Enhanced 3D X-ray Tomography: Deep Learning-based Advanced Algorithms for Fiber Instance Segmentation

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Abstract:

Identifying specific properties of fibers in paper handsheets has been a challenge for many decades. In this chapter, some of the advanced algorithms for image segmentation to estimate these properties are systematically presented. The process of determining the appropriate operating conditions from the estimated properties is also elaborated. Moreover, the authors introduce a new machine-learning algorithm designed for 3D X-ray tomography. This technique utilizes 3D tomographic images to detect and differentiate intricate fiber structures. The novel four-step hybrid 3D fiber segmentation algorithm presented in the chapter involves deep-learning assisted semantic segmentation, which generates 2D images from 3D ones for fiber extraction. Additionally, the algorithm combines elliptical contour estimation with the marker-controlled watershed technique to separate fibers from the background area. By employing 3D reconstruction, individual fibers are identified. To validate the performance of this approach, the proposed methodology is implemented on a real-time sample of nylon fiber bundle data set under compression and its 3D X-ray image volume. The results demonstrate the algorithm's precision and efficiency compared to off-the-shelf image processing algorithms.

1. Introduction

In the realm of the pulp and paper industry, the meticulous craft of producing high-quality paper handsheets relies heavily on both the inherent properties of the pulp fibers and the operational parameters of the pulping process [1]. Understanding the intricate interplay between the operational variables and their influence on the final product’s fibrous structure is crucial for ensuring the production of paper products with desired characteristics. 3D X-ray tomography has emerged as a powerful tool for studying the microstructure of materials, including paper handsheets. This non-destructive imaging technique enables the visualization of internal structures with high resolution, providing valuable insights into fiber arrangement and distribution. Also, by correlating the fibrous structure with process conditions, operational optimization and improved product quality are achieved [2, 3]. However, achieving this requires thorough analysis and interpretation of fiber characteristics and operating parameters, and necessitates adjusting process conditions.

In recent years, there has been a noticeable trend towards leveraging advanced image processing techniques, particularly utilizing 3D X-ray tomography coupled with deep learning algorithms, to analyze the microstructure of paper handsheets. The deep learning algorithms were built upon the principles of artificial neural networks and possess unparalleled capabilities in discerning intricate patterns and features within visual data. The goal is to capitalize on these capabilities to understand the complex structural properties of fibers embedded within paper handsheets. These algorithms have proven pivotal in the new era of precision and efficiency in image analysis, offering highly accurate models that have transformed various applications, including image segmentation. This work aims to harness the power of these cutting-edge algorithms to delve into the intricate properties of fibers within paper handsheets. Two datasets of Nylon bundle fiber tomographic images were utilized in this study, as illustrated in Figure 1. Data set 1 is large, fully labeled, and annotated, making it threshold friendly. On the other hand, data set 2 is the small, target set, unlabeled, and thus is not threshold friendly, posing challenges for segmentation. The proposed method in this study is applied to data set 2 to demonstrate its effectiveness.

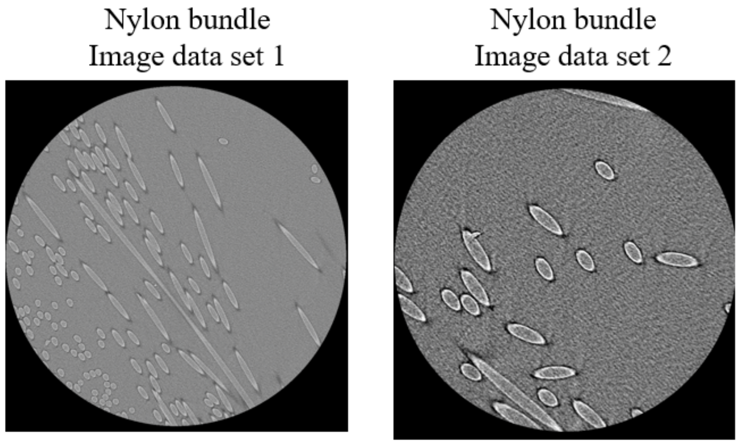


Figure 1 Nylon fiber bundle tomographic data sets

2. Background: Image Segmentation Methods

Image segmentation is a process that involves splitting an image into multiple segments to extract meaningful information. Over the years, advancements in image segmentation techniques have brought about significant changes in various fields, from medical imaging to autonomous driving. These techniques enable the automated analysis and comprehension of visual data by accurately delineating regions of interest through various software tools. Object detection identifies a bounding box corresponding to a class in the image, whereas image segmentation constructs a pixel-wise representation corresponding to an object in the image. This distinction allows for a much deeper understanding of image segmentation, addressing issues with greater precision and leading to more significant outcomes. Additionally, with the developments in deep learning algorithms and computational capabilities, convolutional neural networks (CNNs) are becoming the foundation for modern segmentation methods, offering improved accuracy and efficiency [4]. Image segmentation is divided broadly into two categories, one is semantic segmentation, and the other is instance segmentation.

2.1 Semantic Segmentation

The semantic segmentation method aims to allocate semantic labels to each pixel in an image, thus providing a pixel-wise classification of objects and regions. This approach is critical in tasks such as scene understanding, where the ability to distinguish between different object categories is paramount. State-of-the-art semantic segmentation models, such as U-Net [5] and DeepLab [6], leverage deep learning architectures to achieve remarkable accuracy. For instance, the U-Net architecture demonstrates exceptional performance in segmenting biomedical images [5]. Similarly, the DeepLab model showcases the effectiveness of combining CNNs with conditional random fields (CRFs) for semantic segmentation tasks [6]. To further refine the segmentation results, connected components analysis (CCA) with labeling is employed to detect individual panels in images and convert segment features to fusion decisions [7]. Integrating semantic segmentation with CCA is applied to the Nylon bundle image data set 1, as shown in Figure 2.

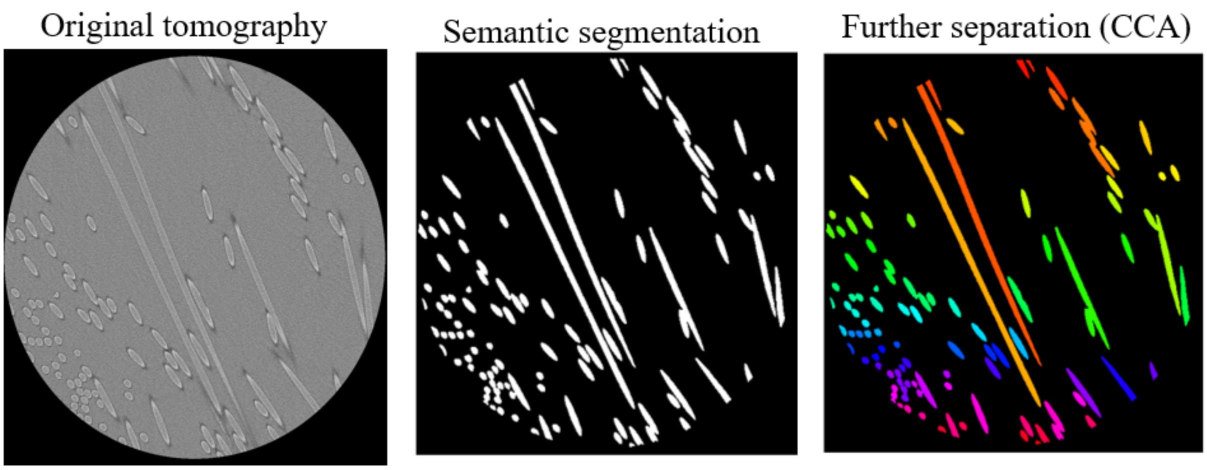


Figure 2 Semantic segmentation of the image data set 1

2.2 Instance Segmentation

Instance segmentation extends semantic segmentation by not only classifying pixels but also describing individual objects within each class. This fine-grained segmentation is particularly useful in scenarios where precise object boundaries need to be identified, such as object detection and tracking. Mask R-CNN [8], a popular instance segmentation framework, integrates region-based convolutional neural networks with mask prediction branches. The Mask R-CNN introduces this architecture, demonstrating its efficacy in accurately segmenting objects in images with complex backgrounds. To further enhance the performance, the Feature Pyramid Network (FPN) [9], is employed, utilizing a top-down network path incorporating lateral connections. This approach facilitates the extraction of features in a staged manner. Additionally, datasets like Microsoft's Common Objects in Context (COCO) [10] capture instances with intricate spatial layouts, further enriching the potential for advancements in image processing methodologies. Instance segmentation is applied to the Nylon bundle image data set 1, as shown in Figure 3.

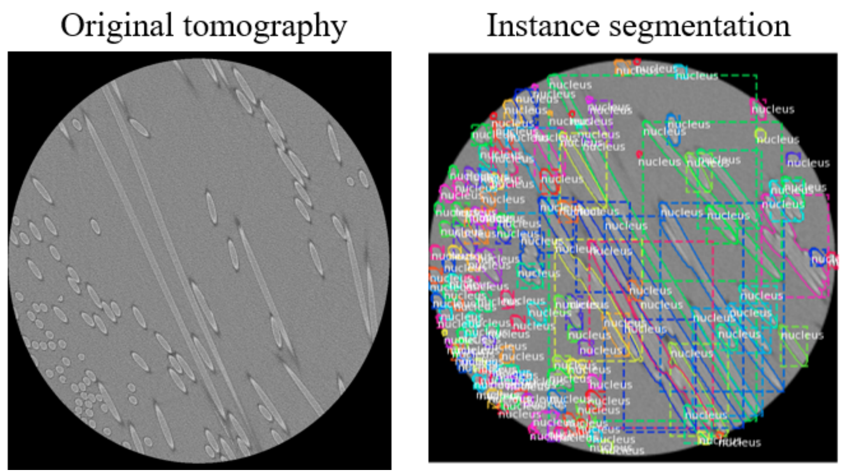


Figure 3 Instance segmentation of the image data set 1

In summary, the selection between semantic and instance segmentation hinges on the unique demands of the application [11]. Semantic segmentation offers a comprehensive view of the scene by categorizing pixels into classes, while instance segmentation provides a more detailed depiction of individual objects. When prioritizing object-level analysis, instance segmentation proves advantageous; however, for broader image comprehension tasks, semantic segmentation may suffice. Ultimately, choosing the segmentation approach should be guided by the specific objectives and constraints of the application at hand.

3. Image Segmentation Algorithms for Fiber Analysis

In the context of pulp fiber analysis, image segmentation plays a crucial role in characterizing nylon fiber bundles and paper pulp. By accurately understanding individual fibers within bundles, segmentation algorithms facilitate quantitative analysis of fiber properties such as length, width, coarseness, and orientation. This information is vital for understanding the structural properties of paper pulp and optimizing the manufacturing process [1, 2]. In [12], the significance of image segmentation in analyzing fiber bundle scale for non-crimp fabric-reinforced composites is elaborated. A graph-based segmentation method [13] is developed and validated on a synthetic fiber data set to identify the individual fibers accurately. A novel three-step algorithm is introduced to isolate individual papermaking fibers in μCT images of paper handsheets [14]. Also, watershed transformation algorithms are utilized for segmenting fiber networks in paper handsheets, emphasizing the utility of these approaches in handling complex fiber arrangements. Moreover, there is a discernible trend towards leveraging 3D imaging modalities, as demonstrated in [15], utilizing X-ray tomography to capture the intricate three-dimensional structure of fibers, enabling more comprehensive analysis.

Researchers are increasingly focusing on hybrid segmentation approaches, combining traditional image processing methods with innovative techniques to enhance segmentation accuracy and robustness [16]. Advancements in computational hardware and software have further enabled the processing of large-scale 3D image datasets, facilitating the development of robust segmentation algorithms capable of handling volumetric data efficiently. In conclusion, these advancements in image segmentation methodologies are poised to revolutionize our understanding of fiber materials and their applications across various industries.

In pulp fiber analysis, semantic segmentation is often preferred over instance segmentation due to several reasons. Firstly, semantic segmentation simplifies the segmentation process by categorizing regions of interest without distinguishing between individual fiber instances, making it suitable for analyzing homogeneous fiber distributions in paper handsheets. Secondly, semantic segmentation algorithms are computationally efficient, making them preferable for processing large-scale image datasets. Since semantic segmentation does not require delineating individual fiber instances, it achieves faster processing speeds while maintaining satisfactory segmentation accuracy. Moreover, semantic segmentation is well-suited for applications where the primary goal is to analyze overall fiber characteristics and distributions rather than identifying individual fibers. Overall, the choice between semantic and instance segmentation depends on the specific requirements of the analysis task, with semantic segmentation offering a streamlined and computationally efficient approach for analyzing overall fiber characteristics in pulp and paper fiber materials.

3.1. Deep-learning Algorithms for Image Segmentation

In recent years, deep learning has significantly advanced semantic segmentation by enabling the creation of highly accurate and efficient algorithms. Various deep-learning architectures have been explored in image segmentation. A fully Convolutional Network (FCN) [17] was introduced to achieve state-of-the-art performance by converting traditional classification networks into fully convolutional ones. Subsequent studies have focused on improving FCNs, including the integration of skip connections in U-Net [18] and the implementation of atrous spatial pyramid pooling [19].

However, in the domain of paper pulp fibers, there is limited literature specifically addressing the semantic segmentation of paper pulp fibers using deep learning techniques. Notably, one recent study utilized deep learning to automate wood species detection and classification in microscopic images [20]. Another study applied supervised machine learning techniques, including Lasso regression, support vector machine (SVM), feed-forward neural networks (FFNN), and recurrent neural networks (RNN), applied to fiber data from pulp testing micrographs [21]. By leveraging the advantages of each of those algorithms, this method achieved a maximum accuracy of 81%, offering the potential for consistent and efficient online quality control in the pulp and paper industry. While these endeavors mark significant progress in the field of paper pulp fiber segmentation, there remains ample opportunity for further exploration to develop specialized deep-learning algorithms that address the specific challenges posed by the complex and heterogeneous nature of paper pulp fiber images. As an effort towards that, a hybrid deep-learning-based fiber segmentation model is proposed and validated in this study.

3.2 Vision Transformers in Image Recognition

The emergence of vision transformers (ViTs) represents a paradigm shift in image recognition tasks. ViTs have demonstrated superior performance on large-scale image datasets [22]. By leveraging self-attention mechanisms, transformers capture long-range dependencies in images, enabling more effective feature extraction and segmentation. The establishment of TextileNet [23], a fashion textile dataset, has provided a standardized framework for training and evaluating Deep Learning models, including CNNs and ViTs. This framework aids in textile material identification and categorization. Incorporating ViTs into the analysis of paper handsheets presents an exciting opportunity for enhancing segmentation accuracy and efficiency. Notably, these algorithms exhibit versatility across diverse environments, showcasing their ability to effectively depict complex real-world scenarios.

3.3 Challenges and Considerations

While deep-learning algorithms have demonstrated their potential for automatic and accurate instance segmentation across various real-world scenarios, their application in fiber segmentation faces several challenges. These include the scarcity of labeled samples, the limited availability of 3D tomographic data, and the inherent difficulties in achieving high accuracy with deep-learning-based instance segmentation methods. Moreover, the dense occurrence of fibers, their arbitrary orientations, and varied locations further complicate the training of deep neural networks like Mask-RCNN, often resulting in lower segmentation accuracy compared to traditional approaches such as watershed segmentation. Additionally, errors in 2D tomogram instance segmentation can propagate and affect the accuracy of 3D reconstruction, posing additional challenges. To address the challenges above, the study introduces a hybrid 3D image segmentation algorithm [3]. This technique focuses on utilizing nylon-fiber bundles as data sets for the initial investigation.

4. Deep-learning-based Hybrid 3D Fiber Segmentation Algorithm

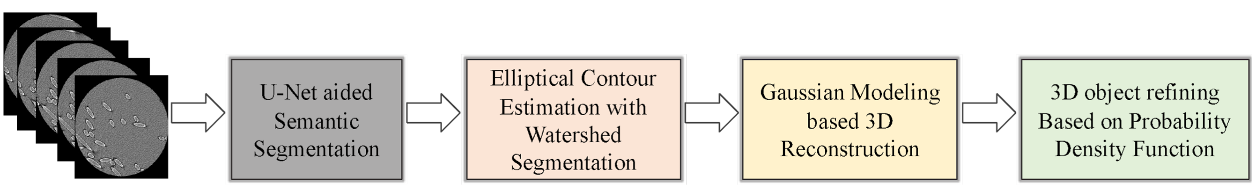
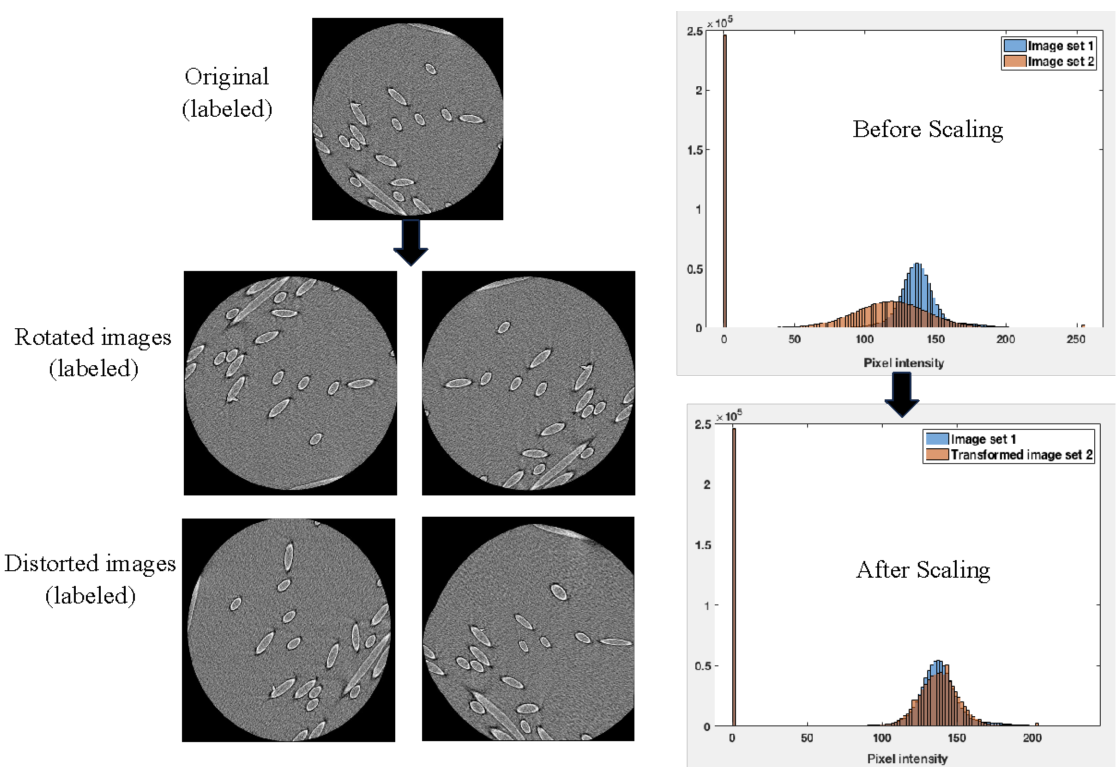


Figure 4 The block diagram of the proposed Deep-learning-based Fiber Segmentation Architecture

Our primary goal is to accurately segment and label the individual nylon fibers within the 3D images. A novel hybrid 3D fiber segmentation algorithm that involves deep-learning assisted semantic segmentation that generates 2D images from 3D images for fiber extraction is proposed in this study. A series of four sequential image processing blocks, as illustrated in Figure 4. These blocks consist of (1) U-net-aided semantic segmentation for fiber extraction, (2) elliptical contour estimation with watershed segmentation for fiber separation, (3) Gaussian modeling for 3D reconstruction, and (4) Gaussian probability density function-based modeling for 3D object refining. Notably, supervised learning is employed only in the initial step, while the subsequent steps do not rely on labeled datasets, thus adopting unsupervised approaches. The upcoming sub-sections provide a comprehensive explanation of the dataset utilized and each of these four sequential function blocks.

4.1 Data Pre-processing and Selection of Dataset

The two Nylon bundle fiber datasets utilized in the study are 2D tomogram slices produced by slicing along their z-axis and differentiated based on their threshold compatibility. Dataset 1, being large, fully labeled, and annotated, is considered threshold-friendly, whereas Dataset 2, smaller in size and lacking labeling, presents challenges for threshold-based segmentation. The proposed methodology is specifically applied to Dataset 2 to demonstrate its effectiveness under these challenging conditions. The Nylon fiber bundle dataset 2 has a dimension of 1013 x 964 x 500 voxels with a resolution of 1μm. To facilitate model training, Dataset 2 is divided into training and validation sets with a ratio of 0.85 and 0.15, respectively. A subset of images from the training set is manually annotated to create ground truth pixel-wise labels. The labeled training dataset is augmented by rotating and distorting the images, as shown in Figure 5 (a). Subsequently, scaling operations expand dataset 2 to enhance model robustness and generalization, which also aligns the intensity distribution of the image data set 1, as shown in Figure 5 (b). The analysis of the X-ray 3D image volume from dataset 2 is conducted using the developed approach for performance evaluation. Each step outlined in the proposed approach is applied to the dataset as described in the subsequent sections.



(a) **(b)**

Figure 5 Image augmentation and Image scaling Intensity distributions of dataset 2

4.2 U-net for Fiber Extraction

U-Net is a CNN commonly employed for segmenting biomedical images, sharing similarities with 2D nylon fiber tomograms. Comprising encoder and decoder components, U-Net efficiently identifies image features through down-sampling and recovers spatial information via up-sampling, making it ideal for semantic segmentation tasks. In our case, segmenting the compressed nylon fiber bundle necessitates training the U-Net model on fully annotated compressed samples. However, as only fully labeled uncompressed samples are available, partially annotated images from the compressed bundle are incorporated into the training dataset. These images undergo manual labeling, with the remaining uncompressed nylon fiber images designated for the test dataset. While some nylon fiber specimens lend themselves well to segmentation via thresholding methods, others, such as those in the target dataset, present challenges for such approaches due to varying experimental conditions and sampling procedures. Two steps are implemented to prepare an effective dataset for training the U-Net model, as shown in Figure 6. Firstly, the dataset is carefully selected through the naïve thresholding method and scaled based on the mean and standard deviation of the image greyscale intensity in the target dataset, ensuring consistency in distribution. This process generates a new scaled dataset. Subsequently, a subset of images in the target dataset is manually annotated and undergoes image augmentation, resulting in a new dataset. These annotated images are combined with the scaled dataset to create an integrated dataset for U-Net training. This U-Net model has a 512x512 input size with four down layers and four upper layers. Each layer uses a 3x3 kernel and ReLU activation. Upon completion of training, the U-Net model efficiently labels the entire target dataset in less than a second of processing time. Following 20 epoch iterations, the U-Net model demonstrates thorough training, achieving high accuracy rates of 97.22% for training and 97.50% for validation. Additionally, the model exhibits low loss values of 0.0262 for training and 0.0313 for validation. These metrics indicate that the U-Net model has effectively learned the features of the dataset during training, resulting in accurate predictions on both the training and validation sets.

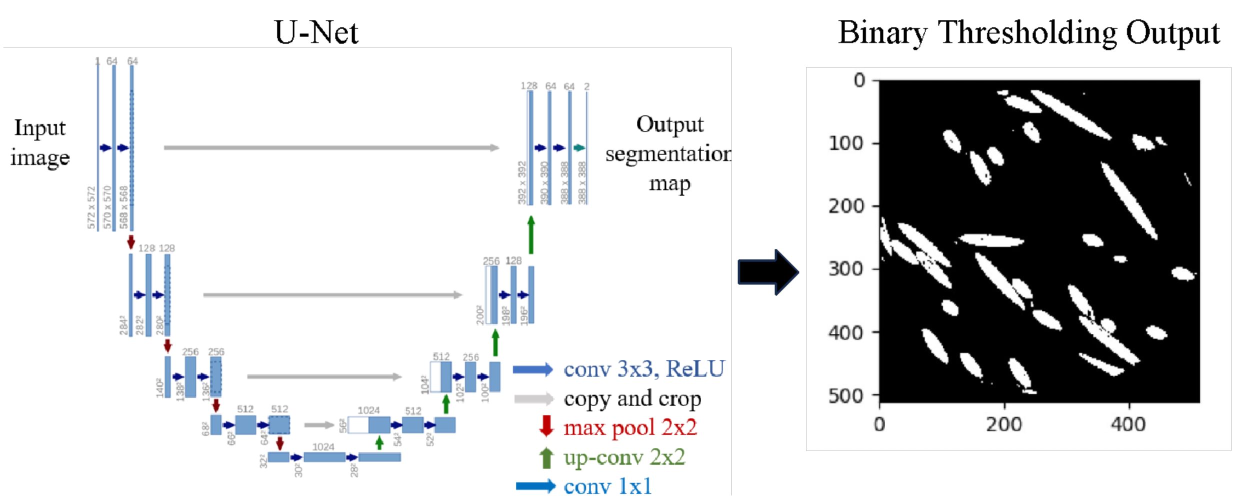


Figure 6 U-Net model and its Binary Thresholding Output

4.3 Watershed Instance Segmentation

Elliptical contour estimation is a vital component in image processing, contributing to various applications such as object detection, recognition, and segmentation. This block presents the concept of elliptical contour estimation and its integration with the watershed algorithm. The U-Net model processes greyscale 2D image slices to produce categorical outputs, effectively distinguishing fibers from background areas. Subsequently, binarized images are generated, initiating the instance segmentation process to separate fibers from each other. Conventional marker-controlled watershed algorithms face challenges in separating elliptical fused objects. To overcome this, the proposed methodology employs the elliptical contour estimation algorithm, providing improved separation between closely connected elliptical fibers. However, overlapping areas between estimated elliptical contours may occur. To achieve smoother instance segmentation, a three-step approach is developed in this block, starting with applying the elliptical contour estimation algorithm to generate multiple contours, reducing the size of contours until they are separate objects, and finally, utilizing obtained markers to apply marker-controlled watershed segmentation, as illustrated in Figure 7. The performance is demonstrated by manually counting the number of fibers across 500 slices and comparing them with the instance numbers provided by watershed segmentation. The developed elliptical contour-based watershed segmentation yields reliable marker locations, enhancing the accuracy compared to non-elliptical contour-based approaches. Analysis of all 500 slices reveals that the proposed approach achieves over 90% accuracy for 77.6% of the slices, with only 6.2% exhibiting accuracy below 85%. Despite potential manual annotation errors, such as recognizing circular and oval shapes, the proposed method yields satisfactory accuracy. Additional steps are developed in the following subsections to tackle these challenges.

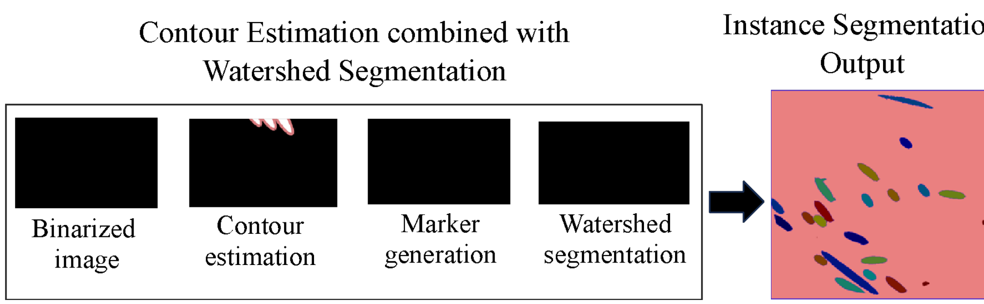


Figure 7 Proposed Elliptical Contour Estimation with Water Segmentation and its Output

4.4 3D Fiber Reconstruction

In the 3D reconstruction step, the segmented 2D slices containing individual nylon fibers are merged into 3D space by aligning and linking labeled cross sections belonging to the same fiber. This process involves stitching together the segmented 2D image slices to create a comprehensive 3D image, considering the spatial and geometric layout of the nylon fiber bundle, as shown in Figure 8. To achieve this, object-tracking algorithms are utilized to track the location of fibers between adjacent 2D slices based on individual IDs. While the centroid matching algorithm has been traditionally employed for its simplicity and processing speed, it tends to lose accuracy in densely distributed nylon fiber scenarios or when instance segmentation biases exist from previous watershed segmentation steps.

A novel fiber tracking approach utilizing a Gaussian probability distribution model is proposed to address the limitations of centroid matching. This model compresses each individual fiber object into a Gaussian distribution on each 2D slice. Instead of tracing centroid movement using Euclidean distance, KL divergence is utilized as a matching criterion to measure the similarity between Gaussian distributions. By computing the KL divergence criterion between the current object distribution and suspected objects in previous slices, fibers with minimal divergence below a predefined threshold are connected, indicating they belong to the same fiber. This approach enhances accuracy in tracking densely distributed or biased instances, improving the overall fidelity of 3D reconstruction. The binarized 3D image volume is re-sliced from the X direction, resulting in 1013 slices. The watershed algorithm is reapplied to each slice for instance segmentation. Each object on a slice is represented by a multivariate Gaussian distribution, and its KL divergence with adjacent objects in the previous six slices is computed. If the minimal KL divergence is less than 1, the object in the previous slice with the minimal divergence is chosen as a potential connection candidate; otherwise, the current object is assigned a new label. For example, ID 3 is highlighted in Figure 8 and is identified as the individual fiber using this proposed methodology.

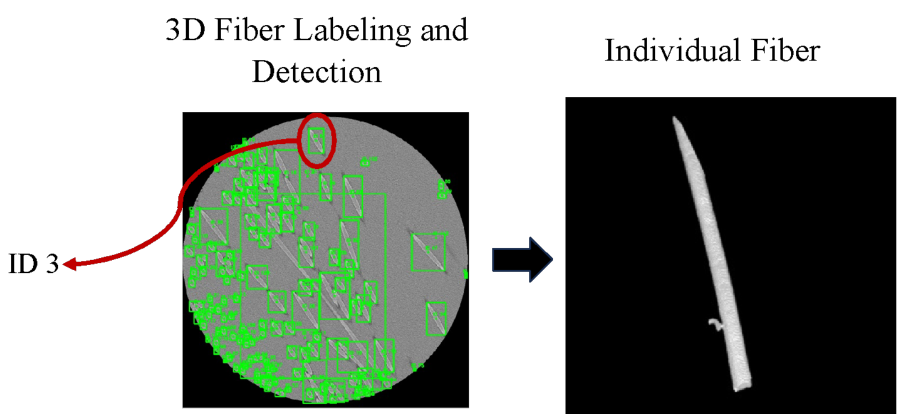


Figure 8 Gaussian Modeling-based 3D Fiber Reconstruction

4.5 3D Object Refining

The Gaussian distribution and KL divergence metrics encapsulate crucial information regarding the segmented nylon fibers. Once the 3D reconstruction process is finalized, individual fibers within the 3D images become identifiable. However, due to inaccuracies in instance segmentation, some extracted 3D fibers may erroneously include attached parts of neighboring fibers. An outlier detection and replacement mechanism are used to address this issue as shown in Figure 9. This approach involves computing and storing the cross-sectional area of each fiber in every slice, facilitating the detection of abnormal increases in fiber cross-section areas indicative of segmentation errors. Outliers are identified based on predetermined detection thresholds, and erroneous slices are corrected through linear interpolation to remove redundant fiber components introduced by faulty segmentation, as shown in Figure 10.

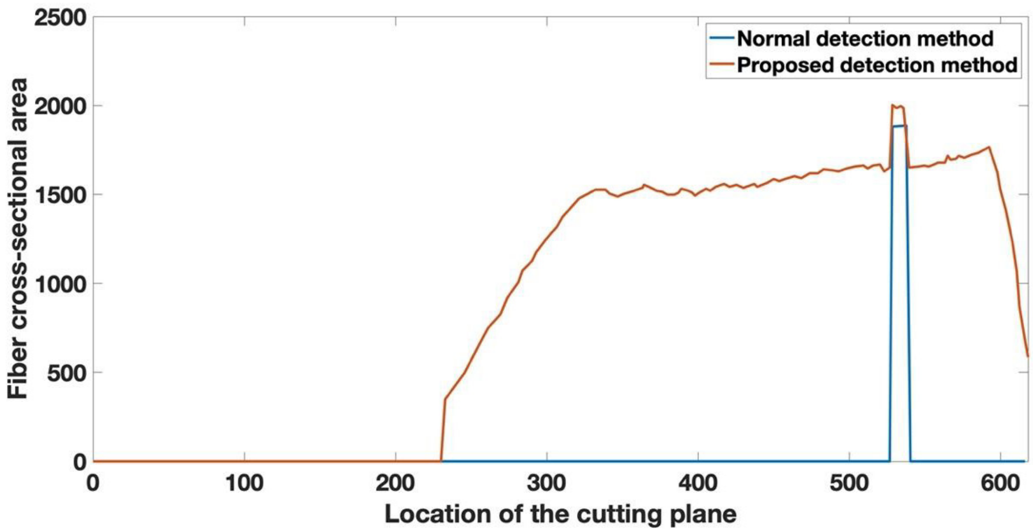


Figure 9 Fiber Cross-section Detection

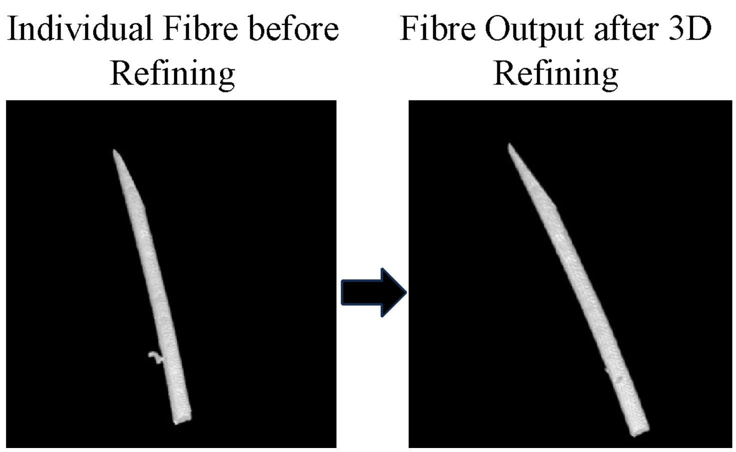


Figure 10 3D Object Refining Output

5. Applications and Future Directions in Fiber Segmentation

The proposed hybrid 3D fiber segmentation methodology holds promise for various applications beyond fiber segmentation in 3D X-ray tomographic images. Firstly, it can be extended to other materials science fields where accurate segmentation of fibrous structures is crucial, such as composite materials or geological samples. Additionally, this methodology could find applications in medical imaging, particularly in fields like histopathology or radiology, where the identification and analysis of intricate structures are essential for diagnosis and treatment planning. Moreover, in industrial settings, such as quality control in manufacturing processes or material characterization in research and development, precisely segmenting and analyzing fibrous materials could improve product quality and process efficiency.

In terms of future directions, integrating deep learning-based image segmentation techniques opens avenues for further advancements. Continued research in developing more efficient and accurate deep-learning models tailored to the unique characteristics of pulp fibers could significantly enhance the segmentation process. Additionally, exploring novel architectures, such as attention mechanisms or graph neural networks, could further improve the performance of segmentation algorithms, particularly in handling complex fiber arrangements or challenging imaging conditions. Furthermore, advancements in computational hardware and algorithms could enable real-time or near-real-time segmentation of large-scale 3D X-ray tomographic datasets, facilitating rapid analysis and decision-making in various industrial and scientific applications.

6. Conclusions

This chapter delves into the integration of deep-learning techniques within 3D fiber segmentation algorithms, aiming to demonstrate their effectiveness. Through an extensive review of existing literature, the study showcases methodologies and techniques employed in leveraging deep learning for 3D fiber segmentation. It elucidates how these methods are applied across different scenarios to enhance segmentation accuracy and efficiency. Additionally, a novel hybrid 3D fiber segmentation algorithm is introduced, which utilizes deep-learning-assisted semantic segmentation to generate 2D images from 3D data for fiber extraction. The algorithm combines an image processing method, elliptical contour estimation, with the marker-controlled watershed technique to approximate the boundaries of fibers within an image with elliptical shapes. Individual fibers are identified using a 3D reconstruction modeling technique that combines KL divergence measurement and the Gaussian method. The proposed method is validated using nylon fiber image data sets, which share similarities with wood fibers in polymer composition. This validation demonstrates the efficacy of the approach in handling various properties of paper handsheets.

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