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An Approach for Defect Detection and Classification of the Yarn Ends for Splicing

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Abstract

This paper presents an automatic vision based system for quality control of yarn ends ready for splicing, which is aimed to establish a standard quality measure and lower manufacturing cost. New approach for defect detection and classification is presented. In this approach, features describing the shape and surface defects are extracted and defects are classified into different classes. Examples of defects are used to train the classification system using neural network. Experimental results show that a high detection and classification rate can be obtained using this approach.

1. Introduction

Reliable and accurate quality control is an important element in industrial textile manufacturing. For many textile products, a major quality control requirement is to judge yarn quality. Ring spinning produces yarn in a package form called a cop. Since cops from ring frames are not suitable for further processing, the winding process serves to achieve additional objectives made by the requirements of the subsequent processing stages. The winding process has the basic function of obtaining a larger package from several small ring bobbins. This conversion process provides one with the possibility of cutting out unwanted and problematic objectionable faults. The process of removing such objectionable faults is called yarn clearing. After removing the faults both yarn ends are joined together using a traditional technique of knotting. It is difficult to keep a high quality of yarn by knotting, as the knot itself is objectionable due to its physical dimension appearance and problem during downstream processes, the knot is responsible for 30 to 60% stoppages in weaving [1,2].

Splicing is the ultimate method to eliminate yarn faults and problems of knots and piecing. Splicing is a technique of joining two yarn ends by intermingling the constituent fibers so that the joint is not significantly different in appearance and mechanical properties with respect to the parent yarn. Splicing technology has grown so rapidly in recent years. Many techniques for splicing have been developed such as Electrostatic splicing, Mechanical splicing and Pneumatic splicing. Among them, pneumatic splicing is the most popular [3]. The splicing consists of untwisting then re-twisting yarn ends using air blast, i.e., first the yarn is opened, the fibers intermingled and later twisted in the same direction as that of the parent yarn. [4,5]Splicing proceeds in two stages with two different air blasts of different intensity. The first air blast untwists and causes opening of the free ends. The untwisted fibers are then intermingled and twisted in the same direction as that of parent yarn by another air blast.

Presently, checking the appearance of the opening and splicing is still accomplished by human experts [6] which is time consuming and suffers from variability due to human subjectivity. Consequently, automated investigation of yarn ends and automated classification of splice joint faults are highly desirable. Such a system would be useful not to objectify quality control of textile articles but also provide a basis to perform online inspection for splice joint at winding machine.

In this paper, we are investigating a novel automated visual inspection system for detection and classification of defects encountered in yarn opening ends ready for splice. Method for detection and description of shape and surface defects of the yarn ends are described and analyzed.

2. The Proposed System Model for Yarn End Inspection

2.1 Defect detection and classification

The most important properties of the yarn end opening inspection are the length and untwist ratio of the opening zone. Each one alone is insufficient for a complex classification task, but the combination of both properties will introduce a good classification capability [7,8], for that reason the proposed system consists of two subsystems, one for untwist inspection and other for length inspection as shown in Figure 1. In Table 1 Samples of the different grades of yarn ends are shown.

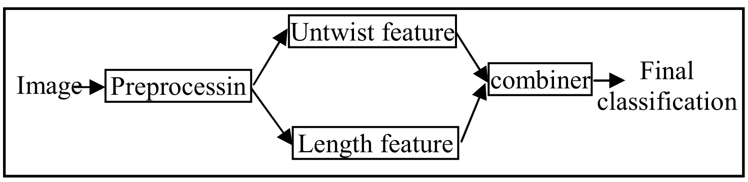
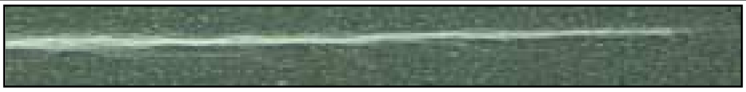
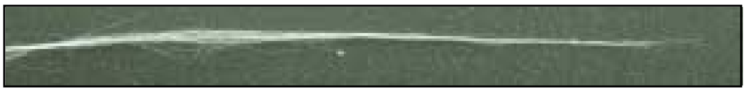
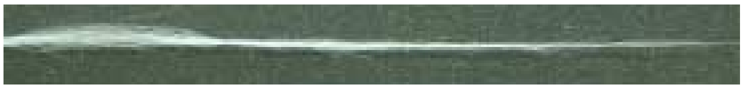


Figure 1. Defect classification system

Table 1. Different grades of yarn ends

Opening criterion	Grade	Opening shape
Length of the opening zone	optimum	
	average	
	short	
Untwist of the opening zone	optimum	
	partially	
	Partially overturn	
	Complete overturn	
	zero	

2.2 Features for defect detection and classification

Preprocessing

We implemented our algorithm in MATLAB using image-processing toolbox. On the beginning, we smoothed the images by standard median filtering on 5x5 pixel neighborhoods [9]. The filtering reduced the graininess of the images and fewer false edges were detected in the next step of segmentation. The segmentation process itself eliminated many small regions of the image that resulted in noise as shown in Figure 2. As we only deal with the contour of the segmented image, all images were transformed to black/white (B/W) ones and contours were extracted from them.

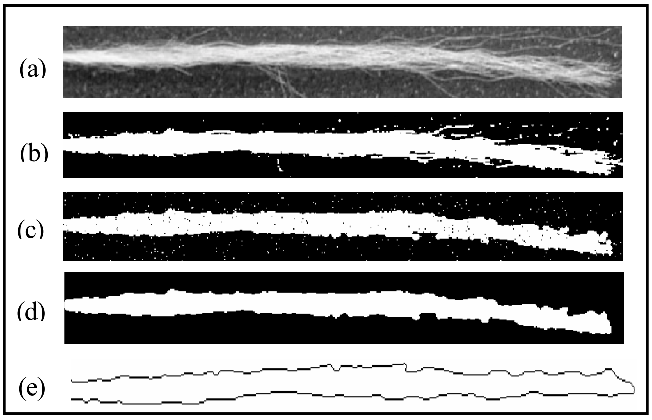


Figure 2. Preprocessing of the image a) original image, b) binary image, c) binary image with noise, d) filtered image, e) B/W contour image

Feature extraction

In the beginning the opening of the yarn end is checked to reduce the time and amount of data to be processed. If the yarn end is opened, the degree of opening and the length of opening zone are checked as shown in Figure 3. In order to explain these as well as the overall classification algorithm, consider the following:

- Y: the width of parent yarn
- L: the length of opening zone
- The opening zone is divided to three equal areas starting from the beginning of the opening. These areas are :
    - Area one : from the start point of the opening zone to 5mm and has average width W1
    - Area two: from 5 to 10 mm and has width W2
    - Area three: for the length greater than 10 mm with average width W3

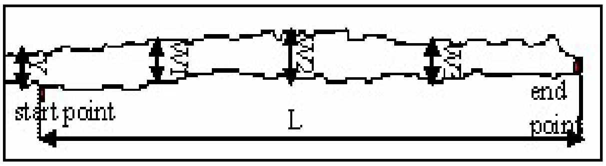


Figure 3. Feature extraction on the image

2.3 Classification procedure

As presented, the procedure for automated visual inspection consists of two modules, one of which is used for untwist defect detection and classification, while the other is used for length detection and classification. The system is based on the classification tree shown in Figure 4 and the procedure is done as follows:

- If W1 is less than or equal Y, then the opening is classified as defect opening (D).
- If W1 is greater than Y and the length of the opening zone is less than 5 mm, then the opening is classified as short length with good opening (C1), or partially opening (C2) according to the degree of untwist (ratio W1 / Y).
- If the length is greater than 5mm and less than 10 mm, then the opening is classified as medium length optimum opening (B1), partially opening (B2), partially overturn (E), or complete overturn (F).
- If the length is greater than 10 mm , the opening is classified as optimum opening (A) or partially overturn (E) according to the ratio between W3 and Y.

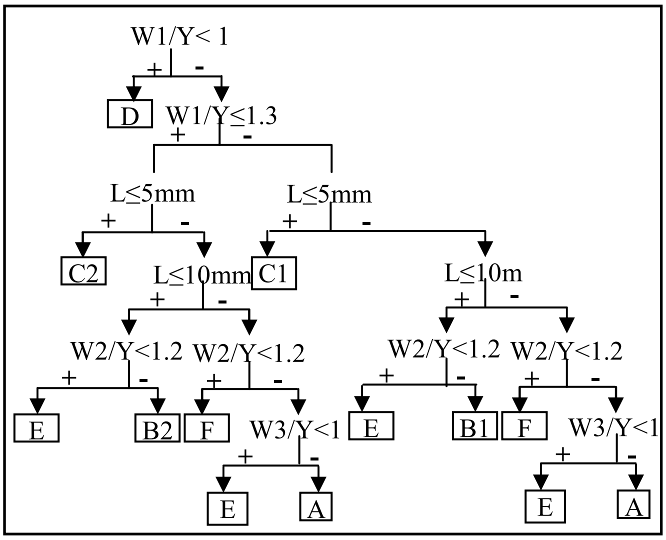


Figure 4. classification tree

The opening is classified as optimum or acceptable opening if it lies above the base line as shown in Figure 5. Otherwise, it is unacceptable opening.

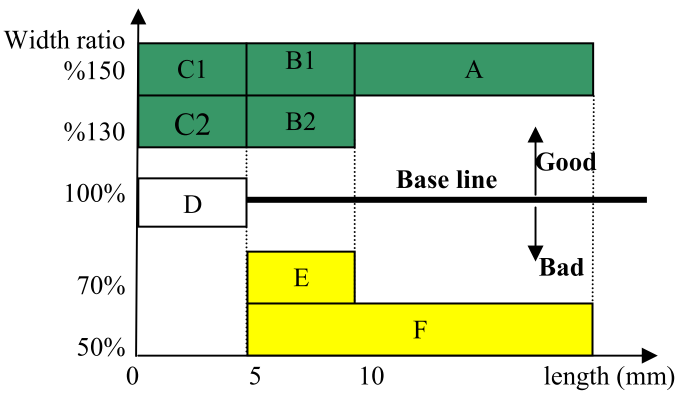


Figure 5. classification system

3. Experimental Results

In order to assess the validity of the method presented here, we have performed two sorts of experiments. One by the proposed approach while the other is done by using neural network approach.

A database of 120 images (640 x 480 pixels) randomly collected from 12 different yarns was used to determine the performance of the system. Images are acquired using digital camera. First, human experts analyze the images and all features were extracted and described, then the image processing is used. The performance of the system was evaluated for classification error and classification time. The definition of classification error is :

$$C.E = \left(I/_{T} \right) \times 100 \quad \text{---------------------} (1)$$

Where, I is the number of incorrect classification, and T is the total number of images.

While the average time needed for classification is calculated from the equation 2:

$$t_c = t_i + t_p \quad \text{-------------------------} (2)$$

Where: t_i is the time required for acquire the image, t_p is the processing time, and t_c is the total classification time.

Table 2 summarizes the classification results obtained by the proposed method. It can be seen from this results that, zero classification errors for classes A,B2,C1,C2,E and F are obtained. While 33% and 13 % classification errors are recorded for B1 and D classes respectively. The reason for that could be, some of B1 classes were classified as C1, and some of D classes were classified as F. In general, the results obtained by this approach are encouraged. The total number of incorrect classification is only three samples, and the average classification error is 6%.

Table 2. Classification results obtained from the proposed approach

criteria	T	Image Processing		
		Correct (C)	Incorrect (I)	Classification error %
A	50	50	0	0
B1	6	4	2	33
B2	8	8	0	0
C1	4	4	0	0
C2	12	12	0	0
D	8	7	1	13
E	24	24	0	0
F	8	8	0	0
Total	120	117	3	6%

Time needed for classification is about 5 seconds on a standard PC. The most time consuming portion of our program by so far was the threshold and edge detection of the image. Translation of our MATLAB code into more efficient language may enable us to reduce the computation time.

4. Neural Network Approach

Our second approach used detailed geometric models of the yarn ends, and neural network. A particular open question we investigated was whether performance can be enhanced by using neural network to recognize subtle differences in global features. Neural network have been successfully applied to many image classification problems [10]. Neural network can run fast, can examine many competing hypotheses simultaneously, and can perform well with noise and distortion. We employ online back propagation neural Network for yarn end classification. Out of 120 samples, 108 samples were used for training the network and the rest were used for the test set. We investigate different network topologies of one or two dimensions and various numbers of nodes. It turns out that one dimension [5-3-8] network architecture with quick propagation algorithm yields the best results. This network had average training correct classification rate 96.67% .

A specific illustration of the classification results is given by a summary of all individual classifications. This function is illustrated in a classification confusion matrix in figure 6. The columns and rows of this matrix represent the eight discrete grades of quality represents by the pervious approach and the net response respectively. The figure shows that for all 91.67% of the samples the classification is correct, and 8.33% classification error obtained specially for classes C2, and E.

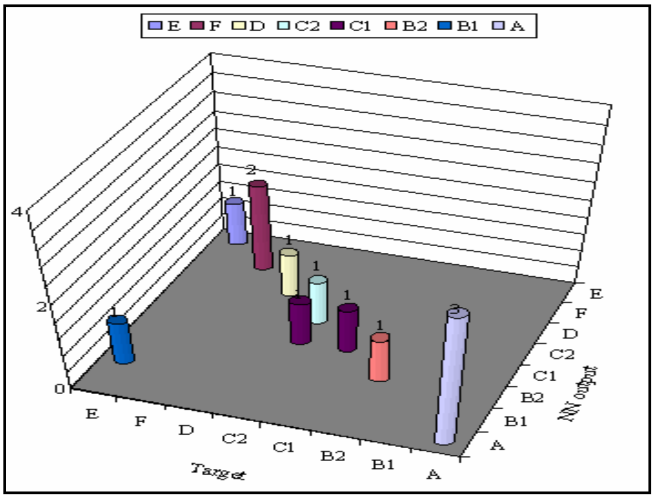


Figure 6. Classification confusion matrix: columns and rows represent the eight grade of quality for the proposed grade system and the net response

Conclusion

An automated visual inspection system for defect detection and classification of yarn ends ready for splicing on winding machine is presented in this paper. The presented method and algorithm were successfully tested on a limited number of yarn end samples and encouraging results were obtained.

The future work will be conducted on testing of currently developed algorithm on larger number of samples and will include investigations of other methods and algorithms for defect detection and classification.

Acknowledgments

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References

[1] Gebald G., and Leven J, Knitting advanced with the knot free yarn specified, Knitting international, 1983-90, No: 1070 February pp 57-60

[2] Kaushik, R.C.D., Hari, P.K., Sharma, I.C., and Sarkar, A.K, Performance of spliced yarn in warping and weaving, Textile Research Journal November 1987, PP 670-673

[3] Gebald G, Remarkable quality improvements by the Autoconer splicer, the results of 10 years practical experience, W. Schlafhorst AG & CO. Blumbenberger str. 143-145 D-41061 Mönchengladbach, The customer day 84, the future of spinning

[4] Hidetoshi Kimura, Pneumatic yarn splicing method and apparatus, USP 4,481,761 11/1984 57/22.

[5] Hiroshi Mima, Splicing method for spun yarns, USP 4,445,317 5/1984 57/22.

[6] Khaled Issa and Rudi Grutz, Investigation to optimize opening process for high twisted and plied yarn, Master thesis, Institut für Textil und Bekleidungswesen, Niederrhein University of Applied Science, Monchengladbach, Germany 1999.

[7] Brzakovic, D. and Vujovic, N. "Designing a defect classification system: A case study," Pattern recognition 29(8), pp. 1401-1419, 1996.

[8] J.livarinen and A.Visa, "An adaptive texture and shape based defect classification," in Proceedings of the 14th International Conference on Pattern Recognition. (Brisbane, Australia), Aug.16-20 1998.

[9] William K. Pratt Digital image processing, 3rd ed., Academic press, New York, 2001.

[10] Claus Bahlmann,Gunther Heidemann, and Helge Ritter: "Artificial neural networks for automated quality control of textile seams", Pattern recognition 32(6), pp.1049-1060,June 1999.

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