Neurocomputing ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Face recognition using adaptive local ternary patterns method

Wankou Yang [a,b,c,*], Zhenyu Wang [a,b], Baochang Zhang [b,d,*]

[a] School of Automation, Southeast University, Nanjing 210096, China
[b] Key Lab of Measurement and Control of Complex Systems of Engineering, Ministry of Education, Southeast University, Nanjing 210096, China
[c] Key Laboratory of Child Development and Learning Science of Ministry of Education, Southeast University, Nanjing 210096, China
[d] School of Automation Science and Electrical Engineering, Beihang University, Beijing 100191, China

ARTICLE INFO

Article history:
Received 26 August 2015
Received in revised form
12 November 2015
Accepted 17 November 2015

Keywords:
LBP
CS-LBP
LTP
Weber's law
Feature descriptor
Face recognition

ABSTRACT

LBP based feature descriptors have gotten encouraging performance in image recognition. As the improved versions of LBP, Local Ternary Pattern (LTP) and Center-symmetric LBP (CS-LBP) have been successfully applied to image recognition and matching. Both use a threshold to address the noise. However, it is difficult to manually set a suitable threshold in LTP and CS-LBP. Here, we propose an adaptive local feature descriptor for face recognition. First, inspired by Weber's Law, we introduce an adaptive Local Ternary Pattern (ALTP) feature descriptor based on an automatic strategy selecting the threshold for LTP; Second, based on ALTP, we further propose a center-symmetric adaptive local ternary pattern (CS-ALTP) feature description method for face recognition. CS-ALTP improves CS-LBP from two aspects: (1) An automatic threshold is proposed based on Weber's law; (2) double channel patterns are exploited to extract more discriminative information. The experiments on ORL and FERET face databases show that ALTP and CS-ALTP have good and robust recognition performance.

1. Introduction

Face recognition is a hot topic in pattern recognition and computer vision [1]. Classical face recognition methods mainly include two categories: subspace learning based methods and local feature description based methods. Subspace learning methods include principal components analysis (PCA) [2], Fisher linear discriminant analysis (LDA) [3], locality preserving projections (LPP) [4], Unsupervised Discriminant Projections (UDP) [5] and so on [6–9]. Fisher linear discriminant analysis (Fisher LDA) is a very effective approach to get discriminative subspace. But Fisher LDA often encounters small sample size (SSS) problems [10]. Subsequently many improved LDAs are given [11–14]. Subspace learning based methods usually ignore local details. On the contrary, the methods based on local feature descriptor have gotten much success in image recognition. Local feature descriptor methods include Gabor wavelets [15], LBP [16,17], LTP [18], scale invariant feature transform (SIFT) [19], speeded up robust features (SURF) [20], histogram of oriented gradient (HOG) [21], histograms of the second-order gradients (HSOG) [22], distinctive efficient robust features (DERF) [23] etc. The kernels of gabor wavelets are similar to the mammalian cortical simple cells's 2D receptive field profiles. Gabor wavelets have excellent characteristics of spatial locality and orientation selectivity, and are optimally localized in the space and frequency domains. Gabor wavelets are successfully used in face recognition. LBP is a robust texture descriptor. The histogram of the binary patterns over a region is used for texture description. LTP is a generation of LBP and is more effective than LBP in face recognition. Zhang et al. [24] presented a local gabor binary patterns (LGBP) method for face recognition. Zhang et al. [25] proposed a histogram of Gabor phase pattern (HGPP) method. Ren et al. [26] presented a band-reweighed Gabor kernel embedding method. SIFT and HOG exploited the gradient information to characterize the image. CS-LBP [27] is proposed for image matching with SIFT framework. CS-LBP could represent a region with less dimensionality than SIFT and LBP. Qian et al. [28] gave a histogram of visual words based on locally adaptive regression kernels descriptors (HWLD) for image feature extraction based on the locally adaptive regression kernel descriptors(LARK), bag-of-visual-words and sparse representation. Qian et al. [29] gave an image decomposition based on local structure for feature extraction. Huang et. al. [30] gave an extend LBP method for 3D face recognition. Guo et. al. [31] gave an completed LBP for texture classification by extracting sign and magnitude features. In recent years, the new feature representation learning methods, such as deep learning, give encouragement results [32,33]. Robust regression techniques has been successfully exploited to face recognition with disguises, occlusions and small-size training data [34–36].

* Corresponding authors at: Key Lab of Measurement and Control of Complex Systems of Engineering, Ministry of Education, Southeast University, Nanjing 210096, China.
E-mail address: bczhang@buaa.edu.cn (W. Yang).

http://dx.doi.org/10.1016/j.neucom.2015.11.134
0925-2312/© 2016 Elsevier B.V. All rights reserved.

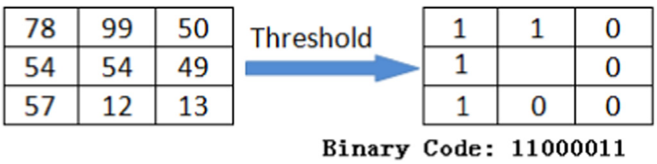

Fig. 1. A basic LBP.

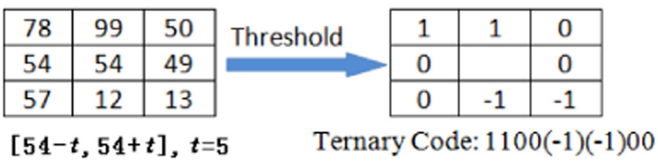

Fig. 2. A basic LTP with $t=5$.

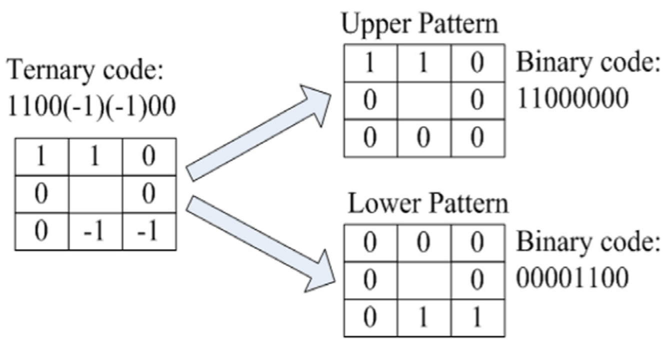

Fig. 3. An example of splitting LTP code into positive and negative code.

CS-LBP is based on LBP. LBP is an efficient and nonparametric local feature description method. LBP is not robust against noise. The final feature dimensionality of LBP is high for image matching. Two important improved LBP are CS-LBP and LTP. CS-LBP and LTP are more discriminant and less sensitive to noise via a threshold t. The threshold t could partly delete the variance of noise. The thresholds in CS-LBP and LTP are manually set and are not data-adaptive. Yang et al. [37] takes the average of the region instead of the central pixel and develop an improved LBP and an improved LTP for face recognition, respectively. LBP is simple, robust and fast. More work about LBP could refer [38].

Ernst Weber et al. [39,40] proved that: (1) only when the ratio the change of a stimulus (i.e. lighting, sound) to the original stimulus satisfies a threshold, the change could be noticeable; (2) when the ratio of the change is smaller than the threshold, a human would recognize it as a background noise. Then Weber's law is presented. Inspired by Weber's law and LTP, we presented two adaptive local feature descriptors for face recognition.

2. Related work

LBP [16] is a famous feature descriptor and widely applied in pattern recognition and texture classification. It encodes the relationship between the pixel and its surrounding neighbors in a circular sequence manner. It describes the local spatial structure of image in Eq. (1).

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

where p_c is the gray value of the center pixel and p_i is the gray value of the neighbor pixels around the center pixel p_c. Fig. 1 shows a basic LBP.

The LBP uses the central pixel as the threshold and is not robust against noise. Tan and Triggs develop the local ternary patterns (LTP) [18]. LTP extends LBP to 3-values code and replaces the sign function $s(x)$ with a 3-valued function as Eq. (2):

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

where t is a given threshold and can make LTP code more robust against noise. Fig. 2 gives an illustration of the basic LTP with $t=5$.

Each ternary pattern is further split into positive and negative parts. The two parts are processed as two separate channels of LBP descriptors. Calculate the histograms on both positive and negative channels, respectively. Concatenate all the histograms as the final feature description of the original image. Fig. 3.

CS-LBP [27] encodes the relationship between the center symmetric pixel pairs using Eq. (3).

$$\mathrm{CS-LBP}_{R,N,T} = \sum_{i=0}^{(N/2)-1} s(p_i - p_{i+(N/2)})2^i$$
$$s(x) = \begin{cases} 1, & x > t \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where p_i and $p_{i+(N/2)}$ are the gray values of center symmetric pairs of pixels of N equally spaced pixels on a circle of radius R. t is the threshold.

LBP could produce 2^N different binary patterns. CS-LBP could

Fig. 4. Ten images of one person in ORL.

Please cite this article as: W. Yang, et al., Face recognition using adaptive local ternary patterns method, Neurocomputing (2016), http://dx.doi.org/10.1016/j.neucom.2015.11.134