LETTER

Face Recognition via Curvelets and Local Ternary Pattern-Based Features

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SUMMARY In this Letter, a new face recognition approach based on curvelets and local ternary patterns (LTP) is proposed. First, we observe that the curvelet transform is a new anisotropic multi-resolution transform and can efficiently represent edge discontinuities in face images, and that the LTP operator is one of the best texture descriptors in terms of characterizing face image details. This motivated us to decompose the image using the curvelet transform, and extract the features in different frequency bands. As revealed by curvelet transform properties, the highest frequency band information represents the noisy information, so we directly drop it from feature selection. The lowest frequency band mainly contains coarse image information, and thus we deal with it more precisely to extract features as the face's details using LTP. The remaining frequency bands mainly represent edge information, and we normalize them for achieving explicit structure information. Then, all the extracted features are put together as the elementary feature set. With these features, we can reduce the features' dimension using PCA, and then use the sparse sensing technique for face recognition. Experiments on the Yale database, the extended Yale B database, and the CMU PIE database show the effectiveness of the proposed methods.
key words: *face recognition, curvelet transform, local ternary pattern, sparse representation based classification*

1. Introduction

Feature extraction is a key step in many classification tasks including face recognition. Various multi-resolution time-frequency analysis methods have been developed to represent signals for different purposes, such as wavelets, contourlets and curvelets. Zhao et al. [1] proposed a face recognition approach based on wavelet transform and weighted modular PCA. Boukabou et al. [2] introduced contourlet-based feature extraction for face recognition using PCA. However, these multi-resolution wavelet-based methods are isotropic and cannot deal with the anisotropic property inherent in face representation. Curvelet transform, developed by Candes and Dohono [3], is a new anisotropic multi-resolution system that can efficiently represent edge discontinuities in face images. Curvelet-based face recognition with dimension reduction was investigated in [4], [5]. LDA is used in [4], and both PCA and LDA [5] are utilized, in which the curvelet coefficients are used directly without analyzing the information characteristics in different curvelet transform frequency band sub-images. In fact, different frequency band sub-images contain different image contents. In general, we can process them using different methods to eliminate the effect of external factors, such as illumination and gait. In addition, these dimension deduction methods of PCA and LDA cannot effectively solve the little sample problem. Wright et al. [6] reported a very interesting work based on sparse representation for robust face recognition, where a query face image is first sparsely encoded over a set of the template images, and then the classification is performed by checking which class yields the least coding error. Sparse representation based classification (SRC) achieves a great success in robust face recognition.

Curvelet transform can effectively delineate the edge characteristics because of its anisotropic multi-resolution property. By observing the detailed information in different curvelet frequency bands, we found that the lowest frequency band information (Part 1) mainly represents the image coarse information, the highest frequency band information (Part 3) mainly represents the noisy information, and the other frequency bands' information (Part 2) mainly represent edge information. These three types of information lead to different intuitions in terms of image analysis. The LBP operator [7] is one of the best descriptors and has been used extensively in various applications. Its key advantages lie in the invariance to monotonic gray level changes and computational efficiency. Tan et al. [8] proposed a LTP-based preprocessing method, which is an extension of the LBP method. However, all these methods are operated on a face image directly. LTP-based preprocessing methods can effectively intensify the edge and contour information by acting as a high- pass filter. So we can process the information in Part 1 obtained in curvelet decomposition using LTP to magnify the important face detail characteristics. On the other hand, since the information in Part 3 mainly includes noisy information, and we can discard it directly. Thus we can combine the preprocessed information in Part 1 and the information in Part 2 to create a set of elementary features. Based on these elementary features, we can use SRC method for face recognition, which is successful in robust face recognition. Our main goal is to improve the recognition rate for the faces under different facial expressions, configurations, and illumination conditions and to solve the problem of the small number of samples.

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2. The Proposed Approach

2.1 Curvelet Coefficients Analysis

The detailed fast calculation of 2D curvelet transform in general can be found in [9]. For a face image with size of 64×64 having the big illumination corruption in Fig. 1 (a), the curvelet decomposition coefficients are shown in Fig. 1 (b) and Fig. 1 (c), in which (b) is the lower frequency information and (c) is the redundant high frequency information. The curvelet coefficients in (b) are described in two parts as follows: (1) The low frequency (coarse scale) coefficients are stored at the center of the display. (2) The Cartesian concentric coronae represents the coefficients at different scales, and the outer coronae corresponds to higher frequencies.

We can see that the main information is in Fig. 1 (b). From the circle region in (a) and (c), (c) contains some noisy information from the environment noise, which usually represents white noise or other sudden changes. We keep the information in the lowest and higher frequency bands in Fig. 1 (b) as the elementary features, and we process Part 1 and Part 2 based on different methods. For Part 2, we normalize the coefficients. For Part 1, we take the logarithm operation, LTP operation and normalization on the coefficients to enhance the important face detail characteristics. Here, we select some examples from the extended Yale B datasets, and deal with them using the Logarithm and LTP operations, and the results are shown in Fig. 2, where the images in the first row are the original images, the second row are the curvelet coefficients of Part 1 after logarithm. The images in the third row are the processed image via LTP.

2.2 The Proposed Approach

With the extracted features of a face image as stated in Sect. 2.1, a robust face recognition approach are proposed here. First, we perform the curvelet transform, logarithm computation and LTP to extract the elementary features. Then we utilize the elementary features, reduce their dimension by PCA and then use the SRC for face recognition. The main process of the proposed approach is shown in Fig. 3. For simplicity, we call this approach as "Curvelet+LTP+PCA+SRC". Now we illustrate the proposed algorithms as follows.

(1) Perform the curvelet transform on all original training images $\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_M$, and decompose each image into N ($N = \lfloor \log_2^K - 3 \rfloor$) levels, where K denotes the minimum value of the row and column numbers of the original image. For simplicity, we divide all coefficients into three parts, in which Level 1 subimage is the first part (Part 1), Level 2, 3, $\cdots$, $N-1$ subimages are the second part (Part 2), and Level N is the third part (Part 3).

(2) Compute the logarithm value of Level 1 subimage (Part 1) according to [8], and take the LTP operation according to [8]. And then reshape it to form a row vector $\mathbf{X}_{iL}$ for

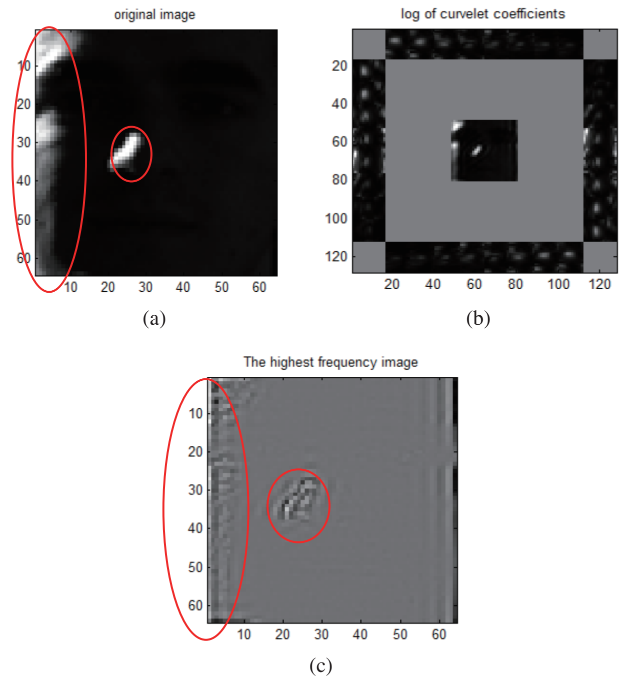

Fig. 1 The original image and its curvelet transform.

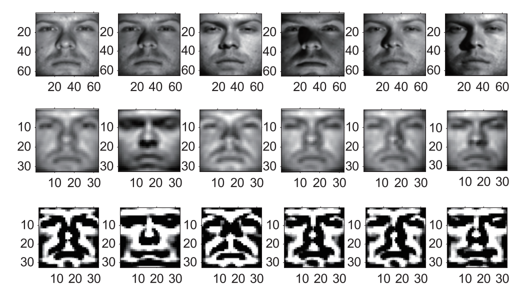

Fig. 2 The original images, their lowest frequency band images by LOG and the processed images by LTP.

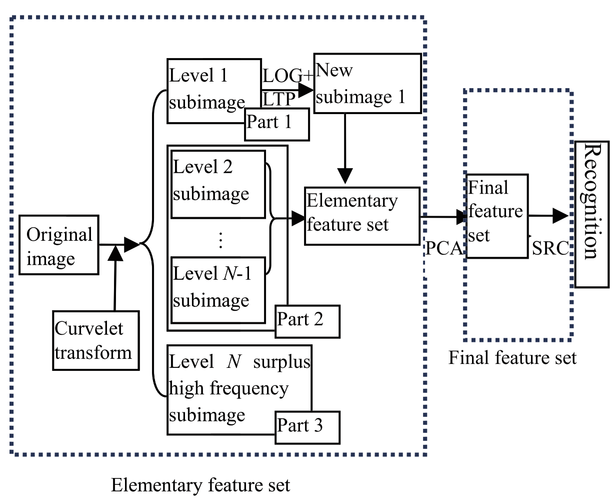

Fig. 3 The face recognition diagram of the proposed methods.

the ith image, $1 \leq i \leq M$.

(3) For part 2, reshape every subimage to a sub-row vector in the different direction and in the level 2, 3, $\cdots$, $N-1$ first, and then combine them to form a row vector $\mathbf{X}_{iH}$ one by one. At last, normalize the row vector $\mathbf{X}_{iH}$ for the ith image, $1 \leq i \leq M$. LTP is not required in this step since Part 2 mainly includes its edge information and the effect of LTP is not obvious.

(4) Construct a row vector $\mathbf{X}_{ir} = [\mathbf{X}_{iL}, \mathbf{X}_{iH}]$ for the ith image to create the elementary features set, $1 \leq i \leq M$.

(5) Obtain the final features via PCA, and then use SRC [6] for face recognition, which realizes the proposed approach "Curvelet+LTP+PCA+SRC".

3. Experimental Results

To evaluate the effectiveness of the proposed method, we use the following benchmark datasets for experiments: (1) the Yale Face Dataset [10], which contains 165 grayscale images of 15 individuals. There are 11 images per subject, which is different in facial expressions and configurations; (2) the extended Yale B Face Dataset [11], which contains 38 people with 64 different conditions; (3) the CMU PIE face Dataset, which contains 68 subjects with 41368 face images, which were captured under 13 poses, different illumination, and expression conditions [12]. For the purpose of computation efficiency, all face images are manually cropped and resized to 64×64 for all databases. We randomly take n images from every person as the training set, the others as the testing set in every experiment. We take the average recognition accuracy (ARA) and standard deviation (SD) of the face recognition rate as the assessment criterion to evaluate the proposed approach performance. In this Letter, 10 experiments are done to compute their ARA and SD values for every dataset. For comparison with the other methods, we do the experiments on the every database using Curvelet+PCA+LDA [5]. In addition, we also do the experiments only using curvelet coefficients without LTP preprocessing for the PCA+SRC-based methods.

3.1 Results on the Yale Face Dataset

For Yale Face Dataset, we choose from 1 to 10 training samples randomly, and the other images are for testing. The results are presented in Table 1. The results in the first and fourth columns are obtained by using the elementary features generated by Curvelet+LTP with PCA+LDA and PCA+SRC methods (CLPL, CLPS), respectively. As a comparison, the results in the second, fifth columns are obtained by the elementary features generated only by the curvelet transform with the PCA+LDA, PCA+SRC methods (CPL, CPS), respectively. For observing clearly, the results with white background are obtained by using curvelet+LTP elementary features with the PCA+LDA, PCA+SRC methods, respectively. The results with gray background are obtained by only using curvelet elementary features with the PCA+LDA, PCA+SRC methods, respectively. The same notations are used in the following Tables 2 and 3. In addition, we extract the edge features from the lowest frequency band using canny operators with the threshold 0.04 as a comparison. The corresponding recognition results using the PCA+LDA, PCA+SRC methods separately are given in Table 1, with the yellow background, denoted as CCPL and CCPS. From Table 1, we can see that the recognition rate is improved in all cases by using the proposed approach, and the recognition performance is also stable in terms of the SD. Especially, in the case of a smaller number of training samples, the recognition rate is improved significantly. Also we notice that the recognition accuracy using the LTP preprocessing method is significantly better than those without LTP and those with the canny operator. At the same time, the experiments also proved that the proposed method can effectively recognize faces with different facial expressions and configurations.

Table 1 Results on the on the Yale Dataset.

n	CLPL ARA(SD)%	CPL ARA(SD)%	CCPL ARA(SD)%	CLPS ARA(SD)%	CPS ARA(SD)%	CCPS ARA(SD)%
1	15.93(3.10)	14.40(3.73)	12.73(2.02)	**64.33**(2.09)	56.27(5.81)	51.20 (6.06)
2	73.26(5.07)	64.37(4.57)	58.96(7.43)	**86.81**(2.88)	79.93(2.85)	72.96(5.00)
3	90.92(2.50)	81.92(3.77)	79.50(1.93)	**93.83**(2.81)	87.17(3.07)	78.92(2.78)
4	94.48(1.67)	88.57(3.70)	87.33(2.66)	**96.38**(2.05)	91.33(3.03)	86.00(2.38)
5	97.56(1.72)	92.89(3.11)	88.89(4.32)	**98.22**(1.41)	94.11(2.16)	85.78 (3.70)
6	98.27(1.17)	93.07(2.44)	90.93(1.97)	**98.80**(1.60)	94.27(3.33)	89.33(2.08)
7	98.50(1.66)	93.33(2.52)	94.17(3.87)	**99.17**(1.18)	95.17(2.54)	91.83(3.19)
8	99.56(0.94)	96.22(2.11)	94.89(3.32)	**99.56**(0.94)	98.44(1.07)	92.67(3.93)
9	99.33(1.41)	96.00(2.63)	95.33(3.91)	**99.67**(1.05)	97.00(2.46)	92.00(5.26)
10	100.00.00 ()	98.67(2.81)	96.67(4.71)	**100.0**(0.00)	98.67(2.81)	96.00(4.66)

Table 2 Results on the extended Yale B Dataset.

n	CLPL ARA(SD)%	CPL ARA(SD)%	CLPS ARA(SD)%	CPS ARA(SD)%
1	3.78(0.53)	3.22(0.36)	**35.00**(3.26)	32.90(2.62)
2	38.39(2.70)	37.37(1.76)	**54.66**(2.34)	52.03(2.33)
3	53.08(2.09)	52.25(2.49)	**64.45**(1.81)	62.51(2.17)
4	64.37(3.49)	63.35(2.87)	**72.73**(1.84)	70.28(1.97)
5	73.05(2.01)	70.33(1.34)	**77.70**(1.43)	75.24(1.28)
6	79.74(1.63)	77.25(1.81)	**82.75**(1.46)	80.65(1.37)
7	82.66(1.11)	80.14(1.37)	**84.40**(1.41)	82.52(1.43)
8	84.23(2.22)	81.49(2.17)	**85.31**(1.86)	83.11(1.73)
9	89.21(0.86)	86.12 (1.76)	**90.44**(0.84)	87.67(1.17)
10	91.22(1.02)	88.23(1.22)	**91.40**(0.72)	88.97(1.12)

Table 3 Results on the CMU PIE dataset.

n	CLPL ARA(SD)%	CPL ARA(SD)%	CLPS ARA(SD)%	CPS ARA(SD)%
1	2.69(0.38)	2.03(0.26)	**62.58**(2.04)	60.01(1.89)
2	69.16(2.67)	67.17(2.57)	**80.41**(1.80)	78.17(2.00)
3	81.03(2.16)	77.73(1.77)	**86.57**(1.61)	84.59(1.37)
4	87.49(1.21)	84.61(1.60)	**89.44**(0.61)	88.20(0.85)
5	90.05(0.61)	88.50(0.95)	**91.15**(0.57)	90.15(0.73)
6	91.50(0.82)	90.36(0.91)	**92.04**(0.63)	91.36(0.65)
7	91.39(0.53)	90.92(0.55)	**92.31**(0.44)	91.49(0.46)
8	92.24(0.71)	91.31(0.76)	**92.56**(0.73)	91.77(0.83)

3.2 Results on the Extended Yale B Face Dataset

For the Yale B extended face dataset, we select 1, 2, 3, $\cdots$, 10 samples randomly for training, and the other images are for testing. The results are presented in Table 2. From them, we can see that the recognition results are improved and also stable as displayed in the Yale dataset for the proposed approach. One can find the performance is lower than those for the Yale dataset since this dataset is much more complicated with a large number of samples. The experiments also proved that the proposed method can effectively recognize faces with different illumination conditions.

3.3 Results on the CMU PIE Dataset

For the CMU PIE dataset, we take 1, 2, $\cdots$, 8 training samples randomly from every pose of every person, thus 13, 26, $\cdots$, 104 training samples from every one, and choose the other 60 images randomly from every person for testing. The results are presented in Table 3, from which we can see that the recognition results are improved and stable as well for the proposed approach. The experiments also proved that the proposed method can effectively recognize faces with different pose, illumination, and expression conditions.

According to Tables 1, 2 and 3, it is proven that the proposed methods in this Letter have better recognition results than the methods reported in [5]. Using the Curvelet+LTP preprocessing method, one can improve the recognition rate in all situations. Also using PCA+SRC approach, one can significantly improve the recognition rate with smaller training samples than using PCA and LDA methods. Therefore, the proposed approach can improve the performance significantly in the case of a smaller training sample set.

4. Conclusion

In this Letter, an approach to face recognition is proposed by using Curvelet, LTP and PCA+SRC. Experiments are done on the Yale dataset, the Yale B extended dataset and the PIE dataset. The experimental results show that the proposed methods can effectively achieve better recognition results than the Curvelet+PCA+LDA [5] and Curvelet+PCA+SRC methods. Also the performance of these approaches is very consistent. SRC approaches can effectively solve the smaller sample problem in comparison with PCA and LDA. And LTP preprocessing can enhance the face recognition rate in all situations.

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