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Micro-expression recognition based on local binary patterns from three orthogonal planes and nearest neighbor method

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***Abstract*—Micro-expression is a very short and rapid involuntary facial expression, which reveals suppressed affect. Recognizing micro-expression can help to accurately grasp the real feelings of people, a result that can have an important practical impact. But the scholars' studies have demonstrated that real micro-expression is difficult to identify. There are two main restrictive factors, one is the need of a comprehensive and typical database, and the other one is the need of a suitable method. This paper proposes a combination of local binary patterns from three orthogonal planes (LBP-TOP) and the nearest neighbor method, and does experiments on a large database. At last, a reasonable result is obtained.**

Keywords—micro-expression; LBP-TOP (local binary patterns from three orthogonal planes); nearest neighbor method

I. INTRODUCTION

Micro-expression is a kind of very rapid facial expression. Its duration is only 1/25 to 1/5 second. It is unconscious and reveals the true feelings people try to suppress [1]. Micro-expression was first discovered by Haggard and Isaacs in 1966 [2]. In an accidental opportunity, Ekman and Friesen also found the micro-expression in 1969 [3]. Micro-expression caused the attention of the scholars once it was found. And it aroused wide concern of the media [4] and the scientific community [5]. Researches on micro-expression have gone through a history of more than 40 years. During this period, scholars have made a lot of researches on micro-expression, including the generation mechanism of micro-expression and the ability for people to recognize micro-expression [6, 7].

Recognizing micro-expression can help to accurately grasp the real feelings of people, a result that can have an important practical impact. Micro-expression is often accompanied by lies. Ekman et al. carried out a series of studies on micro-expression. They analyzed the relationship between micro-expression and lies, and proved that micro-expression is an effective clue to lies. It can be widely used in fields such as security, justice, clinical and so on. The form of micro-expression is the same as the regular expression. It includes seven types of basic expressions: happiness, sadness, fear, disgust, surprise, anger and contempt.

In recent years, a few scholars have begun to research to recognize micro-expression using algorithms. Polikovsky et al. [8] let ten college students show micro-expression and used a camera of 200 frames per second to record. They made the faces of expression in regions and used 3D gradient histogram descriptor to extract the movement of each piece. They successfully identified 13 kinds of micro-expression at last. Shreve et al. [9, 10] let the participants watch the videos of micro-expression and then asked them to imitate. They described micro-expression using strain mode. They also used strain mode to detect micro-expression, and distinguished micro-expression from exaggerated expression successfully. Pfister et al. [11] put forward a spontaneous micro-expression recognition framework. They used psychological method to successfully induce a spontaneous micro-expression database. They made the sequences in blocks and used a special and temporal partial texture descriptor in combination with multi-kernel learning, random forests, and support vector machine (SVM) for classification. Wu et al. [12] designed an automatic micro-expression recognition system. They also used psychological method to induce a spontaneous micro-expression database. They used Gabor filter and the SVM method and successfully recognized micro-expression.

Compared with the ordinary expression, micro-expression is very difficult to recognize. We found some problems from other scholars' study. First of all, the databases used in most experiments are imitative [8, 9, 10, and 13]. Subjects were asked to imitate micro-expression and the expressions they got have a certain similarity model and cannot represent the real situation. Secondly, most experiments make sequences in blocks in order to refine the movement. Sequences in blocks will lead to the increase of the amount of calculation and information redundancy. Finally, the methods used in the classification phase are complex and may lead to loss of characteristics.

According to these situations, this paper uses a large and new spontaneous micro-expression database. We combine the most effective feature extraction method LBP-TOP (Local Binary Patterns from Three Orthogonal Planes) with the most direct classification method the nearest neighbor. We don't make the sequence in blocks. At last, a reasonable result is obtained.

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The structure of this paper is as follows. In Section 2 we discuss the methods we use. Section 3 presents the database of spontaneous micro-expression we use in the experiments. Experimental results are discussed in Section 4. We conclude the paper in Section 5.

II. FEATURE EXTRACTION AND CLASSIFICATION METHODS

A. LBP-TOP Operator

Facial feature extraction is the most critical step in expression recognition. We need to extract facial expression features clearly and effectively, in order to recognize expression accurately. Researches on expression feature extraction based on dynamic image sequences are much less than feature extraction based on static images. Because of the short duration and the small intensity of micro-expression, micro-expression feature extraction based on dynamic image sequence becomes a very difficult task. We need to further analysis the database and choose the appropriate method.

There are no new methods for micro-expression feature extraction. Scholars mostly choose to do a more subtle preprocessing on micro-expression sequences. Then they use the ordinary expression feature extraction methods to extract the features. Through the in-depth study of the database, this paper select LBP-TOP for feature extraction.

LBP-TOP method [14] was put forward by Guoying Zhao team at the University of Oulu in Finland, 2007. The purpose was to overcome the insufficient that LBP used on sequence image processing and make the calculation more simplify.

LBP (Local Binary Patterns) operator was put forward by Ojala [15]. It is a powerful method to describe the texture features. The core idea of LBP is to compare the center pixel value with the neighborhood pixel values. Then we get the binary codes of the neighborhood pixels. If a neighborhood pixel value is greater than the center pixel value, then the corresponding binary code is one, on the other hand, is zero. We put the binary numbers strung together, and let it be the new center pixel value. Finally, convert the binary number to a decimal number, and the new decimal number is the local binary pattern of the center pixel. The calculation process is as shown in (1):

$$LBP(x_c, y_c) = \sum_{i=0}^{7} s(g_i - g_c)2^i \tag{1}$$

Where (x_c, y_c) is the center pixel, g_c is center pixel value, $g_i\,(i = 0, \cdots, 7)$ are neighborhood points values and $s(g_i - g_c) = \begin{cases} 1 & g_i - g_c \ge 0 \\ 0 & g_i - g_c < 0 \end{cases}$.

The calculation process of a basic LBP operator is shown as Fig.1.

For the points not completely on the pixel positions, the gray values are obtained by using the bilinear interpolation algorithm. LBP_P^R means there are P points in the

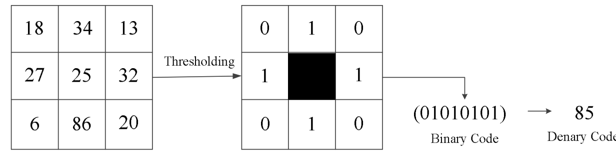


Fig. 1. The calculation process of a basic LBP operator

neighborhood of radius R. LBP_8^1, LBP_8^2 and LBP_{16}^2 are the commonly used LBP operators. Several extended LBP operators are as shown in Fig. 2.

LBP-TOP combines the temporal and spatial features of an image sequence on the basis of LBP, and extracts the dynamic texture features of image sequences from three orthogonal planes. These dynamic texture features are used to express the spatial and temporal and motion characteristics of image sequences.

The same as LBP operator to extract the features, LBP-TOP operator also see a pixel in the image sequence as the center pixel and uniformly extract neighborhood points from its three orthogonal planes. Fig. 3 describes extract neighborhood points from three orthogonal planes.

Using LBP-TOP to extract features on dynamic sequences is very effective. It both considers the distribution of characteristics in each plane and effectively combines the

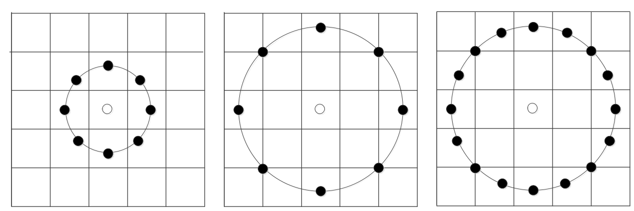


Fig. 2. Several extended LBP operators. (a) LBP_8^1 (b) LBP_8^2 (c) LBP_{16}^2

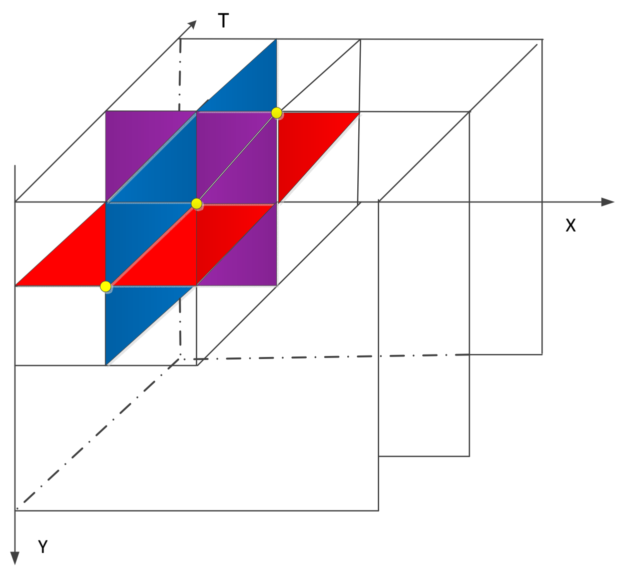


Fig. 3. Extract neighborhood points from three orthogonal planes

characteristics of the three orthogonal planes. But the ordinary LBP-TOP algorithm uses the same LBP operator on the three orthogonal planes, ignoring the differences among the three planes.

Because of not knowing the motion directions of the dynamic texture, it is not reasonable to just think the neighborhood points are on the line whose benchmark is the center pixel. For improvement, we can expand the ordinary neighborhood to circular neighborhood as well as to oval neighborhood.

Generally, the radii in axis X, Y and T, and the number of neighborhood points in the XY, XT and YT planes can also be different. They can be marked as $R_X, R_Y, R_T, P_{XY}, P_{XT}, P_{YT}$, as shown in Fig. 4 and Fig. 5. Fig. 4 shows extract neighborhood points of the circular and elliptical neighborhood from the three orthogonal planes. Fig. 5 shows extract each surface from Fig. 4. Then we can clearly see the selected parameters on the three orthogonal planes.

The corresponding feature is written as $LBP-TOP_{P_{XY},P_{XT},P_{YT},R_X,R_Y,R_T}$. Suppose the coordinates of the center pixel $g_{t_c,c}$ is (x_c, y_c, t_c). Then we can use the following formulas to compute the pixel coordinates of each orthogonal plane.

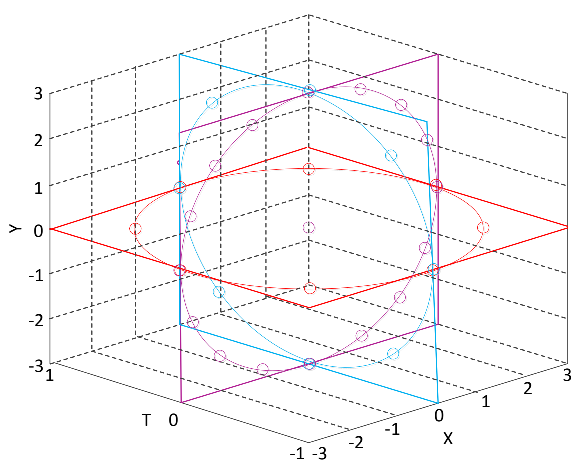
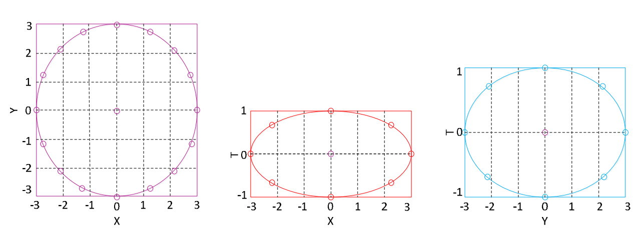


Fig. 4. Different radii and number of neighbor points on three planes

The coordinates of $g_{XY,p}$ are given by:



(a) (b) (c)

Fig. 5. Detailed sampling for Fig. 4. (a)XY plane, $R_X = 3$, $R_Y = 3$, $P_{XY} = 16$, (b) XT plane, $R_X = 3$, $R_T = 1$, $P_{XT} = 8$, (c) YT plane, $R_Y = 3$, $R_T = 1$, $P_{YT} = 8$.

$$\begin{aligned}&\left(x_c - R_X \sin\left(2\pi p / P_{XY}\right),\right.\\&\left.y_c + R_Y \cos\left(2\pi p / P_{XY}\right), t_c\right),\quad p = 0,1,\cdots,P_{XY}-1.\end{aligned} \tag{2}$$

The coordinates of $g_{XT,p}$ are given by:

$$\begin{aligned}&\left(x_c - R_X \sin\left(2\pi p / P_{XT}\right), y_c,\right.\\&\left.t_c - R_T \cos\left(2\pi p / P_{XT}\right)\right), p = 0,1,\cdots,P_{XT}-1.\end{aligned} \tag{3}$$

The coordinates of $g_{YT,p}$ are given by:

$$\begin{aligned}&\left(x_c, y_c - R_Y \cos\left(2\pi p / P_{YT}\right),\right.\\&\left.t_c - R_T \sin\left(2\pi p / P_{YT}\right)\right), p = 0,1,\cdots,P_{YT}-1.\end{aligned} \tag{4}$$

This is different from the ordinary LBP widely used in many papers. It expands the definition of LBP.

B. Nearest Neighbor Method

Expression classification is the final step of facial expression recognition. Its goal is to classify the expressions according to effective features. The features extracted for each sequence in this paper are 3*59 matrixes. They can be transformed to 1*177 dimensional row vectors. Then we can classify the features by calculating the spatial distance between each feature. In this paper, we select the nearest neighbor method as the classification method, because it can directly compare the distances between vectors.

The idea of the nearest neighbor method is to compare the distances between the unknown samples with the entire known samples, and to judge the distances between samples. In all distance decisions, Euclidean distance is very good at measuring the similarity between samples. Here we choose Euclidean distance as the distance measurement.

Euclidean distance is defined as follows: Suppose there is a two-dimensional space. Its coordinate axis are X and Y. The distance d_{12} between two points P_1 and P_2 in this space is:

$$d_{12} = \sqrt{dx^2 + dy^2} \tag{5}$$

Where:

$$dx = x_2 - x_1, dy = y_2 - y_1 \tag{6}$$

The classification rule of the nearest neighbor method is to calculate the distance between each point in the feature space, and see the distances as the similarity measurement of samples. If the distance of two samples in the feature space is close, then the similarity of them is great.

III. DATABASE

In this paper, SMIC database (Spontaneous Micro-expression Database) [17] is used for spontaneous micro-expression recognition.

SMIC includes 164 micro-expression video segments of 16 subjects. In the database, micro-expression is classified as positive, negative and surprise. The positive expression is "happy". The negative expression includes "sad", "fear" and "disgust". The number of each kind of video is 70, 51 and 43. Video length is from 11 to 58 frames.

This database is a new spontaneous micro-expression database. The database contains men and women, Asians and Europeans, wearing glasses and not wearing glasses, and subject with or without whiskers. The database is wide range and is very close to the real situation. In this paper, we select two kinds of micro-expression for experiment. They are negative expression and positive expression. A micro-expression sequence is as shown in Fig. 6.

This is a negative expression. It is a briefly slight frown of the subject. As you can see, the movements between frame and frame in the sequence are too low to see by naked eyes. We need to watch the sequence dynamically and continuously to find the movements.

IV. EXPERIMENTS AND RESULTS

A. *Use the LBP-TOP Operator to Extract Features*

We can see that the facial movements are very delicate through careful analysis of the characteristics of dynamic micro expression sequences in the database. We need a method which is good at describing the texture and extracting the features. This paper selects the most advanced dynamic texture processing algorithm LBP-TOP as the feature extraction method. The clipped pure face region of each sequence is seen as a whole block. Then extract LBP features from the three orthogonal planes.

When scholars use the LBP-TOP method to extract dynamic features, they usually divide the sequences into pieces of x*y*t. So the changes of dynamic texture can be more prominent. The resolution of sequences used in this paper is not very high. Considering the computational complexity, we don't make the sequences in blocks. A micro-expression sequence is seen as a whole block. Then we extract the dynamic features of the sequences according to the following steps:

Fig. 6. A sequence in the database

1) Suppose that a center pixel of a frame in the sequence is (x, y, t). Then extract its LBP features from three orthogonal planes. Calculate the decimal value of the LBP features and record them as:

$$f_0(x_c, y_c, t_c), f_1(x_c, y_c, t_c), f_2(x_c, y_c, t_c)$$

2) For each pixel, calculate its local binary patterns on the three orthogonal planes. The histogram of the local binary patterns of the dynamic image sequence in each orthogonal plane can be defined as:

$$H_{i,j} = \sum_{x,y,t} I\{f_j(x,y,t) = i\}, \quad i = 0, \cdots, n_j - 1; j = 0,1,2 \tag{7}$$

Where n_j is the number of different labels processed by LBP operator in the j th plane $(j = 0: XY, 1: XT, 2: YT)$, $f_i(x, y, t)$ is the LBP code of central pixel (x, y, t) in the j th plane, and $I(A) = \begin{cases} 1, if \quad A \quad is \quad true; \\ 0, if \quad A \quad is \quad false. \end{cases}$

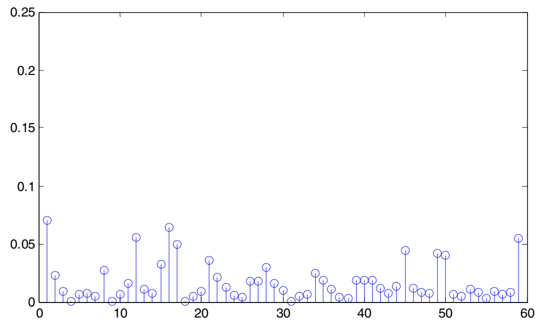
3) Finally, cascade the histograms of three orthogonal planes and get the LBP-TOP feature of the whole sequence.

Due to the differences between individual subjects, the sizes of cutting pure face regions are not the same. Because the lengths of the sequences are different, the dimensions of extracted features are different. We can use (8) to normalize features into a specific dimension:

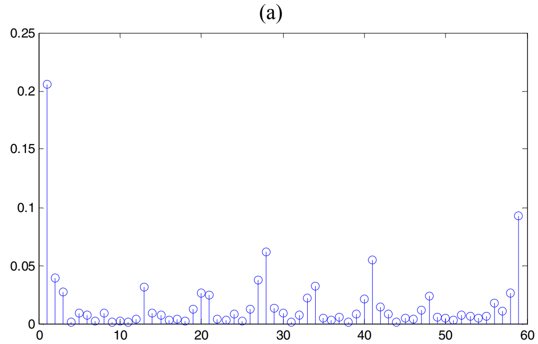
$$N_{i,j} = \frac{H_{i,j}}{\sum_{k=0}^{n_j - 1} H_{k,j}} \tag{8}$$

In this paper, the characteristics extracted are 3*59 matrixes. We normalize them to 1*177 dimensional row vectors, in order to calculate conveniently. One of the result histograms is as shown in Fig. 7. This is the result histogram of Fig. 6.

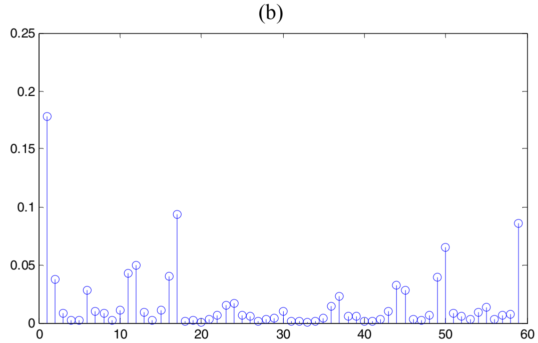
From Fig. 7 we can see that the movement of XY plane is more stable than the other two planes. In XY plane, the fluctuation is not very big. In XT and YT plane, the fluctuations are much bigger than the XY plane. XT and YT plane also contain a lot of features. The movements of the two spatial planes change obviously. It proves that the XT and YT planes are very important for feature classification and expression recognition. So combining features extracted from three orthogonal planes as the final feature is reasonable.



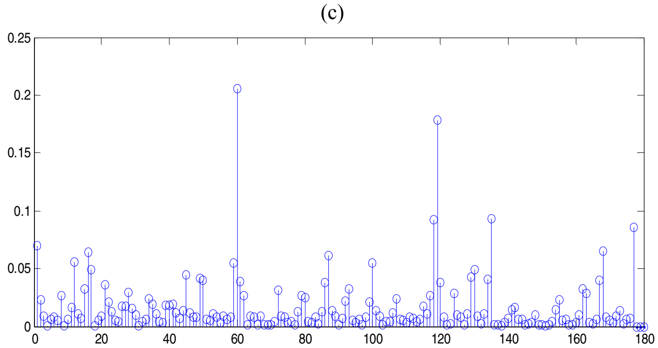
(a)



(b)



(c)



(d)

Fig. 7. LBP features of three orthogonal planes. The horizontal axis represents the features after normalization. The vertical axis represents the corresponding proportions. (a) is the LBP histogram of the XY plane, (b) is the LBP histogram of the XT plane, (c) is the LBP histogram of the YT plane, (d) is the LBP histogram cascaded by three orthogonal planes, namely the LBP-TOP feature of the sequence.

B. Use the Nearest Neighbor Method to Recognize Micro-expression

In the feature extraction part we get a series of 1*177 dimensional row vectors, namely the final feature of the sequence. The dimensions of extracted characteristics are low, so we can directly calculate the distances between the vectors to classify the samples. We randomly select some feature vectors as the training samples, the remaining as the testing samples. Then compare the Euclidean distance between each testing sample and each training sample and use the nearest neighbor method for classification.

Suppose there are m training sample x and n testing sample y. Define the distance between a testing vector y_j and a training vector x_i as:

$$d_{ij} = \sqrt{\sum_{k=1}^{177}\left(x_{ik} - y_{jk}\right)^2} \tag{9}$$

Then, for each y_j, calculate its distances with the entire training samples. For each testing sample, there is a nearest distance. The corresponding training sample indicates the category of that testing sample. The following formula is used to calculate the nearest distance:

$$d_j = \min_{1 \le i \le m} d_{ij} \tag{10}$$

In the experiment we select two kinds of expressions, including 70 negative sequences and 51 positive sequences. In the feature extraction stage, we extract the LBP-TOP feature of these sequences and save them. In the classification stage, we randomly select some feature vectors as the training samples, the remaining as the testing samples.

First of all, a comparison was carried out between person-unrelated experiment and person-related experiment. In the person-unrelated experiment, micro-expression feature vectors of one participant were selected as the testing samples each time, and the rest 15 participants' micro-expression feature vectors were selected as the training samples. In the person-related experiment, one "positive" and one "negative" micro-expression feature vectors were randomly selected from each participant as the testing samples, the remaining as the training samples. The experiment was carried out many times to ensure that every micro-expression feature vector was repeatedly appeared in the training samples and the testing samples. The experimental results are shown in Table 1.

From the table we can see that the recognition accuracy of person-unrelated experiment was far smaller than the recognition accuracy of person-related experiment. The micro-expression recognition accuracy was influenced by individual. When samples of the same participant appeared in the testing

TABLE I. COMPARISON BETWEEN PERSON-UNRELATED EXPERIMENT AND PERSON-RELATED EXPERIMENT.

Experiment type	*Recognition results*
person-unrelated	53.72%
person-related	65.83%

set and the training set at the same time, it is more probably to identify correctly.

The choice of parameters can also affect the final recognition results. In this paper, we select $R_X = R_Y = 1$, $R_T = 2$, $P_X = P_Y = P_T = 8$ .When the parameters change, the results are different. Some of the results corresponding to different parameters are shown in Table 2.

It can be seen from Table 2 that different parameters have a big influence on the results. Compare the results of (1,1,2,8,8,8) with (2,2,2,8,8,8) and (3,3,2,8,8,8), we can see that when R_X and R_Y become bigger, the recognition results become poorer. It proves that the radius in the X and Y axis should not be too big. A big radius is bad for feature extraction as well as the final classification results. Compare the results of (1,1,2,8,8,8) with (1,1,1,8,8,8) and (1,1,3,8,8,8), we can see that the change of R_T also influences the recognition results. It proves that, in order to get a reasonable classification result, we need to select an appropriate radius in T axis. Compare the results of (1,1,2,8,8,8) with the rest combinations of parameters, we can also see that the number of neighborhood points can affect the recognition results. For example, when the feature point is 4, the scale of extracted characteristic is too small, some gradient information is lost and the recognition result is poor.

The distribution of the training set and the testing set will also affect the final recognition result. We did some experiments on this issue. We did experiments when the ratio of the training set and the testing set are 5:1, 4:1, 3:1, 2:1 and 1:1 respectively. In the experiments, all the samples are randomly divided into many groups of roughly equal size. Each time some of these groups are selected to be the training samples, the remaining as the testing samples. For example, in the experiment when the ratio of the training set and testing set is 5:1, 1/6 of the total groups are selected as the testing samples. Change the testing samples and do the experiment many times, in order to achieve the goal of cross validation. Some experimental results are shown in Table 3.

It can be seen from Table 3 that the distribution of the training set and the testing set can also affect the final recognition results. In this paper, the higher the proportion of the training set is, the better the identification effect is. If we increase the training set appropriately, we can achieve an optimize result.

TABLE II. RECOGNITION RESULTS CORRESPONDING TO DIFFERENT PARAMETERS

Parameters($R_X, R_Y, R_T, P_X, P_Y, P_T$ ***)***	***Recognition results***
(1,1,2,4,4,4)	52.78%
(1,1,2,8,8,4)	63.89%
(1,1,2,8,4,8)	59.72%
(1,1,2,4,8,8)	60.00%
(1,1,2,8,8,8)	65.83%
(2,2,2,8,8,8)	51.94%
(3,3,2,8,8,8)	49.17%
(1,1,1,8,8,8)	61.67%
(1,1,3,8,8,8)	60.00%

TABLE III. RECOGNITION RESULTS CORRESPONDING TO DIFFERENT DISTRIBUTIONS OF THE TRAINING SET AND THE TESTING SET

Training set: Testing set	***Recognition results***
5:1	63.00%
4:1	62.15%
3:1	61.67%
2:1	60.36%
1:1	60.00%

V. CONCLUSION

In this paper, we select a new combination of methods and database, and recognize micro-expression successfully. Many scholars think that it is difficult or impossible to identify micro-expression, so the experiments on identifying micro-expression are rare. The main reasons that it is difficult to identify micro-expression are as follows: There isn't a big enough and representative database. The feature extraction methods used are not very appropriate. The classification methods are complicated. This paper avoids these problems. Firstly, we use a large spontaneous micro-expression database. Secondly, in feature extraction part, we use the most effective local texture descriptor. At last, in the classification part, we use the nearest neighbor method to directly compare the extracted characteristics. It avoids the problem of the loss of data. So we think that if we select the right method, we can identify micro-expression successfully.

The methods used in this paper have a limitation. When the dimensions of extracted characteristics become bigger, it is not suitable to use the nearest neighbor method for classification. The nearest neighbor method is to directly compare the distances between the unknown samples with the entire known samples. When the dimensions of samples are small, it is very convenient to calculate. When the dimensions of samples are big, the computational complexity is very big. Then the nearest neighbor method is obviously not suitable to be used.

In this paper, the best facial micro-expression recognition rate obtained is 65.83%. But expression recognition rates for ordinary expressions are mostly more than 90%. Our result is much lower than this value. However we think the experimental result of this paper is reasonable. Reasons are as follows. In fact, the complexity of database is one of the most important reasons restricting micro-expression recognition accuracy. Firstly, in terms of subjects, micro-expression database subjects are asked to suppress their own expressions. The movements of their expressions are slight. The differences between different kinds of expressions of the same person are small. The same kinds of expressions for different people are affected by the individuals. Secondly, in terms of labeling, micro-expression sequences are not easy to label. The start time and the end time of micro-expression are not correct and prone to errors. For example, some subjects' faces with subtle facial movements are captured as micro-expressions. The wrong samples are not easy to identify. Because of the complexity of database the micro-expression recognition rates are not high.

Future research direction can be summed up as the following two points: Firstly, in terms of algorithm, we can combine several feature extraction methods in order to extract the characteristics of dynamic micro-expression sequences effectively. Secondly, in terms of the database, we can make a more subtle processing. For example, we can expand the tiny micro-expression to the exaggerated expression according to a certain proportion to extract the characteristics more easily.

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REFERENCES

[1] P. Ekman, “Telling lies: clues to deceit in the marketplace, politics and marriage,” 2nd Ed. New York; Norton & Company, 2009.

[2] E. A. Haggard and K. S. Isaacs, “Micromomentary facial expressions as indicators of ego mechanisms in psychotherapy,” In: Auerback A, Ed: Methods of Research in Psychotherapy. New York: Appleton Century Crofts, pp. 154-165, 1966.

[3] P. Ekman and W. V. Friesen, “Nonverbal leakage and clues to deception,” Psychiatry, vol. 32, pp. 88−97, February 1969.

[4] M. R. Henig, “Looking for the lie,” New York Times Magazine, pp. 47-53, February 2006.

[5] S. Schubert, “A look tells all,” Scientific American Mind, vol. 17, pp. 26-31, November 2006.

[6] P. Ekman and W.V. Friesen, “Nonverbal behavior and psychopathology,” In: Friedman R, Ed. The Psychology of Depression: Contemporary Theory and Research. Washington D. C.: Winston & Sons, pp. 203-224, 1974.

[7] D. Matsumoto, J. LeRoux and C. Wilsoo-Cohn, “A new test to measure emotion recognition ability: Matsumoto and Ekman’s Japanese and Caucasian brief affect recognition test (JACBART),” Journal of Nonverbal Behavior, vol. 24, pp. 179-209, September 2000.

[8] S. Polikovsky, Y. Kameda and Y. Ohta, “Facial micro-expression recognition using high speed camera and 3D-gradient descriptor,” 3rd International Conference on Imaging for Crime Detection and Prevention (ICDP 2009), January 2009.

[9] M. Shreve, S. Godavarthy, D. Goldgof and S. Sarkar, “Macro-and micro-expression spotting in long videos using spatio-temporal strain,” Automatic Face & Gesture Recognition and Workshops (FG 2011), 2011 IEEE International Conference on. IEEE, pp. 51-56, March 2011.

[10] M. Shreve, S. Godavarthy and V. Manohar, “Towards macro-and micro-expression spotting in video using strain patterns,” Applications of Computer Vision (WACV), 2009 Workshop on. IEEE, pp. 1-6, December 2009.

[11] T. Pfister, X. Li, G. Zhao and M. Pietikainen, “Recognizing spontaneous facial micro-expression,” In Proceedings of IEEE International Conference on Computer Vision, Barcelona, Spain: IEEE Press, pp. 1449-1456, June 2011.

[12] Q. Wu, X. Shen and X. Fu, “The machine knows what you are hiding: an automatic micro-expression recognition system,” Affective Computing and Intelligent Interaction: lectures notes in computer science, vol. 6975, pp. 152-162, October 2011.

[13] S. Polikovsky, Y. Kameda and H. Ohta, “Detection and measurement of facial micro-expression characteristics for psychological analysis,” 3rd International Conference on Imaging for Crime Detection and Prevention (ICDP-09), December 2009.

[14] G. Zhao and M. Pietikainen, “Dynamic texture recognition using local binary patterns with an application to facial expressions,” Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 29, pp. 915-928, June 2007.

[15] T. Ojala, M. Pietikainen and D. Harwood, “A comparative study of texture measures with classification based on featured distributions,” Pattern Recognition, vol. 29, pp. 51-59, January 1996.

[16] T. Ojala, M. Pietikainen and T. Maenpaa, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 24, pp. 971-987, July 2002.

[17] X. Li, T. Pfister, X. Huang, G. Zhao and M. Pietikainen, “A spontaneous micro-expression database: inducement, collection and baseline,” Automatic Face and Gesture Recognition (FG), 2013 10th IEEE International Conference and Workshops on. IEEE, pp. 1-6, December 2013.