IMAGE-BASED CROSS-SECTIONAL ANALYSIS AND MICROMECHANICAL MODELING OF YARN AND COMPOSITE MATERIALS

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ABSTRACT

This study aims to establish a comprehensive methodology for determining the microstructural properties of hybrid yarns used in composite materials. By developing accurate models of hybrid yarns and composites based on detailed microstructural information such as fibre orientation, fibre diameter and distribution, this approach lays the foundation for future advances. These models, enriched with accurate microstructural data, will facilitate the creation of new modelling techniques that can be used in future research to explore the correlation between microstructural properties and mechanical performance of composite materials.

KEYWORDS

Hybrid composite; Microstructural properties; Intermixing; Fiber distribution.

INTRODUCTION

Composite materials are particularly valued for their rigidity, strength relative to weight, and other tailored properties which make them indispensable across various applications in Aerospace, Automotive Industry, Biomedical Applications, Sports Equipment, Construction and Civil Engineering [1-3]. The correlation between microstructural properties and mechanical behavior is fundamental for the advancement of material science, leading to better predictive capabilities, enhanced material performance, and innovative processing techniques. Understanding this relationship allows for the strategic design and application of materials across various industries [4] [5]. Recent studies have explored various aspects to enhance performance and understand the mechanisms affecting their behavior. Hoang et al. [6] investigated postprocessing techniques' impact on carbon reinforced thermoplastic composites, focusing on materials like PPS, PEEK, and PEKK. They found that consolidation techniques significantly affect the final quality, including void content and crystallinity. Oztan et al. [7] examined the microstructure of 3D-printed continuous fiber composites, revealing that defects significantly impact stiffness and strength, necessitating further investigation to enhance performance. Ramaswamy et al. [8] studied the mechanical performance of CF/PEEK and CF/PEKK composites, highlighting the tunable nature of their semi-crystalline matrices. They found CF/PEKK to be durable and damage-tolerant but noted the need for more research on matrix properties and fiber-matrix interface behavior. Mehdikhani et al. [9] reviewed the effects of voids in fiber-reinforced polymers, showing that voids predominantly affect matrix-dominated properties. Tunak et. al investigated the blending quality of fibre components in hybrid yarns containing conductive stainless steel fibres [10]. The quality of these datasets depends on the data that are accurate measurement and understanding of microstructural properties remain challenging, requiring precise methodologies. Recent advances in machine learning, as demonstrated by Li et al. [11] and Shah et al. [12], have shown promise in predicting the mechanical properties of composites. While these models are effective, they highlight the need for further research on establishing methodologies to determine microstructural properties of composites to and making valuable datasets from these relyable informations. These advanced Datasets can be used in the future to fill gaps that remain in fully linking microstructural properties to mechanical performance. This study aims to bridge these gaps by providing methodology to find microstructural properties based on digital image correlation methods and preparation to find the correlations between mechanical properties of composites and their microstructural properties.

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MATERIALS

Hybrid yarns, composed of stainless steel (StS), glass fibers (GF), and polypropylene (PP), were utilized in the fabrication of fiber-reinforced composites (FRP) for this study. These hybrid yarns combine the complementary properties of their constituents, optimizing the mechanical performance of the FRP. Stainless steel was incorporated due to its ductility, which enhances the toughness and impact resistance of the composites, while glass fibers were selected for their high tensile strength and cost-effectiveness. Polypropylene, serving as the matrix material, contributes chemical resistance, recyclability, and low density, making it ideal for lightweight applications. Table 1 outlines the key properties of the filament yarns used in this study.

METHODS

Fabrication of hybrid yarns

For the manufacturing of multi-material composites, hybrid yarns were produced using a newly developed multi-level-intermixing process. This process is designed to achieve efficient intermixing of components while maintaining low-damage processing. During the process, mechanical separating elements divide the filament yarns into smaller fiber bundles. These separated bundles are then recombined into a single coherent fiber bundle using a subsequent merging element. This method minimizes damage to the individual filaments, preserving their mechanical properties in the final hybrid yarn. The structure of the machines and detailed descriptions of their components are provided in [13]. In the next step, the hybrid yarns were wound into unidirectional (UD) fabrics using the winding technique on an FW122 winding machine (IWT, Germany). This winding method ensures precise alignment of the yarns to form the composite samples for further testing.

Fabrication of Composite Samples

The unidirectional (UD) fabric samples were consolidated by compression moulding using a P300 PV thermal laboratory press (COLLIN Lab & Pilot Solutions GmbH, Germany). The theoretical volume fractions of the components in the composite were 18.2% stainless steel (StS), 34.5% glass fibers (GF), and 47.3% polypropylene (PP). The consolidation process was performed at 220°C under a pressure of 188 MPa to ensure proper bonding between the fibers and matrix. Following consolidation, test specimens were cut from the composite plates in the 0° direction (parallel to the fiber axis) using a WOCO 50 precision table saw (Uniprec Maschinenbau GmbH, Germany) equipped with a TS322 galvanic-coated blade (TSP Hildebrand, Germany), specifically designed for fiber-reinforced composites. The dimensions of the specimens for microscopic imaging were 20 ± 1 mm in length, 10 ± 0.2 mm in width, and 2 ± 0.2 mm in thickness.

Methodology for determination of microstructural properties of hybrid yarns and FRP

The primary objective of this study is to develop a methodology for modeling hybrid yarns and fiber-reinforced composites (FRCs) by incorporating detailed information about their microstructural properties. This methodology focuses on the segmentation and classification of hybrid yarn and composite regions based on microscopic cross-sections. Key features analyzed include the location and type of fibers, as well as the presence of voids, which significantly influence the mechanical properties of the composites. The information gathered from this analysis is used to create accurate models that capture local variations in fiber distribution and void content, both of which are critical to understanding the mechanical behavior of fiber-reinforced composites.

The methodology is divided into the following key steps (see Fig. 1):

1. Image Acquisition – Microscopic images of hybrid yarns and composite cross-sections are captured to provide detailed visual data on the fiber and void distribution.
2. Image Analysis and Segmentation – Using specialized image analysis software, the images are processed to segment and classify different components such as fibers and voids.

Table 1. Specifications of filament yarns used to manufacture composites.

	Yarn properties			
	Notation	**Manufacturer**	**Diameter of single filament**	**Fineness filament yarn [tex]**
Stainless steel (StS)	chrome nickel steel wire 1.4301	Heinrich stamm GmbH	60±0.2	225
Glassfibre (GF)	EC9- 68tex- Z28 302P	P-D glasseiden GmbH oschatz	7.2±0.9	68
Polypropylene (PP)	Prolen HP 330/66, white, untwisted	Chemosvit fibrochem, s.r.o	15±1.5	2x33

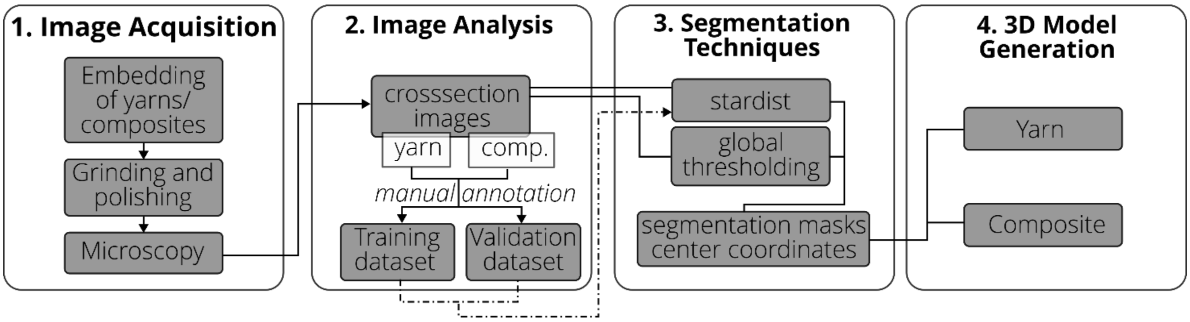

Figure 1. Schematic representation of the methodology for image acquisition, analysis, segmentation, and 3D model generation.

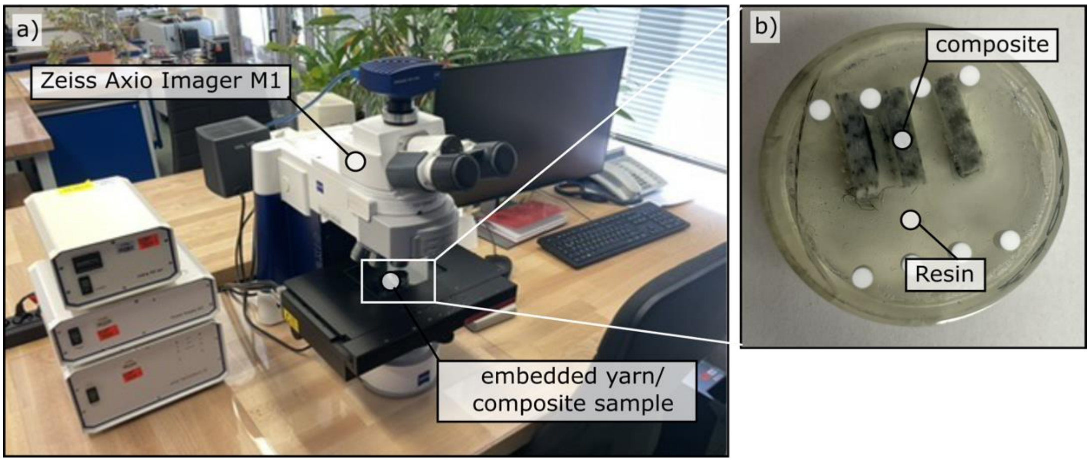

Figure 2. Experimental setup showing a) Zeiss Axio Imager M1 used for imaging composite and yarn cross-sections, and b) resin-embedded samples.

3. Segmentation Techniques – Advanced segmentation techniques are applied to accurately distinguish between fiber types and to identify voids within the composite structure.

4. 3D Model Generation – Based on the segmented data, 3D models are generated to simulate the internal structure of the hybrid yarns and composites, allowing for analysis of local variations in fiber and void content.

To capture detailed images of the yarn and composite cross-sections, both flatbed scanners and microscopy techniques were employed. The samples were first embedded in an epoxy resin matrix and cured at room temperature to preserve their structure during imaging. After curing, the samples were polished and cleaned to obtain smooth surfaces for analysis. High-resolution images of the cross-sections were captured using an Axio Imager M1m optical microscope (Carl Zeiss, Germany) at a magnification of 200x, with the magnification calibrated using Zeiss Zen software. The optical microscope enabled detailed visualization of the fiber and matrix interfaces, which is essential for analyzing the microstructural properties of the composite materials. Additionally, high-resolution images of the yarns' longitudinal sections were obtained using a Perfection V550 flatbed scanner (Epson, Japan). The flatbed scanner provided large-scale images that were particularly useful for observing the alignment of fibers within the yarn. These high-resolution images were critical for identifying and analyzing key microstructural features, such as fiber distribution, voids and fiber angle, which influence the mechanical performance of the composites. Fig. 2(a) shows the imaging technique used to obtain cross-sectional micrographs by microscopy, while Fig. 2(b) shows the composite sample prepared for analysis, with the composites embedded in an epoxy resin matrix.

RESULTS

Image acquisition

Microscopic analysis of the longitudinal sections of the hybrid yarns showed minimal fibre degradation, as indicated by the limited number of fibres protruding from the yarn core (Fig. 3(b)). Slight aggregations of glass and thermoplastic fibres were observed within the hybrid yarns (Fig. 3(a)). Composite cross section images (Fig. 3(c)) showed a uniform distribution of steel fibres. These findings were confirmed by subsequent image analysis and segmentation as discussed in Image analysis and segmentation section.

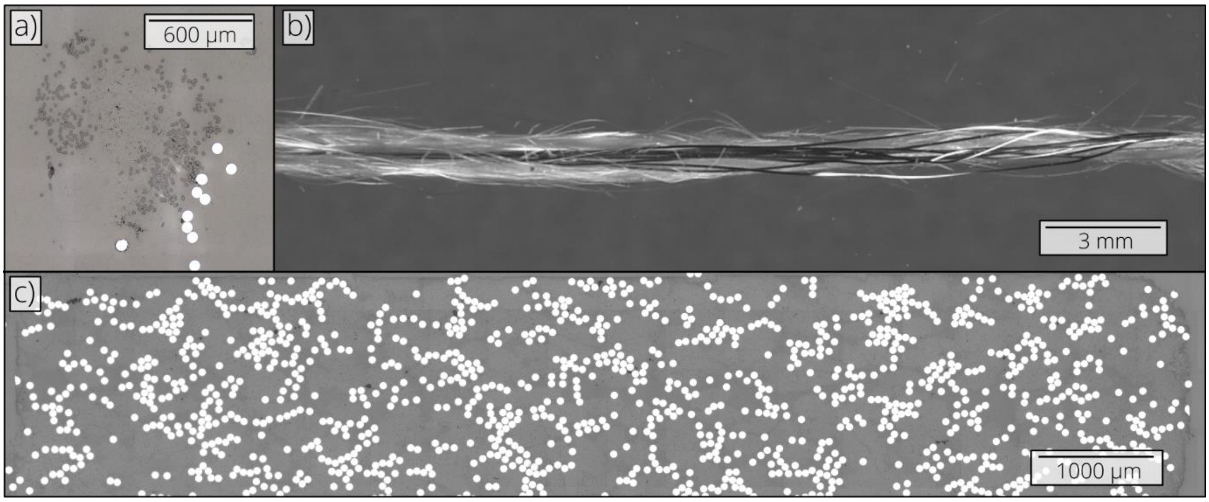

Figure 3. Microscopic images of: (a) hybrid yarn cross-section, (b) composite cross-section, and (c) yarn longitudinal view obtained by flatbed scanning.

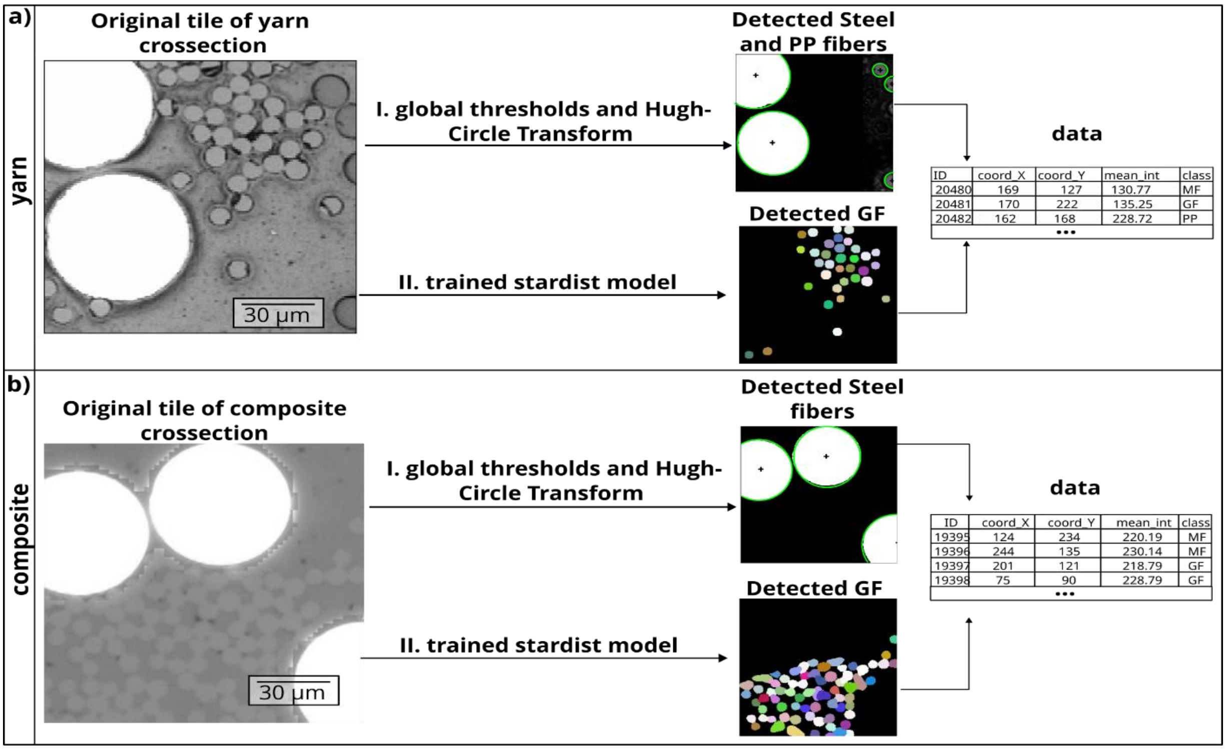

Figure 4. Methodology for determining microstructural properties of: (a) yarn and (b) composite.

Image analysis and segmentation

Digital image analysis was conducted using a combination of conventional and advanced segmentation techniques (Fig. 4). Initial segmentation was performed using global thresholding due to its computational efficiency, with manually set grayscale thresholds for steel, polypropylene (PP) fibers, and voids, which generated binary images. However, global thresholding was insufficient for accurately segmenting glass fibers (GF) due to the low contrast between fibers and the matrix. To improve segmentation accuracy, a machine learning-based approach was employed using the Stardist library [14], which relies on star-convex shapes for segmentation. The model training involved multiple steps: image preparation, manual annotation, data augmentation, and dataset division. Initially, 25 cross-sectional images of hybrid yarns were manually annotated using QuPath software [15], with each image divided into tiles of 256x256 pixels. These images were split into a training dataset (80%) and a validation dataset (20%). Data augmentation included variations in intensity and image flipping to improve model generalization. The model was trained using a convolutional neural network with a U-Net architecture as the backbone. The training process used 30 epochs and a batch size of 4. For the Stardist model, 32 rays were set to describe the star-convex shapes. This method allowed for precise fiber boundary delineation, even in low-contrast images.

Additionally, the Hough-Circle Transform method was applied to identify fibers in the images, although it proved less effective for glass fibers. The Stardist model, however, achieved an Intersection over Union (IoU) accuracy of 93% for yarn cross-sections and 81% for composite cross-sections, demonstrating its suitability for fiber segmentation. Key local descriptors, including fiber center coordinates, void areas, mean image intensity, and fiber classification, were calculated and stored for further analysis.

In the composite analysis, the approach was modified to account for the consolidation of polypropylene (PP) fibers during the thermo-pressing process, which resulted in their absence from the composite cross-sections. Consequently, the focus shifted to identifying voids, which are known to significantly impact the mechanical properties of fiber-reinforced composites. Due to the high contrast between the voids and the surrounding matrix material, global thresholding was sufficient for detecting voids. This method efficiently identified voids, making it unnecessary to apply more advanced segmentation techniques in this case. The determined void content in composites is 2.8 ±0.5%.

Exploratory spatial analysis of fibers

Before initiating the modeling process, an exploratory spatial point pattern analysis of the yarn's cross-sections was performed to gain initial insights into the spatial distribution of fibers. This analysis helps in understanding fiber distribution, interactions, and potential clustering within the yarn, providing valuable information for optimizing textile performance, ensuring uniformity, and predicting mechanical properties. A representative example of this analysis is shown in Fig. 5.

In Fig. 5(a), the distribution of glass fibers (GF), stainless steel fibers (StS), and polypropylene fibers (PP) in a cross-section is displayed. To further investigate the spatial patterns of each fiber type, the fibers were plotted separately (Fig. 5(d)), providing a qualitative overview of their locations within the yarn. In addition, the spatial probability of occurrence for each fiber type was calculated and is displayed in Fig. 5(b), highlighting areas where specific fiber types are most likely to occur. For a more quantitative assessment, spatial distribution functions such as the K, J, F, and G functions were calculated. These functions are commonly used in spatial point pattern analysis to detect clustering or dispersion within a dataset. In this case, the analysis revealed a slight clustering of fibers in the hybrid yarn, as indicated by deviations in the calculated distribution functions compared to a Poisson distribution with complete spatial randomness (CSR). This clustering may be due to the manufacturing process and could influence the mechanical performance of the yarn by creating localized regions of higher or lower fiber density.

3D modeling based on microstructure

The microstructural information obtained from the segmentation process was used to generate 3D models of the yarn and composite structures (Fig. 6). The local descriptors, including the center coordinates of the fibers and their respective types, were used to set the starting points of the fibers in the model. Scans of longitudinal sections were analyzed to calculate the average fiber angle deviation from the yarn's longitudinal axis, an important factor due to the slight twist introduced during processing. These data were combined to create a realistic 3D representation of the yarn, which can be used to correlate microstructural features with mechanical properties.

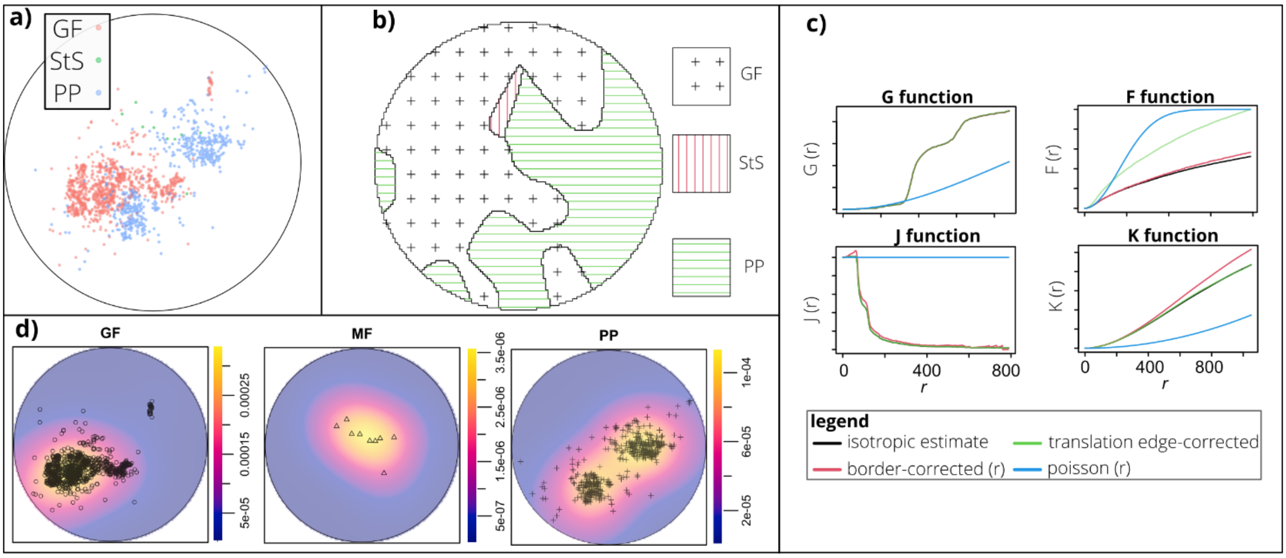

Figure 5. Example results of exploratory spatial analysis of yarn: (a) determined local positions of GF, StS, and PP in the yarn, (b) probability map of different fiber types, (c) resulting spatial summary functions, and (d) specific locations of different fibers.

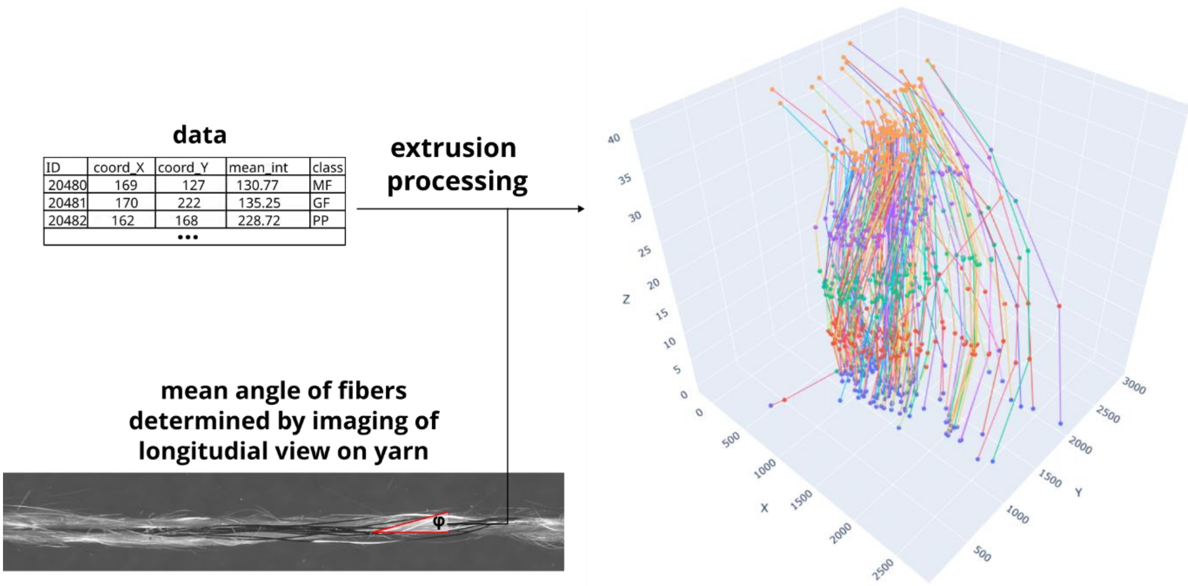

Figure 6. Example of the 3D model determined using the DIC-based method.

An algorithm was developed for this process, which takes the initial coordinates and corresponding fiber types as input. Then to represent the rotation of the yarn, the center of gravity was first determined by calculating the overall centroid of the x and y coordinate using the NumPy library. Subsequently, new planes were generated at equal intervals parallel to the initial plane. The coordinates, rotated relative to the initial points of the first plane, were positioned around the calculated centroid. These rotated points were then connected to their corresponding points on the adjacent planes, forming the desired representation.

The developed DIC-based process enables future work to include voids and fiber distribution in composite models, allowing for more accurate representations of the material's behavior under mechanical stress. By incorporating these features, particularly voids—known to significantly impact mechanical performance by serving as points of weakness—future research can leverage these enhanced 3D models to better predict and optimize the mechanical behavior of composites based on their internal microstructure.

CONCLUSION

In this study, a comprehensive methodology for the analysis and modeling of hybrid yarns and fiber-reinforced composites (FRCs) was developed. The combination of advanced image acquisition techniques, segmentation processes, and 3D modeling allowed for a detailed understanding of the microstructural features critical to the mechanical behavior of these materials. By utilizing optical microscopy and flatbed scanning, high-resolution images of both yarn cross-sections and longitudinal views were captured, enabling the precise identification and classification of fiber types and voids. The image analysis process was enhanced through the use of machine learning-based segmentation, particularly the Stardist algorithm, which significantly improved the accuracy of fiber and void identification. The resulting segmented data allowed for the construction of 3D models of the yarn and composite structures, incorporating key microstructural elements such as fiber orientation, distribution, and void content. These models provide valuable insights into how these features influence the overall mechanical properties of the materials.

The exploratory spatial analysis of the fiber distribution further revealed slight clustering, which could have implications for the material's uniformity and performance. The spatial distribution functions and probabilistic models enabled a deeper investigation into fiber interactions and clustering tendencies, shedding light on potential improvements for yarn manufacturing processes. Looking ahead, the developed DIC-based process opens new avenues for future research. The ability to incorporate detailed microstructural data, such as fiber distribution and void content, into composite models will enable more accurate predictions of material behavior under various mechanical stresses. This will not only enhance the understanding of how microstructural features affect performance but also facilitate the optimization of hybrid yarns and composites for a wide range of engineering applications.

In conclusion, the methodologies and models developed in this study offer a powerful framework for investigating and optimizing the microstructure and mechanical performance of hybrid yarns and fiber-reinforced composites, opening the way for improved material design and industrial applications.

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