

Textile Fibre Identification Research based on S²A-Net

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Abstract

Deep learning-based target detection algorithms have been a hot research topic in recent years, however, in fibre recognition, fibre targets are distributed in arbitrary directions and the horizontal rectangular box annotation used can contain a large number of blank non-target areas, which affects the detection accuracy. Therefore, this paper investigates the application of the rotating target detection algorithm S²A-Net in fibre recognition. The results show that the average accuracy of fibre recognition reaches over 89%, and its prediction frame fits closely to the fibre edge, which provides a basis for subsequent research on automatic fibre diameter measurement, indicating that the rotating target detection algorithm has a good application prospect in fibre recognition.

Keywords

S²A-Net; Object Detection; Fibre Identification.

1. Introduction

Textile fibres are fibres used in the manufacture of textiles and are divided into natural fibres and chemical fibres, of which natural fibres can be divided into plant fibres (such as cotton, linen, ramie etc.) and animal fibres (such as wool, cashmere, rabbit wool, mohair etc.) and chemical fibres can be further divided into recycled fibres (such as viscose fibres, acetate fibres, lyocell fibres, modal fibres etc.) and synthetic fibres (such as polyester, acrylic, spandex, nylon, etc.). In the textile industry and garment manufacturing, the composition of the fibres used in cloth has always been a very important factor affecting the quality of the raw material. In the textile testing process, samples sent by textile product sellers for testing can take up more than 90% of the number of items tested by textile testers, whereas traditional textile fibre composition testing relies on manual visual identification, aided by combustion and its complex chemical dissolution steps, etc., which is not only time consuming and labour intensive, but also requires extremely high manpower training costs. The training time required for a mature testing worker ranges from 3-4 months. With the development of deep learning technology, the use of deep learning technology to identify the fibre content of textiles is a fast and cost effective way to reduce costs and is one of the directions of development.

At present, the main methods used by traditional textile testing institutes for fibre identification are: the combustion method, the microscope method and the dissolution method. The combustion method refers to the initial identification of fibre types according to the state of the fibres near the flame, in contact with the flame and when leaving the flame, as well as the odour produced during combustion and the characteristics of the residue after combustion; the microscope method for fibre identification is based on the principle of observing the longitudinal and cross-sectional morphology of unknown fibres through a microscope and identifying the type of unknown fibres against standard photographs and morphological descriptions of the fibres; the dissolution method is based on the dissolution characteristics of different textile fibres are identified on the basis of their solubility properties in different chemical reagents at different temperatures.

With the development of deep learning technology, it has become common to apply target detection to the exploration of fibre recognition. The classical deep learning-based target detection algorithms can be divided into candidate region based target detection algorithms and regression based target detection algorithms. Candidate region based target detection algorithms, also known as Two-Stage methods, divide the target detection problem into two stages: one is to generate a candidate region proposal, and the other is to put the candidate region into the classifier to classify and correct the position. This detection method has high detection accuracy, but is slow. The representative algorithms are: R-CNN[1], SPP-Net[2], Fast R-CNN[3], Faster R-CNN[4], etc. The regression-based target detection algorithm search is also called One-Stage method, which directly calculates the image to generate detection results, the detection speed is faster, but the detection accuracy is low, the representative algorithms are YOLOv1[5], YOLOv2[6], YOLOv3[7], YOLOv4[8] and SSD[9], etc.; but the above target detection algorithms However, the above-mentioned target detection algorithms use horizontal rectangular boxes for data annotation, which will make the annotation boxes contain a large number of blank non-target areas and affect the accuracy of the model.

2. Experimental Preparation

2.1. Sample Acquisition

In target testing, the closer the dataset distribution is to the real application scenario, the more positively it will drive the research work, and obtaining the dataset from the real application is more meaningful for algorithm evaluation. Relying on the fibre identification needs of a real textile testing organisation, the textile samples involved in the experiments in this paper were obtained from real samples sent for testing.

2.2. Image Capture

Once sufficient textile samples are available, the samples are sampled according to the provisions of the national standard FZ/T 01057.1-2007. The general sample size should be at least one complete loop pattern or tissue. The textile products are first cut to a size of 5cm*5cm, then the fibres are prepared with the aid of a Haar slicer, etc., and a transparent medium is used to disperse them sufficiently before they are made into slides for observation under a microscope. A fibre fineness meter with an Olympus BX43 microscope is used for this work, and the built-in software is used to capture fibre images. A two-component blend of cotton and linen was selected as the textile sample for this paper, and images of two fibres in the field of view were collected, including cotton-linen and cotton-ramie fibres, i.e. there were three fibre categories in the self-collected data set.

2.3. Data Labeling

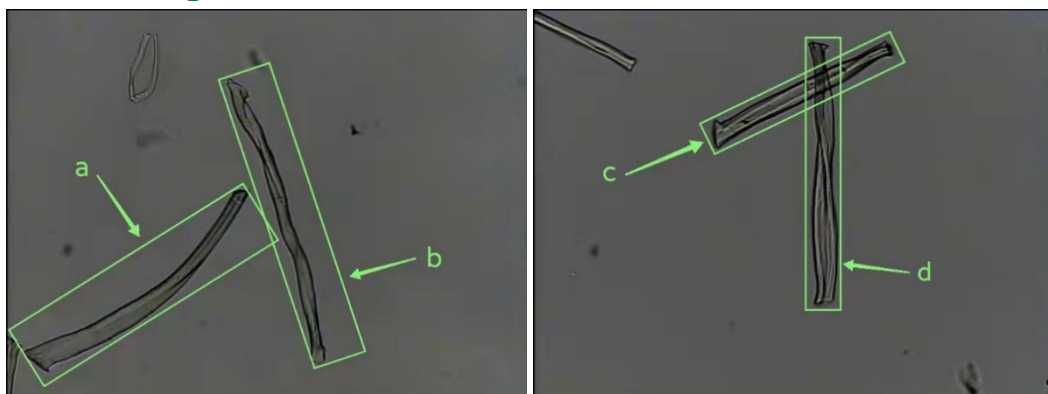


Figure 1. Example of a rotating rectangular box annotation for a fibre target

In this paper, the rolabeling annotation tool was used to annotate each fibre category with a rotating rectangular box by manual identification. When annotating the rotated rectangular box for the fibre data, a uniform annotation guideline is followed for all fibre images, i.e. all fibres present in the image are annotated as far as possible, with the exception of damaged or too short fibres, as shown in Figure. 1. We can see that when annotating fibres with rotated rectangular boxes, the two fibre targets have fewer intersecting annotation boxes, and the annotation boxes contain less background information in the blank non-target area.

3. Model Construction

The S²A-Net algorithm is a single alignment network based on RetinaNet [10], which was proposed by J. Han et al. The network was proposed mainly to solve the target detection problem in aerial images. As both aerial images and fibre images of textile fibres have the property that targets are aligned in any direction within the image, inspired by the S²A-Net target detection algorithm for aerial images based on the DOTA dataset, the S²A-Net algorithm is used in this paper in the exploration of fibre recognition.

3.1. Structure Introduction

The overall architecture of S²A-Net consists of four parts: the backbone, the feature pyramid, the Feature Alignment Module (FAM) and the Oriented Detection Module (ODM), as shown in Figure 2.

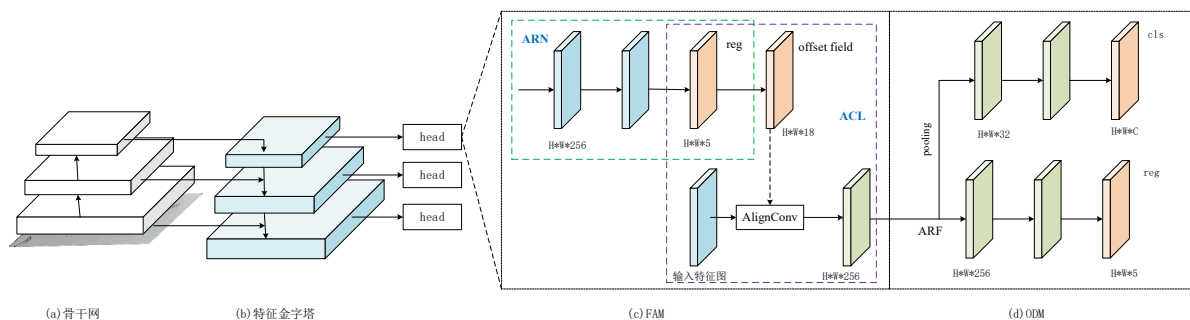


Figure 2. S²A-Net structure

In S²A-Net the FAM and ODM comprise the detection head applied to each scale of the feature pyramid. The FAM consists of an Anchor Refinement Network (ARN) and an Alignment Convolution Layer (ACL), where the FAM generates high quality rotational anchors via the ARN, then feeds the anchors and input features into the ACL, and adapts the features to the corresponding anchor boxes (ABs) via the Alignment Convolution in the ACL layer. (AlignConv) in the ACL layer, and then adaptively align the features according to the corresponding anchor boxes (ABs). The feature maps extracted by the adaptive alignment convolution in the ACL layer are used as input to the ODM, where orientation-sensitive features are generated by first encoding the orientation information with Active Rotating Filters (ARF)[11], pooling the features to extract orientation-invariant features, and finally applying classification and regression subbranches to generate the final predictions.

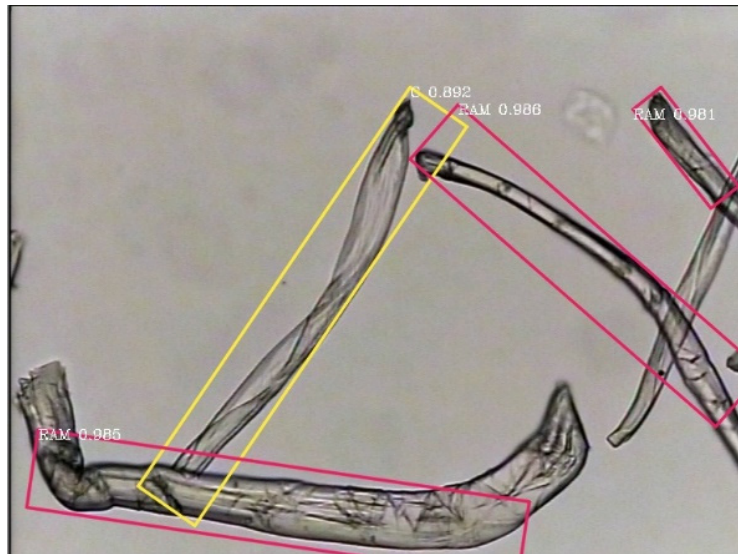
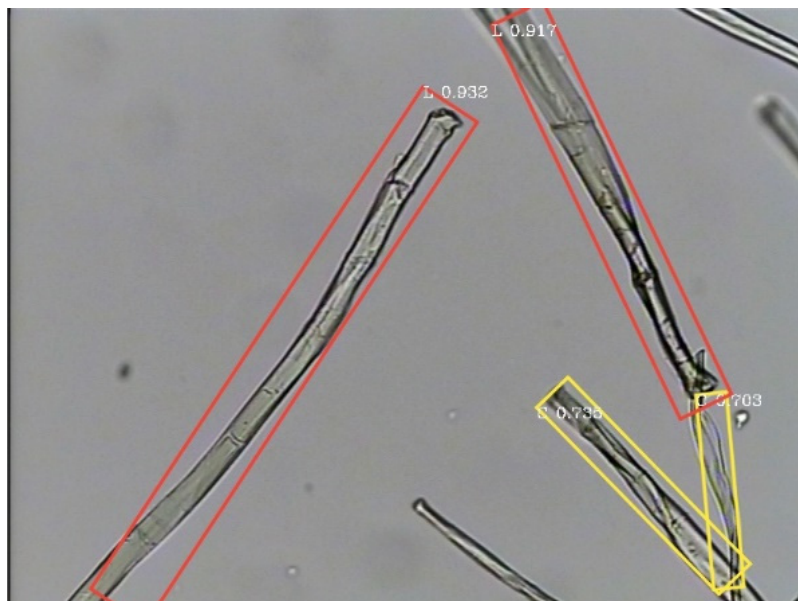
3.2. Results

This paper uses Python as the programming language and NVIDIA Geforce GTX 1080Ti as the GPU. 406 cotton fibres, 383 flax fibres and 392 ramie fibres were labelled in the two-component fibre dataset in this paper, and the fibre identification results of the model were compared with those of the manual fibre identification, and the results are shown in Table 1.

Table 1. Performance of the algorithm on a two-component fibre dataset

Fibre types	Quantity / Root	Consistent with manual identification Quantity/Root	Identification agreement ratio/%
Cotton fibre	406	358	88.18
Linen fibre	383	346	90.34
Ramie Fibre	392	352	89.80

Its qualitative detection of the output rectangular frame for the two component fibres is shown in Figure 3 and Figure 4.

**Figure 3.** Cotton-Ramie fibre identification**Figure 4.** Cotton-Linen fibre identification

3.3. Analysis of Results

Fibre identification using the S²A-Net algorithm achieved an average agreement of over 89% with manual inspection and its predicted number of fibre identifications beyond the frame to

fit closely to the fibre edge, facilitating subsequent studies for automated fibre diameter measurement.

4. Summary

This paper first briefly introduces the background of textile fibre recognition and traditional fibre recognition methods, constructs a fibre dataset applicable to this paper from practical application scenarios, and then selects the rotating target detection algorithm S2A-Net based on fibre imaging characteristics, forming the following conclusions.

(1) By training on a two-component fibre dataset, the average recognition accuracy of cotton, flax and ramie fibres reached over 89%, laying the foundation for an alternative to traditional manual detection.

(2) The predicted output frame of fibre identification using the rotating target detection algorithm is close to the fibre edge, which facilitates the subsequent measurement of fibre diameter and quantitative analysis of fibres.

(3) Due to the limited number of samples collected in this paper, the accuracy of the model is still some distance away from being put into practical application. It is necessary to continue to enrich the fibre dataset, as well as optimise the model and train it on more fibre component datasets to improve the fibre recognition accuracy.

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