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Machine Vision Method for Quantitative Statistics Analysis of Industrial Product Images

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***Abstract*—To address the problems of unstable accuracy, low efficiency, and subjective influence of manual counting, a machine vision-based method to count the quantity of tobacco shreds is proposed for the first time. In this paper, the complex tobacco shred image is obtained by backlight imaging. The adaptive threshold segmentation method is used to segment tobacco shreds. The pixel area of the tobacco shred area is calculated by connected domain labelling. Second, independent tobacco shreds and adhesive tobacco shreds were identified based on the pixel area, and the quantity of segmented tobacco shreds was counted for the first time. Subsequently, in complex scenarios (such as tobacco shreds adhesive and overlapping), an image is usually obtained by manually drawing the contours of the adhesive and overlapping tobacco shreds on the basis of primary statistics. Finally, different individuals are distinguished, segmentation is completed, and tobacco shred quantity statistics are realised. The experimental results show that the average accuracy is 100.0 % for quantitative statistics of independent tobacco shred images. For tobacco shred images with adhesive and overlapping interference, the minimum accuracy is 90 %, and the accuracy increases with the increase in tobacco shred quantity. Furthermore, the efficiency of the tobacco shred quantity statistics conducted by the method in this paper was only affected by complex scenarios. Compared to artificial processing, the efficiency was increased by more than 100 %. The work in this paper can provide the technical basis for measuring the dimensions of tobacco shreds.**

***Index Terms*—Image processing; Machine vision; Industrial application; Sensing technique.**

I. INTRODUCTION

As the basic material of cigarette, the form of tobacco shred is closely related to the quality of the cigarette. According to the requirements of the Quality Inspection Operations Instruction for the measurement of the width of the leaf filament in the enterprise standard of a tobacco shred company, sample 20 g of leaf filament in a random cross section and measure the average width of the spread tobacco shred filament using a tobacco shred projector (20 times the magnification of the objective lens). The manual method is highly recognised in the industry, but is inefficient, time-consuming, and laborious, and the results are greatly affected by the frequency of sampling and other factors. The development of automatic/semi-automatic tobacco shred width identification technology is needed for the development of the industry, and the premise of automatic tobacco shred width identification [1] is to carry out automatic statistics on the number of tobacco shreds, so it is very meaningful to deal with adhesion, overlap, and other special scenes of tobacco shred.

With the rapid development of machine vision technology, target recognition, measurement, and statistics through algorithms have been widely used in various fields [2]–[6]. For example, detection of egg crack targets [2], automatic cell count [4], and population count [5], [6]; but in the tobacco industry, it is more focused on the classification and recognition of tobacco leaves. He *et al.* [7] proposed a machine vision-based tobacco grade recognition method to classify tobacco samples from the set of models and the set of prediction by extracting features of the tobacco appearance. Chao, Kai, and Zhiwei [8] developed a detection algorithm for tobacco packaging transparent film residue based on surface characteristics, which can effectively identify and remove various foreign bodies in the tobacco packaging production process, with an accuracy of 97.8 %. Guru, Mallikarjuna, Manjunath, and Shenoi [9] proposed a method of classification of tobacco leaf based on machine vision for automatic harvesting in a complex agricultural environment. Li *et al.* [10] proposed a fast and lossless classification method for tobacco leaves in the paper. Particle swarm optimisation and limit learning machine algorithm were used to construct different training models. The developed model could predict the category of test samples, providing a new classification method for the classification of tobacco leaves in the field procurement process. Zhang and Zhang [11] proposed a method for automatic classification of tobacco leaves based on digital image processing and fuzzy set theory, and developed a classification system based on image processing technology for automatic detection and classification of flue-cured tobacco leaves. Taking 79,165 flue-cured tobacco leaves of two different grades in southern

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Anhui as research samples, Lu, Jiang, Wang, Chen, and Chen [12] proposed a tobacco grading method combining a convolutional neural network and a double-branch integral, which provided a method for the industrialisation of tobacco grading.

In summary, tobacco leaf classification and recognition have made great progress. Because tobacco shred is close to production, as well as the particularity of its own form and physical properties, automatic recognition of the quantity of tobacco shreds is rarely studied. To solve this problem, this paper proposes a statistical method of estimating the quantity of tobacco shreds based on machine vision. Firstly, binary segmentation of tobacco shred image is carried out; secondly, interference factors existing in the binary image are removed, and then connected domain marker is used to make initial statistics of tobacco shred quantity. Secondly, the pixel value is used to identify and locate the adhesive and overlapping tobacco shred. The region of interest (ROI) curve was used to extract the contour of the adhesive and the overlapped tobacco shred, and the ROI region of each tobacco shred was obtained. Different individuals were distinguished and the segmentation was completed. Finally, the statistics of the quantity of the tobacco shreds in complex scenarios were realised.

The work content of this paper is described as follows. The first part explains the background research and the current situation of this paper, the second part gives the test platform built by the technology realisation, the third part is the preliminary statistics of the quantity of tobacco shreds based on the technical basis, the fourth part is the complex scene segmentation based on the preliminary statistics, the fifth part contains the test results, and the sixth part presents the conclusions.

II. PROPOSED METHOD

The visual detection system for the quantity of tobacco shreds is shown in Fig. 1, which is mainly composed of computer, LED light box, industrial camera, white transparent gasket, etc.

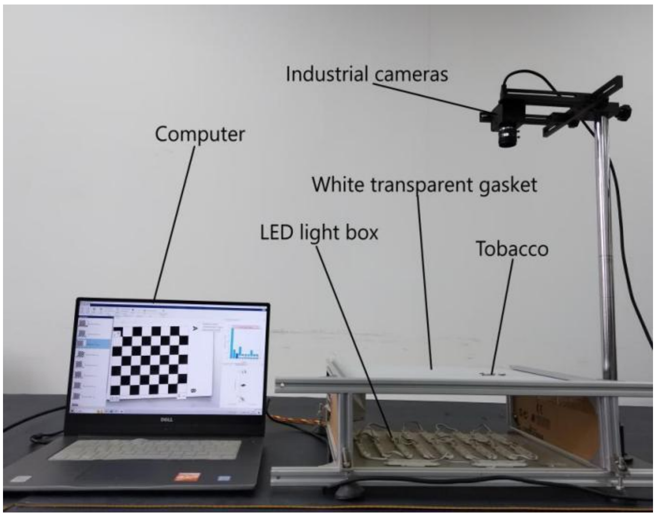


Fig. 1. Visual detection system of the quantity of tobacco shredded.

The operating principle of the tobacco shred quantity visual detection system is as follows: the white transparent gasket is the carrier after the tobacco shred is thrown, the LED light box provides the backlight, the industrial camera obtains the tobacco shred attitude, and the picture is transmitted to the computer through the USB3.0 interface for processing and the computer outputs the result. The JHSM300f has a resolution of 2048×1536 and a frame rate of 79.1FPS. The light source uses a special 5730-3LED surface light source. The computer processor is Intel(R)Core(TM)i5-8250U with 16G of running memory.

A. Image Segmentation

Figure 2 shows a picture of the original tobacco shred. The maximum intergroup variance method is used to segment the image of the original tobacco shred. The maximum interclass variance method is simple to calculate and is less affected by the brightness and contrast of the image, which makes it the best algorithm for selection of thresholds in image segmentation [13]. Figure 3 shows the image after binarization. It can be seen that the contour edge details are well preserved, indicating that this method can ensure the accuracy and authenticity of tobacco shred counting.

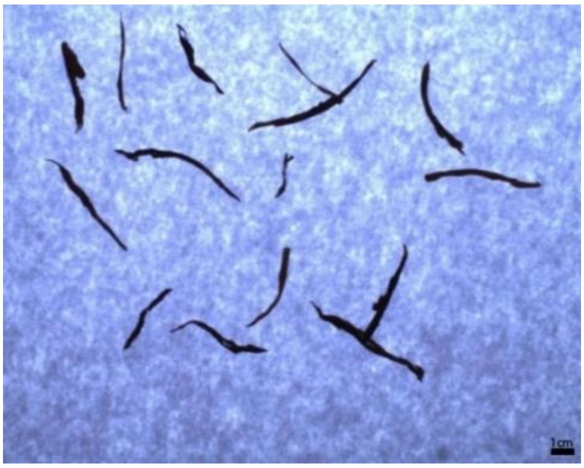


Fig. 2. Original image.

Fig. 3. Binary image.

B. Remove Small Target in Binary Images

In the process of acquisition of the image of the tobacco shred, there will be impurities such as the residue of the tobacco shred, and some points or areas will be dark in binary processing (Fig. 3) [14]–[17]. These factors will affect the subsequent tobacco shred count. To ensure the accuracy of counting, in this paper, a morphology operation function was used to carry out small target removal processing for binary tobacco shred images, i.e., to delete objects with fewer than 500 pixels, as shown in Fig. 4.

Fig. 4. Tobacco shred image after removing small target.

C. Statistics of Cut Tobacco

To identify the number of objects in the binary image (the connected domain formed by object pixels), the existing object recognition methods first carry out the connected domain labelling processing on the binary image and use different label values to label pixels belonging to different objects in the image, so as to distinguish different objects and generate labelled images.

Connected domain labelling is to label all object pixels belonging to the same connected domain in the image with a unique label value. In the binary image shown in Fig. 5, there are 5 connected domains, and the result after label processing is shown in Fig. 6.

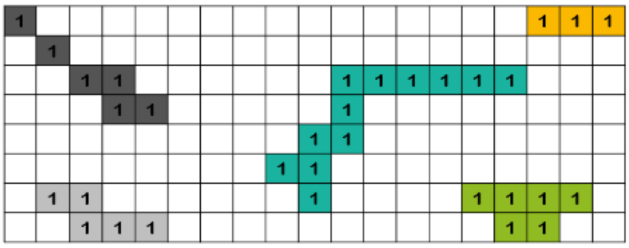


Fig. 5. Binary image with connected domain.

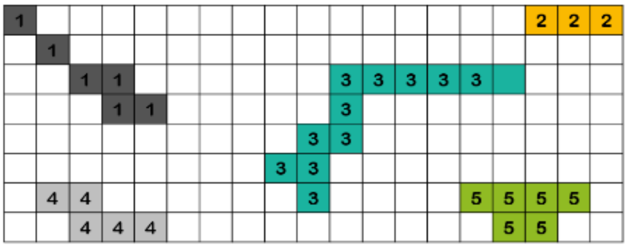


Fig. 6. Label image of connected domain marker.

To calculate the quantity of tobacco shreds, the tobacco shred in the image is marked with the connected domain, and different tobacco shreds are marked with different labels. In theory, the maximum value of the label is the result of the tobacco shred count. However, in the actual complex images of tobacco shreds, there will be multiple objective conditions for tobacco shred adhesions and overlaps. Even if the image is preprocessed by morphological processing methods such as corrosion and expansion, the inherent problems of adhesion and overlap cannot still be solved. Figure 4 is a binary image of tobacco shred after morphological processing. There are multiple instances of two adhesion and overlap tobacco shreds in the image. However, the accuracy of counting results will be affected by over or undersegmentation of image segmentation technology. To accurately count complex tobacco shreds, adhesive and overlapping tobacco shreds were extracted and separated separately on the basis of label processing.

For independent tobacco shred images, the actual quantity can be obtained by the first statistics, while for the adhesive and overlapping tobacco shred images in Fig. 7, human-computer interaction processing is required on the basis of the initial statistics.

Fig. 7. Image of the adhesive and overlapping tobacco shred.

III. ADHESIVE AND OVERLAPPING TOBACCO SHRED SEGMENTATION

A. Position of Adhesive and Overlapping Shred Cut

In a binary image, the area of tobacco shred can be represented by the amounts of pixels of the current object. Based on the process of connected domain labelling, all temporary labels in a connected domain are stored in the same set of equivalent labels and have unique and identical representative labels. Therefore, the area of the corresponding tobacco shred can be represented by the numbers of pixels in the set of temporary labels.

30 g of cut tobacco shred was taken from a tobacco shred company and counted manually. Then the value of the pixel area of each tobacco shred was measured, involving each width (0.6 mm, 0.7 mm, 0.8 mm, 0.9 mm, and 1.0 mm). Counting the pixel area value of each cut tobacco, and recording it as W and the average cut tobacco pixel area value as H, the formula for obtaining the average cut tobacco pixel area value is as follows

$$H = \frac{W}{100}. \tag{1}$$

Pixel values were measured for each of the tobacco shreds taken, and the final average area of pixels of the tobacco shred was found to be 9,500.

To obtain the position of the adhesive and overlapping tobacco shreds, the pixel area of each tobacco shred in the image is measured and compared with the set average pixel area to judge the state of the tobacco shred. The red number in Fig. 8 is the value of the pixel area of the target tobacco shred. Tobacco shred less than the average pixel area of tobacco shred is judged as independent tobacco shred, the quantity of automatic readout, i.e., the initial count of the number. The tobacco shred that is greater than or equal to the average pixel area of the tobacco shred is judged as an adhesive and an overlapping tobacco shred, and the position of the tobacco shred is intercepted by the centroid method and the minimum external moment. The formula for judging adhesion and overlapping tobacco shreds is shown in (2)

$$T = \{R \geq 9500,\ R \in N\}, \tag{2}$$

where R is the area of the tobacco shred, T is the value of the pixel area of the adhered and laminated tobacco shred, and N is a natural number.

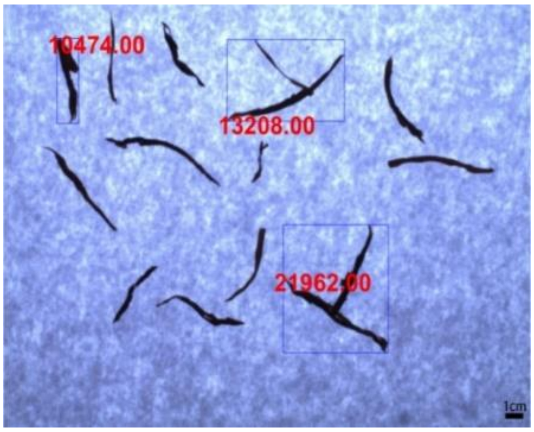


Fig. 8. Position of the adhesive and the overlap of the tobacco shreds.

After the processing of (2), the tobacco shred with a pixel area greater than 9500 is screened out, and the result is shown in Fig. 8. The centroid method is used to determine the position of each tobacco shred, using the minimum external moment to select each tobacco shred.

B. ROI Region Extraction of Target

ROI zones (complex zones) are parts of an image that can be irregular shapes of points, lines, and surfaces, often used as samples, masks, cropping zones, or other operations for image classification. There are two methods to extract ROI region, automatic extraction based on machine vision and manual extraction based on human-computer interaction. In this paper, the method of manually extracting the ROI region based on human-computer interaction is adopted to segment the adhesion and overlap images of tobacco shreds, and the mask is used mainly for extraction [18].

The mask is a binary image with a mask value of 255 for complex areas and 0 for noncomplex areas. To obtain the mask, the contour of the tobacco shred must be extracted. Due to the irregularity and variability of the tobacco shred, it is impossible to extract the contour automatically of the adhesive and the overlapping tobacco shred, so the contour drawing of the binary image of the adhesive and the overlapping tobacco shred can only be done manually.

Firstly, one of the separately extracted overlapping tobacco shreds was selected as the target, and a convex point of the target tobacco shred was taken as the starting point. The lines were connected along several convex points of the target tobacco shred until the lines were connected back to the starting point, and the contour drawing was completed, as shown in Fig. 9. After the drawing is completed, the mask image is obtained by using polygon filling to complete the binary mask extraction of the target tobacco shred. The results are shown in Fig. 10.

When the mask image is added to the original image, only the nonzero region is visible, and all the regions in the mask where the pixel value is zero and overlaps the original image will be invisible. In this paper, the acquired target tobacco shred mask is added to the original laminated tobacco shred binary image to complete the ROI region extraction of the target tobacco shred and realise the binary image segmentation of laminated tobacco shred. The results are shown in Fig. 11.

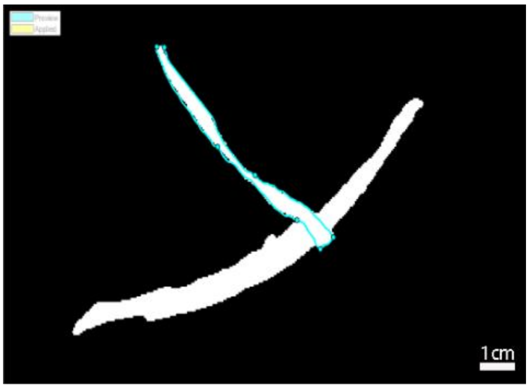


Fig. 9. Drawing of the manual tobacco shred outline.

Fig. 10. Mask extraction.

Fig. 11. ROI region extraction.

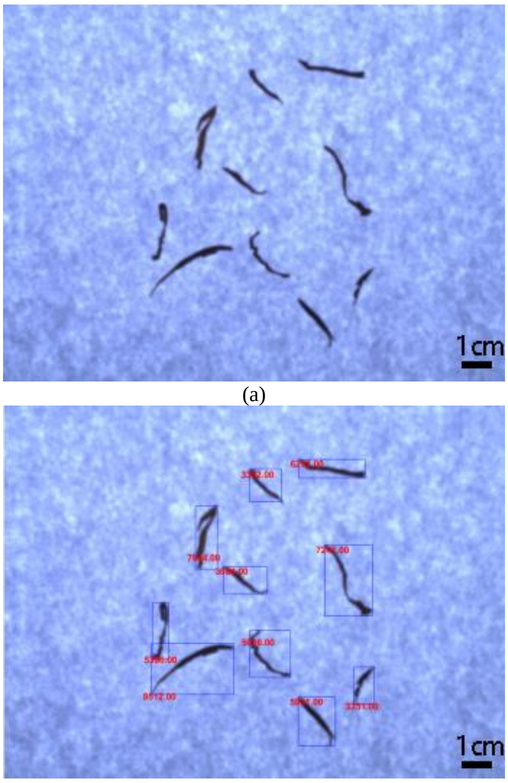
After the tobacco shred is divided, it is counted manually to obtain the exact quantity of adhesive and overlapping tobacco shreds, and the total number of tobacco shred is counted on the basis of the initial count.

IV. EXPERIMENTAL DATA ANALYSIS

A. Experimental Evaluation

In experimental testing, the tobacco shreds are randomly selected from the cut tobacco bag and placed on a white transparent gasket without overlap. Through the visual detection method in this paper, the quantity of independent tobacco shreds placed at random was counted. This paper involves the calculation of the maximum quantity of 20 tobacco shreds, and considering that the tiling area of 20 tobacco shreds is large, and value of the pixel area of single sticks of tobacco shreds is about 9500, to ensure the clarity of the image of each stick of tobacco shred, the resolution of the final generated image is 2048 pixels ×1536 pixels.

It can be seen from Fig. 12 that 10 independent tobacco shreds are counted using the connected domain labelling method. The accuracy of the algorithm is 100 %, and the average time is 1.0 s.



(a)

(b)

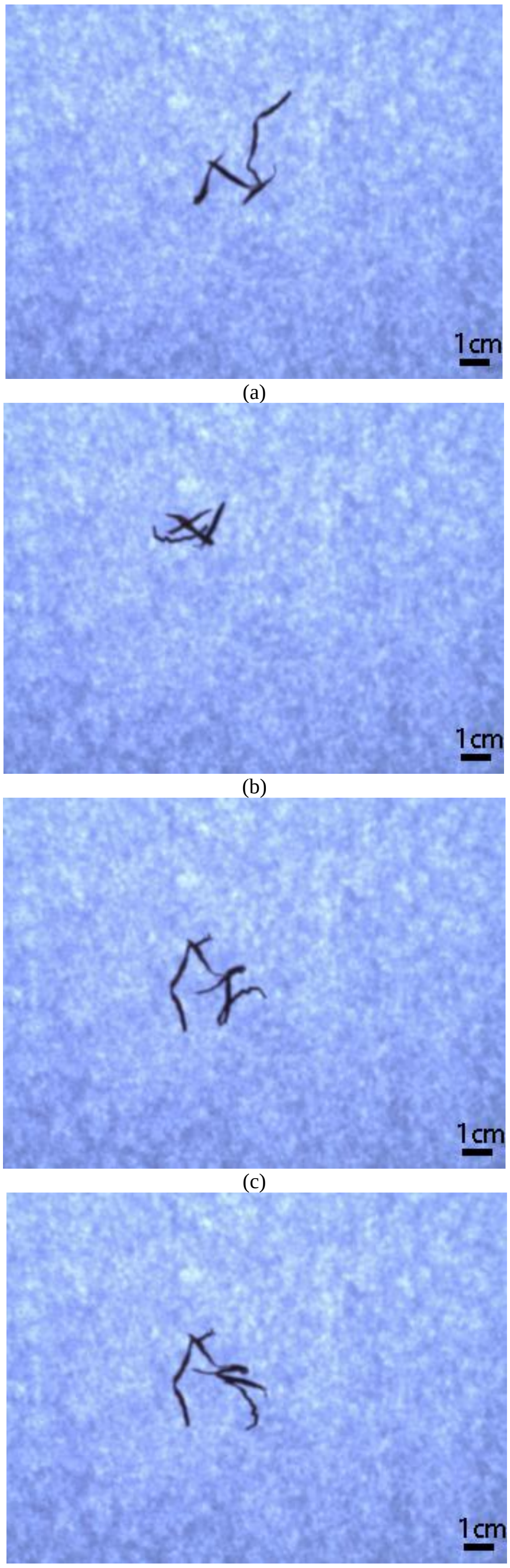
Fig. 12. Counting effect on the sample image: (a) Sample; (b) Counting effect.

Statistical analysis of testing results. Two groups of 4 and 5 tobacco shreds were randomly selected from the cut tobacco shred bag of a tobacco shred company and placed in the state of adhesion and overlapping, and quantitative statistics were carried out, as shown in Fig. 13.

It can be seen from Table I that the method of extracting the ROI region is more accurate in the quantity statistics of adhesive and overlapping tobacco shreds, with an average accuracy of 90 % and an average time of 4.5 s. The error mainly comes from the artificial judgment based on the image or the misjudgment, i.e., the artificial assignment in the complex scene will also lead to the recognition error.

TABLE I. STATISTICAL RESULTS.

Sample	**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**
Actual quantity	4	4	5	5
Statistical quantity	4	4	4	4
Accuracy rate	100 %	100 %	80 %	80 %
Time consuming	4 s	4 s	5 s	5 s



(a)

(b)

(c)

(d)

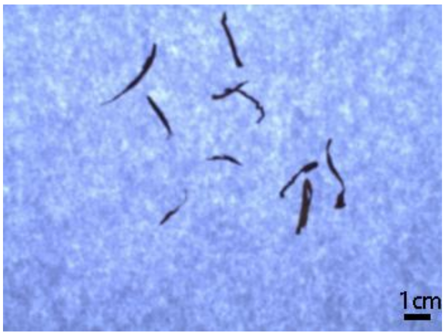
Fig. 13. Sample and counting effect of adhesive and overlapping tobacco shreds: (a) Sample 1; (b) Sample 2; (c) Sample 3; (d) Sample 4.

B. *Tobacco Shred Quantity Statistics*

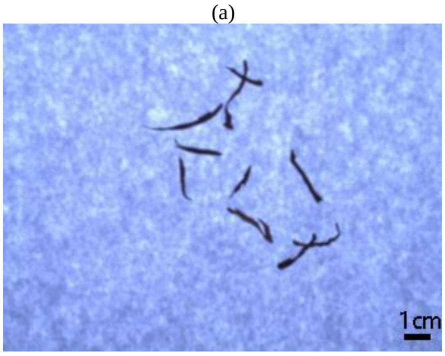
Randomly select 10, 15, and 20 tobacco shreds from a tobacco shred company cut tobacco shred bag, and scatter the tobacco shreds at a height of 20 centimeters from the transparent white gasket. After the first count of the same group of tobacco shred samples, they are randomly scattered again and counted twice by the same experiment. In the operation process, the broken tobacco shred should be avoided as much as possible to prevent the subsequent counting of tobacco shreds from being affected.

Because this experiment is carried out indoors and there is no external force, so the tobacco shred is only affected by gravity and air resistance, the collision between the tobacco shred is less, as long as the gravity is greater than the air resistance, the tobacco shred will randomly fall on the white transparent gasket. The statistical effect of the method in this paper is verified by comparing the actual quantity with the statistical quantity error of the method in this paper. The statistical results are shown in Figs. 14–16.

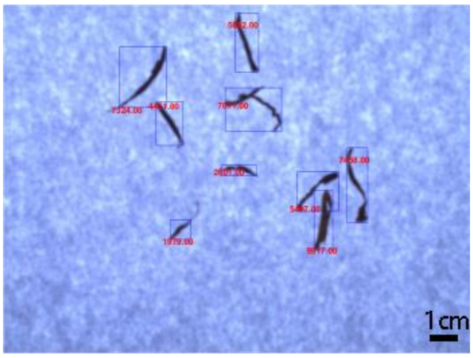
As can be seen from Table II, samples 1-2, 3-4, and 5-6 constitute a comparison scheme with different numbers (varying degrees of complexity). Affected by random scattering, they have different degrees of adhesion and overlap at different levels of complexity. For example, sample 3 has three adhesions and overlaps, while sample 5-6 has only two. The accuracy rates of sample 1 and sample 2 are both more than 90 %, but there is a difference. The reason is the influence of adhesion and overlap, which leads to an increase in the calculation time (the calculation time of sample 2 is 1 s longer than that of sample 1). Compared to manual labour, efficiency is improved by 100 %. For samples 3-4 and 5-6, the accuracy of the recognition times is consistent due to the influence of adhesion and overlap, but the recognition rate is improved due to the increase in the quantity of tobacco shred. When the influence of adhesion and overlap is constrained (such as controllable human error), the total time is basically maintained at the same level (about 3 s), while the manual time is linearly increased due to the increase in number. Therefore, for different complex scenes, the method in this paper basically keeps the error number of recognition at 1. With increasing the quantity of samples, the statistical accuracy of the number increases and the minimum accuracy is 90 %. Meanwhile, the calculation time is basically unchanged and the efficiency can be improved by more than 100 % compared with manual counting.



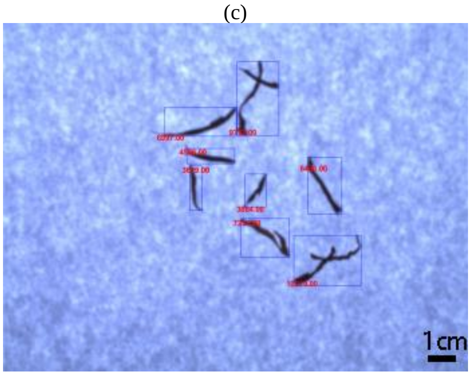
(a)



(b)

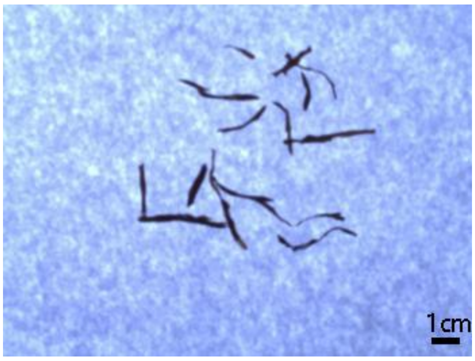


(c)

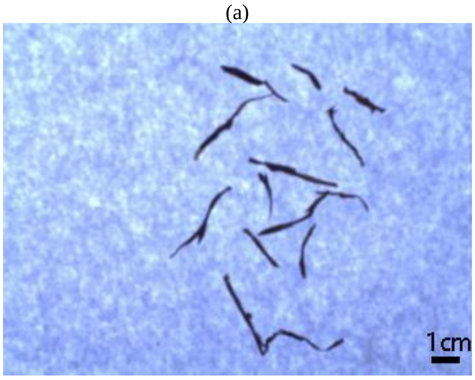


(d)

Fig. 14. Ten tobacco shred samples and counting effect: (a) Sample 1; (b) Sample 2; (c) Counting effect of Sample 1; (d) Counting effect of Sample 2.



(a)



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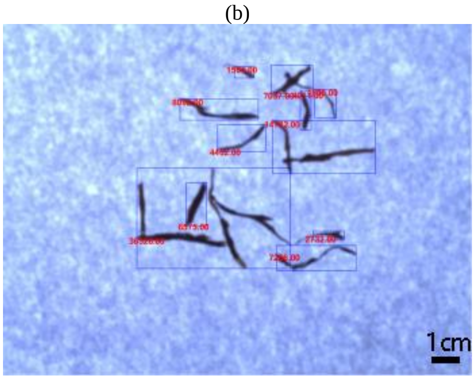

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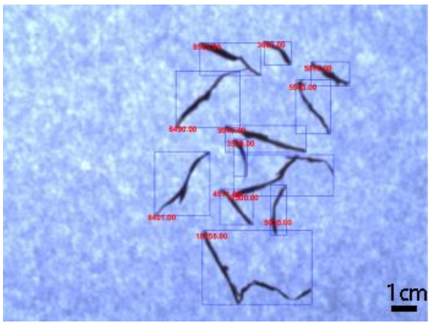
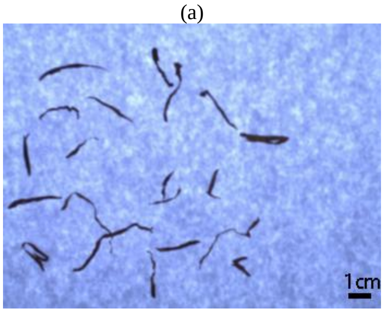


(d)

Fig. 15. Fifteen tobacco shred samples and counting effect: (a) Sample 3; (b) Sample 4; (c) Counting effect of Sample 3; (d) Counting effect of Sample 4.

(a)



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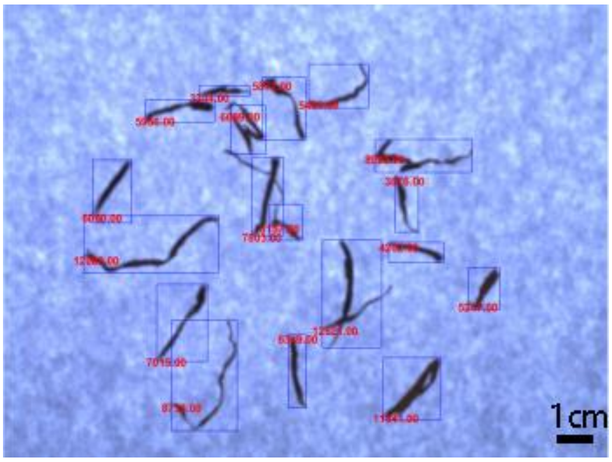

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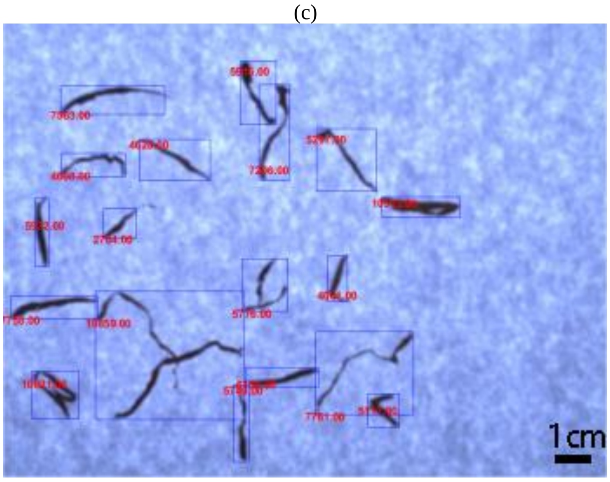

(d)

Fig. 16. Twenty tobacco shred samples and counting effect: (a) Sample 5; (b) Sample 6; (c) Counting effect of Sample 5; (d) Counting effect of Sample 6.

TABLE II. STATISTICAL RESULTS OF TOBACCO SHRED QUANTITY IN COMPLEX SCENARIOS.

Sample	**Preliminary statistics**	**Adhesive and overlapping tobacco shred**	**Total time consuming**	**Total statistics**	**Actual number**	**Accuracy rate**	**Manual meter Counting time**
1	9	1	2 s	10	10	100.0 %	5 s
2	8	2	3 s	9	10	90.0 %	5 s
3	11	3	5 s	14	15	93.3 %	7 s
4	12	2	3 s	14	15	93.3 %	7 s
5	18	2	3 s	19	20	95.0 %	10 s
6	18	2	3 s	19	20	95.0 %	10 s

V. CONCLUSIONS

Aiming at the problems of unstable accuracy and low efficiency of tobacco shred quantity statistics, a noncontact tobacco shred quantity statistics method based on machine vision was established for the first time to carry out tobacco shred quantity statistics. The results showed that:

1. The average accuracy is 100.0 % for the quantitative statistics of tobacco images of independent tobacco. For the quantity statistics of cut tobacco images with adhesive and overlapping interference, the minimum correct rate is 90 %, and the accuracy increases with the increase of cut tobacco quantity.
2. For tobacco shred quantity statistics, the efficiency of this method is only affected by complex scenarios (complex scenarios are controlled, and the processing time is about 3 s). Efficiency increases by more than 100 % compared to manual handling.

Due to the limitation of the characteristics of tobacco shred, it is impossible to segment the adhesive and overlapping tobacco shred by extracting ROI region from the plane perspective to achieve fully automated tobacco shred quantity statistics. Therefore, the next step requires multiperspective in-depth data processing to improve the degree of automation and accuracy. At the same time, the work in this paper also provides an achievable technical basis for the next step of measuring the width of tobacco shreds.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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