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An Enhanced Local Ternary Patterns Method for Face Recognition

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Abstract: Feature descriptor based methods (e.g. Local Binary Patterns, Local Ternary Patterns) have gained encouraging results in face recognition. However one needs to manually set the threshold in Local Ternary Patterns (LTP). The threshold in LTP is not data adaptive and not robust to noise. In some cases, we may not give a suitable threshold for LTP. Inspired by Weber's Law, here a data adaptive threshold strategy is prosed for LTP and an enhanced LTP is given for face recognition. We evaluate the enhanced LTP on ORL and FERET face databases and the results demonstrate that the enhanced LTP significantly improves the performances.

Key Words: local ternary patterns, Weber's Law, feature descriptor, face recognition.

1 Introduction

Face recognition has attracted much attention in pattern recognition and computer vision [1]. To find effective representation is a key issue in face recognition. Common face recognition methods include two types: holistic methods and local feature descriptor methods. Different holistic methods such as: principal components analysis (PCA) [2], linear discriminant analysis (LDA) [3], Locality Preserving Projections (LPP) [4] and Unsupervised Discriminant Projections (UDP) [5] and sparse representation methods [6-9]. Linear discriminant analysis (LDA) is a famous approach to learning discriminant subspace. But LDA cannot be applied directly due to small sample size (SSS) problems [10]. There are many improved works about LDA [11,12,13,14]. Holistic methods tend to blur out small details owing to residual spatial registration errors. On the other hand, local feature descriptor methods have successfully applied in image recognition since they can capture small appearance details. Local descriptor methods include Gabor wavelets [15], Local Binary Patterns (LBP) [16, 17], Local Ternary Patterns (LTP) [18] and so on. The Gabor wavelets kernels are similar to the 2D receptive field profiles of the mammalian cortical simple cells, exhibit desirable characteristics of spatial locality and orientation selectivity, and are optimally localized in the space and frequency domains. Gabor wavelets were successfully used in face recognition. The LBP is a powerful illumination invariant texture primitive. The histogram of the binary patterns computed over a region is used for texture description. LTP is an improvement of LBP and gets better performance than LBP in face recognition. W. Zhang et al. [19] gave a Local Gabor Binary Patterns (LGBP) method for face recognition by combining Gabor wavelets and LBP. B. Zhang et al. [20] gave a histogram of Gabor phase pattern (HGPP) method for face recognition. More work about LBP could be found in paper [21, 24].

In this paper, we mainly focus on LTP. LBP is a computationally efficient nonparametic local feature descriptor method. LBP has been widely used in different applications such as: texture classification, image retrieval, face recognition, etc. X. Tan et al. gives a feature descriptor, named LTP, a generalization of LBP. LTP is more discriminant and less sensitive to noise. X. Tan introduces a threshold to overcome the variance of noise. But it is difficult to set a suitable threshold in LTP. W. Yang et al. [22] use the average instead of the central pixel in the region and present an improved LBP and an improved LTP for face recognition.

Weber's law [23, 24] shows that the change of a stimulus (such as sound, lighting) that will be just noticeable is a constant ratio of the original stimulus. When the change is smaller than this constant ratio of the stimulus, a human being would recognize it as a background noise rather than a valid signal. Inspired by Weber's law, here we give an enhanced LTP method via a strategy to automatically set the threshold.

2 Local Ternary Patterns

Ojala and Pietikäinen [16] give a feature descriptor, named the local binary patterns (LBP), which is widely used in texture classification. It encodes the difference between center pixel and its surrounding ones in a circular sequence manner. It characterizes the local spatial structure of image in equations (1).

$$f_{R,N} = \sum_{i=0}^{N-1} s(p_i - p_c)2^i \ , \quad s(x) = \begin{cases} 1\,, x \ge 0 \\ 0,\, x < 0 \end{cases} \tag{1}$$

where p_i is one of the N neighbor pixels around the center pixel p_c, on a circle or square of radius R. An illustration of the basic LBP is shown in Fig. 1. LBP favors its usage as a

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feature descriptor is its tolerance against illumination changes and computational simplicity.

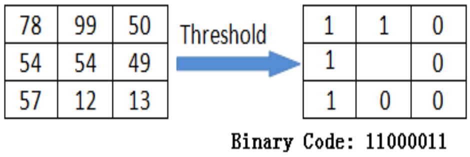

Fig 1. The basic LBP operator

LBP is robust against the variations of illumination in the monotonic gray level transformation images. But the threshold in LBP is the central pixel and is sensitive to noise in the near uniform image regions. X. Tan et al. generalizes LBP and propose the local ternary patterns (LTP) [18], in which LBP is extended to 3-values code and gray levels in a zone of width $\pm t$ around p_c are quantized to zeros, ones above this are quantized to +1 and ones below it to -1, i.e. the indicator $s'(x)$ is replaced by a 3-valued function:

$$s'(x)=\begin{cases} 1 & x \ge t \\ 0 & |x|<t \\ -1 & x \le -t \end{cases} \tag{2}$$

where t is a specified threshold and can made LTP code robust to noise, and the binary LBP code is replaced by a ternary LTP code. An illustration of the basic LTP with $t=5$ is shown in Fig. 2.

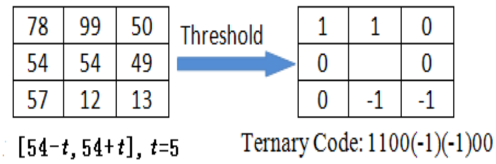

Fig. 2. The basic LTP operator

For simplicity, each ternary patters is split into positive and negative parts as illustrated in Fig.3. The two parts are then processed as two separate channels of LBP descriptors containing values of either 0 or 1. Their histogram and similarity metrics are therefore computed independently. They will be then combined in the final step of computation. The following works of LBP and LTP for recognition are same.

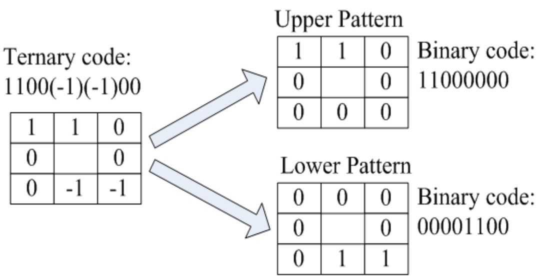

Fig. 3. An example of splitting LTP code into positive and negative code

3 Our Work

3.1 Idea

As LBP is sensitive to noise, so the threshold t is introduced to make LTP resistant to noise. But it is difficult to manually set a threshold t for LTP. The influence of noise should depend on the central pixel. For two cases: (a) the central pixels with value 5, the neighbor pixel with value 8, (b) the central pixel with value 200, the neighbor pixel with value 203. All the differences in two cases are 3. If the threshold in LTP is set as t=3, all of the binary codes are 0. Obviously, it is not reasonable and the above two cases should be different. The influence of the difference should be related with the current pixel.

Ernst Weber [23], an experimental psychologist in the 19th century, observed that the ratio of the increment threshold to the background intensity is a constant. The relationship, known since as Weber's Law, could be expressed as:

$$\frac{\Delta I}{I}=k \tag{3}$$

where ΔI represents the increment threshold (just noticeable difference for discrimination); I represents the initial stimulus intensity and k signifies that the proportion on the left side of the equation remains constant despite variations in the I term. The fraction $\Delta I/I$ is known as the Weber fraction. Weber's Law, more simply stated, says that the size of a just noticeable difference (i.e. ΔI) is a constant proportion of the original stimulus value. So, for example, in a noisy environment one must shout to be heard while a whisper works in a quiet room [24].

According to this point, the threshold of LTP should be set based on the central pixel (i.e. the background pixel) as follows.

$$t=p_c \times k \tag{4}$$

where k is the Weber's Law parameter. The following work is like LTP.

3.2 The Algorithm

As aforesaid, the enhanced LTP for face recognition algorithm can be described as follows:

Step1. Calculate the threshold of LTP using Eq.(4).

Step2. Calculate the enhanced LTP on the image and get the code images;

Step2. Divide the code images into m*n sub-regions,

Step3. Count the histogram on each sub-region and concatenate these histograms to get the total histogram;

Step4. Classify with the nearest neighbor classifier based on χ^2 histogram distance.

The χ^2 histogram distance is as follows:

$$\chi^2(p,q)=\sum_i \frac{(p_i-q_i)^2}{p_i+q_i} \tag{4}$$

where p, q are the two image feature descriptors (histogram vectors). In the experiments, we use 58 uniform patterns and each uniform pattern accounts for one bin. The remaining 198 binary patterns are all put on another bin, which makes a 59-bin histogram.

4 Experiments

In this section, we conduct experiments on ORL and FERET databases to evaluate the proposed method, LBP, LTP, MLBP and MLTP. In the experiments, k in Eq. (4) is set as k=0.15.

4.1 Using ORL database

The ORL (http://www.cam-orl.co.uk) database contains 40 persons, each having 10 different images. The images of the same person are taken at different times, under slightly varying lighting conditions and with various facial expressions. Some people are captured with or without glasses. The heads in images are slightly titled or rotated. The images in the database are manually cropped and rescaled to 112*92. Fig. 4 shows ten images of one person in ORL. To evaluate the robustness of our proposed method against the noise, we add Gaussian noise on the ORL face database (by the 'imnoise' function in Matlab with mean=0, std=0.05). Some noised images are shown in Fig. 5. In the experiments, we choose first $l(l=1,2,3,4,5,6,7,8,9)$ images per class as training samples and the rest as testing samples. In the experiments, we divide the images into $m*m$ ($m=3,4,5,6$) sub-regions. In the LTP, we set the threshold t as $t=5$ in sequence. In the proposed method, we set k as $k=0.15$. The experimental results are shown in Table 1. From Table 1, we find that the proposed method explicitly improves the performance of LBP and the Improved LTP (ILTP). The proposed method improves the performance of LTP in most cases.

Fig. 4. Ten images of one person in ORL

Fig. 5. Ten noised images of one person in ORL database

4.2 Using FERET database

The FERET face image database is a result of the FERET program, which was sponsored by the US Department of Defense through the DARPA Program [25,26]. It has become a standard database for testing and evaluating state-of-the-art face recognition algorithms.

The proposed algorithm was tested on a subset of the FERET database. This subset includes 1,400 images of 200 individuals (each individual has seven images). This subset has variations of facial expression, illumination, and pose. In our experiment, the facial portion of each original image was automatically cropped based on the location of eyes and the cropped images were resized to 40 by 40 pixels. Some example images of one person are shown in Fig. 6.

Fig. 6. Images of one person in FERET

In the experiments, we choose first $l(l=1,2,3,4,5,6)$ images per class as training samples and the rest as testing samples. In the experiments, we divide the images into $m*m$ ($m=3,4,5,6$) sub-regions. In the LTP, we set the threshold t as $t=5$ in sequence. In the proposed method, we set k as $k=0.15$. The experimental results are shown in Table 2. From Table 2, we find that the proposed method explicitly improves the performance of LBP, LTP and the Improved LTP (ILTP). The proposed method improves the performance of LTP in most cases.

5 Conclusions

As we know, it is difficult to manually set the threshold in LTP. To overcome the shortcoming, we present an enhanced LTP for face recognition. The threshold in the proposed method is data adaptive, which is inspired by Weber's Law. The experiments show that our present method is data adaptive and robust to the noise, expression and illumination variations than LBP and LTP.

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Table 1: Recognition results on ORL database

	l=1	*l=2*	*l=3*	*l=4*	*l=5*	*l=6*	*l=7*	*l=8*	*l=9*
LBP(3*3)	0.5722	0.6500	0.6821	0.7250	0.7400	0.7875	0.8417	0.8625	0.8250
ILBP(3*3)	0.6500	0.7063	0.7464	0.7792	0.8050	0.8500	0.8583	0.8375	0.8500
LTP(3*3)	0.6417	0.7188	0.7643	0.8333	0.8550	0.8688	0.8917	0.8875	0.9250
ITLTP(3*3)	0.6556	0.7469	0.8000	0.8417	0.8750	0.9000	0.9417	0.9125	0.9000
Proposed(3*3)	**0.7361**	**0.8469**	**0.8786**	**0.9208**	**0.9300**	**0.9563**	**0.9667**	**0.9625**	**1.0000**
LBP(4*4)	0.6083	0.7312	0.7786	0.8208	0.8350	0.8812	0.9000	0.8750	0.8750
ILBP(4*4)	0.6556	0.7500	0.7893	0.8750	0.8800	0.9437	0.9417	0.9375	0.9750
LTP(4*4)	0.6722	0.7500	0.8036	0.8542	0.8700	0.9187	0.9333	0.9250	0.9000
ILTP(4*4)	0.6778	0.7469	0.8107	0.8667	0.8750	0.9125	0.9667	0.9500	0.9750
Proposed(4*4)	**0.7333**	**0.8469**	**0.8750**	**0.9000**	**0.9350**	**0.9812**	**0.9833**	**0.9875**	**0.9750**
LBP(5*5)	0.5889	0.6906	0.7393	0.8083	0.8300	0.8562	0.8917	0.9125	0.9000
ILBP(5*5)	0.6750	0.7781	0.8071	0.8708	0.8800	0.9125	0.9417	0.9625	0.9500
LTP(5*5)	0.6444	0.7594	0.8036	0.8583	0.8700	0.9063	0.9500	0.9625	0.9250
ILTP(5*5)	0.6583	0.7688	0.8143	0.8667	0.8800	0.9000	0.9500	0.9500	0.9250
Proposed(5*5)	**0.7444**	**0.8344**	**0.8607**	**0.9250**	**0.9300**	**0.9500**	**0.9500**	**0.9375**	**0.9500**
LBP(6*6)	0.6111	0.7094	0.7357	0.8083	0.8100	0.8313	0.8583	0.8625	0.8750
ILBP(6*6)	0.6306	0.7750	0.8000	0.8917	0.8550	0.8938	0.9083	0.9250	0.9250
LTP(6*6)	0.6139	0.7469	0.7857	0.8500	0.8350	0.8750	0.9000	0.9000	0.8750
ILTP(6*6)	0.6278	0.7500	0.7821	0.8500	0.8400	0.8750	0.9083	0.9125	0.9000
Proposed(6*6)	**0.6944**	**0.8313**	**0.8607**	**0.9250**	**0.9300**	**0.9500**	**0.9500**	**0.9375**	**0.9500**

Table 2: Recognition results on FERET database

	l=1	*l=2*	*l=3*	*l=4*	*l=5*	*l=6*
LBP(3*3)	0.6217	0.6860	0.6138	0.6967	0.5700	0.3550
ILBP(3*3)	0.5450	0.6300	0.5487	0.6217	0.4750	0.2700
LTP(3*3)	0.7317	0.7750	0.7288	0.7733	0.6800	0.4600
ILTP(3*3)	0.6808	0.7490	0.6887	0.7250	0.6125	0.3750
Proposed(3*3)	**0.6167**	**0.7430**	**0.6987**	**0.8283**	**0.8100**	**0.7450**
LBP(4*4)	0.6817	0.7490	0.6913	0.7517	0.6550	0.4400
ILBP(4*4)	0.5958	0.6860	0.6188	0.6900	0.5825	0.4100
LTP(4*4)	0.7725	0.8210	0.7775	0.8233	0.7475	0.5750
ILTP(4*4)	0.7292	0.7990	0.7500	0.7817	0.6950	0.5100
Proposed(4*4)	**0.6667**	**0.7890**	**0.7462**	**0.8667**	**0.8825**	**0.8450**
LBP(5*5)	0.6942	0.7710	0.7175	0.7800	0.6875	0.5050
ILBP(5*5)	0.6250	0.7240	0.6587	0.7350	0.6325	0.4500
LTP(5*5)	0.7642	0.8280	0.7850	0.8333	0.7575	0.6050
ILTP(5*5)	0.7317	0.8050	0.7562	0.8083	0.7225	0.5200
Proposed(5*5)	**0.6342**	**0.7760**	**0.7300**	**0.8450**	**0.8775**	**0.8650**
LBP(6*6)	0.7192	0.7950	0.7450	0.8417	0.7925	0.6600
ILBP(6*6)	0.6692	0.7640	0.7100	0.7867	0.7550	0.6500
LTP(6*6)	0.7817	0.8410	0.8013	0.8850	0.8475	0.7700
ILTP(6*6)	0.7517	0.8260	0.7837	0.8150	0.7225	0.7000
Proposed(6*6)	**0.6375**	**0.7730**	**0.7275**	**0.8733**	**0.9225**	**0.9100**