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# Real-time Segmentation of Yarn Images Based on an FCM Algorithm and Intensity Gradient Analysis

**Abstract**
*This paper presents a new method for real-time segmentation of yarn images which are captured by a real-time image acquisition device. The first frame of the images is clustered by the local average intensity and entropy of the image based on the FCM (Fuzzy C-means) algorithm to obtain a segmentation threshold value. The pixels with an intensity below the threshold value in each column of the image are convolved with a convolve template to construct an intensity gradient curve. The points of maximum value and minimum value in the curve are considered as the upper and lower edge points of yarn. A robust real-time segmentation algorithm of yarn images is obtained for evaluating yarn diameter more precisely. Finally two indices of SE (Segmentation Error) in % and ADE (Average Diameter Error) in % are proposed to evaluate the segmentation method, which is then compared with the manual method.*

**Key words:** *real-time segmentation, image processing, yarn evenness, FCM algorithm, gradient analysis.*

## Introduction

The appearance of yarn, one of the primary qualities, affects its commercial value in the market [1]. The unevenness of yarn is an important index to evaluate the quality of yarn [2], which causes a high fracture rate and produces cloud and shadow in appearance. The diameter of yarn is the direct parameter to evaluate yarn unevenness, and hence a rapid way of obtaining accurate yarn diameter is meaningful in the textile industry. The Uster Evenness Tester is a dominant instrument for testing yarn evenness, which uses capacitive sensors to check the distribution of yarn mass [3]. However, this method depends on the testing environmental conditions, as the capacitors are usually affected by the temperature and ambient humidity, and the resolution of this method is relatively low when the capacitors sample the data every 8 mm (e.g. early versions of the Uster Evenness Tester) [4].

With the development of image-processing technology, it is advantageous to utilise computer vision to inspect yarn appearance quality. In this method, the most important step is to segment the moving yarn in real-time and accurately. In this paper, a new method is proposed for real-time segmenting of yarn images to measure yarn diameter unevenness. Yarn is a thread of indefinitely great length and small cross section, consisting of comparatively short fibres combined by twisting or cementing as well as possessing definite strength and uniformity [5]. It consists of the yarn core and two hairy parts. Therefore the most important work of segmenting real-time images in this paper is actually to separate the hairiness from the yarn core.

Some research about segmenting a yarn image has been reported in the literature. Fabijańska & Jackowska-Strumiłło [6] used the graph cut method and high pass filtering to extract the yarn core from yarn images. The algorithms proposed were compared with computer methods previously used for yarn property assessment. Anirban Guha et al. [7] and Vítor Carvalho et al. [8] used the Ostu segmentation method to convert a yarn image to a binary image. Subsequently a new method of yarn core determination and a filter were applied for processing their results, respectively. Then the hairiness was separated from the yarn core. Wang et al. [9] used the Canny detection method and morphological processing to obtain the yarn core for calculating the yarn diameter. Anna Fabijanska [10] used the region growing-based approach and morphological opening to extract the yarn core from a yarn image. However, these methods cannot be applied to moving yarns in real-time processing because of the longer computation time and smaller application scope. The segmentation results of these methods are better only for some images captured by a specific visual system.

This paper describes a new method for real-time segmentation of yarn images based on the FCM (Fuzzy C-means algorithm) and intensity gradient. A threshold value is confirmed by an FCM algorithm based on the local intensity characteristics of the average intensity value and entropy of the image. A convolution template is used to convolve the intensity value (which is below the threshold value) of every line in the image. Then the intensity-gradient curve is constructed, from which the upper and lower edge points of the yarn are confirmed. Finally real-time processing for moving yarn segmentation is preserved.

## Theoretical work

### Fuzzy C-means algorithm (FCM)

The FCM algorithm is an unsupervised clustering method which divides $n$ data vectors, $x_k$ into $c$ fuzzy categories, and determines the clustering center of each category for further minimisation of the fuzzy target function [11]. The fuzzy clustering target function is as shown below:

$$J(U,V) = \sum_{i=1}^{n} \sum_{j=1}^{c} (u_{ij})^m \|x_i - v_j\| \quad (1)$$

where, $u_{ij}$ is the fuzzy membership of an individual $x_i$ belonging to the $j$th category, $m$ the fuzzy weight index, and $v_j$ is the clustering center of the $j$th category.
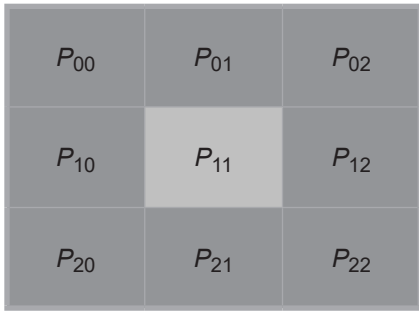
**Figure 1.** *Schematic diagram of 8-neighborhood structure.*

The update equations for $u_{ij}$ and $v_j$ are as below:

$$u_{ij} = \sum_{k=1}^{c} \left[ \frac{\left\| x_i - v_j \right\|^{\frac{2}{m-1}}}{\left\| x_i - v_k \right\|^{\frac{2}{m-1}}} \right]^{-1} \left\| x_i - v_j \right\| \neq 0 \quad (2)$$

$$v_j = \frac{\sum_{i=1}^{n} u_{ij}^m x_i}{\sum_{i=1}^{n} u_{ij}^m} \quad (3)$$

### Local intensity characteristics

A 3×3 template is used to scan the yarn image from top to bottom and left to right. Two characteristic values, the average intensity value and entropy value, are calculated in the template. These are used to classify the image pixels into two classes by means of the FCM algorithm. For a given pixel $P_{11}$, the 8-neighborhood points are applied to gain the following two values.

The average intensity value of the regional subspace $A(P_{11})$ is:

$$A(P_{11}) = \frac{1}{9} \sum_{i=0}^{2} \sum_{j=0}^{2} P_{ij} \quad (4)$$

The entropy value of the regional subspace $E(P_{11})$ is:

$$E(P_{11}) = \sum_{i=0}^{2} \sum_{j=0}^{2} \rho_{ij} \log(\rho_{ij}) \quad (5)$$

$$\rho_{ij} = P_{ij} / \sum_{i=0}^{2} \sum_{j=0}^{2} P_{ij} \quad (6)$$

where, $P_{ij}$ represents the grayscale value of the 8-neighborhood points of $P_{11}$, and $\rho_{ij}$ represents the proportion of every point in the template.

### One-dimensional convolution

One-dimensional convolution is used to detect the edge outline of yarn in this paper. Convolution is a mathematical way of combining a matrix and template to form a gradient matrix. The mathematical definition of convolution in the discrete time domain is as follows:

$$y[n] = x[n] * h[n] = \sum_{k=-\infty}^{\infty} x[k] \cdot h[n-k] \quad (7)$$

where, $x[n]$ is the input matrix, $h[n]$ the template, and $y[n]$ is the output value. * denotes convolution. In this paper, $x[n]$ represents the intensity (below a threshold value) of each line in yarn image, and $h[n]$ - the convolution template, which is defined as:

$$h[n] = \begin{bmatrix} -2, & -1, & 0, & 1, & 1 \end{bmatrix} \quad (8)$$

### ■ Experimental
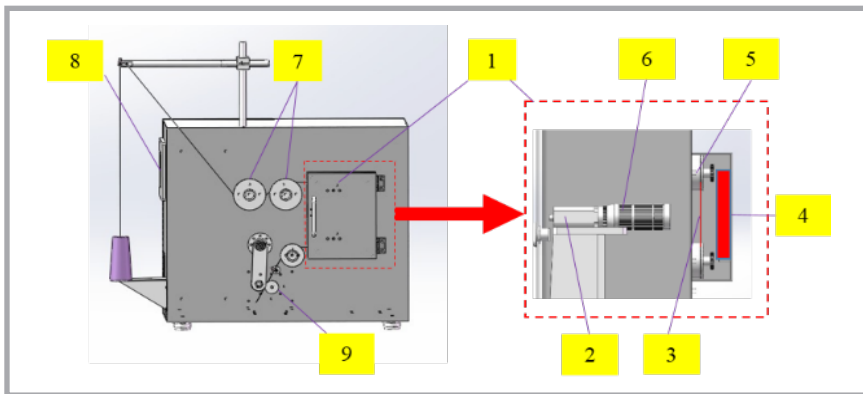
#### Real-time image acquisition and processing system

In order to meet the requirements of real-time processing, an image acquisition device is designed to acquire the yarn images, as shown in *Figure 2*. Snapshot photographs of yarn are taken in succession along the yarn by a digital video camera at a resolution of 768 ×1024 pixels. In the device designed, a closed imaging box is
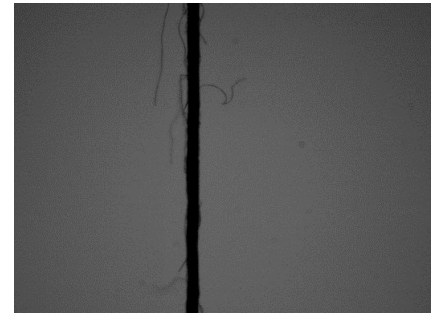


**Figure 3.** *Sample image of yarn captured by the real-time device.*

used as the image acquisition platform to shield the disturbance of stray light. Meanwhile a special light source is set up in the closed box. In addition, a yarn motion driver and tension controller are employed to obtain better simulation and meet the requirements of measuring the yarn diameter. In this paper, real-time segmentation for a yarn image and accuracy analysis of the segmentation results are made. Therefore yarn unevenness evaluation can be realized on the basis of the continuous yarn image sequence. *Figure 2* shows the integrated structure of this system.

The yarn image acquisition and processing system is mainly composed of four parts: the first part is the yarn drawing device, including the yarn tension control panel-7, yarn guiding device-5 and the servo motor-9. The yarn tension control panel is used to keep the yarn tension constant during the process of testing, because the cross-section shape of the yarn tested is different with a change in yarn tension. The yarn can be drawn with the servo motor through a pair of output rollers of 30 mm diameter. The second part is the speed control module, including the servomotor controller (inside the device), touch screen - 8 and PLC (inside the device). Using the touch screen as a man-machine interface and the PLC as the control core, controlling the movement speed of the yarn is realised. Yarn speed of 1 - 100 m/min is adjustable. The third part is the real-time image acquisition module, including a matrix CCD image sensor - 2, camera lens - 6 and light source - 4. In this part, dynamic images of a running yarn are recorded by the matrix CCD image sensor. To minimise the influence of the outside, a closed box - 1 is adopted. The centers of the light source, yarn and camera lens are at the same height. The fourth part is the computer system and testing software. In the testing system, the computer is the control center and also the common platform for



**Figure 2.** *Real-time image acquisition device: 1) closed imaging box, 2) matrix CCD image sensor, 3) yarn, 4) light source, 5) yarn guiding devices, (6) camera lens, 7) yarn tension control panel, 8) touch screen, 9) output rollers with servo motor.*

processing the real-time image or image sequence in order to measure the diameter and evaluate unevenness.

To satisfy the requirement of coordination of the real-time image acquisition and real-time image processing, the yarn moving speed is set less than 10 m/min and the camera frame rate - less than 45 fps. 9 m/min and 40 fps are set in this paper for real-time processing of the yarn images. The processing flow is presented in the following parts.

***Image acquisition and pre-processing***
While yarn images are captured by the device developed, they are processed by the method proposed in this paper. One of the real-time yarn images captured by the device is shown in ***Figure 3***. According to image calibration, a pixel in the vertical direction occupies 5.21 μm in the image. The real length of yarn in this image is approximately 4 mm.

Image vertical projection is applied to crop the original image of yarn to reduce the computation time and save storage space. To obtain cut points of the yarn image, the projection curve is drawn by averaging the brightness value of the pixels in each column of the yarn image [12]. Vertical projection of the yarn image is performed by the following equation:

$$V'_j = \frac{1}{H}\sum_{i=1}^{H} V_{i,j} \qquad (9)$$

where, $V'_j$ is the brightness value of pixels in the yarn image, $j= 1, 2, \dots , L$, $L$ - the width of the yarn image, and $H$ is the height of the yarn image. The projection curve in each column can be got as shown in ***Figure 4***.

From ***Figure 4***, we can find that the yarn core forms a low valley of certain width in the projection curve of the yarn image. The left and right borders of the low valley are roughly the edge points of the yarn core and hairiness. To obtain the two edge points, a difference curve is drawn by the following equation:

$$PV'_j = V'_j - V'_{j-1} \qquad (10)$$

where, $PV'_j$ is the difference value, $j = 2, \dots , L$. The difference curve of ***Figure 4*** can be got as shown in ***Figure 5***.

As can be seen from ***Figure 5***, the points with a maximum and minimum value in the curve (point M and N) are obtained after difference disposal. These two points can be considered as the edge
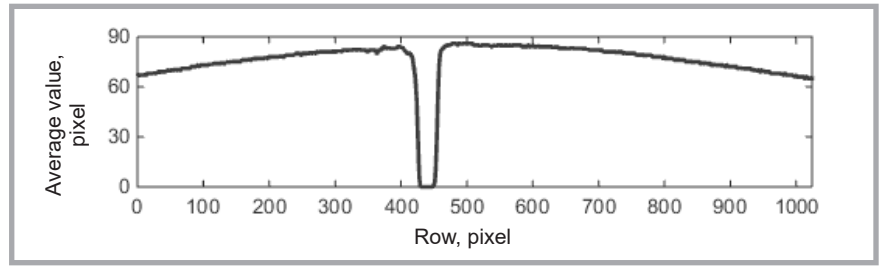


*Figure 4. Projection curve of yarn image.*
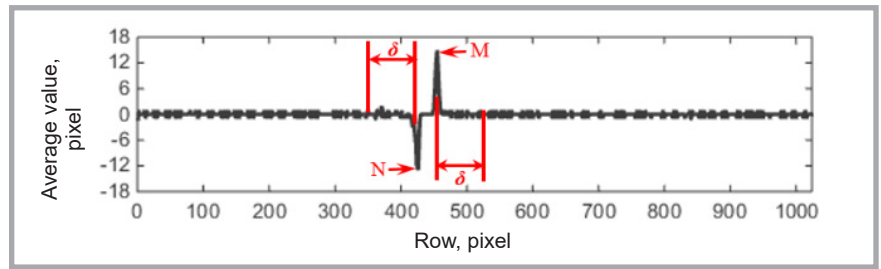


*Figure 5. Difference curve of **Figure 4**.*



*Figure 6. Image after cropping and rotating.*



*Figure 7. FCM clustering category label.*

points of the yarn core and hairiness. However, some parts of the yarn core will be cropped if only the two points are used to crop the yarn image, which will result in negative influences on diameter measurement. Therefore a parameter $\delta$ is proposed to determine the edge of the image cropping. If the horizontal coordinate of M and N are $x_1$, $x_2$, respectively, the image after cropping $Cut$ can be defined as:
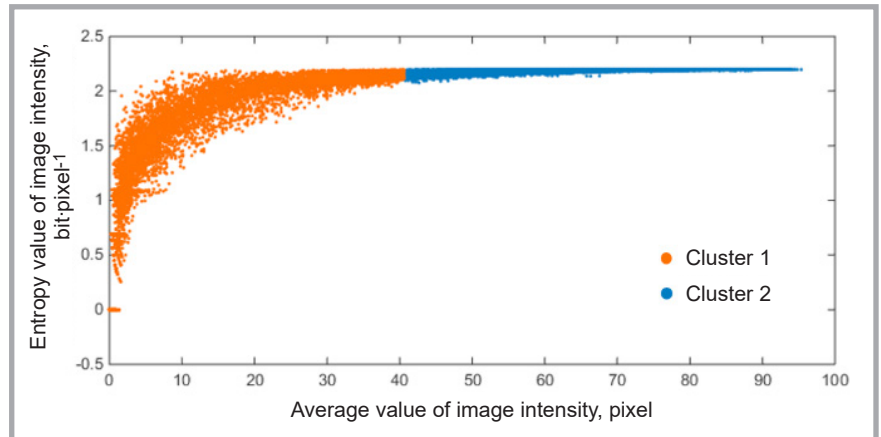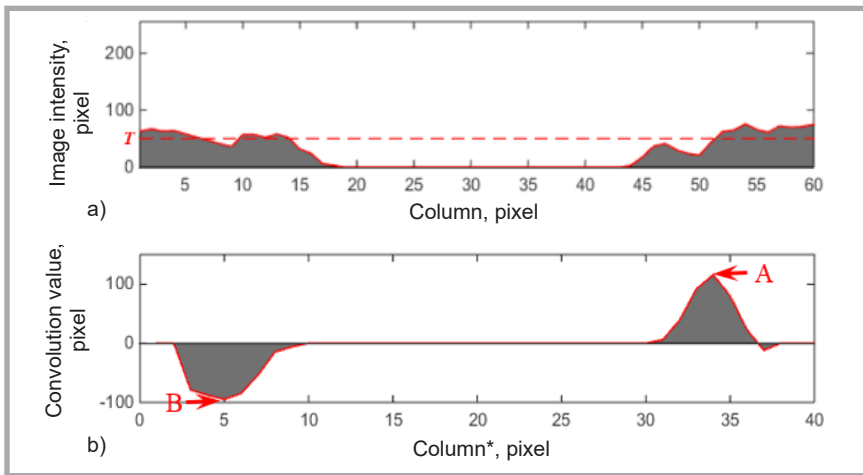
$$Cut = \{(x,y)|x = \\ = x_2 - \delta ... x_1 + \delta, y = 1 ... H\} \qquad (11)$$

In this paper, we set $\delta =15$ pixels to crop the yarn image. The image after cropping and rotating is shown in ***Figure 6***.

After the yarn image is cropped, all pixels are traversed from the current pixel in the eight-neighborhood direction in the image, and then the average intensity value $A$ and entropy value $E$ are calculated in a 3×3 template. The FCM algorithm is applied to classify the image pixels into two classes with two characteristic values. The yarn image in ***Figure 6*** is taken as an example to explain the algorithm. The parameters of the FCM algorithm are set as follows: the cluster number $c = 2$, the fuzzy weight index $m = 2$, and the terminative precision $e = 0.00001$. The classification result of the pixels in the image is shown in ***Figure 7***.
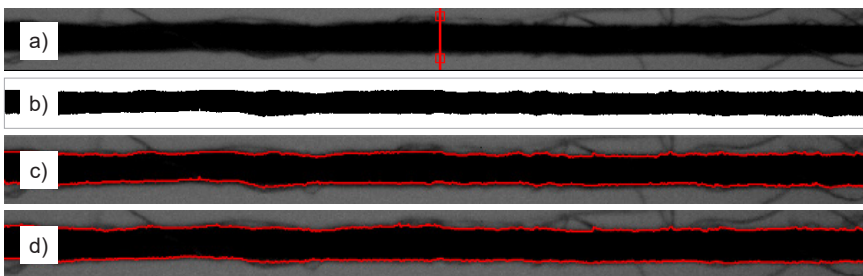
*Figure 8. Line profile of one line in the yarn image: a) distribution curve of the column intensity, b) intensity gradient curve.*



*Figure 9. Results of segmentation: a) the segmentation result of one line, b) the segmentation result of the yarn image by the method proposed (yarn core image), c) the result in the original image, d) the result of manual segmentation.*



*Figure 10. Comparison of yarn segmentation results and computation time; a) result by Otsu's thresholding: 0.21 s, b) result by FCM clustering: 1.14 s, c) result by region growing algorithm: 6.33 s.*
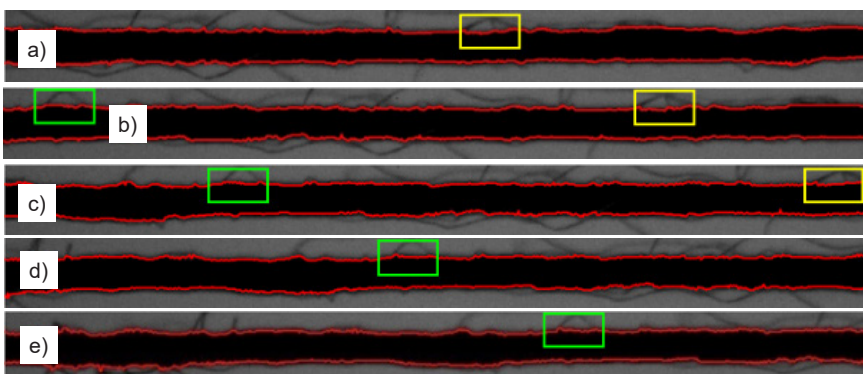


*Figure 11. Processed results and computation time of method proposed for five frames of a sequence; a) Frame 1: 0.78 s, b) Frame 2: 0.022 s, c) Frame 3: 0.021 s, d) Frame 4: 0.024 s, e) Frame 5: 0.022 s.*

When the pixels in the first frame of real-time images are classified into two classes by the FCM algorithm, a threshold value $T$ is proposed and set as the maximum of Cluster 1, labeled as orange. This value is employed to restrict the intensity value for all real-time images. The pixels with an intensity less than $T$ in each column are

convolved with the template $h[n]$ to construct an intensity gradient curve. Take the middle column of the yarn image in **Figure 6** as an example; the distribution of intensity is shown in **Figure 8.a**, and the corresponding curve of the intensity gradient obtained by one-dimensional convolution is shown in **Figure 8.b**.

In **Figure 8.a**, the dotted red line represents the value of $T$ obtained from FCM clustering. In **Figure 8.b**, Column* represents the column number corresponding to the intensities less than $T$ in **Figure 8.a**.

As can be seen from **Figure 8.b**, the points with a maximum and minimum value in the curve (point A and B) are obtained after the convolution. These two points are considered as the upper and lower edge points of the yarn core, respectively. Therefore Segmentation results can be obtained from the edge points, as shown in **Figure 9**.

**Figure 9.a** shows the segmentation result of one column of the image. The two red rectangular boxes represent the edge points determined by the intensity-gradient curve. All columns in the yarn image are processed by the same method, as shown in **Figure 9.b**. **Figure 9.c** displays the segmentation result of all columns for the original yarn image.

To evaluate the edge segmentation effect of the yarn image with our method, the manual yarn edge segmentation method is used in the experiment and the result is used for further accuracy validation. In the manual operation, the yarn image is magnified using the software Photoshop CS 8.0 and the edges of the yarn core and hairiness are marked by human vision. The manual segmentation result is shown in **Figure 9.d**. As shown in the figure, the manual segmentation is also consistent with the method proposed. It clearly shows that the method proposed is very effective at segmenting the yarn core from the background.

Some common segmentation methods are selected to compare with our method. The exemplary yarn image of **Figure 6** is chosen as the sample. The comparison is performed in two parts: the computation time and accuracy of segmentation. The experiment results of the method proposed are compared with those provided by the traditional, well-established approaches. Specifically Otsu's thresh-

olding, FCM clustering and the Region growing algorithm are considered. Comparisons of the results obtained are presented in *Figure 10*.

From *Figure 10*, it can be seen that the FCM algorithm has the worst segmentation result, for it cannot separate the hairiness from the yarn core and be used to detect the yarn diameter. Although the segmentation result of the Region growing algorithm is better than for the other two methods, it is still worse than the result obtained using our method (see *Figure 9.b*). More over the computation time of this algorithm lasts for about 6.33 s, which means that it cannot be used for real-time processing. Otsu's threshold algorithm segments the image within 0.21 s, which is the fastest of the three methods. But its segmentation result is still not as good as in our method, and its computation time is ten times longer. Therefore we can say that, compared with our method, these three methods are not suitable for real-time segmentation of yarn images.

To further validate the result and computation time of the method proposed for real-time processing, four other frames of a sequence are processed with the same threshold value confirmed by the first frame. The results processed and computation time of five yarn images are shown in *Figure 11*.

In *Figure 11*, the regions in green and yellow rectangles in different images represent the same part of five images, which proves the five images are in a sequence. For Frames 2, 3, 4, and 5, the threshold value *T* is provided by Frame 1. The object in the first frame takes more time to be segmented because the FCM algorithm is applied to obtain the threshold value *T*. For other frames, the segmentation was achieved in less than 0.0025 s/frame (with Intel Core i5 at 3.30 GHz and MATLAB 2014), which can meet the requirement of real-time processing.
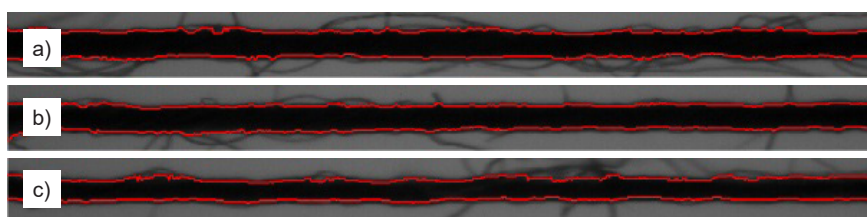


*Figure 12. Segmentation results of three kinds of yarns segmentation result of; a) 18.22, b) 12.96, c) 9.72 tex yarn.*

*Table 1. Difference the yarn average diameter and CV% between the manual segmentation and proposed method.*

| Yarn sample | Method proposed | | Manual Segmentation Method | |
|---|---|---|---|---|
| | Average diameter, mm | CV, % | Average diameter, mm | CV, % |
| #1 | 0.217 | 7.61 | 0.208 | 7.89 |
| #2 | 0.133 | 10.84 | 0.129 | 10.42 |
| #3 | 0.123 | 12.15 | 0.129 | 11.89 |
| #4 | 0.085 | 14.97 | 0.091 | 14.65 |

Therefore the comparison presented in *Figures 10* and *11* shows that the segmentation method proposed significantly outperforms well-established, traditional methods for image segmentation, and is suitable for real-time segmenting.

Additionally three kinds of cotton yarns with different linear densities, 18.22, 12.96 and 9.72 tex, are applied to test the application scope of the method proposed. Experimental results in *Figure 12* show that the method proposed can also achieve good image segmentation results with different kinds of yarns.
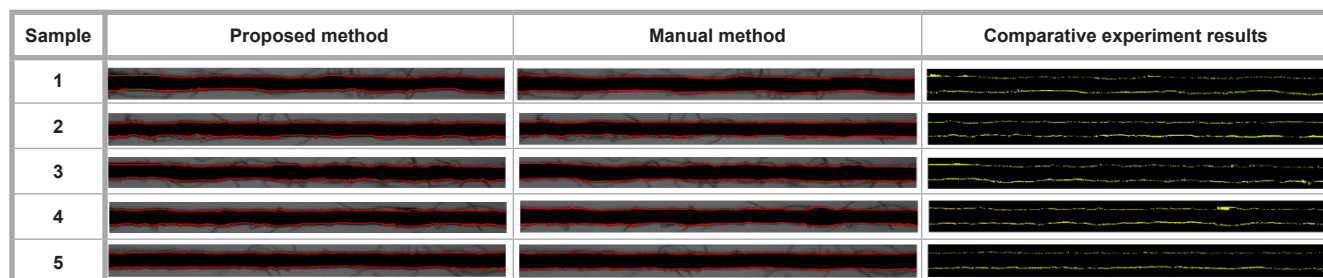
### Method comparison

The aim of the method proposed for real-time yarn imaging is to measure the yarn diameter and evaluate the yarn unevenness. Therefore the diameter data extracted from the method proposed must be compared with more precise data. In this paper, manual segmentation of a yarn image is utilised. As manual segmentation is time-consuming, 3000 yarn images of four kinds of cotton yarn, which are 27.8 tex (#1), 14.6 tex (#2), 9.7 tex (#3), and 7.3 tex (#4), are segmented by the method proposed and manual segmentation, respectively. Results of the two methods with the average diameter and CV in % are summarised in *Table 1*.

From *Table 1*, we can see that the difference the yarn average diameter and CV% between the manual segmentation method and the method proposed is very small. Compared with the manual segmentation method, the calculation error of the two average diameter values of four kinds of yarn are +4.32%, +3.10%, -4.65% and -6.59%, respectively. Therefore the method proposed is able to segment the real-time yarn image accurately.

In order to further validate the difference in the single frame between the manual segmentation method and the method proposed, another five random yarn images, which have the same linear density, are used to compare the segmentation error processed by the method proposed and the manual method, as shown in *Figure 13*.

In *Figure 13*, the method proposed and the manual method are applied to segment the same images. The results of the two methods are fused together to show the difference. Take Sample 1 as an ex-



| Sample | Proposed method | Manual method | Comparative experiment results |
|---|---|---|---|
| 1 | | | |
| 2 | | | |
| 3 | | | |
| 4 | | | |
| 5 | | | |

*Figure 13. Comparative results of two different methods.*

**Table 2.** *Test results of the manual method and that proposed.*

| Sample | Area value, pixels | | ADE, % | SE, % |
|--------|---------------------|---------------------|--------|-------|
|        | Method proposed - A($F_1$) | Manual method - A($F_2$) | | |
| 1 | 19503 | 20589 | 5.27 | 6.54 |
| 2 | 18530 | 19838 | 6.59 | 7.64 |
| 3 | 20815 | 21804 | 4.54 | 6.77 |
| 4 | 19641 | 21014 | 6.53 | 7.44 |
| 5 | 20893 | 21718 | 3.80 | 5.70 |

ample, where the binary image (only 0 and 1; the yarn core is "0" and the background "1") of the first image is $F_1$, and the binary image of the second image is $F_2$. The binary image is the part between the two red lines in the first or second image. The third image $F_3$ can be obtained by the following:

$$F_3 = |F_1 - F_2| \qquad (12)$$

Therefore compared with the manual method, the more points the third image of the five samples has, the worse the segmentation result is. In the "Comparative experiment results" part in **Figure 13**, the yellow areas represent the difference in segmentation results between the two methods. To quantify the difference, a detection index of *SE* (%) (Segmentation Error)is used to evaluate the precision degree of the method proposed, as shown in **Table 2**. The specific formula for *SE* is as follows:

$$SE = \frac{A(F_3)}{A(F_2)} \times 100\% \qquad (13)$$

where, $A(F_2)$ and $A(F_3)$ are the area value in pixels of the image $F_2$, $F_3$, respectively.

**Table 2** shows that the values of *SE* are all below 8%. This value consists of two parts: the segmentation lines of the method proposed below those of the manual method and the segmentation lines of the method proposed above those of the manual method. When the segmentation lines (up and down) of the method proposed are below or above one pixel of those of the manual method, the value of *SE* is about 7%(($2 \times 768$)/A($F_2$)). Therefore compared with the manual method, the precision degree of the method proposed can be accepted.

Another index of Average Diameter Error *ADE* in % is also calculated to evaluate the average diameter of yarn. The calculation formula is as follows:

$$ADE = \frac{|A(F_1) - A(F_2)|}{A(F_2)} \times 100\% \qquad (14)$$

The values of *ADE* in **Table 1** are below 7%, showing that the yarn diameters detected by the two methods are similar. In this paper, we aim to illustrate the accuracy and real time of the method proposed for segmenting real-time images. Thus we do not collect a great number of data to detect the yarn evenness. In a further work, we will massive data of yarn diameters and compare the results with those of an Uster Evenness Tester.

## ■ Conclusion

In this paper the problem of textile yarn real-time segmentation was considered. A robust algorithm for yarn segmentation was introduced. Generalising the theoretical and experimental studies presented here, it can be stated that the method developed for real-time segmenting of the yarn images meets the requirements for precision and speed. The segmentation results of the yarn image are currently being used for detecting the yarn diameter to evaluate the unevenness of yarn appearance. The method proposed for real-time processing yarn image will lay the foundation for real-time detection of yarn unevenness based on image-processing technology.

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