Automatic Recognition of Fabric Weave Patterns by a Fuzzy C-Means Clustering Method

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ABSTRACT

A new robust recognition algorithm is proposed for fabric weave pattern recognition. The gray-level images of solid woven fabrics are captured by a color scanner and converted into digital files, then enhanced images are obtained by a gray-level morphological operation. Based on the interstices of yarns, warp and weft crossed areas are located, and four texture features of these areas are obtained by first-order and second-order statistics. Unsupervised decision rules for recognizing warp and weft floats are developed using a fuzzy c-means clustering method. The experimental materials include plain, twill, and satin woven fabrics. Experimental results demonstrate that three basic weave patterns can be clearly identified.

Conventional means of identifying weave patterns often require manual operations, which are time-consuming and easily tire an operator's eyes. Thus, it is highly desirable to develop an automatic recognition system for fabric weave patterns. Image processing has proved to be an efficient method of analyzing fabric structures, and fabric weave pattern recognition by image analysis has been studied since the middle of the 1980s. The main methods so far are Fourier transform techniques for identifying weave patterns [7, 9]. The major principle here is the peak in the power spectrum image, representing frequency terms of periodic elements from which basic weave patterns can be recognized. But similar weave patterns have similar power spectra, making it difficult to distinguish them. Indeed, it is very difficult to recognize the weave pattern of a woven fabric automatically using an unsupervised method from the power spectrum of the computer. Another identification method is using warp and weft floats to determine weave patterns [3, 4]. The main principle here is to first locate warp and weft crossed areas by analyzing gray value changes in both horizontal and vertical directions, and then to use these areas' geometric shapes to determine warp floats or weft floats. However, due to differences in yarn material, count, and density, different fabrics have diverse geometric shapes for warp and weft floats. This means the criteria developed from the supervised method for a fabric may be improper for another fabric. Therefore, in order to recognize fabric weave automatically, it is necessary to develop an unsupervised automatic recognition method.

Regardless of different materials and different weaves, such as plain, twill, or satin, the fabric image is composed of two basic structures: warp floats and weft floats. Thus, to recognize the weave pattern of a fabric, one first simply takes out the cross areas of warp and weft, then calculates the image characteristics and categorizes them into warp float clusters and weft float clusters. The most difficult part is to develop an unsupervised criteria method for different kinds of fabrics. The fuzzy C-means method used here is a powerful tool. For this method, there is no need to learn the criteria for all fabrics before classifying a single fabric. This clustering method recognizes the similarities of targets for unsupervised classification. Moreover, fuzzy technology leads to better cluster results. Thus, in this study, we provide a robust recognition algorithm that can be used for automatic recognition of fabric weave patterns. We acquire an image from the surface of a solid woven fabric with a color scanner. Then, using the top-hat and bottom-hat transforms of gray-level morphology to emphasize the regional texture feature in the image, and based on the locations of the yarns' borders, we can find the warp and weft crossed areas. Next, we calculate the values of four pattern characteristics of each warp and weft cross area, including first-order statistics of mean and standard deviation and second-order statistics of contrast and homogeneity of the co-occurrence matrix [8, 5]. Finally, we can automatically recognize fabric weave patterns by using a fuzzy c-means algorithm to cluster the texture features of warp and weft floats.

Research Method

GRAY-LEVEL MORPHOLOGY

Gray-level images can be thought of in three dimensions: the x and y axes represent pixel positions and the z axis represents the intensity of each pixel. The intensity value represents the elevations in a topographical map. The areas of high intensity and low intensity in an image are important morphological features. We may only be interested in significant minima or maxima and not in these minima and maxima caused by background texture. We can emphasize specific bright and dark textures in the woven fabric image by using the top-hat and bottom-hat transforms. Therefore, the fabric image can be enhanced by adding the top-hat transform and then deducting the bottom-hat transform from the original image [2, 6]. The equation is

$$A_{\mathrm{Top}} = A - (A \circ S) \quad , \tag{1}$$

where A_{Top} is the top-hat transform, $\circ$ is the gray-scale opening operator, S is the structuring element, and

$$A_{\mathrm{Bot}} = A - (A \cdot S) \quad , \tag{2}$$

where A_{Bot} is the bottom-hat transform, $\cdot$ is the gray-scale closing operator, S is the structuring element, so that

$$A_{\mathrm{Enhance}} = (A + A_{\mathrm{Top}}) - A_{\mathrm{Bot}} \quad . \tag{3}$$

FUZZY C-MEANS CLUSTERING METHOD

In many fields such as segmentation, pattern recognition, and vector quantization, a clustering process is an indispensable step in these problems. Clustering is a tool that attempts to assess relationships between patterns of a data set by organizing them into clusters, such that patterns within a cluster are more similar to each other than patterns belonging to different clusters. Since the data are real-value vectors, the Euclidean distance between data can be used as a measure of the similarity. One of the widely used clustering algorithms is the fuzzy c-means (FCM) algorithm, which has been the dominant approach in both theory and practical applications of fuzzy techniques for unsupervised classification. This technique was originally introduced by Bezdek in 1981 [1]. FCM clustering can be viewed as an optimization problem that tries to optimize the following objective function:

$$J_{FCM} = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}{}^{m} d_{ij}^{2} \quad , \tag{4}$$

where C is the number of clusters, $u_{ij} \in [0, 1]$ expresses the membership degree of the data point x_j belonging to the ith fuzzy group, $d_{ij} = \|w_i - x_j\|$ is the Euclidean distance between the ith cluster center w_i and jth data point x_j, and $m \in (1, \infty)$ is a weighting exponent that influences the fuzziness of the clusters [10].

The FCM starts with an initial guess for the cluster centers, which is intended to mark the mean location of each cluster. The initial guess for these cluster centers will most likely be incorrect. Additionally, the FCM assigns every data point a membership grade for each cluster. By iteratively updating the cluster centers and the membership grades for each data point, the FCM iteratively moves the cluster centers to the "right" location within a data set. This iteration is based on minimizing an objective function that represents the distance from any given data point to a cluster center weighted by that data point's membership grade. The FCM algorithm is implemented by the following steps:

1. Choose the number of clusters C.
2. Choose m, $1 < m < \infty$.
3. Choose a precision for termination ϵ.
4. Initialize the fuzzy C-partition $U^{(0)}$.
5. Set the iteration counter $t = 1$.

6. Update the centers using

$$w_i = \frac{\sum_{j=1}^{n} (u_{ij}*)^m x_j}{\sum_{j=1}^{n} (u_{ij}*)^m} \quad \text{for} \quad 1 \le i \le C \quad .$$

7. Update the memberships of all feature vectors in all the clusters using

$$\text{if} \quad \|x_j - w_k\| = 0 \quad \text{then} \quad u_{kj}* = 1 \quad \text{and}$$

$$u_{kj}* = 0 \quad (\text{for } i \neq k) \quad ,$$

$$\text{if} \quad \|x_j - w_k\| \neq 0 \quad \text{then}$$

$$u_{ij}* = \left[\sum_{k=1}^{c} \frac{\|x_j - w_i\|^{2/(m-1)}}{\|x_j - w_k\|^{2/(m-1)}} \right]^{-1} \quad .$$

8. If $|U^{(t+1)} - U^{(t)}| \Leftarrow \epsilon$ THEN stop or ELSE $t = t + 1$, go to step 6.

Result and Discussion

We used an Epson scanner 2400 Photo (2400 dpi photo resolution) to digitize three solid woven fabric images (plain, twill, and satin) in 256 gray levels. The resolution of the scanner was 2400 dpi, and the captured images of the fabrics consisted of 300 × 300 pixels. We used Matlab as a software tool to develop this system.

Figure 1a shows the original plain woven fabric image, revealing comparatively unapparent weft floats, darker areas between the yarns. In addition, some warp and weft borders show vague images not suitable for follow-up image analysis. From the histogram of the gray-level values, these values center on the small region between 140 and 225, so the image that has smaller contrast values cannot reveal the texture feature. In light of this, we used gray-level morphology image processing to enhance the images. We employed a 4 × 4 structure element (a 4 × 4 matrix with all the elements set at 1) to the entire gray-level morphology process, and then obtained the texture image with regional bright fine lines and dark fine lines with top-hat and bottom-hat transform Equations 1 and 2. Finally, as shown in Figure 1b, we obtained the enhanced image using Equation 3. We expanded the range of gray-level values through gray-level morphology image processing to somewhere between 120 and 240 and enhanced the contrast, emphasizing only the important texture feature on the fabric image.

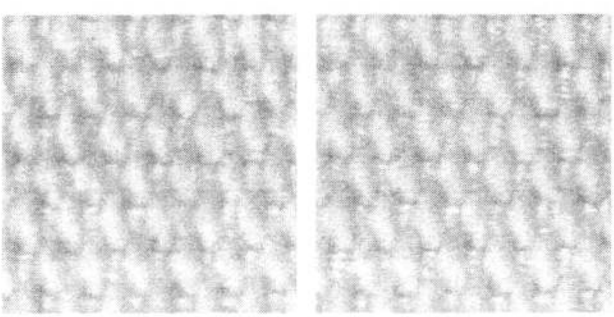

FIGURE 1. (a) Original plain woven fabric image, (b) enhanced image of Figure 1a.

The curve shown in Figure 2a can be obtained by accumulating gray-level values of the vertical- and horizontal-direction pixels from Figure 1b. The borders between warp or weft can segment the fabric image into several warp and weft crossed areas [3]. However, in order to avoid verifying the warp and weft floats affected by incomplete warp and weft crossed areas at the edge of the fabric image, these borders must be eliminated. The eliminated border image is shown in Figure 2b. Eventually, 12 × 15 complete warp and weft crossed areas are obtained for clustering analysis.

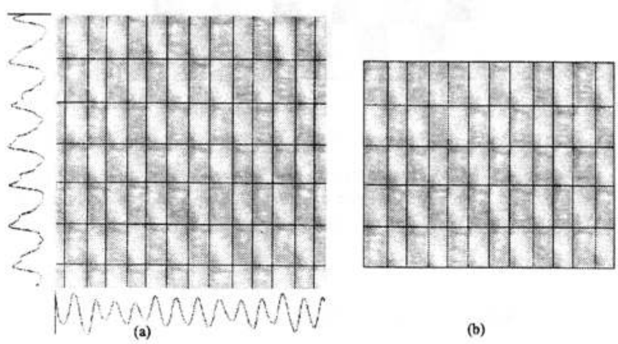

FIGURE 2. (a) Grid figure of fabric image, (b) grid figure of edge-eliminated fabric image.

Before proceeding with the clustering analysis, every warp and weft crossed area must be labeled by numbers: two kinds for first-order statistics value (mean and standard deviation) and two others for the second-order statistics value (contrast and homogeneity of the co-occurrence matrix, $d = 1$ with $\Theta = 90°$) must be calculated for the clustering method [8]. On the cluster coordinates, in order to have the same scale for different characteristic values, all characteristic values will be normalized between 0 and 1. The initial setting of the FCM clustering algorithm, the cluster number C, is set at 2, the ϵ of the stop calculating objective function is 0.00001, and the m of the weighting exponent is 1.5. The FCM method can process unsupervised classification for multi-characteristic values, which cannot be done by a traditional classi-

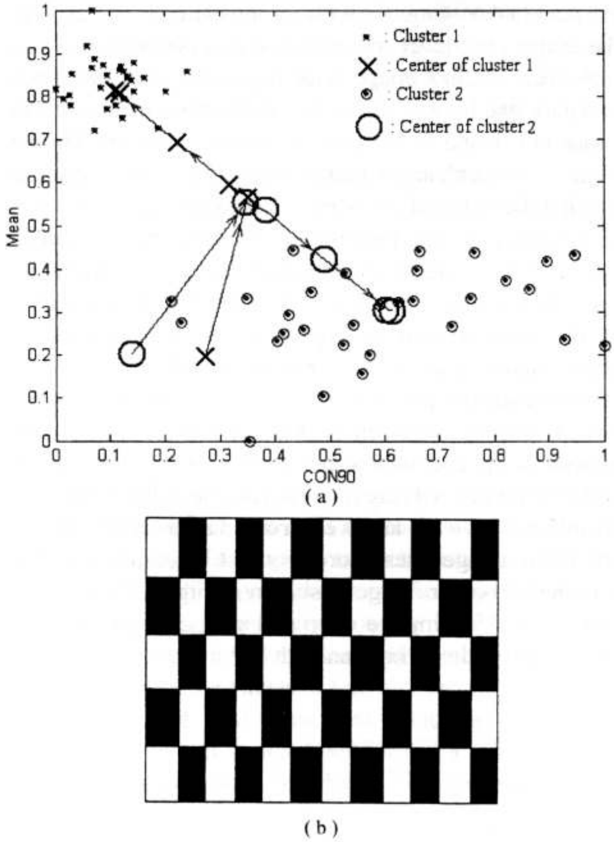

FIGURE 3. (a) FCM cluster figure, (b) weave pattern diagram (black ones are warp float areas where cluster 1 locates and white ones are weft float areas where cluster 2 locates).

fied algorithm. Indeed, multi-characteristic values are helpful for image recognition. However, if the classification has more than three characteristics, it will not be able to be shown as figures. Figure 3a illustrates the clustering of FCM by the two weave pattern characteristic values of mean and contrast for the plain woven fabric in the experiment. The center of cluster 1 is marked by X on the figure, and the center of cluster 2 is marked by ○. Although the center position of the two clusters is randomly chosen by the computer at the beginning, from the figure we see that the center positions of the two clusters are automatically adjusted to the right position when the clustering algorithm is calculating. In the clustering calculation process, all the data will be divided into two clusters by the best segmenting method, and the members for each cluster will be found. Figure 3b shows the black areas where cluster 1 is located, *i.e.*, the location of warp float areas, and the white areas where cluster 2 is located, *i.e.*, the location of weft float areas.

Figure 4a is the original image of the twill woven fabric, and Figure 5a is the original image of the satin

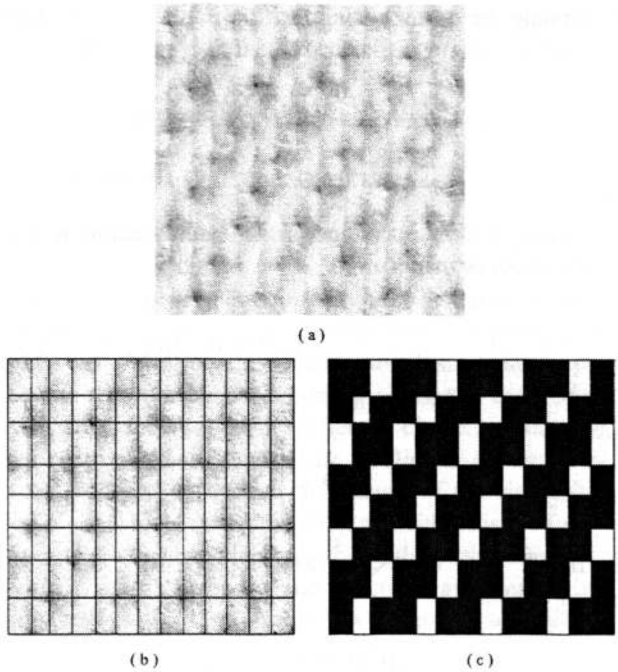

FIGURE 4. (a) Original twill woven fabric image, (b) enhanced and segmented image, (c) weave pattern diagram (black ones are warp float areas where cluster 1 locates and white ones are weft float areas where cluster 2 locates).

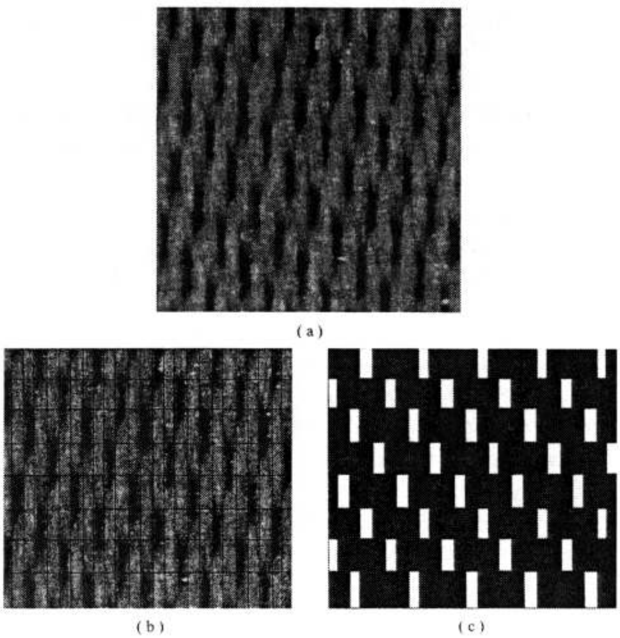

FIGURE 5. (a) Original satin woven fabric image, (b) enhanced and segmented image, (c) weave pattern diagram (black ones are warp float areas where cluster 1 locates and white ones are weft float areas where cluster 2 locates).

woven fabric. Figures 4b and 5b are the enhanced images by gray-level morphology and the grid for warp and weft crossing areas. The cluster results of warp and weft floats are shown as Figures 4c and 5c, which are similar to the fabrics shown in Figures 4a and 5a.

Conclusions

Our results prove that since the weave pattern on the fabric image obtained by the scanner can be automatically identified, the methods adopted in this study are both practical and economical. The gray-level morphology processing adopted in this study is a powerful tool for highlighting the special texture features of a woven fabric image. By accurately segmenting the warp and weft crossed areas, the characteristic value of each area can be calculated. Furthermore, with FCM a cluster algorithm can be processed by segmenting the characteristic space to obtain the warp and weft float clusters unsupervised, thus reaching the goal of automatic recognition of fabric weave. Without doubt, the method we have adopted in this study is still limited to a single layer fabric with only one color, and the scanning must be maintained in the vertical and horizontal directions. Also, if the surface of the fabric is too hairy, that leads to a poor analysis, and a singe process is required for removing excess hair on the fabric surface.

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