TEXTURE REPRESENTATION AND APPLICATION OF COLORED SPUN FABRIC USING UNIFORM THREE-STRUCTURE DESCRIPTOR

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Abstract:

The local binary pattern (LBP) and its variants have shown their effectiveness in texture images representation. However, most of these LBP methods only focus on the histogram of LBP patterns, ignoring the spatial contextual information among them. In this paper, a uniform three-structure descriptor method was proposed by using three different encoding methods so as to obtain the local spatial contextual information for characterizing the nonuniform texture on the surface of colored spun fabrics. The testing results of 180 samples with 18 different color schemes indicate that the established texture representation model can accurately express the nonuniform texture structure of colored spun fabrics. In addition, the overall correlation index between texture features and sample parameters is 0.027 and 0.024, respectively. When compared with the LBP and its variants, the proposed method obtains a higher representational ability, and simultaneously owns a shorter time complexity. At the same time, the algorithm proposed in this paper enjoys ideal effectiveness and universality for fabric image retrieval. The mean Average Precision (mAP) of the first group of samples is 86.2%; in the second group of samples, the mAP of the sample with low twist coefficient is 89.6%, while the mAP of the sample with high twist coefficient is 88.5%.

Keywords:

colored spun fabric, non-uniform texture, texture representation, three-structure descriptor, uniform mode

Texture is an essential property of a surface, and it embodies the slow or periodic changes in the structure, organization, and arrangement of an object. In addition, it is also taken as the identification information for perception [1]. Colored spun fabric is woven by uneven yarns mixed with different colors. For the textile image, texture representation plays an important role in its description, reconstruction, classification, and automatic identification and detection. Furthermore, its texture characteristic is also a crucial element which influences the overall coloration of the fabric. The algorithm of fabric image extracted from the construction and optimization of texture feature is the key point and difficulty of this research field at present [2].

Nowadays, the common algorithms among texture representation can be classified as the statistical, structural, model, filtering, and deep learning methods [3]. Originating from the field of texture analysis, the local binary pattern (LBP) method was first proposed by the University of Oulu in Finland [4], and has been applied to image processing and computer vision fields represented by face recognition. Based on LBP, the texture statistical analysis method has been widely used by research and development teams at home and abroad, so some variants of LBP in projects and researches have been proposed. These variants can be broadly summarized into three categories [5]: first, by changing the coding and mode selection strategies; second, by changing the neighborhood topologies and sampling structures; and third, by combing LBP with other complementary features. There are also other algorithms that combine deep learning and neural network.

These enhanced algorithms are widely applied in fabric detection, face recognition, image segmentation, and other texture analysis fields. A novel approach was proposed by Merabet and Ruichek [6] for constructing local texture image descriptors, and evaluating the effectiveness of this descriptor on 13 texture datasets. The results showed that the proposed LCvMSP, LCxMSP, and LCCMSP operators achieve performances that are competitive or better than most promising state-of-the-art LBP variants. Banerjee et al. [7] developed a new texture descriptor, called the local neighborhood intensity pattern (LNIP), which considered the relative intensity difference between particular and center pixels for image retrieval. In order to enhance the LBP’s performance, Veerashetty et al. [8] provided a new texture descriptor (IRSLBP) by considering the circular neighbor set of every central pixel, and classified the different textures using the combination descriptor and multi-kernel support vector machine (SVM) approach. Completed discriminative local features (CDLF), put forward by Zhang et al. [9], is to learn discriminative encoding strategy in a data-driven way for texture classification. Lan et al. [10] combined quaternion representation and local binary coding to generate the local descriptor called the quaternionic local ranking binary pattern (QLRBP) for color image. Wang et al. [11] proposed an organizational structure classification algorithm of fabric based on a combination of LBP and gray level co-occurrence matrix
(GLCM). Wang et al. [12] constructed a two-dimensional local binary pattern (2D-LBP) for the LBP operator and used it for texture image recognition, which easily ignored the correlation between image mode values.

Different from single-colored textiles, colored spun fabric (colored spun fabric are as shown in Figure 1) uses dyed fibers as the basic carrier, during the course of spinning or weaving, and the dyed fibers appear as a spiral shape related to twist. Moreover, the fibers are stacked and aggregated with each other, rendering the texture structure to have rich layers with uneven spatial distribution. The proposed methods of the LBP operator and its variants mentioned above ignore the spatial contextual information in the process of the extracting texture feature. Therefore, they could not effectively describe the nonuniform complex modes.

In this paper, the model of a uniform three-structure descriptor (UTSD) was proposed by three different structure discriminant functions to describe the local nonuniform texture structure of fabric. At the same time, the uniform mode is used to simplify the complexity of the descriptor in the coding process. In addition, UTSD could reflect the underlying troubles, which the LBP operator lacks, of the ability to describe the local spatial structure information.

1. Uniform Three Structure Descriptor

The original LBP encodes the relationship between a pixel and its neighborhoods of a local 3×3 window in one image, and it describes the local information around this pixel. The main idea of the proposed UTSD is to first take a certain pixel as the center pixel, and take the inner and outer circles as the domain pixels and compare them with the central pixel value, respectively. Then it forms three different binary coding modes according to the three kinds of discriminant functions. Finally, it obtains the three-structure descriptor.

1. The gray value of the center pixel point is $l_c$, inner circle radius is $R$, and $P$ pixels are evenly distributed on the inner circle with a radius of $R$; the inner circle pixels are described as $l_{R,P,M}(M = 0,1,2,\ldots,P-1)$.

2. In order to compare with the inner circle pixels, the outer circle radius is $R+1$, and $2P$ pixels are evenly distributed on the outer circle with a radius of $R+1$. Taking the average gray value between the adjacent pixels on the outer circle into account, the new outer circle pixels are described as $L_{R+1,P,M}(M = 0,1,2,\ldots,P-1)$; the average value of the outer circle can be written as follows:

$$
L_{R+1,P,M} = \frac{1}{2} \sum_{k=0}^{1} l_{R+1,2P,2M+k}, M = 0,1,2,\ldots,P-1
$$

where $L_{R+1,P,M}$ indicates the new outer circle with a radius of $R+1$ and $P$ pixels, and $l_{R+1,2P,2M+k}$ represents the outer circle with a radius of $R+1$ and $2P$ pixels.

3. On this basis, the local differences are obtained by comparing the central pixel with the inner circle pixels and the inner circle pixels with the new outer circle pixels, respectively; the formulas are defined as follows:

$$
\Delta \theta_1 = l_c - l_{R,P,M}, M = 0,1,2,\ldots,P-1
$$

$$
\Delta \theta_2 = l_{R,P,M} - L_{R+1,P,M}, M = 0,1,2,\ldots,P-1
$$

where $\Delta \theta_1$ indicates the differences between $l_c$ and $l_{R,P,M}$, and $\Delta \theta_2$ indicates the differences between $l_{R,P,M}$ and $L_{R+1,P,M}$.

4. By comparing the local differences $\Delta \theta_1, \Delta \theta_2$, three kinds of coding structures can be obtained, among which the discriminant function formulas are as follows:

$$
g_1 = \begin{cases} 1 & (\Delta \theta_1 < 0, \Delta \theta_2 > 0) \\ 0 & \text{others} \end{cases}
$$

$$
g_2 = \begin{cases} 1 & (\Delta \theta_1 > 0, \Delta \theta_2 < 0) \\ 0 & \text{others} \end{cases}
$$

$$
g_3 = \begin{cases} 1 & (\Delta \theta_1 = \Delta \theta_2 = 0) \\ 0 & \text{others} \end{cases}
$$

where $g_1, g_2, g_3$ indicate the three kinds of discriminant functions of the three-structure descriptor.

The three-structure descriptor is defined by the following formula:

$$
G_1 = \sum_{M=0}^{P-1} 2^M \times g_1
$$

$$
G_2 = \sum_{M=0}^{P-1} 2^M \times g_2
$$

$$
G_3 = \sum_{M=0}^{P-1} 2^M \times g_3
$$

where $G_1, G_2, G_3$ represents three kinds of encoding of the three-structure descriptor accordingly.

Next, the encoding calculation process of the three-structure descriptor is introduced in detail, as shown in Figure 2.

As shown in Figure 2, a local area in the image is represented as follows: the gray value of the central pixel is 8, the radius $R$ is 1, and the number of sampling points in the inner circle is 8. In order to compare with the inner circle, the area pixels with a

![Figure 1. Colored spun fabric.](http://www.autexrj.com/)

http://www.autexrj.com/
The texture representation ability of the UTSD is related to parameters such as the radius of the inner and outer circles and the number of pixels in the inner and outer circles. It also needs to be selected in combination with specific analysis objects. In order to simplify the analysis process, the parameters of the UTSD are set to $R = 1, P = 8$.

2. Materials

There are many factors that affect the texture change of precolored fiber blends, including the mass ratio of the dyed fiber, the kinds or character traits of the dyed fabric, the twisting coefficient, and so on. These factors can change the texture caused by a change in the adjustment of the mass ratio significantly and directly. The cotton fibers used in the experiment had a linear density of 13.5 dtex, fineness of 17 µm, and average length of 38 mm. The five selected colors of cotton fibers are red, yellow, blue, black, and white. Among them, all blended yarns are spun by their ring spinning. The warp and weft yarn density of the fabric is 20 tex, the twist coefficient is 350, and the fabric specifications are 30 cmx30 cm, 160 gsm, 6 epi, 5 ppi; the fabric structure is a plain weave. It adopts No. 130 reed and the lower weft density is 280 threads/(10 cm).

According to the differences in color and the proportion of fibers, 18 samples were divided into two groups. One group, shown in Table 1, included 10 samples, which were mainly composed of three kinds of dyed fibers: white, red, and yellow. The change in mass ratio among the samples varies randomly from 0.8% to 4.3%. The second group included 8 samples as shown in Table 2, which were mainly composed of three kinds of dyed fibers: white, black, and blue. The difference in mass ratio among the samples alters regularly from 0.2% to 8%.

| Samples | Mass ratio of dyed fibers |
|---------|--------------------------|
|         | Raw undyed (%) | Bright red (%) | Golden yellow (%) |
| 17001#  | 95.05          | 3.93           | 1.02              |
| 17002#  | 94.60          | 3.90           | 1.50              |
| 17004#  | 93.60          | 3.90           | 2.50              |
| 17005#  | 93.10          | 3.90           | 3.00              |
| 17006#  | 94.96          | 3.06           | 1.98              |
| 17007#  | 94.51          | 3.52           | 1.97              |
| 17009#  | 93.38          | 4.60           | 2.02              |
| 17010#  | 92.90          | 5.10           | 2.00              |
| 17011#  | 93.90          | 4.60           | 1.50              |
| 17012#  | 94.00          | 3.53           | 2.47              |

Colored spun fabric samples of the first and second groups are shown in Figure 4.
between the texture characteristics of the fabric surface and the mass ratio of dyed fibers. In this paper, the correlation between the extracted value of local spatial texture feature and the difference value of the mass ratio of dyed fabric is quantitatively analyzed to explain the validity of the texture representation model.

The Pearson correlation coefficient can measure the degree of linear correlation [13], whose definition is as follows:

\[
Pearson(r_i, r_j) = \frac{\sum_{k=1}^{N} (r_{i,k} - \overline{r_i})(r_{j,k} - \overline{r_j})}{\left(\sum_{k=1}^{N} (r_{i,k} - \overline{r_i})^2\right)^{1/2} \left(\sum_{k=1}^{N} (r_{j,k} - \overline{r_j})^2\right)^{1/2}}
\]

where \(r_i\) and \(r_j\) represent the difference value of normalized local spatial texture feature and the difference value of normalized mass ratio of dyed fibers of colored spun fabrics, respectively; \(N\) indicates the number of samples.

In addition, as shown in Table 3, in order to comprehensively analyze the texture representation ability of the UTSD for fabrics with different fabric structures, another 30 colored spun fabrics made of polyester-dyed fibers blended into yarns were prepared. All the samples were woven by mixing the white, red, and green-dyed fibers into yarn. The dyed fiber is 38 mm in length, the linear is 1.65 dtex in density, the twist direction of the double yarn is S-twist, and the mass ratio of dyed fiber varies from 0.5% to 4.0%. The organizational structure of the fabric adopted the classical plain weave, twill weave (three up and one right diagonal twill), and stain weave (five two-fly warn satin) structures. Some colored spun fabric samples in the third group are shown in Figure 5.

### Table 2. Mass ratio parameter of colored spun fabric samples in the second group.

| Samples   | Raw undyed (%) | Super black (%) | Sapphire blue (%) |
|-----------|----------------|-----------------|-------------------|
| 17018#    | 92.00          | 4.00            | 4.00              |
| 17019#    | 90.00          | 4.00            | 6.00              |
| 17020#    | 88.00          | 4.00            | 8.00              |
| 17021#    | 90.00          | 2.00            | 8.00              |
| 17022#    | 89.00          | 3.00            | 8.00              |
| 17023#    | 88.10          | 4.00            | 7.90              |
| 17024#    | 91.00          | 3.00            | 6.00              |
| 17025#    | 92.00          | 2.00            | 6.00              |

The Pearson correlation coefficient ranges from \(-1\) to \(1\), and the greater the absolute value has, the higher the degree of linear correlation. In order to simplify the calculation results, based on the Pearson correlation formula, the normalization method is combined to form the following formula:

\[
Pearson(r_i, r_j) = \frac{\sum_{k=1}^{N} (r_{i,k} - \overline{r_i})(r_{j,k} - \overline{r_j})}{\left(\sum_{k=1}^{N} (r_{i,k} - \overline{r_i})^2\right)^{1/2} \left(\sum_{k=1}^{N} (r_{j,k} - \overline{r_j})^2\right)^{1/2}}
\]

In addition, as shown in Table 3, in order to comprehensively analyze the texture representation ability of the UTSD for fabrics with different fabric structures, another 30 colored spun fabrics made of polyester-dyed fibers blended into yarns were prepared. All the samples were woven by mixing the white, red, and green-dyed fibers into yarn. The dyed fiber is 38 mm in length, the linear is 1.65 dtex in density, the twist direction of the double yarn is S-twist, and the mass ratio of dyed fiber varies from 0.5% to 4.0%. The organizational structure of the fabric adopted the classical plain weave, twill weave (three up and one right diagonal twill), and stain weave (five two-fly warn satin) structures. Some colored spun fabric samples in the third group are shown in Figure 5.
parameter correction are performed on the DigiEye system camera through the pantone before the acquisition processes. Each sample image is segmented to obtain four sample images of 4,096x2,048 pixels.

The texture analysis of the first group of 10 samples of colored spun fabric was carried out by using the optimized UTSD, and the specific results are shown in Table 4, where T Div indicates the normalized differences in local texture features, while M Div indicates the normalized difference in mass ratio.

The above statistical analysis shows that the extracted texture feature values of textile are highly consistent and correlate with the change in the mass ratio of the sample dyed fibers; hence the nonuniform texture structure can be accurately characterized due to the change in proportion. Meanwhile, the correlation coefficients of different samples are analyzed independently, and the results are shown in Table 5.

The average correlation coefficient between the local texture feature value and the mass ratio is $Cor = 0.027$, and the variance of correlation coefficient $Cor$ is 0.026. The analysis shows that there exists a low correlation coefficient value between the normalized difference of the texture feature value of the first group of samples and the normalized difference of the mass ratio. It means that the correlation between the two is high, that is to say, the established UTSD texture representation model possesses statistical effectiveness and stability for different samples. It also indicates that the UTSD texture representation model can recognize the changes in fabric texture on the mass ratio of colored spun fibers.

The normalized characteristic difference in the texture feature and its mass ratio are shown in Figures 6 and 7.

Table 6 shows the results of the texture feature extraction for the second group of samples, for which a similar conclusion can be drawn. Table 7 shows the results of correlation analysis, and it can be found that the established UTSD texture representation model also has ideal validity and stability for testing samples.
The correlation coefficient between texture feature value and mass ratio is \( Cor = 0.024 \), and the variance of correlation coefficient \( Cor \) is 0.035.

Table 4. Sample testing results of colored spun fabric of first group.

| Sample no. | Comparison sample no. | T Div | M Div |
|------------|------------------------|-------|-------|
| 17001#     | 17002#                 | 0.186 | 0.209 |
| 17001#     | 17004#                 | 0.241 | 0.658 |
| 17001#     | 17005#                 | 0.475 | 0.880 |
| 17001#     | 17006#                 | 0.283 | 0.427 |
| 17001#     | 17007#                 | 0.234 | 0.422 |
| 17001#     | 17009#                 | 0.496 | 0.742 |
| 17001#     | 17010#                 | 0.614 | 0.956 |
| 17001#     | 17011#                 | 0.371 | 0.511 |
| 17001#     | 17012#                 | 0.409 | 0.644 |
| 17002#     | 17004#                 | 0.091 | 0.489 |
| 17002#     | 17005#                 | 0.232 | 0.671 |
| 17002#     | 17006#                 | 0.410 | 0.378 |
| 17002#     | 17007#                 | 0.194 | 0.213 |
| 17002#     | 17009#                 | 0.375 | 0.547 |
| 17002#     | 17010#                 | 0.455 | 0.760 |
| 17002#     | 17011#                 | 0.247 | 0.316 |
| 17002#     | 17012#                 | 0.146 | 0.436 |
| 17004#     | 17005#                 | 0.208 | 0.222 |
| 17004#     | 17006#                 | 0.445 | 0.604 |
| 17004#     | 17007#                 | 0.221 | 0.404 |
| 17004#     | 17009#                 | 0.332 | 0.311 |
| 17004#     | 17010#                 | 0.412 | 0.533 |
| 17004#     | 17011#                 | 0.235 | 0.444 |
| 17004#     | 17012#                 | 0.126 | 0.178 |
| 17005#     | 17006#                 | 0.478 | 0.827 |
| 17005#     | 17007#                 | 0.230 | 0.627 |
| 17005#     | 17009#                 | 0.444 | 0.436 |
| 17005#     | 17010#                 | 0.487 | 0.533 |
| 17005#     | 17011#                 | 0.349 | 0.667 |
| 17005#     | 17012#                 | 0.113 | 0.400 |
| 17006#     | 17007#                 | 0.297 | 0.204 |
| 17006#     | 17009#                 | 0.702 | 0.702 |
| 17006#     | 17010#                 | 0.847 | 0.916 |
| 17006#     | 17011#                 | 0.606 | 0.684 |
| 17006#     | 17012#                 | 0.420 | 0.427 |
| 17007#     | 17009#                 | 0.496 | 0.502 |
| 17007#     | 17010#                 | 0.600 | 0.716 |
| 17007#     | 17011#                 | 0.401 | 0.480 |
| 17007#     | 17012#                 | 0.172 | 0.227 |
| 17009#     | 17010#                 | 0.255 | 0.222 |
| 17009#     | 17011#                 | 0.224 | 0.231 |
| 17009#     | 17012#                 | 0.388 | 0.476 |
| 17010#     | 17011#                 | 0.297 | 0.444 |
| 17010#     | 17012#                 | 0.465 | 0.698 |
| 17011#     | 17012#                 | 0.290 | 0.476 |

Table 5. Correlation coefficient testing results of the first group of samples.

| Sample no. | Cor |
|------------|-----|
| 17001#     | 0.004|
| 17002#     | 0.078|
| 17004#     | 0.077|
| 17005#     | 0.055|
| 17006#     | 0.007|
| 17007#     | 0.019|
| 17009#     | 0.005|
| 17010#     | 0.005|
| 17011#     | 0.013|
| 17012#     | 0.014|

Figure 7. Fitting curves of evaluation results of texture representation of 17009# samples.

Figure 8. Fitting curves of evaluation results of texture representation of 17018# samples.

with different color schemes. The correlation coefficient between texture feature value and mass ratio is \( Cor = 0.024 \), and the variance of correlation coefficient \( Cor \) is 0.035.
The normalized characteristic difference in texture feature and its mass ratio are shown in Figures 8 and 9.

As shown in Figure 10, it is worth noting that abnormal fluctuations in the testing indexes occurred in some testing experiments. After the analysis and detection of the samples, it is found that there is a large area of abnormal aggregation of dyed fibers in the color measurement samples, which is caused by the weaving process, as shown in Figure 11.

2.3. Fabric image retrieval based on UTSD

To verify the effectiveness and practicability of the descriptor proposed in this paper for texture representation, a fabric image retrieval based on UTSD was carried out. According to the differences in the mass ratios of different dyed fibers among the fabrics, and the smaller difference in the mass ratio as the distribution principle, the fabrics in the first and second groups are divided into 10 categories; there are 100 images in each category, that is, a total of 1,000 images. During the...
experimental process, 15 images were randomly selected from each category for retrieval, and a total of 150 queries were carried out. The top 10 most similar images were selected as the experimental results in each retrieval. The precision ratio and mean Average Precision (mAP) are used as the experimental performance evaluation criteria; the retrieval results are shown in Table 8. The formulas of precision ratio and mAP are defined as follows:

$$P = \frac{b}{a} \quad (12)$$

$$mAP = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{m_i} \sum_{x=1}^{m_i} x \quad (13)$$

where $b$ indicates the number of images with similar labels in the search results, and $a$ is the number of search results returned. $n$ is the number of retrieved samples, $i$ represents the $i$-th image, $m_i$ represents the total number of images with similar labels in the returned results of the $i$-th image, $x$ is the position of the image with similar labels in the image with similar samples, and $y$ is the position of the image with similar labels in the returned search results.

**Figure 11.** Abnormal aggregation of dyed fibers and heterochromatic fiber clusters.

**Table 8.** Average retrieval precision ratio in each category.

| Category number | Sample composition          | Retrieval precision ratio (%) | Average retrieval precision ratio (%) | mAP (%) |
|-----------------|----------------------------|-------------------------------|--------------------------------------|---------|
| 1               | 17001# and 17002#          | 87.3                          | 91.4                                 | 86.2    |
| 2               | 17004# and 17012#          | 83.3                          |                                      |         |
| 3               | 17005# and 17011#          | 91.3                          |                                      |         |
| 4               | 17006# and 17007#          | 95.3                          |                                      |         |
| 5               | 17009# and 17010#          | 97.3                          |                                      |         |
| 6               | 17018#                     | 93.3                          |                                      |         |
| 7               | 17019# and 17024#          | 86.0                          |                                      |         |
| 8               | 17020# and 17023#          | 89.3                          |                                      |         |
| 9               | 17021# and 17022#          | 92.7                          |                                      |         |
| 10              | 17025#                     | 98.0                          |                                      |         |

mAP, mean Average Precision.

**Table 9.** Retrieval results with low twist coefficient.

| Fabric structure | Sample no. | Retrieval precision ratio (%) | Average retrieval precision ratio (%) | mAP (%) |
|------------------|------------|-------------------------------|--------------------------------------|---------|
| Plain weave      | SS41A      | 82.7                          | 87.9                                 | 89.6    |
|                  | SS51A      | 85.3                          |                                      |         |
|                  | SS61A      | 96.0                          |                                      |         |
|                  | SS71A      | 91.3                          |                                      |         |
|                  | SS81A      | 84.0                          |                                      |         |
| Twill weave      | SS41D      | 86.7                          | 91.9                                 |         |
|                  | SS51D      | 93.3                          |                                      |         |
|                  | SS61D      | 94.0                          |                                      |         |
|                  | SS71D      | 90.0                          |                                      |         |
|                  | SS81D      | 95.3                          |                                      |         |
| Stain weave      | SS41F      | 87.3                          | 90.8                                 |         |
|                  | SS51F      | 93.3                          |                                      |         |
|                  | SS61F      | 93.3                          |                                      |         |
|                  | SS71F      | 90.0                          |                                      |         |
|                  | SS81F      | 90.0                          |                                      |         |

mAP, mean Average Precision.
Calculating the retrieval precision ratio in Table 8 shows the average retrieval precision ratio to be 91.4%; this shows that the texture features extracted by UTSD can retrieve fabrics with different color quality ratios, and the value of mAP is 86.2%, which is scientific and feasible for fabric texture description.

In addition, in order to comprehensively analyze the universality of the UTSD, texture features of the third group of samples with different organizational structures are extracted, and then image retrieval is performed; the retrieval experiment results are shown in Tables 9 and 10.

It can be seen from the table that when the twist coefficient of the fabrics with three kinds of fabric structures is 330, the average retrieval precision ratios of plain weave, twill, and stain weave are 87.9%, 91.9%, and 90.8%, respectively. When it is 370, the average retrieval precision ratios of plain weave, twill, and stain weave are 87.9%, 91.9%, and 90.8%, respectively. This shows that UTSD can retrieve fabric images with different fabric structures. Among them, the retrieval precision ratio of twill weave is the highest, and the retrieval effect is the best, which verifies the effectiveness of the operator. In addition, when the twist coefficient is 330, the mAP value of the image is 89.6%, while when the twist coefficient is 370, the mAP value of the image is 88.5%. This indicates that UTSD can retrieve images of fabrics with different twist coefficients, and the retrieval effect is better for fabrics with a low twist coefficient.

Taking the two groups of experimental results, for example, it can be seen that the UTSD image retrieval algorithm established in this paper has ideal robustness and effectiveness for colored spun fabric with different fabric structures, and can also accurately retrieve fabric images with different twist coefficients.

### 2.4. Comparative experimental results and analysis

Furthermore, in order to comprehensively compare and analyze the effectiveness and stability of the UTSD in this paper, the first group experimental samples are used as the object. Three methods, rotation invariant uniform LBP [7] (marked as: Method. 1), rotation invariant uniform LBP + GLCM [11] (marked as: Method. 2), and 2DLBP [12] (marked as: Method. 3), were used to establish the contrast experimental model. The parameters of the different methods have been optimized in combination with references and testing sample set, and quantitative comparative analysis has been carried out through formula (11); the experimental results are shown in Table 11, where T Div indicates the normalized difference in local texture feature.

The results of analysis of feature similarity and variants are shown in Table 12, where Cor indicates the value of correlation and Var indicates variance between the values of correlation. The contrast results explain that compared with the three typical methods, the model proposed in this paper possesses stronger texture representation capabilities, and the overall relevance value reaches to 0.027. At the same time, the variance in the correlation value is 0.001, which possesses ideal stability. The experimental results of partial comparison are shown in Figure 12.

### Table 10. Retrieval results with high twist coefficient.

| Fabric structure | Sample no. | Retrieval precision ratio (%) | Average retrieval precision ratio (%) | mAP (%) |
|------------------|------------|-------------------------------|--------------------------------------|---------|
| Plain weave      | SS43A      | 86.0                          | 89.6                                 | 88.5    |
|                  | SS53A      | 93.3                          |                                      |         |
|                  | SS63A      | 91.3                          |                                      |         |
|                  | SS73A      | 89.3                          |                                      |         |
|                  | SS83A      | 88.0                          |                                      |         |
| Twill weave      | SS43D      | 83.3                          | 89.7                                 |         |
|                  | SS53D      | 91.3                          |                                      |         |
|                  | SS63D      | 93.3                          |                                      |         |
|                  | SS73D      | 90.6                          |                                      |         |
|                  | SS83D      | 90.0                          |                                      |         |
| Stain weave      | SS43F      | 84.0                          | 88.0                                 |         |
|                  | SS53F      | 85.3                          |                                      |         |
|                  | SS63F      | 94.7                          |                                      |         |
|                  | SS73F      | 91.3                          |                                      |         |
|                  | SS83F      | 84.7                          |                                      |         |

mAP, mean Average Precision.
3. Conclusions

It is difficult to accurately characterize the texture features of colored spun fabrics using the LBP method. Based on UTSD, a texture representation model of colored spun fabric is proposed. In this model, three kinds of discriminant functions are used to describe the local structure of fabric image. At the same time, uniform mode is introduced into the pattern encoding process to simplify the computational complexity of the representation model. The testing results indicate that the established UTSD texture representation model possesses statistically effectiveness and stability for different samples, and the correlation coefficient between the texture feature value and mass ratio are 0.027 and 0.024, respectively. At the same time, the UTSD image retrieval algorithm established in this paper has ideal robustness and effectiveness for colored spun fabric with the different fabric structures, and can also accurately retrieve fabric images with different twist coefficients. In addition, compared with the LBP and its two improved algorithms, the established UTSD is optimal. The research in this paper provides technical support for the texture representation and fabric retrieval of colored spun fabrics. How to adjust and select the best parameters of UTSD for further improvement of the description ability of texture information needs further research.

Table 11. Comparative experimental results of samples in first group.

| Sample no. | Comparison sample no. | T Div  |
|------------|-----------------------|-------|
|            |                       | Method. 1 | Method. 2 | Method. 3 |
| 17001#     | 17002#                | 0.195   | 0.046    | 0.133    |
| 17001#     | 17004#                | 0.210   | 0.174    | 0.156    |
| 17001#     | 17005#                | 0.409   | 0.078    | 0.549    |
| 17001#     | 17006#                | 0.371   | 0.055    | 0.323    |
| 17001#     | 17007#                | 0.184   | 0.115    | 0.236    |
| 17001#     | 17009#                | 0.646   | 0.374    | 0.251    |
| 17001#     | 17010#                | 0.620   | 0.270    | 0.420    |
| 17001#     | 17011#                | 0.427   | 0.389    | 0.331    |
| 17001#     | 17012#                | 0.289   | 0.558    | 0.268    |
| 17002#     | 17004#                | 0.143   | 0.131    | 0.145    |
| 17002#     | 17005#                | 0.426   | 0.122    | 0.587    |
| 17002#     | 17006#                | 0.450   | 0.074    | 0.427    |
| 17002#     | 17007#                | 0.268   | 0.161    | 0.291    |
| 17002#     | 17009#                | 0.567   | 0.329    | 0.181    |
| 17002#     | 17010#                | 0.508   | 0.226    | 0.331    |
| 17002#     | 17011#                | 0.350   | 0.434    | 0.286    |
| 17002#     | 17012#                | 0.283   | 0.603    | 0.304    |
| 17004#     | 17005#                | 0.371   | 0.242    | 0.477    |
| 17004#     | 17006#                | 0.453   | 0.171    | 0.413    |
| 17004#     | 17007#                | 0.228   | 0.285    | 0.293    |
| 17004#     | 17009#                | 0.529   | 0.202    | 0.186    |
| 17004#     | 17010#                | 0.477   | 0.097    | 0.303    |
| 17004#     | 17011#                | 0.345   | 0.562    | 0.233    |
| 17004#     | 17012#                | 0.212   | 0.729    | 0.195    |
| 17005#     | 17006#                | 0.479   | 0.075    | 0.690    |
| 17005#     | 17007#                | 0.423   | 0.045    | 0.694    |
| 17005#     | 17009#                | 0.750   | 0.444    | 0.587    |
| 17005#     | 17010#                | 0.703   | 0.339    | 0.558    |
| 17005#     | 17011#                | 0.545   | 0.324    | 0.400    |
| 17005#     | 17012#                | 0.204   | 0.488    | 0.299    |
| 17006#     | 17007#                | 0.363   | 0.120    | 0.222    |
| 17006#     | 17009#                | 0.884   | 0.374    | 0.536    |
| 17006#     | 17010#                | 0.905   | 0.268    | 0.711    |
| 17006#     | 17011#                | 0.704   | 0.399    | 0.615    |
| 17006#     | 17012#                | 0.421   | 0.561    | 0.457    |
| 17007#     | 17009#                | 0.685   | 0.487    | 0.371    |
| 17007#     | 17010#                | 0.649   | 0.382    | 0.553    |
| 17007#     | 17011#                | 0.517   | 0.280    | 0.517    |
| 17007#     | 17012#                | 0.302   | 0.444    | 0.422    |
| 17009#     | 17010#                | 0.275   | 0.105    | 0.223    |
| 17009#     | 17011#                | 0.337   | 0.762    | 0.277    |
| 17009#     | 17012#                | 0.600   | 0.931    | 0.346    |
| 17010#     | 17011#                | 0.307   | 0.659    | 0.219    |
| 17010#     | 17012#                | 0.569   | 0.826    | 0.391    |
| 17011#     | 17012#                | 0.407   | 0.176    | 0.224    |

Table 12. Comparative experimental results of relevance of samples.

| Statistical method | Method. 1 | Method. 2 | Method. 3 | Method of UTSD |
|--------------------|-----------|-----------|-----------|----------------|
| Cor                | 0.099     | 0.251     | 0.125     | 0.027          |
| Var                | 0.082     | 0.047     | 0.009     | 0.001          |

UTSD, uniform three-structure descriptor.

Figure 12. Fitting curve of contrast experimental results of 17001# samples.
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