Advances in Computer Science Research, volume 88

International Conference on Computer, Network, Communication and Information Systems (CNCI 2019)

Research on Improved LBP Algorithm Based on Euclidean Distance and Differential Coding

Xuefei Jia[1, a], Yang Jiao[1, b], Wenhao Zhang[1, c] and Junxi Zhao[1, d]

[1]Nanjing University of Posts and Telecommunications, Nanjing 210046, China.

[a]1017010411@njupt.edu.cn, [b]1016010632@njupt.edu.cn, [c]junxi_zhao@163.com

Abstract. Local Binary Pattern (LBP) algorithm is a classical algorithm in the field of face recognition. It can capture local detail features, but its robustness and recognition rate are easily affected by external environmental changes.In this paper, an improved LBP algorithm which combines Euclidean distance and differential coding is proposed. The improved EDLBP operator is applied to feature extraction and compared with various improved LBP algorithms in different databases.The experimental results show that the correlation between the EDLBP algorithm and the LBP, MBP, LTP and ELBP algorithms is improved in the databases with illumination diversity and texture rotation. When compared to the recognition rate changes obtained using the CUReT database at different training samples, the highest recognition rate of EDLBP algorithm is 55.49%, 23.36% and 2.46% higher than that of LBP, MBP and LTP algorithms respectively. By comparing similarity of the two face images, the EDLBP algorithm is 1.04%, 2.94%, 4.69%, and 5.56% higher than the latest ELBP algorithm.

Keywords: LBP algorithm, feature extraction, recognition rate, euclidean distance.

1. Introduction

Face recognition is a biometric technology for identifying facial features of humans. Its application prospects are very broad. Such applications include video surveillance, public security, justice and criminal investigation, and other security areas. The key to facial recognition is the extraction of appropriate information to identify faces.. In the past few decades, relevant researchers have proposed many algorithms for feature extraction. Geometric feature-based methods [1], linear discriminant analysis [2], eigenface method [3], and neural network method [4] can well describe the shape and texture of faces, however, it is difficult to process images with too many dimensions and it is susceptible to objective factors such as lighting.. In recent years, local-based methods have become more and more popular among researchers. This is because local-based methods can not only solve the problem of excessive data dimension, but also have invariance to illumination and expression. Local Binary Pattern (LBP) [5] is a very effective texture description operator. The LBP algorithm was originally used in texture description and was used for face recognition due to its simple calculation and strong feature classification ability[6]. However, the local binary mode generates a large amount of noise information when calculating the LBP operator, and the computational quantity becomes larger due to the large dimension of the feature vector, which affects the recognition efficiency. Based on the LBP algorithm, a series of improved algorithms are proposed, including MBP [7], LTP [8], ELBP [9] algorithms, but they all did not consider the effect of the Euclidean distance of the neighborhood pixel on the central pixel point.

Based on the above problems, this paper proposes an improved LBP algorithm based on Euclidean distance-differential coding(EDLBP). Firstly, when encoding with neighborhood pixels, it is no longer simply comparing the neighborhood pixels with the central pixels, but using the neighborhood pixels. The point is compared with the previous pixel point and the intermediate pixel point respectively, and then the two code words compiled according to different Euclidean distances are recombined into new codes by different weights, and finally verified by different face database experiments. When compared to the original LBP algorithm, the improved algorithm has better represenation and descriminating ability for face images.

2. Improved LBP Algorithm Implementation Based on Euclidean Distance-differential Coding

2.1 EDLBP Coding Method and Steps.

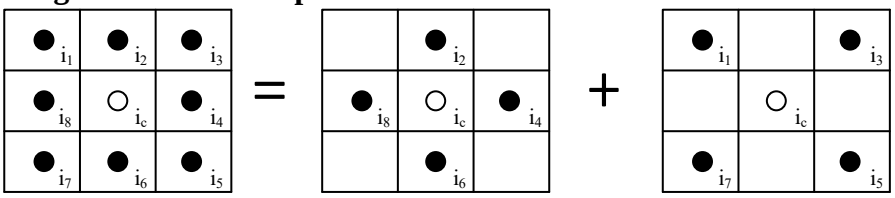

Fig. 1 Composition of pixel points in different fields with different Euclidean distances

Fig. 1 shows the classification of field pixels in terms of Euclidean distance. There are two types of Euclidean distances between the field pixels and the intermediate pixels, which are 1 and $\sqrt{2}$, respectively. The Euclidean distance is defined as the normalized distance from the neighborhood pixel to the central pixel. (x_c, y_c) represents the central pixel, which i_c represents the gray value of the central pixel, $i_k (k = 1,2,3,4)$ represents the gray value of the neighborhood pixel, by encoding the intermediate pixel according to certain rules. The rules are as follows:

For the initial pixel point i_1, the encoding rules are as follows:

$$S_1 = \begin{cases} 11 & i_k > i_c, i_k > \bar{i} \\ 10 & i_k > i_c, i_k < \bar{i} \\ 01 & i_k < i_c, i_k > \bar{i} \\ 00 & i_k < i_c, i_k < \bar{i} \end{cases} \qquad k = 1 \tag{1}$$

Where $\bar{i} = \frac{1}{4}\sum_{k=1}^{4} i_k$ is the mean of the pixels of the 4 fields.

For the remaining pixels, the encoding rules are as follows:

$$S_k = \begin{cases} 11 & i_k > i_c, i_k > i_{k-1} \\ 10 & i_k > i_c, i_k < i_{k-1} \\ 01 & i_k < i_c, i_k > i_{k-1} \\ 00 & i_k < i_c, i_k < i_{k-1} \end{cases} \qquad k = 2,3,4 \tag{2}$$

Since there are two kinds of Euclidean distances, the respective 8-bit codes $c_1c_2c_3c_4c_5c_6c_7c_8$ and $c_1^{'}c_2^{'}c_3^{'}c_4^{'}c_5^{'}c_6^{'}c_7^{'}c_8^{'}$ corresponding to the two Euclidean distances are coded according to the above coding rule, and the two binary sequences are converted into decimal numbers.The LBP value of the central pixel point is obtained, and the value indicates the grayscale around the area:

$$LBP(x_c, y_c) = \sum_{p=0}^{7} 2^p c_{p+1} \tag{3}$$

Due to the different Euclidean distances, the LBP values of the central pixel points obtained after calculation are respectively labeled as m and $m^{'}$, where m and $m^{'}$ correspond to neighborhood codes with Euclidean distances of 1 and $\sqrt{2}$, respectively.

2.2 Determination of the Weight of the Two Different Gray Values and Re-encoding.

After $m, m^{'}$ has been obtained, it is necessary to determine the corresponding specific gravity. Since the Euclidean distance between the neighborhood and the central pixel is 1 and $\sqrt{2}$, respectively, the basic knowledge of image processing shows that the closer it is to the central pixel, the larger the neighborhood pixel coding's coefficient of the central pixel, so the weights of the two different neighborhood pixels are redistributed. The specific allocation is as follows:

$$l = \frac{\sqrt{2}}{1+\sqrt{2}}, \quad l^{'} = \frac{1}{1+\sqrt{2}} \tag{4}$$

Where l and $l^{'}$ satisfied the following relationship: $l^2 + l^{'2} = 1$.

After the determination of the weight values of the two gray values is completed, the gray value of the central pixel point needs to be re-determined, specifically as follows:

$$\hat{m} = [lm + l^{'}m^{'}] \tag{5}$$

Where $\hat{m}$ represents the gray value of the final center pixel and $[]$ represents the rounding. After the EDLBP algorithm, the grayscale and histograms extracted are as shown below:

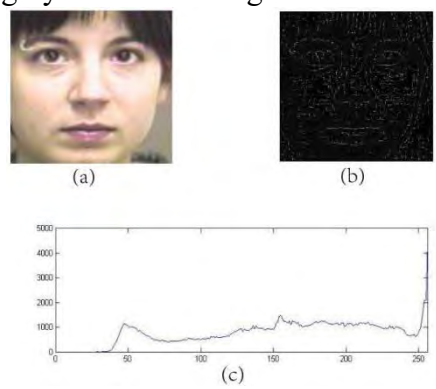

Fig. 2 EDLBP algorithm extracts feature map

(Fig. 2 (a) is the original image, 2.b is the grayscale image, 2.c is the corresponding histogram)

According to [10], the above extracted EDLBP histogram can measure the similarity of two facial images by the distance χ^2, which is defined as:

$$\chi_{\omega}^{2}(H,H^{'})=\sum_{k,i,j}\omega_k\frac{(H_{k,i,j}-H_{k,i,j}^{'})^2}{H_{k,i,j}+H_{k,i,j}^{'}} \tag{6}$$

Where H and $H^{'}$ represent the histogram statistics corresponding to the two images, and ω_k represents the weight of each region.

2.3 Experimental Results and Analysis.

Table 1 Recognition rates of different algorithms in texture databases of Brodatz, TC14, etc.

Database	LBP	MBP	LTP	ELBP	EDLBP
Brodatz	0.7816	0.8235	0.9681	0.9711	0.9772
TC14	0.6706	0.7162	0.8398	0.9021	0.9255
UIUC	0.7824	0.7961	0.9235	0.9467	0.9528
KTH-TIPS	0.7695	0.8112	0.9446	0.9573	0.9712

The improved EDLBP algorithm is compared with various LBP improved algorithms on Brodatz, OuTex, UIUC and KTH-TIPS databases with illumination diversity and texture rotation changes. According to the Brodatz database classification, it can be seen that the classification recognition rate of the EDLBP algorithm is 25.02%, 18.66%, 0.94%, and 0.63% higher than the LBP, MBP, LTP, and ELBP algorithms respectively. For the TC14, UIUC and KTH-TIPS database with simultaneous illumination diversity and texture rotation, the recognition rate of EDLBP algorithm is higher than those algorithms, respectively, indicating that the EDLBP algorithm can effectively improve the robustness.

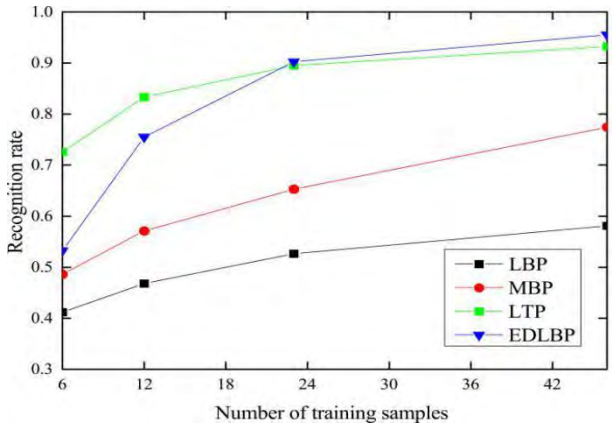

Fig. 3 Variations of the number of training samples with different improved LBP algorithm recognition rates on the CUReT database

Fig. 3 shows the variation of the LBP algorithm recognition rate with the number of training samples in the CUReT database. By comparing the performance of the proposed algorithm with

various LBP variants to the complex external environmen changes. Under the condition of different training samples, the algorithm classification recognition rate increases significantly with the increase of the number of training samples. The EDLBP algorithm proposed in this paper has better classification effect than LBP and its various improved algorithms. The recognition rate of EDLBP algorithm is increased by 55.49%, 23.36% and 2.46%, respectively, which indicates that EDLBP algorithm can be effectively used for texture classification with complex environment changes.

Table 2 Recognition rate of EDLBP-based algorithm and other algorithms (FERET database)

Algorithm	Recognition rate			
	fb database	fc database	dup1 database	dup2 database
EDLBP+χ^2distance	0.97	0.70	0.67	0.57
LBP+χ^2distance	0.95	0.62	0.58	0.50
MBP+χ^2distance	0.95	0.65	0.59	0.50
LTP+χ^2distance	0.96	0.67	0.61	0.51
ELBP+χ^2distance	0.96	0.68	0.64	0.54

Table 2 uses the FERET database test experiment using the complete set of fa database(1196 images) as a template set , using the complete set of fb database(1195 images), fc database(194 images), dup1 database(722 images), and dup2 (234 pictures) as the test set. It can be seen from the table that, the recognition rate of the EDLBP algorithm is 2.11%, 12.90%, 15.52% and 14.00% higher than the traditional LBP algorithm. Compared with the latest ELBP algorithm, it also increased by 1.04%, 2.94%, 4.69% and 5.56%. This shows that the EDLBP algorithm has great advantages when using χ^2 distance to measure the similarity between two face images.

3. Summary

In this paper, we consider variations in Euclidean distance between adjacent pixels and intermediate pixels, determine the weight of pixels with different Euclidean distances, and combine the differential encoding to re-encode the central pixel.When compared with other algorithms in different databases, the experimental results show that the EDLBP algorithm has different degrees of improvement in different databases.

Acknowledgments

National Natural Science Foundation of China (61475075)，Postgraduate Research & Practice Innovation Program of Jiangsu Province(KYCX17_0771)

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