

A New Finger Vein Recognition Method Based on the Difference Symmetric Local Graph Structure (DSLGS)

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Abstract

Local Graph Structure (LGS) and its variation Symmetric Local Graph Structure (SLGS) have been proven to be effective for image recognition. However, they have shortcomings without considering the contribution of the difference between the target pixel and the surrounding pixels, and the difference between surrounding pixels to the feature value of the target pixel. To overcome the shortcomings of the traditional methods, this paper proposes a Difference Symmetric Local Graph Structure (DSLGS) algorithm for finger vein recognition. The DSLGS operator considers the contribution of different value to the feature of target pixel, making the extracted feature more stable. The experiment results show that the proposed algorithm has better performances than the traditional methods, such as Local Binary Pattern (LBP), LGS, SLGS and so on.

Keywords: *Biometrics; Finger Vein; Difference Symmetric Local Graph Structure; Symmetric Local Graph Structure; Local Graph Structure*

1. Introduction

With the advent of the information age, the security and confidentiality of the information have aroused widespread attention, while the rich human physiological characteristics, make biometric identification technology [1] become an important means in the identity authentication field. Finger vein recognition [2] emerged as a new biometric identification method in recent years. Compared to the traditional fingerprint recognition, face recognition, iris recognition and other biometric identification methods, finger vein characteristic is a living body characteristic, which makes the finger vein recognition able to meet the high uniqueness, non-contact, high recognition accuracy. Currently, the finger vein recognition has been widely used in building access control, banking, ATM teller machine, PC login, vehicle safety and other areas.

Finger vein image has rich edge information and direction information. Therefore, Operators to extract the direction information and the edge information in finger vein image, such as Local Binary Pattern (LBP) [3], Local Directional Code (LDC) [4] are widely used for finger vein recognition. In 2012, Meng *et al.* [4] proposed a Local Directional Code (LDC) method, which used the gradient information between pixels to encode the finger vein image. Yang *et al.* [5] applied (2D) 2PCA for finger vein recognition, which improved the recognition rate. Yang *et al.* [6] used the biological optical model (BOM) to eliminate the scattering effects for finger vein recognition. In 2014, Lu *et al.* [7] proposed a local descriptor named histogram of salient edge orientation map (HSEOM) to predefine direction, and obtained a salient edge orientation map by choosing the maximum value of edge direction for finger vein recognition. Yang *et al.* [8] introduced the width of the finger joints as a new soft biometric trait of finger vein recognition, and made a certain improvement for finger vein recognition. However, these methods didn't consider the relationship between surrounding pixels, which makes the extracted features incomplete and will decrease the recognition performance.

Recently, the graph theory and the dominating set are proposed for image recognition [9, 10]. Abusham *et al.* [9] introduced the concept of dominating set to the biometric field, and the pixel point was considered as the collection point. Then, they also used dominating set theory to construct the local graph structure (LGS) operator with a stable structure, and applied it to face recognition. Experiments show that there have some improvement in the recognition rate, and LGS was robust to the impact of light. Mohd *et al.* [10] proposed the concept of Symmetrical Local Graph Structure algorithm (SLGS), which took balanced advantage of the pixels in the right side and left side of target pixel. However, the SLGS operator only considers the magnitude relationship between adjacent pixels, without considering the contribution of the difference between the target pixel and the surrounding pixels, and the difference between surrounding pixels to the feature value of the target pixel, which cause some deficiencies. Dong *et al.* [11] proposed the Multi-Orientation Weighted Symmetric Local Graph Structure (MOW-SLGS) method and applied it in finger vein recognition. However, the MOW-SLGS method didn't consider the contribution of the difference value between the pixels. Therefore, this paper proposes a new Difference Symmetric Local Graph Structure (DSLGS) operator for finger vein recognition. The DSLGS operator considers the contribution of different value to the feature of target pixel, making the extracted feature more stable. And the experimental results show that the DSLGS operator has advantages better performances than other traditional methods.

The remaining paper is structured as follows: Section 2 introduces the theoretical basis of LGS and SLGS; Section 3 the proposed method is demonstrated in details; Section 4 shows the experimental results; and Section 5 gives the summary.

2. Related Theory

2.1. LGS

Inspired by the dominating set, LGS [9] first applied the local graph structure in face recognition. In LGS operator, they simplify the relationship between pixels and take the relationship between surrounding pixels into consideration.

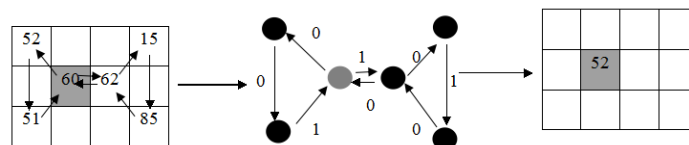


Figure 1. The Calculation Process of LGS Operator

The calculation process of LGS operator by arrows points is shown in Fig. 1. Starting from the target pixel, we first calculate it in the left direction. The value of the arrow's tail pixel subtracts the value of pixel at the arrow points. Then we can obtain 8 difference values. If the difference value is greater than 0, then the weight of corresponding edge is set to 1; otherwise it is set to 0. Thus, we obtain the value of each edge. Finally, we multiply the values with the weight vector ω_i corresponding to the sides respectively, and the feature value of the target pixel was gotten through summing the values together.

2.2. SLGS

The SLGS [12] takes balanced advantage of the pixels in the right side and left side of target pixel as shown in Fig. 3. For the calculation procedure, we start from the target pixel, and first calculate the value in the left direction. Shown by directions of arrows in Fig. 4, the value of the arrow's tail pixel subtract the value of pixel at the arrow points, then we can obtain 8 difference values. If the difference value is greater than 0, then the weight of corresponding edge is set to 1; otherwise it is set to 0. Thus, we can obtain the

value of each edge. And we multiply the values with the weight vector ω_i . Corresponding to the sides respectively, we can get the feature value of the target pixel through summing the values together.

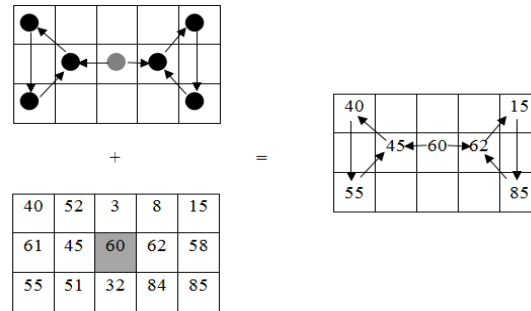


Figure 2. The Calculation Process of SLGS Operator

For example, the center value is computed as follows:

$$\omega = \{0, 0, 1, 0, 1, 0, 1, 0\};$$

$$\text{Feature}(00101010) = 0 \times 128 + 0 \times 64 + 1 \times 32 + 0 \times 16 + 1 \times 8 + 0 \times 4 + 1 \times 2 + 0 \times 1 = 42.$$

3. Proposed Method

In finger vein recognition, a robust and effective feature extraction method is essential. In this session, we propose a finger vein recognition approach based on the DSLGS operator, and show the detail information of this system. The flow chart of the finger vein recognition system is shown in Fig. 3.

The finger vein recognition system consist of three steps, namely, preprocessing, DSLGS feature extraction, LDA dimension reduction, and 1-NN classifier. At first, we need to get the ROI area through preprocessing to the image. Then, we use the DSLGS operator to extract the features from the finger vein images. Further, we use the Linear Discriminant Analysis (LDA) algorithm to reduce the feature dimension. In the registration phase, we register the features into the feature template database. In the authentication phase, we compare the input features with the features in the template database to determine whether it matches or not. Finally, we use the Nearest Neighbor Classification to classify.

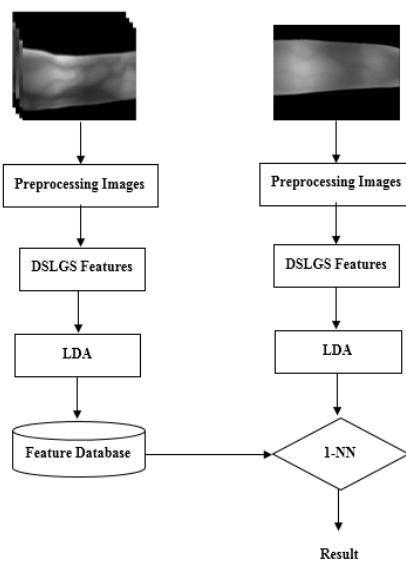


Figure 3. The Flow Chart of Finger Vein Recognition System

3.1. Preprocessing

In the finger vein recognition, we identify different person mainly based on the structure and towards of vein portion, but a finger vein image acquired under the experimental environment containing a lot of background information, which affected the accuracy of identification, therefore, in order to improve the recognition efficiency, we first do ROI region extraction [13]. After the ROI extracted, the finger vein image is shown in Figure 4.



Figure 4. Finger Vein Image after ROI

3.2. DSLGS to Extract the Feature of Finger Vein Image

In finger vein recognition system, feature extraction is an important step. In our finger vein recognition system, we use DSLGS to extract finger vein features. For case of description, we mark the pixels in accordance with the method shown in Figure 5. In the figure, the gray pixel g_0 is the target pixel, and the gray pixel g_1 - g_{16} are the surrounding pixels.

g_1	g_2	g_3	g_4	g_5
g_6	g_7	g_0	g_8	g_9
g_{10}	g_{11}	g_{12}	g_{13}	g_{14}

Figure 5. Symbols of pixels in DSLGS

In DSLGS operator, we calculate the difference value between the pixels, and consider it as the difference coefficient, which makes the extracted feature more stable. DSLGS operator is calculated as follows.

(1) We first calculate the edge difference value set d which is the same with SLGS, then, we set the edge value as 0 or 1 according to the positive and negative value denoted by S . Then, a row vector consisting 8 elements with the edge values in turn are built.

(2) Calculate the difference coefficient vector D (8×1).

Step 1: Calculate in accordance with SLGS in the same direction, we calculate the difference value d in turn as the formula (1) and formula (2).

$$\begin{aligned}
 d_1 &= g_0 - g_7; d_5 = g_0 - g_8; \\
 d_2 &= g_7 - g_1; d_6 = g_8 - g_5; \\
 d_3 &= g_1 - g_{10}; d_7 = g_5 - g_{14}; \\
 d_4 &= g_{10} - g_7; d_8 = g_{14} - g_8;
 \end{aligned}
 \tag{1}$$

(2)

Step 2: Calculate the difference coefficients using the difference value. Then, a column vector consisting 8 elements with difference coefficients in turn is formed:

$$D_i = d_i / 255 \tag{3}$$

Step 3: Calculate the feature value of the target pixel. We product S with D, and obtain the feature value:

$$\text{Feature} = S \cdot D \quad (4)$$

Finger vein images has rich direction information, therefore, the use of directional operator can improve the efficiency of feature extraction. Compared with the traditional LBP algorithm, DSLGS takes the difference between the surrounding pixels into account, which has certain advantages in terms of feature extraction. Compared with LGS, SLGS algorithms, DSLGS takes the difference value between target pixel and the surrounding pixels into account, so it is a more comprehensive feature extraction method.

3.3. LDA to Reduce the Feature Dimension

LDA [14], also called Fisher Linear Discriminant (FLD), is good for classification. We used the LDA method [14] to get the effective DSLGS features.

3.4. Nearest Neighbor Classification to Classification

In the experiment, we use Nearest Neighbor Classification (1-NN) [15] to classify the finger vein images. The biggest advantage of this algorithm is effective and fast.

4. Experiments and Analysis

4.1. Experimental Database

In this paper, we use the MMCBNU_6000 database [16] provided by Chonbuk National University, Republic of Korea. Images are from 100 volunteers' left and right hand middle finger, index finger, ring finger composition coming from China, India, Pakistan, South Korea and other countries, and the image size is 640×480 .

One of the examples of the finger vein images of MMCBNU_6000 database is shown as below.

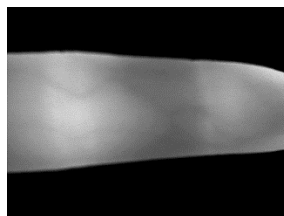


Figure 6. Finger Vein Image in MMCBNU_6000 Database

All the experiments are conducted on the Intel (R) Pentium (R) CPU, 8G memory, 32 bit operating system, Window 8, and Matlab R2014a.

4.2. Recognition Performance of Different Algorithms

4.2.1. Processing Time of the Different Algorithms

As a real-time system, finger vein recognition system needs less time consumption, therefore, in the experiment, we use different algorithms to test the processing time in order to compare the efficiency of the algorithm. The results are shown in Table 1.

Table 1. Processing Time of Different Algorithms

Algorithms	LBP	LGS	SLGS	DSLGS
Time(second)	0.1593	0.1648	0.1581	0.1582

From Table 1, the processing time of LBP, LGS, SLGS and DSLGS are 0.1593s, 0.1648s, 0.1581s and 0.1582s, so the proposed method has advantages than LBP, LGS, while similar with SLGS on the processing time.

4.2.2. Recognition Performance of the Different Algorithms

As shown in Table 2 and Figure 7, we compare the recognition rate of LBP, LGS, SLGS, DSLGS under the same finger vein database. Where N represents the number of training samples. When N is 5, the recognition rates of LBP, LGS, SLGS, DSLGS are 83.27%, 84.73%, 85.10%, 88.60% respectively, so the DSLGS method has the highest recognition rate. When N is 7, the recognition rates of LBP, LGS, SLGS, DSLGS are 81.89%, 81.89%, 83.06%, 89.28% respectively. We can see from the Table 2, DSLGS has the best result when comparing with other traditional methods.

Table 2. Recognition Rate of the Different Algorithms (N=number of training samples)

Algorithm \ N	LBP	LGS	SLGS	DSLGS
N=4	0.8247	0.8436	0.8461	0.8836
N=5	0.8327	0.8473	0.8510	0.8860
N=6	0.8213	0.8354	0.8438	0.8938
N=7	0.8189	0.8189	0.8306	0.8928
N=8	0.8042	0.8092	0.8367	0.8925
N=9	0.7800	0.8050	0.8067	0.8950

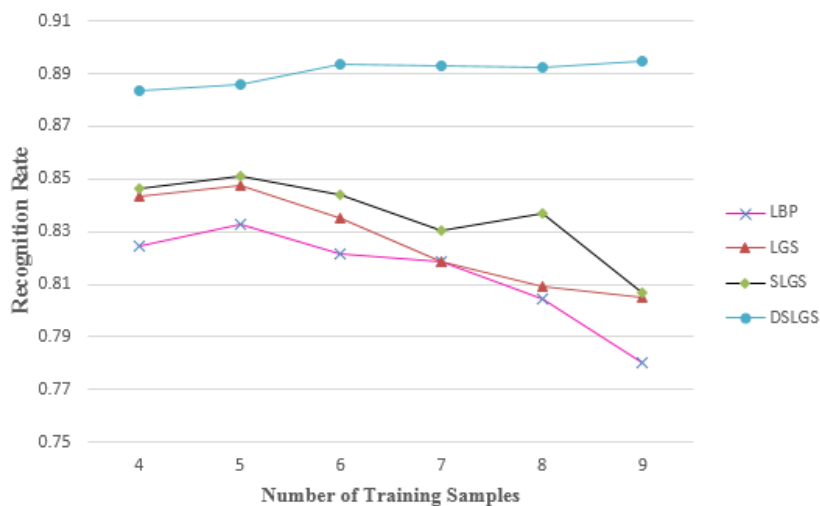


Figure 7. Recognition Performance Comparison of Different Algorithms

Compared with the traditional LBP operator, DSLGS not only considers the relationship between the target pixel and the surrounding pixels, but also takes advantages of the surrounding pixels' relationship, therefore, the performance has certain advantages. Compared with LGS, SLGS, DSLGS takes difference value of pixels contribution into account, so that the weight of the distribution is more reasonable, and the efficiency of the finger vein recognition has certainly improved.

4.2.3. ROC Curves of the Different Algorithms

ROC curves of LBP,LGS, SLGS, DSLGS algorithms are shown as follow in Figure 8. The False Acceptance Rate (FAR) and False Rejection Rate (FRR) are evaluated with $600 \times (600-1) \times 9 = 3234600$ imposter matches versus $600 \times 9 = 5400$ genuine matches, respectively. In the experiment, we use Nearest Neighbor Classifier with the Mahalanobis distance for classification.

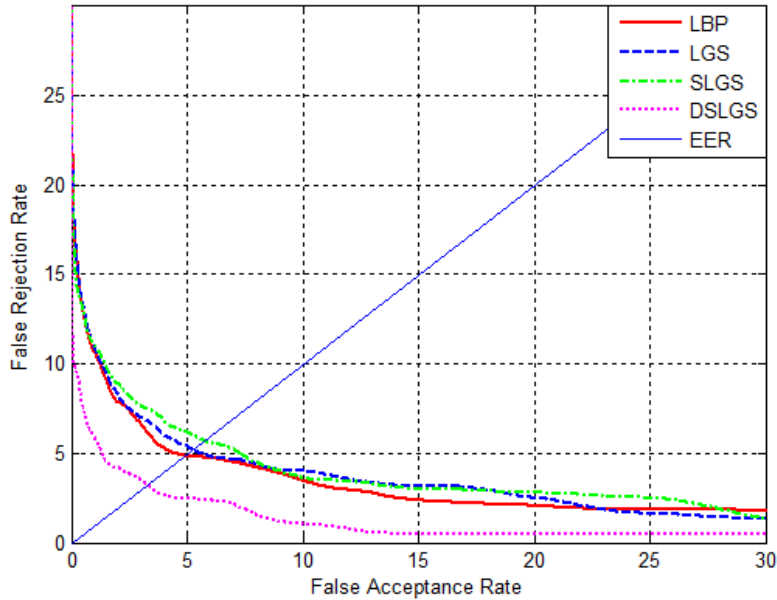


Figure 8. ROC Curve of the Different Algorithms

From the figure we can see, the ROC curve of the DSLGS is in the bottom of all curves, and the EER of the DSLGS is the smallest, which means that DSLGS has the best performance.

Table 3. EER of Different Algorithms

Algorithms	LBP	LGS	SLGS	DSLGS
EER (%)	4.87	5.22	5.72	3.28

The EER are shown in Table 3. The EER of LBP, LGS, SLGS, DSLGS are 4.84%, 5.22%, 5.72% and 3.28%. The DSLGS has the lowest EER, which indicates our proposed method has the best performance.

5. Conclusion

In this paper, we propose a Difference Symmetric Local Graph Structure (DSLGS) operator for finger vein recognition. The DSLGS operator uses the position information and gradient information of the target pixel, and multiplies the weight of the edge with the corresponding difference coefficient to obtain the feature value of the target pixel. The experimental results show that, compared with the traditional method, the DSLGS algorithm has advantages in terms of recognition rate and also time consuming.

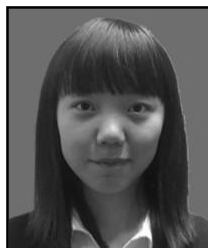
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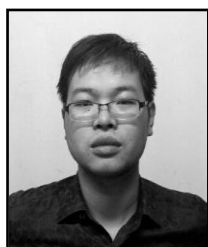
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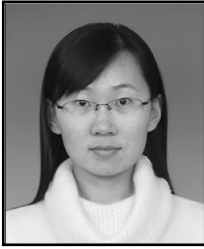
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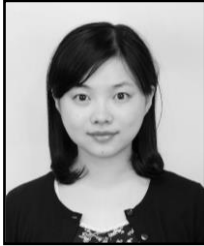
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