# Research on an Improved MB-LBP 3D Face Recognition Method

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**Abstract:** In order to improve the accuracy and speed of 3D face recognition, this paper proposes an improved MB-LBP 3D face recognition method. First, the MB-LBP algorithm is used to extract the features of 3D face depth image, then the average information entropy algorithm is used to extract the effective feature information of the image, and finally the Support Vector Machine algorithm is used to identify the extracted effective information. The recognition rate on the Texas 3DFRD database is 96.88%, and the recognition time is 0.025s. The recognition rate in the self-made depth library is 96.36%, and the recognition time is 0.02s. It can be seen from the experimental results that the algorithm in this paper has better performance in terms of accuracy and speed.

**Key words:** Average information entropy, depth data, MB-LBP, Support vector machine, 3D face recognition.

## 1. Introduction

With the rapid development of technology, face recognition technology is a relatively safe method of identity recognition. Face recognition has good application potential in education, mobile phones, finance and other industries [1]. Two-dimensional face recognition has certain limitations. Three-dimensional face recognition is produced. The three-dimensional face image contains the depth information of the face, which can overcome the problems of illumination, posture change and makeup. It has good robustness in many cases, so it is favored by more and more researchers.

Local Binary Pattern (LBP) was first proposed by Ojala *et al.* [2] to extract texture feature information, which was later used in the field of face recognition. Under certain conditions, it has a good recognition rate. Literature [3] uses neutral and expressive three-dimensional face scan data to construct a 3DMM, and then uses a non-rigid ICP algorithm to match the three-dimensional point cloud to obtain the shape parameters and expression parameters of the 3DMM. This method requires a long time for modeling. Hawraa H. Abbas *et al.* [4] applied the recognition analysis method to a coherent set of parts. The non-negative matrix factorization method is used to divide the 3D face into coherent regions. Literature [5] proposed a hidden Markov model (HMM) face recognition method, which alleviates the problems of overfitting and local maximum, but it takes a long time to train the data set module. In order to improve the performance of 3D face recognition algorithm, this paper proposes an improved MB-LBP 3D face recognition algorithm based on the original algorithm. It can be seen from the simulation results in Section 5 that the algorithm proposed in this paper has good performance.

## 2. Local Binary Pattern

Local Binary Pattern (Local Binary Pattern) is an operator used to describe the local characteristics of the image. The local binary mode (LBP) is to compare the size of the surrounding pixels and the central pixel to binarize the pixel values in the neighborhood. Its expression is:

$$\mathrm{LBP}\ (x_c, y_c) = \sum_{p=0}^{p-1} 2^p s(i_p - i_c) \tag{1}$$

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{2}$$

The principle of the LBP algorithm is to take the pixel value of each point in the image as the central threshold and take out the area around this pixel. Comparing the two pixels is worth producing a relative binary value. Take the resulting binary number as the center LBP eigenvalue. The calculation process of the LBP operator of a 3×3 neighborhood is shown in Fig. 1.

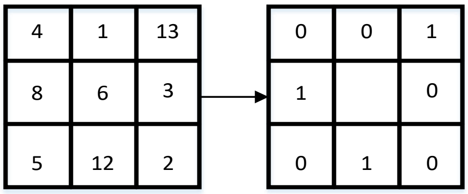


Fig. 1. Schematic diagram of LBP operator calculation process.

## 3. Support Vector Machine

The idea of Support Vector Machine (SVM) is to separate the data set and classify the hyperplane to maximize the distance between the training sample sets. As shown in Fig. 2, it is the separation hyperplane.

In the case of linearly separable data sets, there are an infinite number of hyperplanes that can be classified. However, only one hyperplane satisfies the largest classification interval. The schematic diagram of classification is shown in Fig. 2.

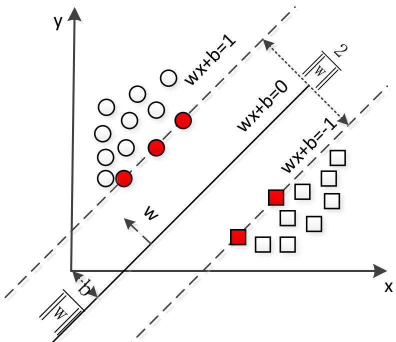


Fig. 2. Classification diagram.

In terms of nonlinear classification, to achieve linear classification in a certain dimension feature space, a method of nonlinear transformation can be used. Learn linear support vector machines from low-dimensional space to high-dimensional feature space. In the dual problem of linear support vector machine learning, the objective function and the classification decision function only involve the inner product between the instances. So there is no need to specify the nonlinear transformation obviously, but the inner product is replaced by the kernel function. The inner product between two examples is realized by a nonlinear change. Suppose that given a training data set $T=\{(x_1,x_1),(x_2,x_2),\ldots,(x_N,x_N)\}$ on the feature space, where $x_i \in R^n$, $y_i \in \{+1,-1\}$, $i=1,2,\ldots N$. K $(x,z)$ is a kernel function. There is a mapping $\phi$ (x) from the input space to the feature space. For any input space x, z, K $(x,z)=\phi$ $(x)\cdot\phi$ $(z)$, and the nonlinear support vector machine is obtained as follows:

$$f(x)=sign(\sum_{i=1}^{N}\alpha_i * y_i K(x,x_i)+b*) \tag{3}$$

where, $\alpha_i$ is the Lagrange multiplier, and $\alpha_i \geq 0$.

## 4. Improved MB-LBP Algorithm

### 4.1. MB-LBP Algorithm

Although the traditional LBP operator can extract the texture of the image to a certain extent, it is less robust to noise. The traditional LBP operator extracts texture features through comparison between individual pixels, which has a weak overall control over the image. MB-LBP (Multiscale Block LBP) [6] has improved the traditional LBP algorithm. The basic principle of MB-LBP is to divide an image into small blocks, then divide these small blocks into small areas, and use the average value of pixels in the small area as the pixel value of the small block. The averaged pixel value is compared with the pixel value in the neighborhood to obtain the LBP feature value. The texture feature information generated at the end is called MB-LBP. The block size is 9×9, and the size of the small area is 3×3. The process of obtaining MB-LBP operator is shown in Fig. 3.

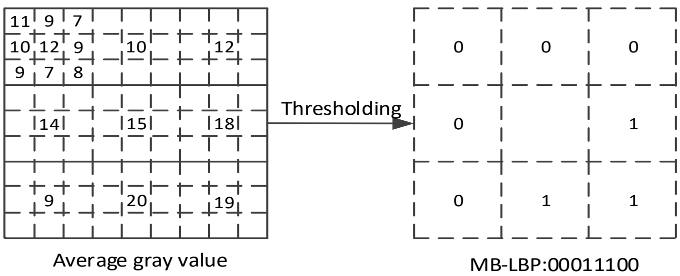


Fig. 3. MB-LBP operator.

In the process of MB-LBP feature operator extraction, the selection of block is particularly important. Block changes will have a greater impact on the final recognition rate. In this paper, the size of the block is selected to be 3×3 through experiments. At this time, the size recognition rate is the highest compared with other sizes.

### 4.2. Average Information Entropy

The principle of average information entropy is to use statistical features to reflect the amount of information in an image. The average information entropy can extract the effective information of the image, and can well filter out the influence of noise. The accuracy of 3D face recognition can be improved by the way of labeling image information. There is a discrete random variable X in the neighborhood, and its probability distribution is as follows

$$\begin{bmatrix} X \\ p(x) \end{bmatrix} = \begin{bmatrix} x_1 x_2 \ldots x_n & x_{n+1} \\ p_1 p_2 \cdots p_n & p_{n+1} \end{bmatrix} \tag{4}$$

The information entropy formula of X is as follows

$$H_{n+1} = -\sum_{i=1}^{n+1} p_i \ln p_i \tag{5}$$

When the information entropy of the image is known, the average information entropy is

$$\overline{H} = \frac{\iint_V \cdots \int H(p_1, p_2 \ldots, p_i) dp_1 dp_2 \ldots dp_i}{\iint_V \cdots \int dp_1 dp_2 \ldots dp_i} \tag{6}$$

where, $V = \left\{ (p_{11}, p_{12}, \ldots, p_{ij}) \mid p_{ij} > 0, \sum_{i=0}^{255} p_{ij} \le 1 \right\}$ (7)

$$\Omega = \{ (t_1, t_2 \ldots, t_n) \mid t_i > 0, \sum_{i=1}^{n} t_i \le 1 \} \tag{8}$$

$$\iint_\Omega \cdots \int dt_1 dt_2 \ldots dt_n = \frac{1}{n!} \tag{9}$$

$$\iint_\Omega \cdots \int (-t_i \ln t_i)\ dt_1 dt_2 \ldots dt_n = \frac{1}{(n+1)!} \sum_{i=2}^{n+1} \frac{1}{i} \tag{10}$$

Get the average information entropy

$$\overline{H} = \sum_{i=2}^{n+1} \frac{1}{i} \tag{11}$$

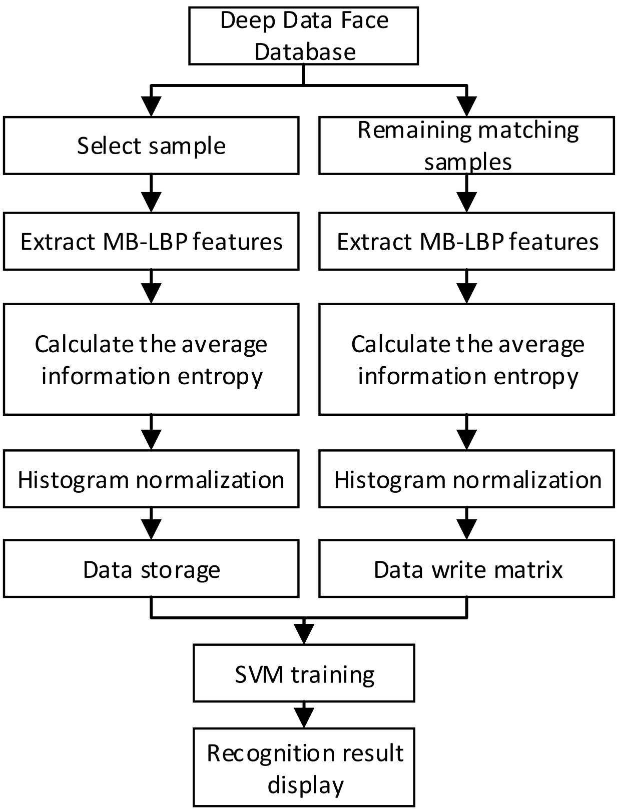


Fig. 4. Schematic diagram of 3D face recognition process.

### 4.3. Improved MB-LBP Algorithm

In order to improve the performance of 3D face recognition, this paper proposes an improved MB-LBP algorithm. First, the MB-LBP algorithm is used to extract the features of the three-dimensional face depth map, then the average information entropy algorithm is used to extract the effective feature information of the image, and the SVM algorithm is used to classify and recognize the 3D face information. The schematic diagram of 3D face recognition process is shown in Fig. 4.

As shown in the Fig. 4, in the process of making the face database, samples are selected from the Texas 3DFRD three-dimensional face depth library, and MB-LBP feature extraction is performed on the samples. An average information entropy calculation is performed on the extracted feature information, and a histogram is calculated on the effective image feature information. Normalize the obtained histogram, and save the processed facial feature data to an excel table. In recognition, the remaining depth maps in the Texas 3DFRD 3D face depth library are selected as recognition samples. The MB-LBP features of the sample are extracted, and the average information entropy is calculated on the extracted feature information. A histogram is calculated on the effective image feature information, and the obtained histogram is normalized. Write the characteristic data into the matrix, and read the data in the library in the excel table. Finally, the SVM algorithm is used to classify and identify the library data and sample data, and the recognition results are displayed.

## 5. Experiment

The structural parameters of the experimental platform used in this paper are shown in Table 1. The experimental environment of this article is Visual Studio 2013, realized by C++.

Table 1. Structural Parameters of Experimental Platform

| Names | Related configuration |
|---|---|
| Operating system | Windows |
| CPU /GHz | Inter Core I5 -3230M 2.6 |
| RAM /GB | 8 |
| GPU | NVIDIA GeForce 610M，6 |

### 5.1. Analysis of Recognition Results in Texas 3DFRD Library

To verify whether the algorithm in this paper has rapidity and short recognition time, the algorithm of this paper is evaluated on the Texas 3DFRD library, and samples are selected for experiments. The Texas 3D Face Recognition Database [7] (Texas 3DFRD) includes 2149 images and depth images of 105 adult subjects, for a total of 1149 pairs. They were produced by the Image and Video Engineering Laboratory (LIVE) at the University of Texas at Austin. They are obtained by a stereo imaging system and a high spatial resolution of 0.32 mm. All images are normalized to the forehead position, and the tip of the nose serves as the center of the image. There are some changes in facial expressions, races, and light intensity in the library.

In order to calculate the recognition rate and recognition time of the algorithm in Texas 3DFRD database, 17 people were selected from the Texas 3DFRD data set, and 5 images per person were used as the library, and the test sample is selected from the remaining images of 17 people. The experimental results are shown in Table 2.

Literature [8] provided a general application to replace the manually-designed key point descriptors for rough point cloud registration. CPN unifies feature extraction and clustering into a network, eliminating the time-consuming feature matching process. Literature [9] proposed a new three-dimensional face recognition framework. In order to solve the problem of image distortion caused by facial expressions, geometric and local shape descriptor techniques are used in the process of image matching and recognition. Literature [15] applied the monocular 3D face reconstruction method to 2D image extraction and face matching. Literature [4] applied the recognition analysis method to a coherent set of parts. The non-negative matrix factorization method is used to divide the 3D face into coherent regions. The deep belief network is used for deep learning of the rigid region and the depth image of the spherical vector modulus projection. Finally, the learning results are fused and identified. It can be seen from Table 2 that the algorithm in this paper has the highest recognition rate, so the algorithm in this paper has better performance in accuracy.

Table 2. Recognition Rate Comparison

| Algorithm | Recognition rate/% |
|---|---|
| Literature[8] | 92.40 |
| Literature[9] | 93.40 |
| Literature[15] | 94.10 |
| Literature[4] | 96.40 |
| The algorithm of this article | 96.88 |

Samples were screened from the Texas 3DFRD database, and a feature extraction time comparison experiment was set up. The experimental results are shown in Table 3.

Table 3. Feature Extraction Time Comparison

| Algorithm | Feature extraction time of each picture/s |
|---|---|
| Literature[11] | 23.54 |
| Literature[12] | 22.63 |
| Literature[13] | 9.81 |
| The algorithm of this article | 0.0168 |

It can be seen from Table 3 that compared with other algorithms, the feature extraction time of this paper can basically be ignored, so this algorithm has great advantages in feature extraction time.

By adding a timing function method to both ends of the face recognition function, set up a recognition time comparison experiment on the sample data, and compare it with other algorithms. Table 4 shows the experimental results.

Table 4. Recognition Time Comparison

| Algorithm | Recognition time/s |
|---|---|
| Literature[12] | 64.00 |
| Literature[10] | 5.20 |
| Literature[14] | 1.88 |
| The algorithm of this article | 0.025 |

It can be seen from the experimental data in Table 4 that compared with other documents in the table, the recognition time of the algorithm in this paper is greatly reduced. Therefore, the algorithm in this paper is superior in recognition time.

### 5.2. Analysis of Recognition Results in Self-made Face Database

By setting up experiments on the self-made 3D face database, the effectiveness of the algorithm in this paper is verified. The algorithm in this paper can be applied in the mobile phone industry. In the face recognition process of the original mobile phone, the methods of preventing forgery are blinking and shaking his head. However, under the method of this paper, the introduction of 3D face depth map solves this problem. The self-made face depth map is obtained using the RealSense D435i camera produced by Intel Corporation. The self-made three-dimensional face depth library includes a total of 10 people, each with 5 depth maps. The depth map in the library has certain changes in lighting and posture.

In order to verify whether the algorithm in this paper is still effective in practical applications, a comparative experiment was set up, starting from the recognition rate, recognition time, and feature extraction time, and compared the performance of the algorithm in the Texas 3DFRD database and the self-made face database. Table 5 shows the experimental results.

Table 5. Comparative Results

| Compare content | Texas 3DFRD | Self-made library |
|---|---|---|
| Feature extraction time of a depth map/s | 0.0168 | 0.0172 |
| Recognition time/s | 0.025 | 0.020 |
| Recognition rate/% | 96.88 | 96.36 |

It can be seen from Table 5 that in terms of recognition time, the recognition time consumed by the self-made library is reduced by 0.005s, and the recognition time is shorter. In terms of feature extraction, it is basically the same under the self-made library and the Texas 3DFRD library. In this paper, 5 face data of a person is selected as the training data set in both the self-made face database and the Texas 3DFRD database. The recognition rate on the self-made face database drops slightly, but the two are similar. Therefore, the algorithm in this paper has practical value.

## 6. Conclusion

This paper proposes an improved MB-LBP three-dimensional face recognition method. First, the MB-LBP algorithm is used to extract the feature information of the three-dimensional face image. Then, the average information entropy is used to extract the effective information. Finally, the SVM algorithm is used to classify and identify the feature information. It can be known from experiments that the algorithm has better performance in terms of accuracy and speed.

### Conflict of Interest

The authors declare no conflict of interest.

### Author Contributions

Liangliang Shi is responsible for code debugging and data collection; Xia Wang is responsible for data sorting and detail modification. The paper was written by Liangliang Shi and Xia Wang. Teacher Yongliang Shen is responsible for the guidance and revision of the thesis.

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