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Texture Characteristics Parsing of Basic Stitch in Simulation Embroidery

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Abstract. In order to fast identify and realistic simulate embroidery art, the respective texture characteristics of basic stitch in Simulation embroidery were extracted and preferred. Concretely, three feature extraction methods--gray co-occurrence matrix method (GLCM), Tamura method and gray difference statistics method (GDS), are combined to extract the features of embroidery needlework, and the best respected characteristics were compared and verified. Results shows that the best feature combination of needle texture in this paper is energy standard deviation, energy mean, standard deviation of moment of inertia, and mean of moment of inertia, which is defined as energy-moment of inertia feature. The proposed method effectively solves the inaccurate problem with single feature in the recognition of needle texture features, can be help for needlework recognition and virtual simulation.

Keywords. Texture characteristics, stitch, Tamura, image processing, texture recognition

1. Introduction

As one of the famous Chinese folk handicrafts, traditional embroidery has a long history and contains cultural connotation. Embroidery stitch has been developed more than two thousand years, presents exquisite workmanship and perfect needlework system. Traditional embroidery production can be classified dozens kinds of stitches [1], and the collocation of various needling techniques can make the embroidery works present better ornamental value [2]. At present, researches on embroidery focuses on weaving technology, development history and culture and artistic expression, while lack the analysis and research on the digital texture.

In previous studies of embroidery, structural methods [3] were used to define texture features and extract the analytical expressions of primitive features [4-7]. Studies on extract texture features include statistical methods, geometric methods and model methods. Besides, Trace transform [8] is also an effective feature extraction

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algorithm. Among above methods has its own advantages and disadvantages. For example, the model methods have a large computational burden. The structural method is computationally simple and emphasizes regularity [9].

Thus, this paper combined signal processing and statistical methods to transfer bitmap to frequency domain. Five basic stitches of Nantong's simulation embroidery were chosen as the research samples. In addition, the features of the frequency domain images of different stitches were extracted by comprehensively using Tamura method, GLCM method and image gray histogram statistics method, and then the texture features of the images were optimized. Finally, the feature set that could effectively recognize stitches was obtained.

2. Experiment

2.1. experiment scheme

Five standard basic stitches of Nantong’s simulation embroidery were captured by scanner and the original images were preprocessed. Then, the images were converted into frequency domain to obtain the corresponding edge high-frequency image blocks by Fast Fourier transform (FFM). Tamura, GLCM and gray histogram statistics methods were combined to extract 15 kinds of texture features. Finally, building the optimal set of features by extracting features in different cases.

2.2. Samples

Five classic stitches, plain stitch, roller stitch, oblique stitch, seed stitch and chain stitch, which were sewn by the successor of simulated embroidery, were selected as representative samples. Samples were photographed using a Canon CanoScan LIDE 210 scanner (Figure 1).

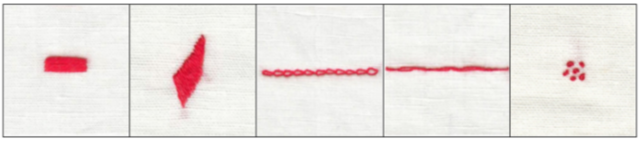

Figure 1. The samples of stitches (Respectively as flat, oblique, chain, roller and seed needle).

3. Image Pre-processing

3.1. Image Segmentation

Fabric structure texture structure could cause interference with the needle texture. Here we used K-means algorithm [10] to segment the target (stitch) and background (fabric texture). Image color are segmented as pixels into K clusters. Assuming that the cluster is divided into C1,C2...Ci ($1 \leq i \leq k$), the clustering objective is to continuously reduce the sum of squared errors of the cluster SSE:

$$SSE = \sum_{i=1}^{k} \sum\nolimits_{x \in C_k} \left\| X - \mu_i \right\|_2^2 \tag{1}$$

After the segmentation is completed, morphological processing was used to further process the segmented image. The processed image is shown in Figure 2.

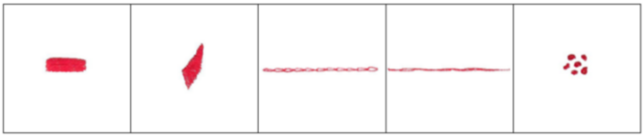

Figure 2. Stitches image segmentation diagram

3.2. The Fourier Transform

The traditional Fourier transform calculation is long and slow. Therefore, this paper adopts Fast Fourier transform (FFT) to improve the computational efficiency [11]. FFT is an efficient algorithm to compute the Discrete Fourier transform (DFT) of a signal and its inverse. It is obtained by improving the algorithm of discrete Fourier transform according to the properties of odd, even, virtual, real etc.

4. Features Extraction

Texture features describe the image local properties, such as roughness, density and smoothness. As its wide range of variation, it is difficult to be defined. Therefore, this paper combined three methods: gray co-occurrence matrix (GLCM), Tamura method and gray difference statistics (GLDS) to extract various texture features. It improved the accuracy of description, and optimized the extracted features.

4.1. Gray Co-occurrence Matrix

GLCM is a method proposed by Haralickt to describe texture by studying the spatial correlation of gray level from the perspective of mathematics [12]. It can reflect the comprehensive information of the image in the direction, pixel interval, change amplitude and speed, and is the basis for analyzing the gray arrangement of the image[13].

The features extracted by the GLCM used in this paper are as follows: energy (ASM) reflects the uniformity of the distribution of the image and the thickness of the texture. Contrast (CON) reflects the clarity of the image and the depth of texture extent of the striation. Entropy (NET) indicates the level of non-uniformity texture or the complexity. As in Table 1, these parameters were selected to be taken as the required texture features in this paper.

Table 1. GLCM feature set

Feature name of GLCM	ASM	NET	CON
Mean	Mean ASM	Mean NET	Mean CON
Standard Deviation	Standard ASM	Standard NET	Standard CON

4.2. Tamura Features

Tamura texture character are six basic texture features proposed by Tamura et al. based on human subjective psychological measurement, which are contrast, directionality, roughness, line granularity, regularity, and roughness [14]. The Tamura texture feature includes five properties are used in this paper, including coarseness (CRS), contrast (CON), directionality (DIR), linearity (LIN) and regularity (REG).

4.3. Gray - Level Difference

The basic principle of the gray difference statistics method is to approximate the pixel value of the approximate point in the image by describing the gray level change between each pixel and its adjacent pixels, so as to use it to disturb the pixel point [15]. If (x, y) is a point in the image f(x,y), the gray difference of the point (x+Δx, y+Δy) with a slight difference from this point is:

$$g\Delta(x,y) = g(x,y) - g(x+\Delta x, y+\Delta y) \qquad (2)$$

Four feature vectors are selected in this paper: contrast, angular second moment, entropy and mean value.

5. Optimize the Characteristics

15 features were selected from the above three methods. In order to facilitate analysis and function image generation, the corresponding feature data were scaled by 10n times to keep the feature value between the value interval 0-1. The adjustment value was defined as n and the adjustment unit was defined as 10n times. The Table 2 listed feature names, numbers, and corresponding n values:

Table 2. Feature description table

Feature name	Serial Number	Symbol	Category	N values
Roughness	1	CRS	Tamura	-2
Contrast	2	CON	Tamura	-3
Line granularity	3	LIN	Tamura	-2
Directionality	4	DIR	Tamura	0
Regularity	5	REG	Tamura	-3
Mean ASM	6	mASM	GLCM	0
Standard ASM	7	sASM	GLCM	0
Mean NET	8	mNET	GLCM	-1
Standard NET	9	sNET	GLCM	0
Mean CON	10	mCON	GLCM	-2
Standard CON	11	sCON	GLCM	-2
Mean COR	12	mCOR	GDS	1

Mean Value	13	m	GDS	0
Angular Second Moment	14	σ	GDS	0
Entropy	15	e	GDS	-1

6. Results and Discussion

6.1. Effective Features Selection

In order to obtain the feature data with the best resolution. A total of 10 Windows in the range of 50-500pt were obtained. The average standard deviation of all feature data was calculated for each window. Finally, we choose 300x300pt as the optimal window size.

As can be seen in the Figure 3, the low dispersion of some feature data made it impossible to effectively distinguish the texture patterns of different stitches. Therefore, in order to further distinguish, the introduction of coefficient of variation (*CV*) was as a basis for the judgment in this paper. The size of a *CV* is used to compare data dispersion degree, the result of the judgment is more objective and reliable. The computation formula is shown in Eq. (3).

$$CV = S / E \tag{3}$$

Where S is the standard deviation and E is the average.

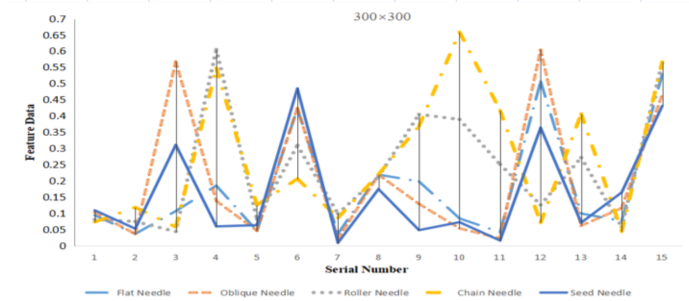

Figure 3. The functional image of the original feature

As shown in Table 3, the CV corresponding to each eigenvalue:

Table 3. CV of characteristics

Feature Number	Mean	Standard Error of Mean	Standard Deviation	CV
1	0.0919	0.0067	0.0150	0.1631
2	0.0635	0.0153	0.0343	0.5406
3	0.2173	0.0998	0.2231	1.0270
4	0.3069	0.1120	0.2506	0.8164
5	0.0727	0.0148	0.0331	0.4554
6	0.3695	0.0497	0.1113	0.3012
7	0.0500	0.0179	0.0400	0.8009

8	0.2090	0.0087	0.0195	0.0935
9	0.2297	0.0686	0.1534	0.6679
10	0.2515	0.1192	0.26658	1.0596
11	0.1497	0.07983	0.1785	1.1923
12	0.3342	0.1039	0.2323	0.6952
13	0.1820	0.0678	0.1517	0.8337
14	0.0916	0.0218	0.0488	0.5323
15	0.5112	0.0271	0.0606	0.1186
Mean	0.2087	0.0542	0.1213	0.6198

CV > *CVm* (the mean of *CV)* is taken as the judgment criterion. The effective feature linear image obtained after removing invalid features is shown in Figure 4.

Then, three effective features including feature 4, 7 and 12 were obtained from the Figure 4 according to the feature value greater than 0.05.

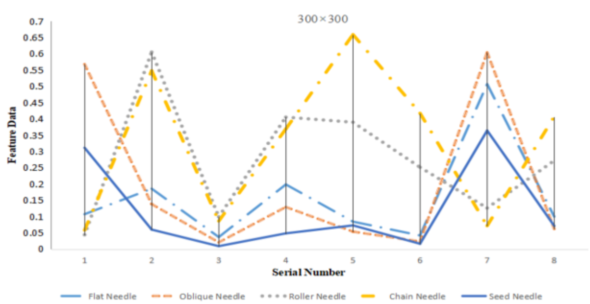

Figure 4. The linear graph of the effective features

6.2. Feature Analysis

In the process of making actual embroidery, different embroidery angle, range and combination will make its texture image produce size, angle and other changes. Therefore, in order to studying the different changes of needle textures to obtain more stable features. we rotated and scaled the stitches images to simulate the changes in the sewing process. Then transformed into Fourier spectrum image (Figure 5).

we obtained the features sensitive to the rotation change (the scale change) of needle texture and defined as the effective features of rotation change (the scale change) by using the above method.

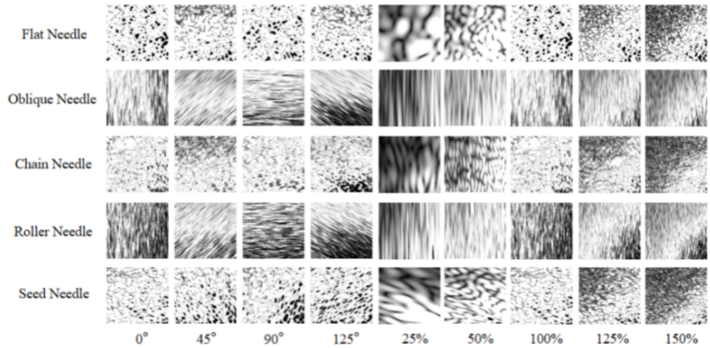

Figure 5. Fourier diagram under the optimized window

6.3. Discussion

Through the above research, we summarize the obtained effective features set as shown in Table 4.

Table 4. Summary of valid features set

The Name of the Stitch	Stitch Texture Feature Set	Rotation Changes	Scaling Changes
Flat Needle	4、6、12、9、3	6、10、13、14	6、7、10
Oblique Needle	4、6、12、9、3	2、3、11、12	6、7、10、13
Chain Needle	4、6、12、10、11、13	9、10、12	6、13
Roller Needle	4、6、12、10、11、13	3、6、7、14	4、10、11、14
Seed Needle	4、6、12、9、3	7、9、14	6、10、11、12

It can be seen from the table 4 that the single feature is not effective for comprehensive discrimination of needle texture images. Therefore, this paper proposes to define the features based on the same index data as the same family features, such as energy mean and energy standard deviation; the features reflecting similar attributes of texture are defined as belonging features; the features extracted by the same method are called homogeneous features. Then, the combination priority is set as follows: the same family feature > the same genus feature > the same class feature > cross-class feature. Combine the effective features in the feature set in turn. It is compared with the comprehensive feature table to verify whether the feature can meet all the sub-feature sets, and the optimal set is obtained.

The best feature combination of needle texture in this paper is: energy standard deviation + energy mean value + standard deviation of moment of inertia + mean value of moment of inertia, which is defined as the energy-moment of inertia feature. The function image is shown in Figure 6. Based on the analysis of the feature value greater than 0.05, it can be seen that most stitching textures can be resolved, which proves that the feature combination proposed in this paper is reasonable.

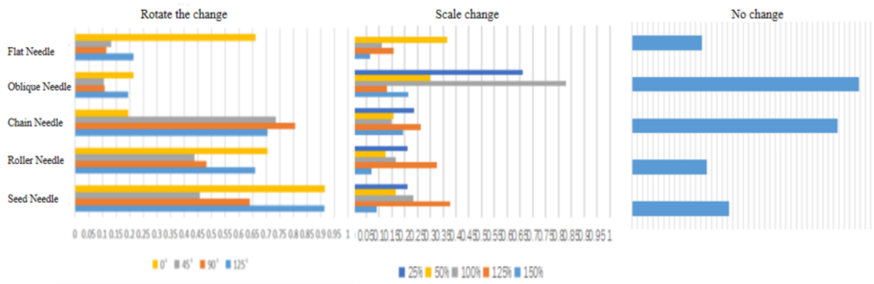

Figure 6. Energy-moment of inertia of images with different stitches

7. Conclusion

In this study, the feature extraction is expanded based on the Fourier transform of the embroidery texture image. For single method to describe the texture characteristics has certain limitations, so this paper, three methods GLCM, Tamura and GDS, were used to obtain 15 features. The 15 needle texture features were extracted, screened and integrated according to different situations. Finally, the best feature combination of energy-moment of inertia was proposed, and it was proved that the energy and moment of inertia could distinguish many kinds of needle texture recognition.

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