A Fast Feature Extraction Algorithm for Detection of Foreign Fiber in Lint Cotton within a Complex Background

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Abstract A novel algorithm is presented in this paper to extract the features of foreign fibers in lint cotton within a complex background. The 2D wavelet transform is used to implement the edge detection based on the gray contrast between foreign fibers and cotton background, while the color features are extracted in CrCgCb color cube to solve the problem of luminance fluctuation. Morphological analysis is a critical procedure of the algorithm and the discontinuity of object features and operation time must be considered. Therefore, the proposed approach integrates a two-level connected component labeling algorithm and a morphological identification algorithm based on equivalent length-width ratio. Tests on five typical kinds of foreign fibers were implemented, and the results show that the identification rate of the above-mentioned algorithm is about 95 %. The experimental results demonstrate that the feature extraction algorithm can identify foreign fibers effectively and can be used in real-time application.

Key words Foreign fiber, feature extraction, length-width ratio, connected component labeling, real-time application
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The foreign fibers in cotton, including cloth strips, plastic film, jute or hair, polypropylene baler twine and rubber, are a serious threat to the textile and cotton industry[1]. Such contaminants have impact on cotton grade and can cause color spots in fabric, thus reduce the textile value as well. Currently, these contaminants are removed during the ginning procedure by human visual inspection and hand picking. For the foregoing reasons, there has been great interest in developing automated instruments for detecting and removing foreign fibers in cotton. As machine vision technology has been developed rapidly, automated visual inspection (AVI) systems have been used in this field[2]. An AVI system usually requires real-time operation to enable the inspection process to keep up with the manufacturing process[3]. Therefore, it is vital to develop a fast and efficient vision algorithm.

Foreign fibers are not simple to detect due to their unpredictable size shape, material, position, and orientation especially within a complex background. In the actual working environment, the appearance of the contaminants is random and the thickness of the cotton layer is not constant, which leads to variation in light intensity. Besides, the cotton layer is nonuniform and it runs through the field of view discontinuously. This causes holes through the cotton layer, which has adverse effects on image processing. Furthermore, foreign fibers are likely to be covered by cotton, which undermines the integrity of the object features.

Earlier research work on contaminant detection in cotton was designed for cotton grading. Xu et al. analyzed the differences between trash and cotton in Lab color space and distinguished them with three different clustering methods[4]. Siddaiah et al. proposed a scheme with shape parameters[5]. They structured a feature hyperspace with default features and computed features and then classified them with a trained artificial neural network. The forgoing methods achieved great accuracy but were time-consuming. For real-time application, several fast feature extraction algorithms were proposed. Zhi modeled a RGB color cube and put cotton and trashes in the different parts of the cube[6]. HIS color space was used with the advantage of its insensitivity to light-intensity alteration[7]. Jin et al. extracted the edge features of image and detected the contaminants with the help of gray contrast against the background[8]. Yang et al. analyzed the histograms of cotton and foreign fibers, and achieved the image segmentation by the improved Otsu′s methods[9]. The above-mentioned methods paid no attention to the complex background of the actual working environment.

In this paper, a fast feature extraction algorithm is presented for the detection of foreign fibers in lint cotton within a complex background. The edge and color features of the foreign fibers are extracted in YCbCr space. Then, a criterion based on length-width ratio is proposed to achieve fast morphological analysis.

The rest of the paper is organized as follows. The feature extraction method in YCbCr space is described in Section 1. The morphological analysis process is presented in Section 2. In Section 3, the experimental study is given. Conclusions are given in Section 4.

1 The proposed feature extraction methodology

1.1 Image characteristics

In the actual working environment, the images captured online have a complex background. As shown in Fig. 1, there are four typical characteristics in the original image: 1) The cotton layers are non-uniform and with shading or overlapping conditions; 2) The cotton layers are discontinuous, which causes holes and borderlines in the image; 3) The light-intensity is unstable; 4) There are many small dots in the cotton image. If we judge them as foreign fibers and trigger the air nozzles to blow them off, the system will be in busy action conditions. And, they should be distinguished from foreign fibers. And, the algorithm designed should be effective to solve the aforementioned problems.

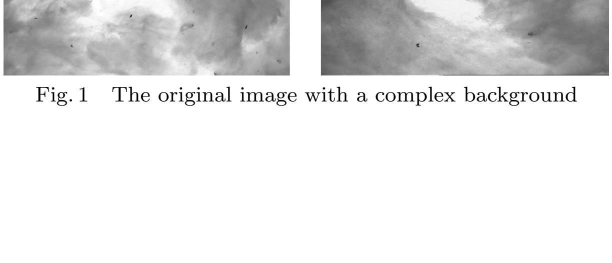

Fig. 1 The original image with a complex background

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1.2 YCrCb color space

RGB is the most common color model in use. In RGB color space, each pixel is indicated by three color components (R, G, B). But the three components change according to the luminance fluctuation, which has an impact on the efficiency of the algorithm. It is known to be an effective solution to transform RGB color space to other color spaces with separated luminance component. YCrCb color space is a widely-used color model, which works with separated luminance (Y) and chrominance (Cr, Cb) components. In this paper, YCrCb color model is adopted to obtain the edge features and color features of the foreign fibers separately. To be specific, the gray contrast between foreign fibers and background is used to implement edge detection in Y channel, while the chromatic aberration is used to implement color segmentation in Cr and Cb channel. The relationship between RGB and YCrCb is as follows:

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.169 & -0.331 & 0.5 \\ 0.5 & -0.419 & -0.081 \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

To form a color cube, a Cg component corresponding to the G channel is derived by[10]

$$Cg = 128 - 0.318R + 0.439G - 0.121B \tag{2}$$

1.3 Edge feature extraction algorithm based on 2D wavelet transform

In the luminance component (Y channel) of the original image, cotton can be treated as background, while foreign fibers are expressed as foreground. Consequently, edge detection is a feasible way to our problem. In this paper, 2D wavelet transform is adopted to achieve the edge feature extractions.

2D wavelet transform is a direct advancement of 1D wavelet transform. It is one of the most prevalent techniques for edge detection and texture extraction. In practical application, we utilize filter banks to realize the fast algorithm. The decomposition process of 2D wavelet transform is shown in Fig. 2. Lo_D, Hi_D denote the low-pass filter and high-pass filter of wavelet decomposition; R(Lo_D) and C(Lo_D) denote the process of row convolution and column convolution with the low-pass filter banks; R(Hi_D) and C(Hi_D) correspond to the high-pass filter banks; R(2↓1) and C(2↓1) denote the row down-sampling and column down-sampling by factor of 2.

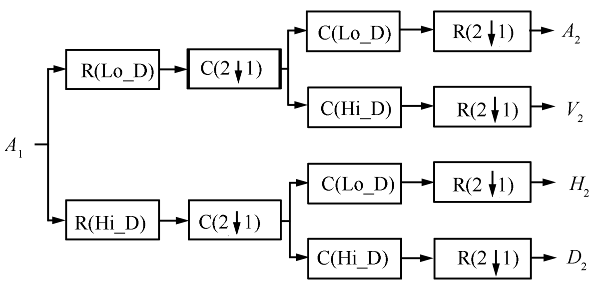

Fig. 2 Process of 2D wavelet transform

Through the 2D wavelet decomposition (Haar wavelet function is adopted as the filter in this paper), the original cotton luminance image A_1 is transformed to four parts. A_2 denotes the morphology component; H_2 denotes the detail component in vertical orientation; V_2 denotes the detail component in horizontal orientation; D_2 denotes the detail component in diagonal orientation. In three detail components, high-frequency features are enhanced and the contrast is indicated by the wavelet coefficients.

Through the histograms of the detail components (if the wavelet coefficients are negative, the absolute values are used), it is obvious that most of the wavelet coefficients are distributed in small-value side, which consist of background image. The other parts are consisted of edge features and high-frequency noise. The threshold of the binarization process is defined as follows:

$$T_l = K \times \frac{\sum\limits_{i=1}^{M} \sum\limits_{j=1}^{N} G_{ij}}{M \times N} + T_0 \tag{3}$$

where M and N denote the row and column of the detail component image; G_{ij} denotes the wavelet coefficient of the corresponding position; K is the weight; T_0 is the offset, which helps to preserve the cotton features in clean conditions (no contaminants in the image). The object features in omni-orientation are obtained with logical "or" operations (merging three detail components).

1.4 Elimination of cotton layer borderlines

Besides contaminant features, borderlines of cotton layer are represented as edge features, which cannot be distinguished in binary image. Through analysis and comparison, two factors are found to be helpful to solve the problem (for convenience, the cotton layer side of the borderline is defined as cotton area, while the other side with no cotton layer is defined as background area): 1) The illumination of background area is larger than the cotton area. In cotton area, light is weakened by reflection and absorption caused by cotton layer. While light is directly received by the camera in background area, which makes the illumination bright and stable; 2) The wavelet coefficients (detail components) in background area are small (around zero), while in cotton area, the wavelet coefficients are bigger due to the texture of cotton and contaminants. The complete algorithm is described as follows:

1) As shown in (4), image binarization is implemented to the luminance component and wavelet coefficients.

$$f(i,j) = \begin{cases} 255, & I(i,j) > T_I \text{ and } G(i,j) < T_G \\ 0, & \text{else} \end{cases} \tag{4}$$

where $I(i,j)$ denotes the luminance component; $G(i,j)$ denotes the wavelet coefficients; T_I and T_G denote the corresponding thresholds.

2) A $k \times k$ block is utilized as a slide window to scan the binary image $f(i,j)$ block by block. If the number of pixels valued 255 is larger than the threshold T_f, label the block as background area.

3) Search the borderline block, which is the background area with cotton area around, and label the 8-neighbor of the block as border blocks. Neglect the border blocks when extracting the edge features.

1.5 Color feature extraction algorithm in CrCgCb color space

Conventionally, cotton is white and its distribution is centered at one point (128, 128, 128) of the color cube spanned by Cr, Cg, Cb, while colored contaminants are distributed around it. Consequently, the differences between chrominance components are utilized to distinguish the contaminants and cotton.

The equivalent distance among three chromatic aberrations is defined by

$$D(i,j) = |Cr(i,j) - Cb(i,j)| + |Cr(i,j) - Cg(i,j)| + |Cb(i,j) - Cg(i,j)| \tag{5}$$

where i and j denote the row and column position of the pixel in the image.

Though CrCgCb color space has no luminance component, the three chrominance components are not completely irrelevant to luminance fluctuation. A mean-based binarization threshold is chosen to enhance the algorithm efficiency. The threshold is defined as follows:

$$T_c = \frac{\sum\limits_{i=1}^{M}\sum\limits_{j=1}^{N} D(i,j)}{M \times N} + q \tag{6}$$

where M and N denote the row and column of the image. q denotes the offset.

Thus, the color features of the contaminants are extracted. As shown in Fig. 3, the integrated object features are obtained by logical "or" operations between luminance and chrominance features.

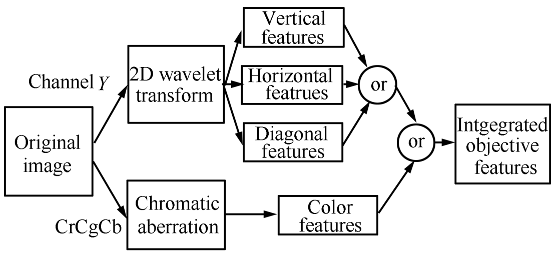

Fig. 3 Schematic diagram for the process of the feature extraction algorithm

2 Morphological analysis

2.1 Connected components labeling

The above-mentioned binary results include not only the foreign fiber features but also false features. To distinguish them, morphological analysis should be the next procedure.

Firstly, a connected components labeling algorithm is utilized to determine the processing area. In this paper, a two-level connected components labeling algorithm based on core area and expansion area is illustrated. In the binary image, 255 denotes the feature pixel while 0 denotes the background pixel. The main steps of the approach can be specified as follows:

1) An advanced pixel-labeled algorithm is adopted, which can achieve the labeling process within just one scan procedure in most cases. The details of the algorithm can be seen in [11].

2) In the labeling process, record the pixel number of each labeled component and save it in an array called $PixN[i]$. There are some small dots in the binary image caused by noise, which have adverse effects on the algorithm accuracy and the computational time. A threshold is set to solve the problem. If the value of $PixN[i]$ is smaller than the threshold, the labeled component is judged as noise and it is set to zero.

3) In the labeling process, record the left, right, top, and bottom positions of the minimum enclosing rectangle (MER) outside the labeled component and save them in four arrays, called $left[i]$, $right[i]$, $top[i]$, and $bottom[i]$, respectively. Considering the intertwining between cotton fibers and foreign fibers, the features obtained are discontinuous. Consequently, a two-level connected component labeling algorithm is used. As shown in Fig. 4, the above-mentioned MER is treated as a core area. The expansion area is formed by expanding the MER in four directions with certain offsets and refresh the four corresponding arrays simultaneously. According to (7) $\sim$ (9), whether the two expansion areas are overlapped is determined.

$$OverLH[k] = \begin{cases} 1, & right[i] \geq left[j] \text{ and} \\ & right[j] \geq left[i] \\ 0, & \text{else} \end{cases} \tag{7}$$

$$OverLV[k] = \begin{cases} 1, & bottom[i] \geq top[j] \text{ and} \\ & bottom[j] \geq top[i] \\ 0, & \text{else} \end{cases} \tag{8}$$

$$OverL[k] = \begin{cases} 1, & OverLH[k] = 1 \text{ and} \\ & OverLV[k] = 1 \\ 0, & \text{else} \end{cases} \tag{9}$$

where i, j denote the two compared labeled components; 1 denotes the areas that are overlapped; 0 denotes the areas that are non-overlapped. As shown in Fig. 4, the two expansion areas in the right side of the figure are overlapped; therefore, they are judged as a whole body. After finishing the judgments of all labeled components, the overlapped parts are treated as a whole component, and the position parameters of the MER are saved to the four corresponding arrays called $left'[p]$, $right'[p]$, $top'[p]$, and $bottom'[p]$ (p is the index of the merged component).

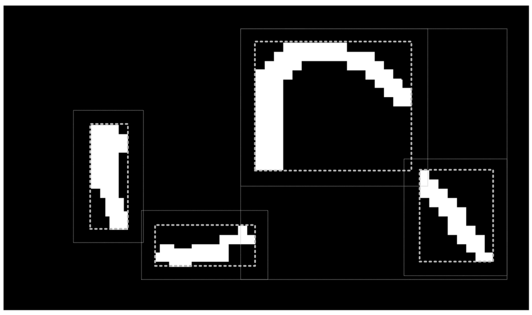

Fig. 4 Example of the two-level connected component labeling algorithm (The core area is shown with the sparse dotted line box; the expansion area is shown with the dense dotted line box.)

Through the above-mentioned steps, the binary image is separated into several parts. Each of the parts is treated as an integrated feature waiting for morphological analysis.

2.2 Morphological analysis algorithm

Foreign fibers are one kind of fiber-like materials. The most distinctive feature of foreign fibers is the "slender" physical shape. Consequently, a parameter called fineness (FN) is used, which is defined as the length-width ratio (LWR) of the measured feature. It is known to be a difficult task to calculate the FN of foreign fibers in the actual working environment for three reasons: 1) The features to be measured are discontinuous; 2) The appearances of the foreign fibers are different and nonuniform; 3) The foreign fibers are not stretched, which leads to wound and twisted status. A widely-used substitute parameter for length-width ratio is area-perimeter ratio (APR). However the discontinuous bodies increase the perimeter of the features, which causes the wrong answers. In this paper, a novel methodology is utilized to solve the problem, the procedure of which is presented as follows:

1) Form a working region with $left'[p]$, $right'[p]$, $top'[p]$, and $bottom'[p]$ for a feature waiting for morphological analysis.

2) Scan the first line of the image. As shown in Fig. 5, find edge pixels $X_{\rm start}$ and $X_{\rm end}$. A threshold called T_x is set to eliminate mistakes caused by small holes. If there are some labeled pixels in the following T_x pixels after $X_{\rm end}$, the $X_{\rm end}$ is treated as a hole-edge within one integrated feature and the search of valid $X_{\rm end}$ is continued until there is no labeled pixel in the following T_x pixels. Then, the middle point is calculated as follows:

$$R_{\rm mid} = \frac{x_{\rm start} + x_{\rm end}}{2} \tag{10}$$

where $x_{\rm start}$ and $x_{\rm end}$ denote the column index of $X_{\rm start}$ and $X_{\rm end}$. Save the row index of the line in array $X_{\rm mid}[i]$ and $R_{\rm min}$ in array $Y_{\rm mid}[i]$. Then, one feature middle point (FMP) indexed as ($X_{\rm mid}[i]$, $Y_{\rm mid}[i]$) is found. Start the same scanning process after the $X_{\rm end}$ and search for other feature middle points.

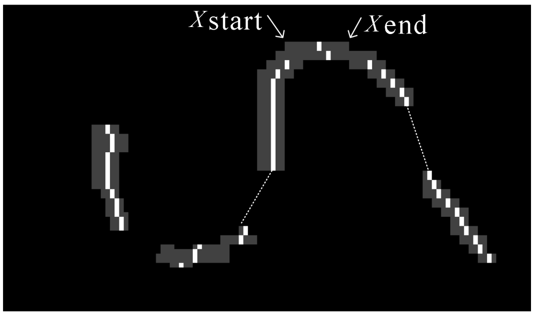

Fig. 5 Example of the equivalent length

3) Scan the next line of the image. Once FMP (named as J is obtained, it is indexed as ($X_{\rm mid}[j]$, $Y_{\rm mid}[j]$), and the distance between J and previous FMP is calculated. For reducing the computational time the distance formula is defined by

$$D(i, j) = |X_{\rm mid}[i] - X_{\rm mid}[j]| + |Y_{\rm mid}[i] - Y_{\rm mid}[j]| \tag{11}$$

Distances between FMPs with the same row index are not calculated. The FMP with minimum distance is chosen as the object FMP and refreshed as FMP J. If the row indices of FMP J and the object FMP are adjacent, add the distance between them to the parameter called *LengthC* (The initial value of *LengthC* is zero). Otherwise, add the distance between them to the parameter called *LengthB* (The initial value of *LengthB* is zero), which denotes the distance between broken parts (The white lines between two separate parts are shown in Fig. 5). Continue the above-mentioned method until the whole image scan process is over. The equivalent length (EL) of the labeled feature is defined as the sum of *LengthB* and *LengthC*.

4) Repeat the same scan algorithm in column orientation and choose the bigger EL as the final result. Considering that there are false features caused by small dots gathering together, their ELs are incorrect and hard to distinguish by the addition of *LengthB*. *LengthC* is the parameter calculated by the real-labeled pixels, which can be seen as the length of features shrinking together. In general, the length of dots are small after shrinking them together, while the foreign fibers keep their slender shape after connecting their broken parts. Therefore, a threshold called T_{lc} is utilized to solve the problem. We treat the feature as small dots if the *LengthC* is smaller than T_{lc}.

5) The area of the labeled feature can be expressed by the number of pixels ($NumP$) in the processing region, which is calculated at the scan process. Therefore, the equivalent width (EW) is defined by

$$EW = \frac{NumP}{LengthC} \tag{12}$$

Therefore, the FN of the labeled feature is given by

$$FN = \frac{EL}{EW} \tag{13}$$

$$F = \begin{cases} foreignfiber, & FN > T \\ falsefeature, & \text{else} \end{cases} \tag{14}$$

where T is the threshold for FN judgment. Using (14), we can distinguish foreign fibers against false features through their shapes.

3 Experimental study

3.1 Identification rate

The performance of the image processing algorithm is evaluated by the foreign fiber identification rate defined as:

$$IR\,(\%) = \frac{N_{\rm identified}}{N_{\rm total}} \times 100\,\% \tag{15}$$

where $N_{\rm identified}$ denotes the number of foreign fibers identified; $N_{\rm total}$ denotes the total number of foreign fibers under test.

In our experiment, five typical foreign fibers were chosen. These were bristle (BRE), hair (HAR), green plastic film (GPF), red polypropylene strip (RPS), and yellow plant stem (YPS). Three tests were carried out to measure the identification rate in different conditions. In the first test, foreign fibers were put on the surface of cotton layers. 20 images of each type of the foreign fibers were taken for test. In the next two tests, foreign fibers were slightly covered by cotton, i.e., just some part of the foreign fibers was covered. 20 images of each type of the foreign fibers were taken for test. In the second test, we used the above-mentioned algorithm based on length-width ratio (LWR) as the morphological analysis method. In the third test, we used the area-perimeter ratio (APR) to substitute for LWR.

Fig. 6 shows the identification rates of the three conditions. In the first test, an integrated feature can be obtained from the original image. Therefore, the IRs are high and there are almost no differences between the LWR and the APR. The IR of RPS is slightly lower due to the uneven surface of polypropylene strips. Due to the cotton covered, the original image of foreign fibers are shown as broken trash features with cotton features on it. In the third test, the seperate parts of an integrated features are too far away to be reconnected. And they are likely to be eliminated as small dots. It is obvious that the LWR mentioned in the paper has better results than APR. The average IR of LWR is 95 %. Otherwise, the types of the foreign fibers have effects on the identification rates. Bristles and hairs, whose length is much larger than width, are similar with slender shape. However, hairs are softer and they are winding under normal condition, which makes it hard to illuminate the morphological expression. The surface conditions of plastic film and polypropylene strip are different. The former is smooth while the latter is uneven, which leads to the complex conditions of reflected lights.

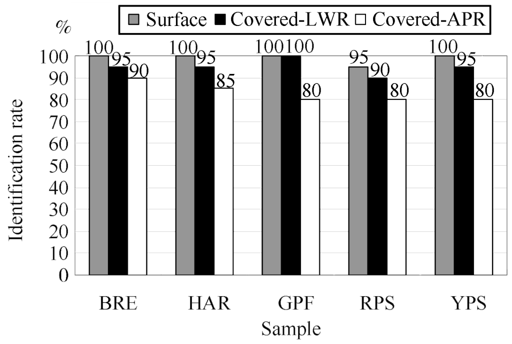

Fig. 6 Comparison of identification rates with the two methods

3.2 Error rate

Besides identification rate, error rate is also a critical index for the algorithm, which represents the cases of detecting cotton or false features as foreign fibers. The foreign fiber error rate is defined as:

$$ER\,(\%) = \frac{N_{\text{error}}}{N_{\text{total}}} \times 100\,\% \tag{16}$$

where N_{error} denotes the number of error identification and N_{total} denotes the total test number.

The main confusing features leading to error identification are small dots, borderlines, and holes of cotton layer and dirty cotton. In our experiment, 40 images with above-mentioned confusing features were taken (no foreign fibers in it). The ER of the experiment is 5 %. Small dots are well identified and dirty cotton is bigger enough to distinguish with the above-mentioned algorithm. The main challenge is the borderlines caused by different cotton layers.

3.3 Operation time

The algorithm is designed to use in real-time application; therefore, the operation time is a critical parameter. In our experiment, the original image is 720×576 and a processing platform based on TMS320DM642 processor is used.

As shown in Table 1, the operation time of feature extraction parts is stable and consumes 28 ms in all. In actual working environment, each original image is different and whether it contains foreign fibers is random. Therefore, in our experiment, not only original images with foreign fibers but also ones without foreign fibers are chosen. The computational time of the morphological analysis process ranges from 10 ms ~ 50 ms generally.

3.4 Comparison with other algorithms

Several algorithms have been reported on earlier researches. Since these algorithms are with different objects, measuring methods, and judgment criteria, we do qualitative comparisons in five critical parameters.

As shown in Table 2, the algorithm in this paper offers 90 % identification rate. Though this IR is not too high, the detection field is wide, which can detect color and gray trashes; the operation time is suitable for real-time application; the error rate is taken into account in this paper; the holes, borderlines, and small dots are eliminated as false features, which makes the algorithm more suitable for real application.

Table 1 Operation time of the algorithm

	Operation time (ms)
Edge feature extraction	18
Color feature extraction	10
Morphological analysis	10 ~ 50
The whole algorithm	38 ~ 78

4 Conclusions

Feature extraction algorithm for foreign fibers in lint cotton within a complex background is known to be a difficult task, especially in real-time use. For the actual working environments, it must conform to three key norms: operation time, identification rate, and error rate. A new methodology is presented herein for dealing with the problem. The novelty of the proposed approach lies in the morphological analysis method based on the judgment of length-width ratio. The rough feature results directly extracted from edge detection and color segmentation include many false features. Also, the features are broken to several parts, which has adverse impact on morphological analysis. In this paper, sectional features, which may belong to an integrated feature, are merged together with the same label. After scanning the labeled feature, the feature middle point (FMP) set is obtained, and based on this set the length-width ratio is calculated. The algorithm has the ability to connect broken parts and correctly judge the shapes of the incomplete features. Considering the operation time, the connected components labeling process is basically achieved by one scan of the image and the FMP set is obtained by two scans. Therefore, the algorithm is time-saving and meets the need of real-time use. Otherwise, the proposed algorithm shields the borderlines of the cotton layer, which appear frequently in actual application.

The algorithm is based on differences of the gray and color features between foreign fibers and cotton. White trashes, such as white hairs and wool, have little contrast in comparison with cotton in above-mentioned features. Therefore, the algorithm is ineffective to detect these white foreign fibers. Besides, with the trends of high-resolution detection and higher cotton production, the operation time is a crucial factor. The operation time of this algorithm should be improved for better performance. Hence, in our future research, more efforts will be made in above-mentioned two aspects.

Table 2 Comparison with other algorithms

Algorithm	Objects (color : gray)	False feature (holes : small dots)	Operation time (ms) (image size)	IR (%)	ER (%)
Algorithm in [7]	√ : ×	UA: ×	< 10 (80 lines)	95.4	NM
Algorithm in [12]	× : √	× : √	1 710 (576 × 432)	99.3	1.4
Algorithm in [13]	√ : √	× : ×	12 (2 048 × 200)	NM	NM
Algorithm in this paper	√ : √	√ : √	< 78 (720 × 576)	> 90	5

UA–unaffected NM–not mentioned

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