Facial Expression Recognition Method Based on Difference Center-Symmetric Local Directional Pattern

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Abstract. To solve the problem of insufficient feature extraction and low feature extraction efficiency of local directional pattern, this paper proposes a new facial expression extraction method based on difference center-symmetric local directional pattern (DCS-LDP). The grey values in the fields of 3×3 neighborhood convolved with eight Kirsch operators to obtain eight edge response values. Combining the mean grey values of 3×3 neighborhood, the response values are compared in three gradient directions of horizontal, vertical and diagonal. The proposed algorithm makes full use of the edge gradient information and extracts multi-level information of facial features on the gradient space. In the recognition step, SVM (support vector machine) is employed to classify facial expressions. The method is tested on CK+ facial expression database and the simulation results show that the method is effective, feasible and robust.

Keywords: Local directional pattern, feature extraction, difference center-symmetric local directional pattern, Kirsch operator.

1. Introduction

The general steps of facial expression recognition are face image acquisition and preprocessing, expression feature extraction and classification. The expression feature extraction is the most important step, which plays a decisive role in the overall system recognition rate and recognition speed. Among them, the local binary pattern (LBP) based feature extraction method has achieved remarkable results in texture analysis and face recognition, and many improved methods have emerged. However, the LBP algorithm compares the gray value of the neighborhood and the center pixel, and can only extract the first-order feature information of the face, which is sensitive to non-monotonic illumination changes and random noise. In order to overcome the shortcomings of the LBP operator, Jabid et al. [1] proposed a feature extraction method based on local directional pattern (LDP), which extracts expression features on the gradient space.

LDP considers the edge response values in all different directions. Since edge response values are more stable than pixel intensity, LDP is more stable in the presence of noise. Despite the great achievement of LDP in image processing area, there are still several disadvantages in their studies. Zhong et al. [2] proposed enhanced local directional pattern (ELDP), which employs the directions of the two most significant edge response values. Results show that ELDP outperforms than LDP. Rivera et al. [3] proposed local directional number pattern (LDN) algorithm, which employs the directions of the maximum edge response values and the minimum edge response, and the simulation results validated the superiority of LDN. However, the proposed algorithms mentioned above take a lot of time to sort the edge response values, but we only obtain 56 or 64 modes in the end, the extracted feature information is not comprehensive enough, and the extraction efficiency is low. Furthermore, these methods ignore the central pixel value, which results in the loss of useful information. Based on the above problems, this paper proposes a new facial expression extraction method based on DCS-LDP. The proposed algorithm makes full use of the edge gradient information and extracts multi-level information of facial features on the gradient space.

2. Feature Extraction

2.1 LDP.

The main idea of LDP is comparing the eight edge response values of a particular pixel in eight different directions. Firstly, we calculate eight edge response values of a particular pixel by using Kirsch masks. The masks with eight directions (M_8^i, $\mathrm{i} = 0, \ldots, 7$) are shown in the Fig. 1.

$$\underset{M_8^0}{\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix}} \underset{M_8^1}{\begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix}} \underset{M_8^2}{\begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}} \underset{M_8^3}{\begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}}$$

$$\underset{M_8^4}{\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix}} \underset{M_8^5}{\begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix}} \underset{M_8^6}{\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix}} \underset{M_8^7}{\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}}$$

Fig. 1 Kirsch compass masking

After convolving the 3×3 neighborhood with the masks in all directions, we obtain eight edge response values (m_i, $\mathrm{i} = 0, \ldots, 7$), each value represents the edge significance in its respective direction. Secondly, we sort the edge response values after taking the absolute value. The top k directional bit responses are set to 1. The remaining bits of the LDP pattern are set to 0. An 8-bit binary code is obtained, and converted it to decimal, which is the LDP code of the center pixel. Finally, we get c_8^k modes of LDP. The formulas of the coding are as follows:

$$LDP_k = \sum_{i=0}^{7} b(|m_i| - |m_k|) \times 2^i \tag{1}$$

$$\mathrm{b(x)} = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{2}$$

2.2 DCS-LDP.

To solve the problem of low extraction efficiency and the loss of useful information, this paper proposes a new facial expression extraction method based on DCS-LDP, which extracts information more comprehensive on gradient space. Firstly, we obtain the eight edge response values $\mathrm{m}_i (\mathrm{i} = 0, \ldots, 7)$ as LDP algorithm. The positive or negative edge response value means a trend of rising or falling in a certain direction, which may contain more information [5]. For this reason, we do not convert the negative responses into their absolute values. Secondly, we calculate the mean value of the center pixel and its 3×3 neighborhood pixel, which is recorded as the center response value (m_c). The formula is as follows (g_i is the grey value of the pixel):

$$\boldsymbol{m_c = \frac{1}{9}\left(\sum_{i=0}^{7} g_i + g_c\right)} \tag{3}$$

Finally, inspired by local gradient coding (LGC) [4], we compared the nine response values (as Fig. 2 shows) in three gradient directions of horizontal, vertical and diagonal. The central value in each direction is chosen as a threshold for the other two neighbor pixels. If the values at both ends are greater than the center value, it indicates that there is a significant change between the three response values in the gradient direction, and the code is 1; otherwise, the code is 0. An 8-bit binary code is obtained, and converted it to decimal, which is the DCS-LDP code of the center pixel. The proposed DCS-LDP has 2^8 modes. The formulas of the coding are shown as (4)-(5):

m_3	m_2	m_1
m_4	m_c	m_0
m_5	m_6	m_7

Fig. 2 response value

$$\left.\begin{array}{l} \mathbf{p_0: b(m_3 - m_2) \times b(m_1 - m_2)} \\ \mathbf{p_1: b(m_4 - m_c) \times b(m_0 - m_c)} \\ \mathbf{p_2: b(m_5 - m_6) \times b(m_7 - m_6)} \\ \mathbf{p_3: b(m_3 - m_4) \times b(m_5 - m_4)} \\ \mathbf{p_4: b(m_2 - m_c) \times b(m_6 - m_c)} \\ \mathbf{p_5: b(m_1 - m_0) \times b(m_7 - m_0)} \\ \mathbf{p_6: b(m_3 - m_c) \times b(m_7 - m_c)} \\ \mathbf{p_7: b(m_1 - m_c) \times b(m_5 - m_c)} \end{array}\right\} \tag{4}$$

$$\mathbf{DCS - LDP} = \sum_{i=0}^{7} \boldsymbol{p_i} \times \mathbf{2^i} \tag{5}$$

3. Experiment

In order to verify the superiority of the algorithm, we compared the performance of the DCS-LDP with LDP and LDN methods on the CK+ facial expression database. Seven emotion sets were selected from the database (angry, disgusted, fearful, happy, neutral, sad and surprise). The selected data set contains 1029 image sequences, and there are obvious lighting changes between different images. SVM is employed to classify all the expression features to ensure that the experimental results are only related to the selection of the feature extraction algorithm. The software environment for the simulation experiment is MATLAB R2017a and python 3.7.0. The experimental steps are as follows:

Fig. 3 part of CK+ database

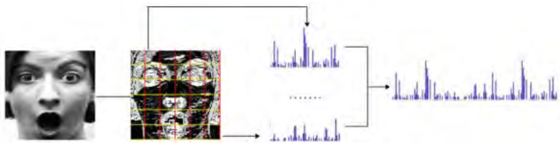

Fig. 4 the process of feature extraction

1) Cropping the face image centered on the connection of eyes to get the expression area. To verify the fact that DCS-LDP is not affected by the noise and illumination changes, no preprocessing was performed. The size of the expression image is normalized to 120×120 pixels (shown as Fig. 3).

2) Encoding all pixels of the facial expression image by using DCS-LDP based feature extraction method. We get an encoded image as shown in Fig. 4.

3) In order to extract more location information, we chose to divide each encoded image into N blocks, and then calculate the histograms of each block. We can obtain the eigenvectors of the image by cascading the histograms of all the blocks in order. The dimension of the eigenvectors is $2^8 \times N$. Fig. 4 shows the specific process.

4) Using SVM classifier to classify facial expressions. Each face image eigenvector is divided into the test library with a probability of 10%, and training libraries with a probability of 90%, which means, the training set and the test set are generated randomly. Inputting the training set and the test set into the SVM classifier respectively for model training and expression recognition. The process is repeated 10 times, and the recognition rate and the number of false judgments are taken as the mean of the results.

Since different number of blocks has different recognition effects, too few blocks will result in incomplete information extraction; too many blocks will lead to information redundancy. In order to get the best recognition rate, we perform different block experiments on the facial expression database. The results of the experiments are shown as Table 1.

Table 1 recognition rate under different block mode

number of blocks	4×4	5×5	6×6	8×8	10×10
recognition rate(%)	94.22	95.14	95.51	94.96	93.54
false judgment	70	61	51	65	84

As Table 1 shows, with the number of blocks increases, the extracted information is more abundant, and the recognition rate is gradually increased. After reaching a certain number, too many blocks will lead to information redundancy, resulting in a decrease in the recognition rate; in the expression classification step, the recognition speed will get slower as the dimension of the feature increases. From Table 1, we chose to divide each encoded image into 6×6 blocks, and the size of each block is 20×20 pixels.

In order to verify the superiority of the algorithm, we compared the performance of the DCS-LDP with LDP and LDN methods. We chose to divide all kinds of encoded image into 6×6 blocks. Table 1 shows the results of the experiments. The result shows that the best recognition rates are achieved by DCS-LDP. Compared with the LDP and LDN algorithm, the total recognition rate of this algorithm is increased by 3.29% and 1.31%, respectively. Fig. 5 shows the recognition rate of each expression under different feature extraction methods (1-7 correspond to angry, disgusting, scared, happy, neutral, sad, surprise), in which happy expression set (label 4) has the best performance.

Compared with the LDP algorithm and the LDN algorithm, the proposed DCS-LDP method gains the highest recognition rate of every expression.

Table 2 recognition rate under different feature extraction methods

	recognition rate (%)	false judgment
DCS-LDP	95.51%	51
LDP	92.24%	82
LDN	94.22%	63

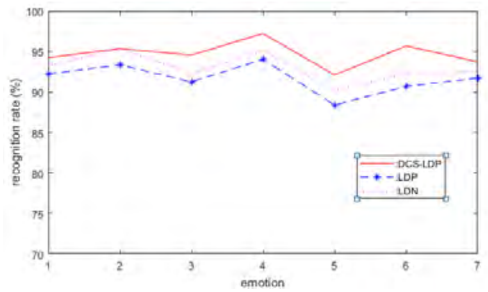

Fig. 5 recognition rate of seven expressions

4. Conclusion

This paper describes a new local feature based on DCS-LDP codes for facial expression recognition. The method combines the gray mean value, and compares the response value from the horizontal, vertical and diagonal directions in the gradient space. Compared with LDP and LDN, the result shows that the method is effective, feasible and robust. Moreover, the texture variation features between different facial expressions can be well described, which has better recognition stability and generalization ability, and can be widely applied to image processing field. However, the time complexity of the algorithm is high, how to improve the speed of the algorithm with the recognition rate guaranteed is still the focus of the next step.

Acknowledgments

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