)map; (3) Each SPBP Map is further divided into non-overlapping rectangle regions with specific size, and histogram is computed for each region; (4) The SPBP histograms of all the SPBP Maps are concatenated to form the final histogram sequence as the model of the face SPBPS (Streerable Pyramid binary Pattern Sequence) figure 3. The above process is formulated as follows: The histogram h of an image $f(x, y)$ with gray levels in the range $[0, L-1]$ could be defined as

$$h_i = \sum_{x,y} I f(x, y) = i, i = 0, 1, ..., L-1 \quad (3)$$

where i is the i^{th} gray level, h_i is the number of pixels in the image with gray level i and

$$\begin{cases} 1, & \text{A is true;} \\ 0, & \text{A is false.} \end{cases} \quad (4)$$

Assume each SPBP Map is divided into m regions $R_0, R_1, ..., R_{m-1}$. The histogram of r^{th} region of the specific SPBP Map is computed by

$$H_{\mu,\nu,r} = (h_{\mu,\nu,r,0}, h_{\mu,\nu,r,1}, ..., h_{\mu,\nu,r,L-1}) \quad (5)$$

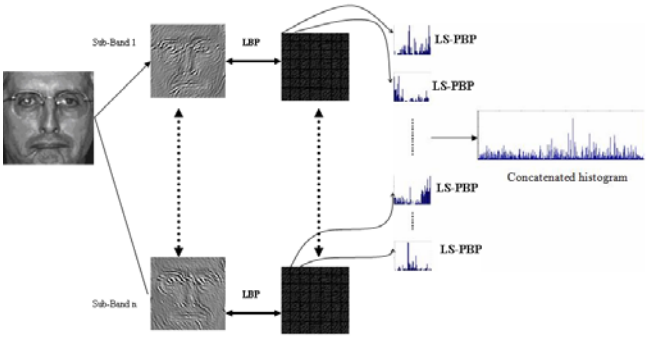

Fig. 3. Diagram of the SPBPS features extraction process

where

$$h_{\mu,\nu,r,i} = \sum I\{G_{LS-PBP}(x, y, \mu, \nu) = i\} \qquad (6)$$

Finally, all the histogram pieces computed from the regions of all the SPBP Maps are concatenated to a histogram sequence SPBPS ,R, as the final face representation $R = (H_{0,0,0}, ..., H_{0,0,m-1}, ..., H_{0,1,m-1}, ..., H_{2,3,m-1})$.

Therefore, we can extract the best features and reduce the size of the data while keeping only the principal discriminant features (R). Figure 3 shows the overall diagram of the proposed face features extraction.

B. Classification

Many similarity measurement approaches have been presented for histogram matching [14]. We use the Chi square statistic (χ^2) $\chi(H^1, H^2)$ as the similarity measurement of two histograms [15]

$$\chi(H^1, H^2) = \sum_{i=1}^{L} \frac{(h_i^1 - h_i^2)^2}{(h_i^1 + h_i^2)} \qquad (7)$$

where h^1 and h^2 are two histograms, and L is the number of bins in the histogram. Using this measurement, the similarity of two face images based on the SPBPS face representation is computed by

$$S(R1, R2) = \sum_{\mu=0}^{j} -1 \sum_{\nu=0}^{k} -1 \sum_{r=0}^{m-1} \chi(H^1_{\mu,\nu,r}, H^2_{\mu,\nu,r}) \qquad (8)$$

where j and k are the number of scales and orientations respectively and $R_1 = (H^1_{0,0,0}, ..., H^1_{0,0,m-1}, ..., H^1_{0,1,m-1}, ..., H^1_{2,3,m-1})$.
and
$R_2 = (H^2_{0,0,0}, ..., H^2_{0,0,m-1}, ..., H^2_{0,1,m-1}, ..., H^2_{2,3,m-1})$.

IV. Experimental Results

To validate the accuracy of the proposed algorithm, we have used two databases: ORL[1], Yale[2]. The ORL databse contains ten different images of 40 distinct subjects in up-right, frontal position with tolerance for some tilting and rotation of up to 20 degrees. Moreover, the most variation of some image scale is close to 10%. Therefore, it is expected that this is a more difficult database to work with. 5 face images per person are chosen randomly as training images while the remaining 5 images are set as test images. Figure 4 depicts some sample images from the ORL database.

[1]http://www.cl.cam.ac.uk/Research/DTG/attarchive:pub/data/att_faces.zip
[2]http://cvc.yale.edu/

Fig. 4. Faces from the ORL Face Database

Fig. 5. Faces from the YALE Face Database

The Yale face database consists of 15 individuals, where for each individual, there are 11 face images containing variations in illumination and facial expression. From these 11 face images, we use 5 for training, chosen randomly. The remaining 6 images are used for testing. Figure 5 depicts some sample images from the Yale database.

The experimental data we used to test the performances of sub-bands against expression changes consists of ORL database. To test the performance of SP sub-bands against illumination variations, we used Yale databases The performance has been measured by Cumulative rank error (error when we consider whether the correct identity is among the best n classifier results)

A. Multi-resolution Comparison

In order to assess the efficiency of the proposed technique described above, comparisons are made against others multi-resolution algorithms. We note that in gabor, contourlet and curvelet algorithms we use the same processing technique as used in section III. Figures 6 and 7 illustrate a comparison of accuracy results for wavelet, gabor, Contourlet, curvelet and SP. The SP based descriptors clearly outperforms all the other descriptors which is not surprising given the fact that the SP transform is able to capture multi-directional features, as opposed to the wavelet transform. Also, SP based descriptors has an even higher performance in comparison to both the gabor, curvelet and contourlet.

B. Holistic approach comparison

Comparisons are also carried out to further demonstrate the best performance of our proposed method (LSPBPS) to

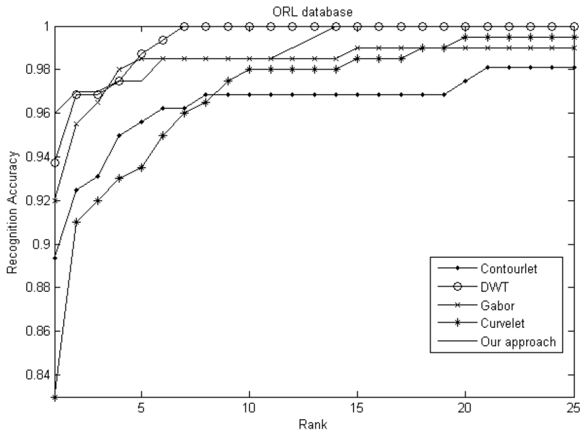

Fig. 6. Recognition accuracy of different Multi-resolution algorithms compared with LSPBPS algorithm on ORL Database

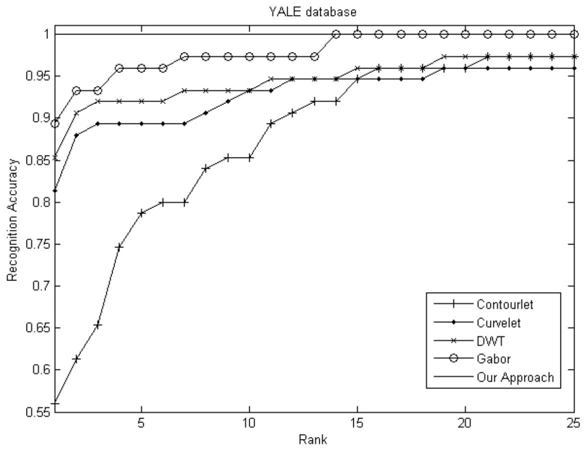

Fig. 7. Recognition accuracy of different Multi-resolution algorithms compared with LSPBPS algorithm on YALE Database

different holistic methods such as, PCA, LDA and BLDA. Table I reports the results obtained for all databases. It is clear from the Table I that the proposed method outperforms the other algorithms.

TABLE I
RECOGNITION ACCURACY OF LSPBP COMPARED WITH HOLISTIC ALGORITHMS

method	PCA	LDA	BLDA	our approach
AT&T	87.5%	75.62%	91.25%	**96**%
YALE	86.97%	89.33%	90.67%	**100**%

V. CONCLUSIONS AND FUTURE WORKS

This paper proposes a new approach for face recognition based on exploiting the features of the SP Transform. For each face image, SP is performed to compute different sub-bands from which LBP features are extracted. Two different databases (ORL and Yale) have been used to evaluate the proposed method. The technique introduced in our paper appears to be robust to changes in facial expression as it shows good results for the ORL databases, and to the lighting variation since the best results are obtained for Yale database. LSPBPS transform is able to capture multi-directional features which make it to be very effective in the face recognition. Our future work would include applying feature selection method to extract the most discriminative SP sub-bands and to include different statistical measures giving higher classification performance.

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