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REVIEW ARTICLE

Computer vision and image analysis in yarn properties analysis: a comprehensive review

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ABSTRACT
Image analysis and computer vision are becoming important tools for studying different yarn characteristics. This review explores how these techniques are applied to measure properties such as yarn diameter, twist, porosity, hairiness, unevenness, and even internal structure. Compared to traditional methods, image analysis is faster, more precise, non-destructive and often more cost-effective as well as environmentally friendly. Several methods, such as Canny edge detection, Hough transforms, clustering approaches and machine learning models, have been used to study and measure these yarn properties. In this review, these algorithms and their roles in yarn analysis have been discussed. The discussion also brings together important studies in the field, points out the challenges researchers are still facing and suggests possible ways forward to improving yarn characterization with computer vision and image analysis.

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KEYWORDS
Image analysis; yarn properties; computer vision; yarn diameter; machine learning

1. Introduction

Yarn forms the foundation of almost all textile products, making it essential to assess its properties regularly to maintain consistent quality. Characteristics such as diameter, unevenness, hairiness, twist, porosity and internal structure are usually measured with specialized testing equipment. However, these traditional methods often involve lengthy and tedious procedures, are susceptible to errors, and in many cases, can even be destructive—leading to considerable material waste (Carvalho, Soares, et al., 2009). Computer vision is a field of technology that enables machines to observe, process, and make sense of visual information. Thanks to recent progress in both computer vision and image analysis, studying yarn has become more efficient—offering quicker, more accurate results while also meeting today's growing emphasis on sustainability and productivity (Li et al., 2019; Li et al., 2020; Roy et al., 2014; Zhang & Xin, 2016). Computer vision technologies apply state-of-the-art imaging processing and artificial intelligence (AI) to achieve greater precision and speed in yarn analysis, optimizing a system's overall operational efficiency (Abdelkader, 2022; Li, Pan, Zhang, et al., 2016). Figure 1 illustrates various yarn properties, such as diameter, unevenness, twist, hairiness, porosity and internal structure, which can be evaluated using computer vision techniques.

Various image analysis techniques—such as Canny edge detection, Hough transforms, clustering methods, and machine learning models—have been applied to study yarn properties. Among edge detection methods, the Canny algorithm is particularly popular because it can identify edges with high accuracy while remaining resistant to image noise. In recent years, researchers have used it for measuring yarn twist and hairiness, where it has shown promise in improving the accuracy and reliability of property evaluation (Ozkaya et al., 2010; Fabijańska & Jackowska-Strumiłło, 2012; Guha et al., 2010; Zhang et al., 2024). In addition, different clustering methods like, K-Means, Fuzzy C-means etc. are used for identification and classification of the yarn images (Li et al., 2019; Li, Pan, Zhang, et al., 2016; Kuo et al., 2010).

Machine learning has shown great promise in detecting yarn properties through image analysis. These algorithms can process images in real time to estimate parameters such as linear mass, diameter and hairiness (Pereira et al., 2023). Beyond speeding up and simplifying evaluation, they also allow for more detailed investigations that were not possible with traditional testing methods. When combined with high-resolution imaging

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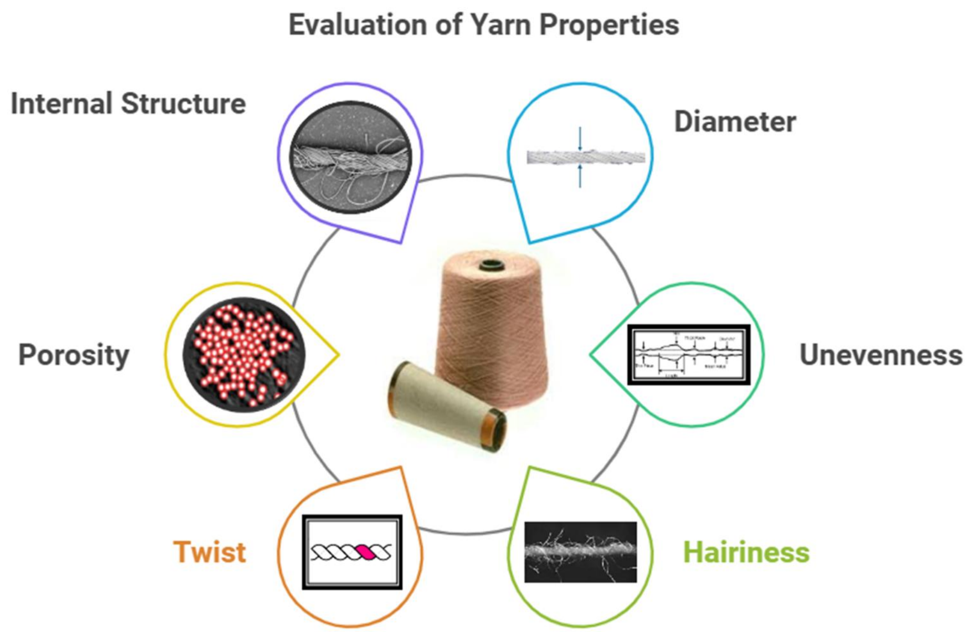

Figure 1. Various yarn properties evaluated by image analysis.

and advanced processing techniques, machine learning opens new avenues for both research and industrial use, offering a deeper understanding of yarn characteristics (Li et al., 2020; Roy et al., 2014).

In this review, we look at the present state of image analysis in this area, focusing on the techniques and algorithms applied. The aim is to highlight significant studies and recent progress while making these findings accessible to both researchers and industry professionals. It also identifies gaps in literature and provides future forward thinking to innovation and development of computer vision to leverage yarn analysis to continue the progression of textile technology. The following table (Table 1) combines the works showing different algorithms used to analyze different properties of yarn applying computer vision and image analysis techniques.

A critical analysis has been carried out comparing traditional yarn testing methods and emerging image analysis techniques. It reveals a clear trend toward the adoption of digital technologies due to their enhanced capabilities in speed, accuracy, and non-destructiveness. However, while computer vision demonstrates promising improvements, challenges remain in standardization, real-time applicability, and integration with existing industrial workflows. Following table (Table 2) demonstrates a comparison of different aspects.

2. Works on yarn properties analysis

Yarn quality is key to the performance, appearance and durability of final textile products. Several factors affecting yarn properties such as diameter, twist and hairiness are crucial and ultimately influence fabric properties and fabric strength, elasticity and comfort (Li, Pan, Zhang, et al., 2016; Li et al., 2015). Yarn diameter and unevenness, which are the most important characteristics of yarn, are not measured directly, indirect measurement systems are used (Abdelkader, 2022; Guo et al., 2010). Conventional twist measuring system is also unable to capture the true twist distribution along the yarn axis, potentially risking quality control (Pan et al., 2011; Carvalho, Vasconcelos, et al., 2009). Image analysis may be a potential alternative to overcome the drawbacks of conventional systems. Yarn image analysis related works are summarized under this section.

2.1. Yarn diameter and unevenness

Yarn linear density or count is used to measure yarn thickness, however it does not correspond directly to actual diameter, as the fiber composition, structure and the processing methods each have their own variation (Luo et al., 2015a). We cannot rely only yarn count, because it may be influenced by some factors like fineness, crimp, twist level and yarn compactness (Liu & Li, 2011). Another property of yarn, yarn evenness is measured by using capacitance sensor which is also an indirect procedure of evenness measurement (Zhang et al., 2014). To address these limitations, innovative systems have been proposed, using advanced image analysis to measure yarn diameter and evenness with high precision, even for few

Table 1. Previous works on yarn properties analysis.

Property	Authors (year)	Object	Algorithms/techniques used	Other relevant works
Yarn Diameter and Unevenness	Abdelkader et al. (2022)	Technique for obtaining cross-sectional images of textile yarns to analyze diameter and unevenness.	Canny Edge Detection, Clustering Algorithms	Carvalho, Soares, et al. (2009); Li et al. (2019); Li et al. (2020); Abdelkader (2022); Ozkaya et al. (2010); Zhang et al. (2024); Pereira et al. (2023); Sengupta et al. (2015); Guo et al. (2010); Lifeng Pan and Liu (2017)
	Abdelkader (2022)	Measure diameter of yarns and fibers through MATLAB algorithms.	Canny Edge Detection, Hough Transform (Circular)	
	Lei et al. (2021), Kuo et al. (2010), Li, Pan, Wang, et al. (2016)	Yarn image segmentation in real-time and diameter calculation	Clustering Algorithms (Fuzzy C-means cluster)	
Yarn Twist	Pei and Tao (2015)	Measuring yarn twist using backward light scattering and small-angle far-field diffraction method	Beckmann's scattering model	Ozkaya et al. (2010); Pereira et al. (2023); Guo et al. (2010); Basu et al. (2003)
	Ozkaya et al. (2010)	Yarn twist detection through digital imaging	Spatial Analysis, Fast Fourier Transform (FFT) method	
Yarn Hairiness	Z. Li et al. (2020)	Yarn Hairiness detection by digital imaging	Poisson matting and a connectivity-based classifier	Carvalho, Soares, et al. (2009); Pereira et al. (2023); Sengupta et al. (2015); Guo et al. (2010); Guo et al. (2023); Fabijanska et al. (2008)
	Majumdar (2010)	Prediction of Yarn Hairiness	Regression analysis and Artificial Neural Network Models	
	Wang et al. (2010)	Yarn hairiness detection based on image processing	Canny Edge	
	Pereira et al. (2023)	Analysis and classification of the characteristics of yarn, such as type of hairiness	Artificial Intelligence (Deep learning)	
Yarn Porosity and Internal Structure	Turan et al. (2012)	Predicts intra-yarn porosity using image processing methods	The Otsu method	Carvalho, Soares, et al. (2009); Li et al. (2018); Li and Fu (2021); Haleem et al. (2019)
	Siddiqui and Sun (2014)	Evaluates porosity in plain weft knitted fabrics, focusing on intra-yarn porosity and its implications for fabric properties.	Mathematical calculation	

millimeters cut length, enabling more accurate calculations of unevenness and a better understanding of yarn quality (Carvalho, Soares, et al., 2009; Li et al., 2020; Zhong et al., 2015; Xu et al., 2010; Semnani et al., 2005).

A work is demonstrated related to tests on jute and cotton yarn diameter using a low-cost yarn parameterization unit developed by Sengupta et al. (2015). Mathematical methods were used by Cybulska (1999) to estimate basic structural parameters of yarn thickness by image analysis (Cybulska, 1999). Zhang et al. (1998) introduced an image analysis system to detect yarn thin places and unevenness for quality enhancement through fault analysis (Zhang et al., 1998).

To fill the gap concerned with online real time defect detection in textile yarns, Noman Haleem et al. suggested an online quality control system based on computer vision. The study demonstrated how an object detection algorithm can be utilized with imaging to improve yarn quality, such as defect (thick, thin places and neps) detection (Haleem et al., 2021). On the other hand, Ibrahim et al. (2023) examined characterization of yarn diameters using diverse commercial instruments, emphasizing the need for instrument validation and interrelationship of different technique (Ibrahim et al., 2014).

Wang et al. (2020) introduced a yarn diameter and unevenness measurement denoising algorithm (Wang et al., 2020). With this, Khaddama et al. proposed a new approach for measuring the diameter of carded cotton applying image processing and artificial neural network obtaining a higher accuracy than that of the conventional method (Khaddam & Ahmad, 2022). Another method of dynamic image processing was also discussed by Eldessouki et al. (2023), which include high-speed camera for measurement of diameter of yarns at far distances in addition to overall complete analysis of yarns (Eldessouki et al., 2014).

The fiber thickness measurement using image processing was investigated by Ülkü et al., who compared accuracy between microscopic and image processing for different textile fibers (Ulku et al., 2015). Tunak et al. introduced a control chart of modified

Table 2. Critical analysis of traditional and image analysis techniques.

Aspect	Strength	Weakness
Testing Principle	Traditional methods have been validated over decades, providing a reliable baseline for yarn quality parameters (Fang et al., 2013; Carvalho et al., 2011). Computer vision approaches leverage advanced image processing and AI algorithms, enabling more comprehensive characterization beyond what traditional sensors can capture (Pereira et al., 2023; Pereira et al., 2018).	Traditional methods are sometimes not fully automatic and sometimes follow indirect system (Xu et al., 2018). Computer vision methods, while innovative, often depend on complex image acquisition setups and sophisticated algorithms that may lack standardization and require extensive calibration potentially limiting reproducibility and industrial adoption (Wang et al., 2014).
Speed and Throughput	Image analysis systems offer real-time or near-real-time testing capabilities, with some studies demonstrating continuous online monitoring (Haleem et al., 2023). The automation inherent in computer vision reduces manual intervention and accelerates data acquisition (Saimon et al., 2024).	Despite advances, some computer vision systems still face challenges in processing large volumes of high-resolution images rapidly (Xu et al., 2018; Eldessouki et al., 2014). Traditional testers, although slower and offline, provide consistent throughput that is well-integrated into existing workflows (Liu et al., 2012; Weigang et al., 2010).
Destructiveness and Sample Integrity	Computer vision methods are inherently non-destructive, analyzing yarn and fabric surfaces without physical contact or alteration, keeping sample integrity for subsequent processing (Zhang & Xin, 2016). Traditional testers may involve mechanical contact that can affect samples or introduce variability (Fang et al., 2013; Kuzanski, 2006).	Some image-based methods require controlled lighting and positioning, which may limit applicability in harsh or variable production environments (Li et al., 2014; Li, Pan, Zhang, et al., 2016). Traditional methods, while sometimes destructive, are robust under diverse conditions and less sensitive to environmental factors (Carvalho et al., 2011).
Accuracy and Scope of Analysis	Computer vision techniques provide enhanced accuracy in detecting yarn features often surpassing traditional testers (Xu et al., 2018; Roy et al., 2014; Fabijańska & Jackowska-Strumiłło, 2012). Traditional methods offer reliable, standardized metrics widely accepted in industry, facilitating benchmarking and quality control (Fang et al., 2013; Kuzanski, 2006).	Accuracy of computer vision methods can be changed by image quality issues such as focus depth, lighting, and fiber overlap, which may introduce measurement errors (Wang et al., 2014; Li, Pan, Zhang, et al., 2016). Traditional testers may not detect certain parameters due to their sensing limitations and provide less comprehensive data (Orcid, 2023; Roy et al., 2018).
Practical Applicability and Integration	Computer vision systems are designed for online, in-line integration, enabling continuous quality monitoring, which aligns with Industry 4.0 paradigms (Haleem et al., 2023). Hybrid systems combining image processing with traditional sensors have been proposed also (Roy et al., 2018).	Integration challenges include high initial costs, sophisticated sensors and cameras and interpret data (Pereira et al., 2023). Traditional testers remain favored for their simplicity, robustness and less technologically advanced settings (Liu et al., 2012; Idzik et al., 2022).

exponentially weighted moving average (EWMA) for image processing based monitoring and detecting defects of chenille yarns in real world production settings, where the control chart is found to be effective (Maroš et al., 2011).

An intelligent computer method to automatically create a mosaic and extract tracer fiber images for automatic evaluation of yarn diameter, comparing to manually measured results, has been developed by Li et al. (2014) (Li et al., 2015). This work demonstrates how computer vision techniques can improve yarn characterization. In a later work, Li et al. (2015) measured yarn apparent diameter unevenness by sequence images, giving credit to image analysis as yarn irregularity indicator (Li, Pan, Zhang, et al., 2016). The work showed that traditional, cut weight-based measurements could be extended with advanced imaging techniques to produce a more complete description of yarn properties. The image acquisition device captured image and processed yarn image for unevenness measurement has been shown in Figure 2.

Examining relationships between yarn characteristics and surface properties of knitted fabrics, Kılıç and Okur (2018) measured unevenness and diameter of yarns, then to the fabric performance. In this study, it is found that the overall quality of knitted textile is generally influenced by yarn diameter (Balci Kilic & Okur, 2019). Ozkaya et al (2010) investigated digital imaging for yarn twist measurement and found that usage of digital imaging was good for performance of yarn twist measurement. It is also found that the accuracy of the diameter measurement affects the yarn twist measurement (Ozkaya et al., 2010).

Li et al. (2019) introduced a computer vision based system of geometrical parameters of slub yarn, where the sequence images were successfully studied with the help of K-means clustering (Li et al., 2019). This new method offers better accuracy in the measurements of the diameter, particularly when dealing with nontrivial structures of yarns. A few years later, Abdelkader (2022) offered MATLAB algorithms to measure a particular diameter of the textile yarns. Here also was emphasized the necessity of proper measuring the diameter to various properties of the yarn, including strength and hairiness (Abdelkader, 2022).

The article by Li et al. (2015) had also proposed a computer vision method that can directly quantify the

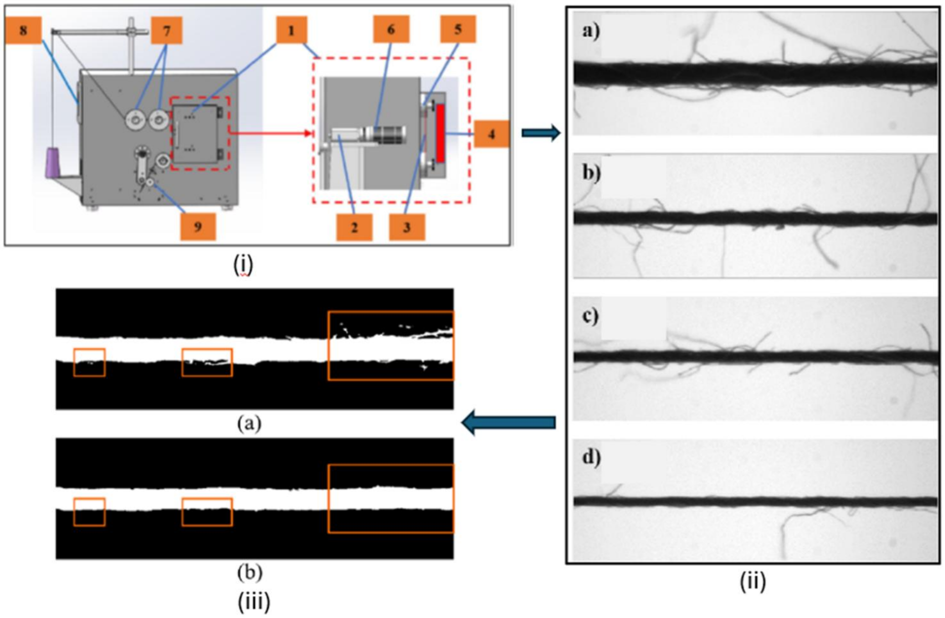

Figure 2. Yarn unevenness measured by Li et al. (2015): (i) Device for image acquisition: (1) imaging box; (2) CCD camera unit; (3) yarn; (4) light; (5) guide; (6) camera; (7) tension control unit; (8) control screen; (9) output rollers. (ii) Four kind of yarn images; (iii) processed result (a) binary image (b) yarn core image (Li, Pan, Zhang, et al., 2016).

unevenness of the yarn directly by taking consecutive pictures. This method proved to be more dependable than other older semi-quantitative methods (Li, Pan, Zhang, et al., 2016). Similarly, Zhong et al. presented an approach in which a series of images were used with address mapping tables, then enabling measurements to be taken automatically at various points on the yarn (Zhong et al., 2015).

Collectively, these research indicates that digital and image-based techniques of analyzing yarn can be faster, not mentioning that it provides opportunities, which have never been possible under traditional methods. As a result of these new methods, the researchers will have a closer insight into the characteristics of the yarns, which will result in the quality and performance increase of the textile products.

2.2. Yarn twist

One of the most important properties of yarn is twist, because it has a strong impact on the strength and the appearance of the yarn. The twist distribution cannot be determined by traditional twist measurement methods with twist tester, which can significantly influence the strength of the yarn. One possible way of overcoming this limitation is image analysis and a few studies have been carried out to quantify twists by image-based methods. Various techniques have been proposed in this field and many of these studies have contributed significantly to it. A precise

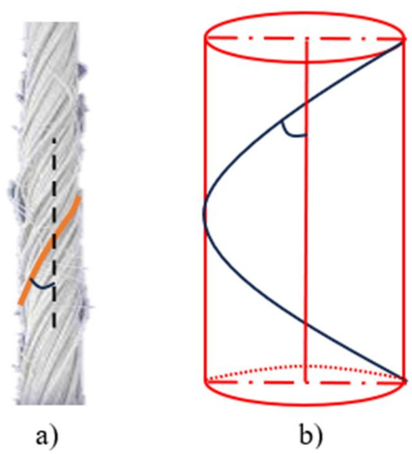

Figure 3. (a) Twisted yarn image, (b) geometric twist model.

computation of yarn twist, clear image with prominent twist line is necessary. Figure 3 shows twisted yarn image (a) and Geometric twist model (b). Geometric model is required for calculating yarn twist from yarn image.

Basu et al. (2003) work on measuring diameter and twist from yarn images (Basu et al., 2003). The results of their findings highlight the importance of this approach for obtaining important information about yarn properties—the very thing that must be controlled during textile manufacturing to ensure product quality. Ozkaya et al (2010) evolved the idea of yarn twist measurement using digital imaging techniques. They discussed importance of backlit yarn images for

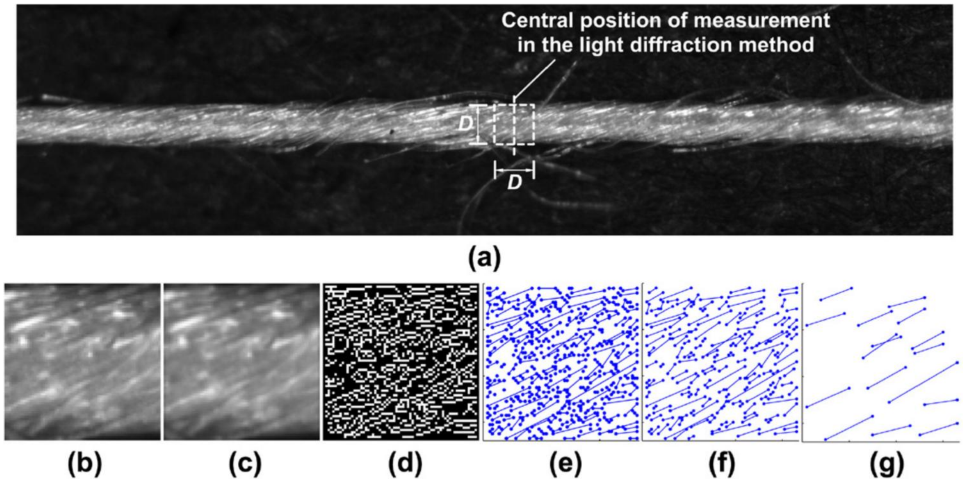

Figure 4. Twist angle measurement based on the microscopic image: (a) and (b) range of measurement for the twist angle; (c)–(g) twist angle determining steps (Pei & Tao, 2015).

accurate measurements of yarn diameters and outlined calculation of twist from yarn images (Ozkaya et al., 2010).

Guo et al. (2010) developed a continuous measurement system employing optics to determine multiple yarn structural parameters such as diameter, twist distribution, and relatively unexplored 3D configurations of fibers. This advancement is important in advancing the knowledge of twist distribution and its effect on yarn performance (Guo et al., 2010).

To measure yarn twists, Pei and Tao (2015) developed a method based on backward light scattering and small angle diffraction. Together, they developed a technique to use digital image processing to analyze microscopic images of yarn to extract surface twist angles and yarn diameters (Figure 4). This method also illustrates the capabilities for fusing optical and digital analysis to improve the measurement precision of twins (Pei & Tao, 2015).

2.3. Yarn hairiness

Evaluation of yarn hairiness has been done through traditional indirect methods used in evenness tester machines that assess light reflection from hairy fibers. Yet, these methods are not suitable for all hairy fibers in yarns, and thus may generate inaccuracies on quality assessment (Yilmaz & Usal, 2012; Carvalho et al., 2008). As a result of this, research was undertaken during recent years to introduce image analysis methods of providing a more direct and accurate measurement yarn hairiness thus enhance the accuracy of measurement (Li et al., 2020; Zhang & Xin, 2016).

Li et al. (2020) create a two-scale attention model that mimics the way humans observe, to create an intelligent computer-based system to grade the surfaces of yarns. Such researches have indicated that the properties of yarns, even hairiness, can be determined precisely by processing digital features of the yarns images using advanced image analysis (Li et al., 2020). Also, by incorporating image processing technology, it is possible to create a digital index of the yarn hairiness that will improve the accuracy of determinations even more (Zhang & Xin, 2016; Lei et al., 2021). Specifically, Wang et al. and Fabijańska et al. have obtained core yarn using graph cut method and yarn segmentation through the use of high pass filtering-based method. In a different research the yarn hairiness is measured using the two suggested measures including index of hair area and index of hair length and then they are compared to USTER hairiness index (Fabijańska & Jackowska-Strumiłło, 2012; Guha et al., 2010).

Moreover, computer vision and artificial intelligence have been used to come up with new defect analysis methods of textile yarns. Using as an example this mechatronic prototype that relies on the strength of YOLOv5 algorithm, this prototype can analyze and classify various yarn characteristics features including the types of hairiness in the yarn with the help of the advanced image processing (Pereira et al., 2023; Majumdar, 2010). Additionally, the algorithm of blending computer vision with a multiscale Hessian feature is created to measure yarn hairiness online. It has been demonstrated to be highly associated with commercial offline hairiness testers (Trung et al., 2023).

Moreover, yarn hairiness has been digitized by applying digital image processing and analysis of the actual length of all hairs under a microscope. With this method, it is seen that the image processing outsmarts the traditional methods on the issue of accuracy and reliability (Fabijańska & Jackowska-Strumiłło, 2012). Similarly, Fabijanska et al. (2008) studied image processing and analysis as applied in other industrial computer vision systems such as the yarn hairiness measurement (Fabijanska et al., 2008). Besides its increased accuracy and efficiency, these methods also produce high quality and performance of yarns in the variety of textile applications (Yu & Sun, 2014; Mirzaei et al., 2012; Haleem & Wang, 2015). A combination of these studies helped us to know more about the yarn hairiness measure and how it can be used in justifying the production of textiles in image analysis.

2.4. Yarn porosity and internal structure

Measuring yarn porosity and analyzing internal structures have been neglected in the industry of textile since it is extremely complex and resources are not there to study these minute details. However, image analysis techniques have been used to measure these properties in several studies, that provide practical information with respect to the various types of yarns. Li and Fu (2021) obtained much in terms of the inner structural quality analysis of cellulosic yarns with the help of image analysis. They also developed a complete automated system that is intelligent and has five modules, which measure and assess the structural properties of these yarns successfully (Li & Fu, 2021). Similarly, Haleem et al. (2019) used the help of micro-computed tomography (micro-CT) and digital image processing to complete research on the structure of cotton ring-spun yarns. According to their findings, the structure of fibers after a long time is significant in tensile properties and exhibited some connection between the behavior of the fibers and a more coordinated structure of the yarn (Haleem et al., 2019).

Turan et al. (2012) proposed a digital yarn image analysis method to predict intra-yarn porosity using MATLAB for image processing. Their results indicated that this approach enhances the understanding of yarn structure and porosity, and can be reliably used to determine porosity values (Turan et al., 2012). Along with this, Haleem et al. carried out a non-invasive study of cotton ring-spun yarns and indicated that longitudinal arrangement of fibers has a significant impact on tensile properties because of fiber migration, which helps to form a more cohesive structure of the yarn (Abdelkader et al., 2022; Haleem et al., 2019). Also, Guo et al. (2010) presented a continuous measurement system based on optical techniques to measure the spatial distribution of several yarn structural parameters. The system was very reliable and repeatable and offered detailed information on the different characteristics of the yarns (Guo et al., 2010).

So, it can be said that image analysis incorporation of the yarn porosity and infrastructure can make a highly significant input to the yarn properties analysis.

3. Techniques used in image analysis

Use of computer vision for yarn properties analysis involves several sequential steps involving capturing yarn images, and deriving measurable output such as diameter, hairiness, and twist. The general workflow is illustrated in Figure 5, where the image acquisition stage, preprocessing stage, feature extraction stage, analysis stage, and the generation of output stage.

Different algorithms are used to extract the features from the image of the yarn to measure the different properties of yarn. This study outlines the application of various algorithms to extract specific properties of yarn.

3.1. Clustering algorithms

Clustering algorithms are used to group similar data points together. K-means is one of the most common clustering algorithms introduced in 1957 by Stuart Lloyd (Lu & Zhou, 2016). Yarn image analysis has a high demand for the use of clustering algorithms such as in the application of color segmentation, pattern recognition and quality evaluation of yarn. Fuzzy C-means (FCM) is also employed to improve accuracy and efficiency for the processing of image data associated with yarn characteristics. Figure 6 shows different clusters of values in different colors by means of k-means cluster algorithm.

Figure 7 illustrates FCM (Fuzzy C-means) algorithm to identify yarn image from the image background and this clustering method is also used for fabric pattern identification. Figure 8 also demonstrates segmentation of yarn by FMC clustering algorithm.

Zhang et al. (2014) have used clustering algorithm for color segmentation, where fabric images are captured then processed to determine the layout of color yarns (Zhang et al., 2015). The work of Luo et al.

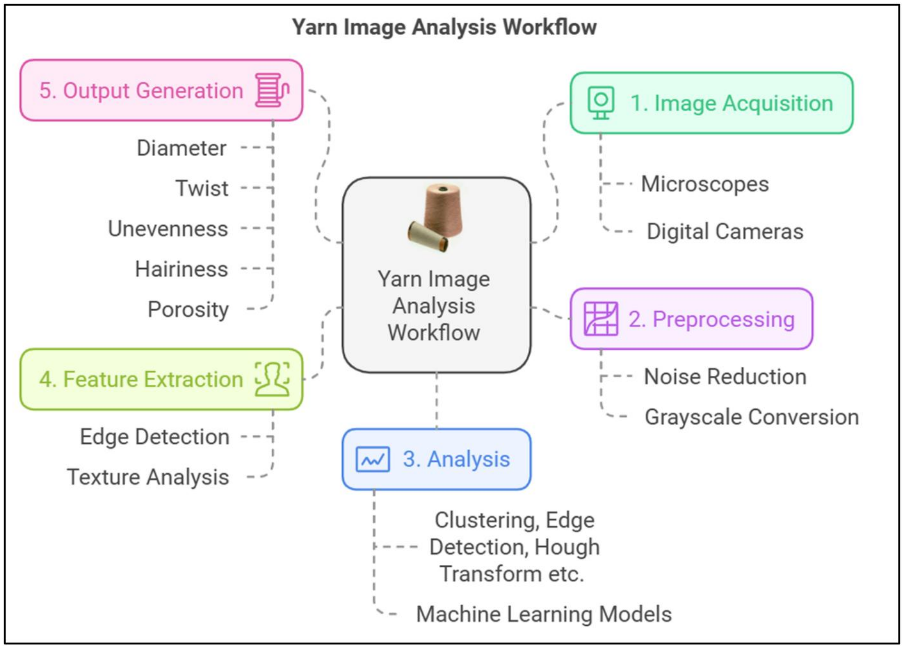

Figure 5. Yarn image analysis workflow.

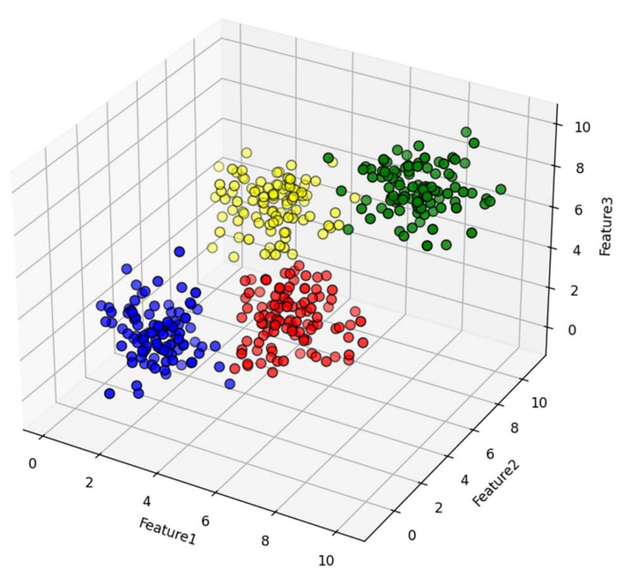

Figure 6. Showing different clusters in different colors by K-means cluster algorithms.

which integrated the FCM algorithm to segment parts of yarn-dyed fabric, is complimentary to this work (Luo et al., 2015b). They noted FCM is effective, but its efficacy is limited by the scattered and uneven nature of colors in yarn-dyed fabrics making it susceptible to further refinement of the algorithm for better results. For instance, Li et al. (2019) used the pixels in sequential images of slub yarns to perform the K-means clustering algorithm for diameter, evenness measurement of the yarn (Li et al., 2019). Since this technique allows real time tracking of the quality of the yarns, it is especially significant to the textile industry. In yarn appearance measurements and evenness, Lei et al. used K-means clustering algorithm to eliminate yarn within foreground images in the sequence (Lei et al., 2021).

Another similar application of clustering in automatic defect detection is that defected regions tend to have a similar appearance. The color coding of yarns is a crucial defect-benefits checking procedure of the yarn-woven fabrics that Zhang et al. (2020) achieved by the K- means clustering algorithm (Zhang et al., 2020). This was also reinforced by Tang and Xin who showed that such clustering algorithms as that of Fuzzy C-Means (FCM) are significant in identifying and eliminating colors of the yarns in an imagery data and boosting accuracy of the color values (Tang & Xin, 2015).

Conclusively, the clustering algorithms, namely the K-means and Fuzzy C-Means are powerful in analyzing the yarn images. They are applied in color sorting, to divide the image of the yarns and a background, geometrical measurements and quality defects that all play great roles in the quality evaluation of the textile industry and other related sectors.

3.2. Canny edge detection algorithm

In 1986 John F. Canny developed Canny Edge Detection, a multi-step edge detector in images (Canny, 1986). This technique has been reported to indicate edges with a high level of accuracy and low errors and thus it suits well to identify the razor thin edges of the yarn structures in the images. The edge

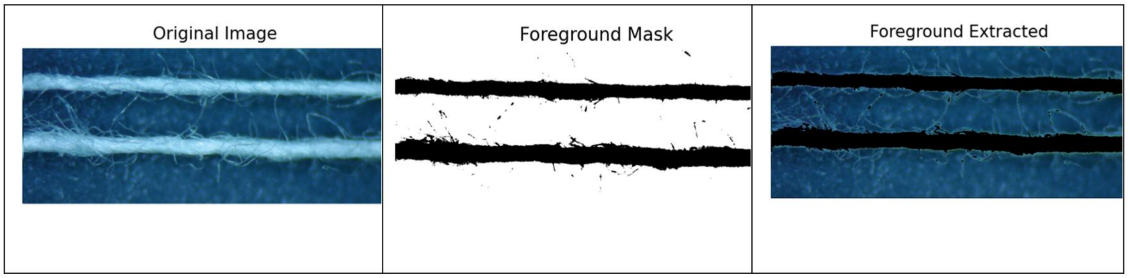

Figure 7. Illustrates FCM (Fuzzy C-means) algorithm to identify yarn image from the image background (Kuo et al., 2010; Li, Pan, Wang, et al., 2016).

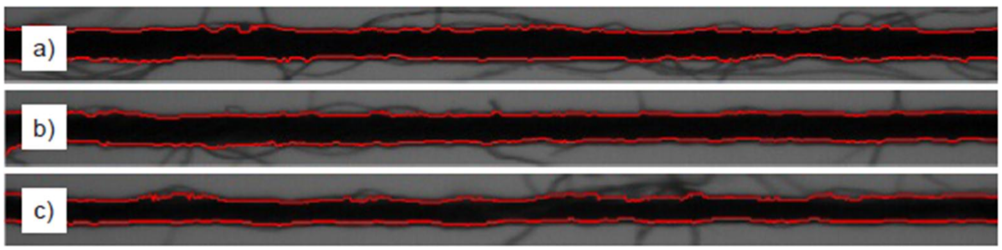

Figure 8. Segmentation of yarn by FCM clustering algorithm (Kuo et al., 2010).

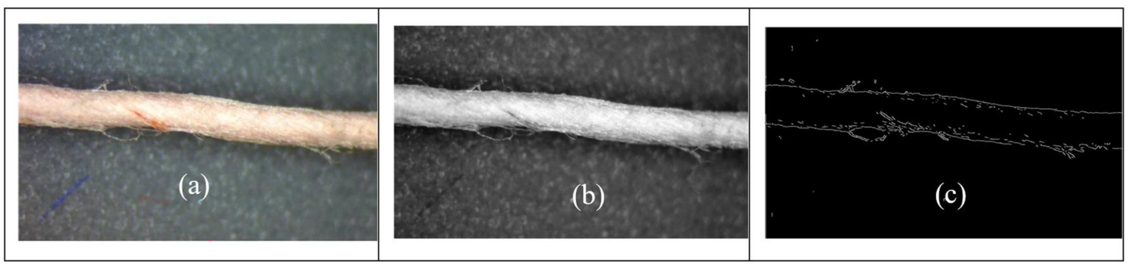

Figure 9. (a) Yarn image, (b) grey yarn image, (c) edge detected image.

detected image in Figure 9c is obtained from the original yarn image in Figure 9a and compare it with the grey yarn image in Figure 9b. This experiment is done by the authors of this article for better explanation of the use of Canny Edge Detection algorithm for yarn edge detection. This technique has been used by many researchers to obtain yarn characteristics.

Zhang et al. suggested a method for analyzing yarn images that comprises of four steps: gradient calculation, preprocessing, non-maximum suppression, and relevant parameter calculation. In the processing stage we apply a Gaussian filter to eliminate noise and any unneeded items from the yarn image. In the x and y axes, a newly developed 5×5 convolution kernel and weighted least- squares approach is used to calculate gradient intensity. After gradient images are created, each is non-maximum suppressed to functionally help identify yarn candidate evenness by locally locating maximally strong edges. Finally, high and low strong edge thresholds are used to compute the final edge curves of the yarn stem, and final edge curves are calculated to determine relevant parameters for yarn evenness. As schematized in Figure 10, the overall framework of the method is comprised (Zhang et al., 2024).

Experiments in yarn hairiness were carried out by Wang et al. where they used the Canny edge detection operator which typically smooths the image with a Gaussian function followed by edge detection with dual thresholds. Figure 11 and 12 shows the parameters set and the results with sharpened ones after Canny edge detection (Wang et al., 2010).

The Canny edge detection algorithms contain a set of procedures that are used to optimize the algorithm. This also includes the noise reduction, the gradient calculation, non-maximum suppression and edge tracking that employs hysteresis (Yang et al., 2023; Baştan et al., 2017). It relies on thinning edges and accurate point of edges required in the measurement of small features in the yarn images (Sundani et al., 2019). As an example, Liu et al. have indicated that, Canny algorithm is more noise resistant and localizes

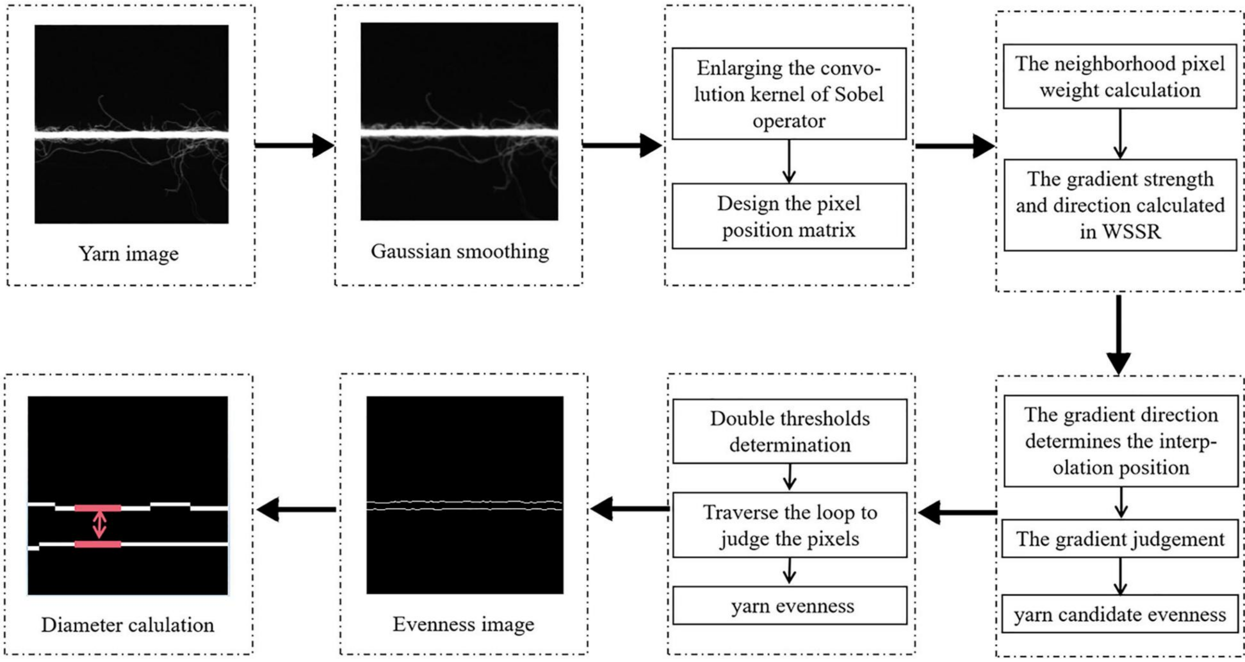

Figure 10. Yarn diameter calculation using Canny Edge algorithm (Zhang et al., 2024).

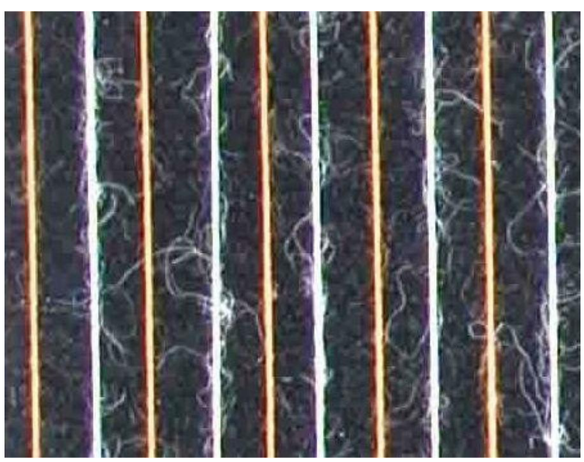

Figure 11. Colored yarn image (Wang et al., 2010).

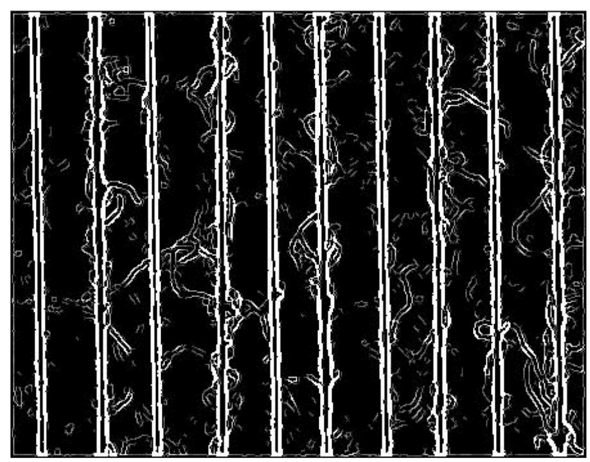

Figure 12. Yarn image after applying Canning Edge Detection (Wang et al., 2010).

edges better than Sobel and Prewitt methods (Liu et al., 2017).

In the article by Telli (2021), the Canny algorithm is applied to detect the edges of the yarn images and to isolate the adjacent fibers and the core yarn (Telli, 2021). The algorithm is also used to isolate the yarn of the background color so that additional analysis is done on the yarn images. The quality assessment of the textile product depends on the ability to assess the quality of the yarns based on their hairiness because hairiness significantly affects the performance and appearance of the product (Sundani et al., 2019; Baloch et al., 2021).

Finally, the Canny edge detection algorithm is useful for yarn image analysis, providing a high edge detection accuracy which is essential for yarn quality assessment.

3.3. Hough Transform (circular)

In 1962, Paul Hough invented the Circular Hough Transform - a technique to find circles in an image (Hough, 1969). The Circular Hough Transform (CHT) is a potent yet widely applied method in image processing to identify circular objects; this is why it is a perfect methodology to apply to the process of the yarn analysis in the textile industry. This approach is based on the fact that a circle can be expressed in terms of its coordinates of the center and the radius. It is also found to identify circular features in yarn

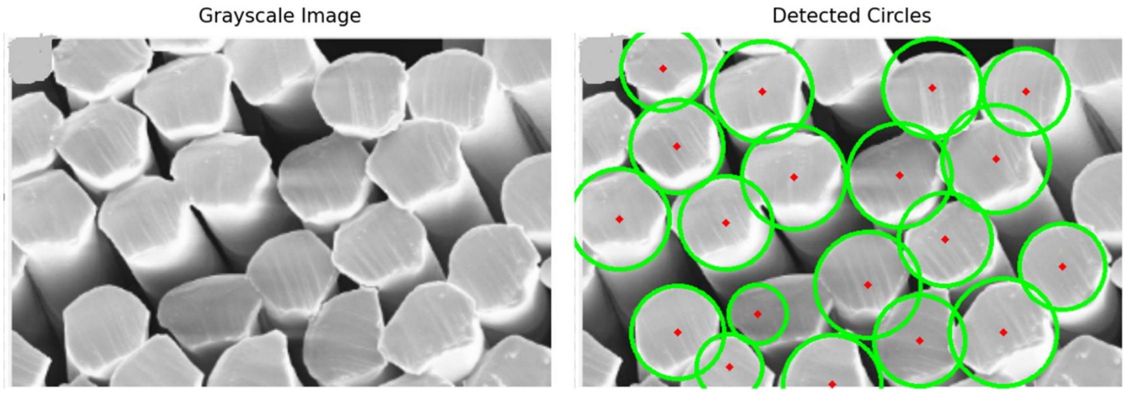

Figure 13. Grey image of yarn cross-section and detected circular fiber cross-sections (original image is from Karaca et al. (2012) and circular Hough Transform is applied by the authors of this article at right side image).

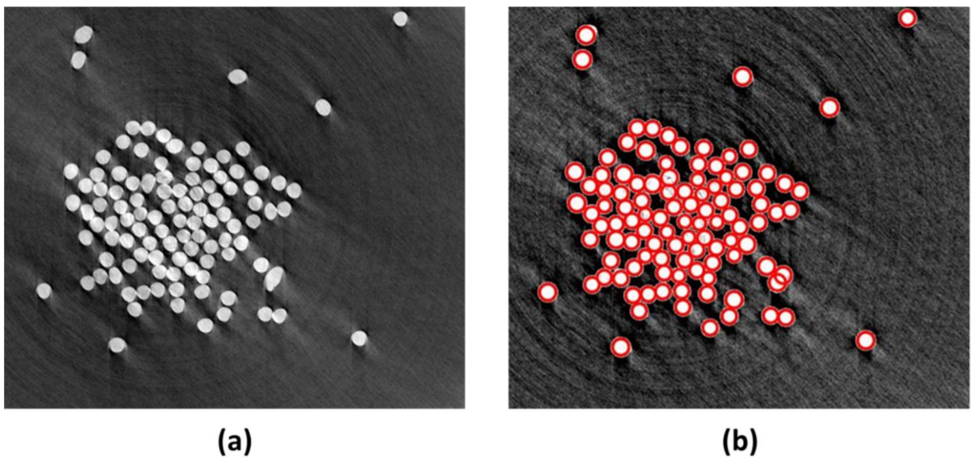

Figure 14. (a) The yarn cross-section before processing, and (b) the cross-section image after being processed by the algorithm (Abdelkader, 2022).

and fiber images very well (Yang & Huang, 2014; Frosio & Borghese, 2008). In Figure 13, the section of the cross-section of yarn image (SEM image) is borrowed by Karaca et al. (2012) and circular Hough Transform is then worked out by the authors of the current article, which is presented at the right side image and fiber cross-sections are measured using the algorithm (Karaca et al., 2012).

In another work, Abdelkader (2022) reported a method for yarn diameter measurement using binarization of the image to isolate the yarn body, then applying the Circular Hough Transform for detecting the circular or near circular cross section fibers (Figure 14). The advantage of this approach is that it makes it feasible to accurately characterize yarn dimensions important for textile manufacturing quality control (Abdelkader, 2022).

It can also be used with the other image processing techniques for additional effectiveness. Yang et al. (2014) introduced a multiscale grayscale Hough Transform, providing circular object detection with consideration of different scales, which will serve as a very useful tool for yarn image evaluation with size and texture change. When using a single scale, a more sensitive technique using this multiscale method increases the likelihood for detection of circular features that would be missed otherwise (Yang & Huang, 2014). In addition, the Hough transform (circular) has been applied by some researchers to automatically evaluate fabric drape and determine quantities of yarn present on a ring cop bobbin (Hu et al., 2021; Suvari, 2021).

Circular Hough Transform is an indispensable tool for yarn image analysis and provides robust methods of yarn image analysis for detecting circular shapes and for measuring yarn characteristics.

3.4. Hough Transform (line)

In 1972, Richard Duda and Peter Hart introduced the Hough Transform, which finds straight lines in images (Duda & Hart, 1972). The Hough Transform for Lines learns the lines in an image from a space of parameters. It is widely used to detect linear features. The line Hough Transform is used in yarn analysis to find the straight element, for example to detect twisted section of yarn with varying twist amount. This technique also measures fabric density and skew angle of yarn (Liu et al., 2012). A fabric image Figure 15a and a vertical yarns detection (b) with Hough transform (Line) is shown in Figure 15. The fabric image is taken by a microscope and Hough Transform lines are illustrated at Figure 15b image.

Pan et al. developed a method for checking the density of solid-colored fabrics, with a focus on a thorough analysis of the procedure. Their method involves using the Hough transform to determine the skew angles of warp and weft yarns. The pixels in the fabric image are then projected along the skew direction. Successful warp and weft yarn segmentation requires discovering real minimum values that represent yarn interstices. The density of solid-colored fabric is determined by counting the strands within a unit length in the fabric image (Figure 16) (Pan et al., 2010).

Hough Transform is defined on the following basic principle: project a point in image space to a parameter space, where the point votes the lines, it may be covering. Hough Transform enables the process of voting in images that are noisy, so it is robust, but at the same time, this is resistant to all types of image defects (Jošth et al., 2011).

In some cases the Hough Transform is especially suitable when it comes to identification of the yarn edges that are critical in terms of finding out the quality and strength of the yarn. One example is the yarn edge identification, which can be involved in the analysis of the parameters of yarn diameter and evenness of the yarn because they are significant in the quality of textile products (Lifeng Pan & Liu, 2017). The linear features that the researchers will obtain when the Hough Transform is applied to the images of the yarn reflect the structure of the yarn and enable further analysis of the yarn properties.

Conversely, Hough Transform can equally be used in other trends of image processing to make it more effective. As an example, edge detection algorithms, like Canny edge detector, are sometimes combined with the Hough Transform, and make line detection in a yarn image more accurate. This combination processing of images is enhanced to a greater level, in such a way that the detected lines of Hough

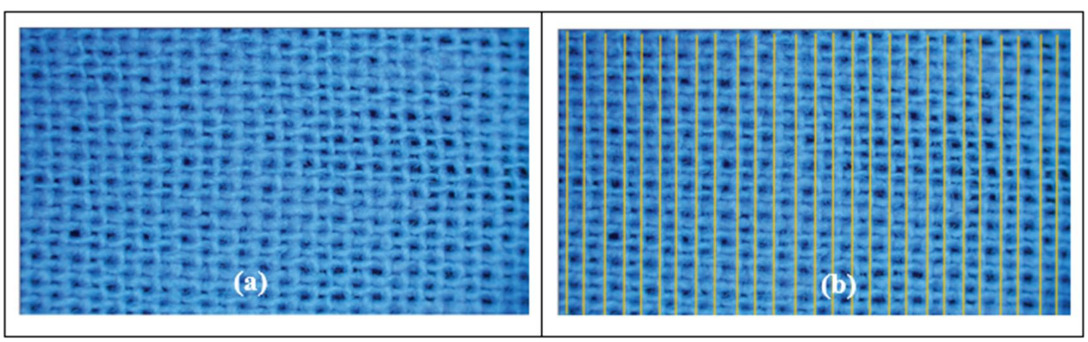

Figure 15. (a) Fabric image (b) detected of vertical yarns by Hough transform (line).

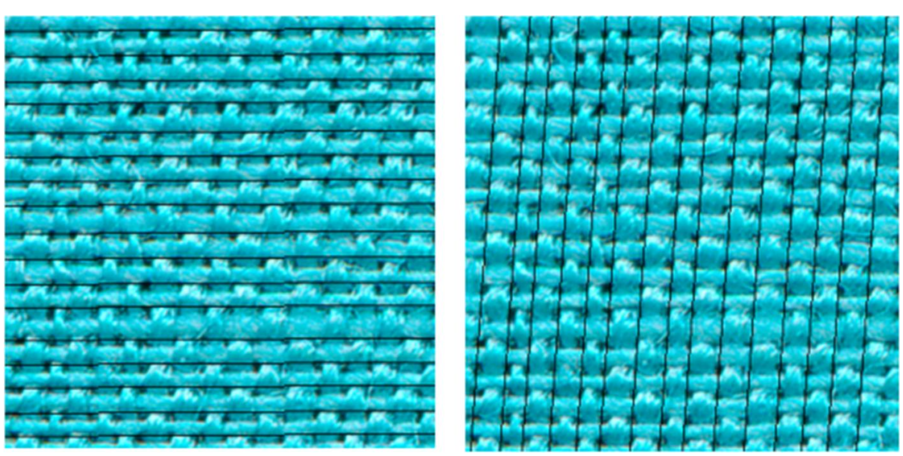

Figure 16. Weft segmentation (left) and warp segmentation (right) by Hough Line Transform (Pan et al., 2010).

Transform are considered to be nearer to what the yarn structure is in reality (Zhang et al., 2015).

Defect detection is also performed with the Hough Transform as, e.g. detecting defects in the yarn (either yarn structure irregularity or change in yarn tension). These defects can be detected using line detection by manufacturers who can take corrective actions to achieve better product quality (Shin et al., 2015).

The Hough Transform is a robust method for detection of linear features necessary for quality assessment in the textile industry. The combination with other image processing techniques in the modern textile inspection systems increases its effectiveness and thus becomes a crucial part of the process.

3.5. Machine learning

Machine learning is the way of training a model so that it can detect patterns and predict according to learning. It can be used for classification, regression or clustering in the fields of image analysis. Machine learning can be used for machine yarn analysis for doing things such as categorizing images with regards to characteristics (e.g. hairiness level), predicting yarn properties or automating pattern searching in the images. Pereira et al. (2023) presented an innovative methodology to analyze defects in textile yarn by associating a computer vision system with artificial intelligence. On the basis of image processing which analyses and classifies the characteristics of yarn, such as type of hairiness, the created mechatronic prototype using the YOLOv5 algorithm showed high precision (Figure 17) (Pereira et al., 2023).

Fabijańska and Jackowska-Strumiłło (2012) developed algorithms that use machine learning technologies to analyze the yarn images from various angles and began to improve hairiness assessments. Roy et al. also showed that image features can be used to classify yarn hairiness using machine learning and therefore, improve classical measurement methods (Fabijańska & Jackowska-Strumiłło, 2012). Machine learning has also been used to detect yarn twists. Digital imaging combined with machine learning was used by Ozkaya et al. (2010) to measure yarn twist and showed that accuracy improved over conventional methods (Ozkaya et al., 2010).

Analogously, deep learning techniques also hold promise for analyzing yarn-dyed fabrics. In the work of Zhang et al., Zhang et al. they proposed an attention-based feature fusion generative adversarial network for defect detection, which greatly improves defect identification (Zhang et al., 2023). Meng et al. (2019) modified a multi-scale convolutional neural network (MSnet) to precisely localize warp and weft yarns, thereby improving fabric density measurements through integration with the Hough Transform (Meng et al., 2019).

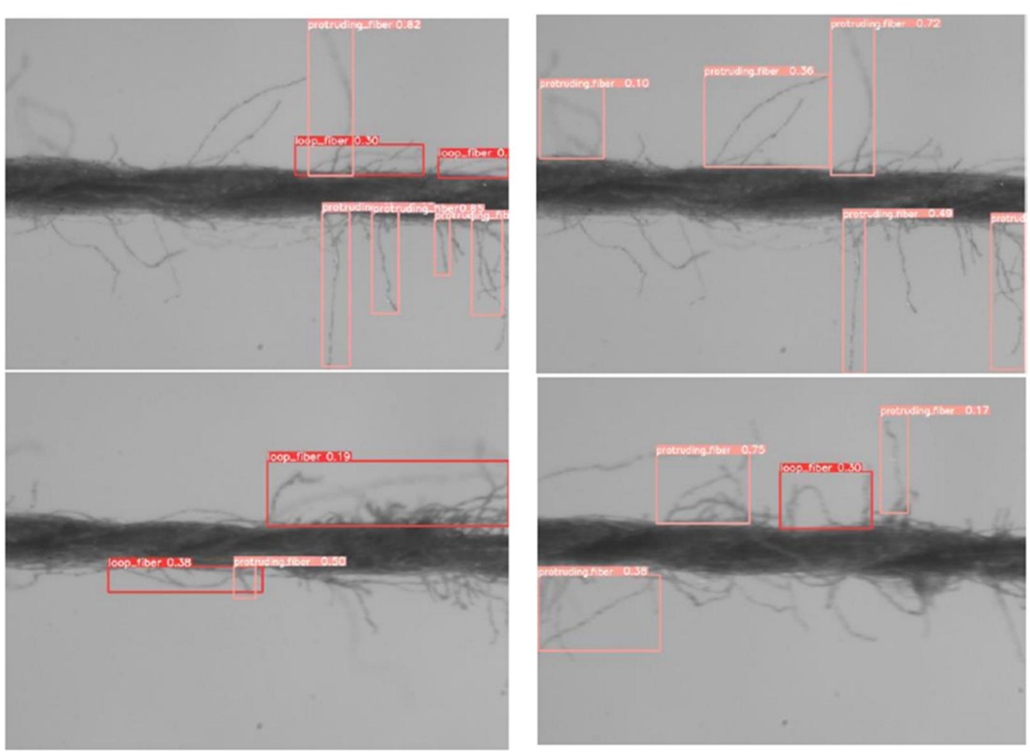

Figure 17. Classification results using the deep learning algorithm (YOLOv5s) (Pereira et al., 2023).

So, machine learning algorithms are helping to revolutionize yarn image analysis by offering robust methods for qualitative assessment of yarn as well as detecting defects while improving the precision and efficiency of textile manufacturing analysis.

4. Limitations and scope

Many innovations and advancement opportunities are presented by the application of modern computer vision techniques and artificial intelligence (AI) to yarn property analysis which are discussed in this article. But for image analysis and extracting insightful features from the image, clear image of the yarn is required which is challenging most of the time. Lack of adequate datasets of yarn is another big problem for training deep learning models. Future research should focus on the creation of large, well annotated datasets of images of yarn which would depict a wide variety of yarn types, structures and manufacturing conditions. The construction of such systems based on these datasets would allow for highly accurate identification and establishment of different yarns, detection of structural variances as well as detection of twists in feature.

Deep learning models are not applied to this field extensively although it has huge potential in this field. Complex aspects in yarn images including twist variations and internal structural patterns could be detected by using deep learning methods including convolutional neural network (CNN) and transformer-based architectures. While these methodologies have the potential to someday provide promising results, there are yet outstanding results in these domains which leave a large gap in literature. It is due to the lack of precise image datasets of fine yarns and fibers.

One of the potential directions is the construction of real-time monitoring based on high-speed photography and AI analytics. These technologies may allow continuous quality monitoring during production which reduces faults and enhances efficiency in production. Moreover, new imaging schemes, like hyperspectral and 3D imaging, can give new information about the material composition, porosity, and mechanical properties of the yarn materials.

Future studies can be done on how to develop an energy saving and environmentally friendly image analysis systems to curb the challenge of sustainability. Such tiny AI code that would be destined to run on edge computing devices may reduce the reliance of heavy hardware and, consequently, render it accessible to industries. These problems can be solved through solutions to enable the field to analyze problems and quality control in the yarn analysis and make massive progress.

5. Conclusion

Image analysis and computer vision used in the analysis of yarn property provides a paradigm shift to research and quality control in the textile industry. The computer vision system can enhance precision, speed and scale in the process of identifying and measuring the properties of yarns. Nonetheless, the problem of the unavailability of clear imaging tools, specific datasets and low research in fields like the yarn type identification and twist variation analysis are obstacles that require further research. Addressing these gaps through dataset generation, sophisticated algorithm development, and academic-industry collaboration will pave the road for novel solutions. The textile sector can improve yarn analysis precision and fulfill industry 4.0 by using developing technology and focusing on sustainability, resulting in better product quality and sustainable practices.

Disclosure statement

No potential conflict of interest was reported by the authors.

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References

Abdelkader, M. (2022). MATLAB algorithms for diameter measurements of textile yarns and fibers through image processing techniques. *Materials (Basel, Switzerland)*, *15*(4), 1299. https://doi.org/10.3390/ma15041299

Abdelkader, M., Adnan, M., & Zafar, S. (2022). Experimental techniques to obtain the cross-sectional images of textile yarns. *Materials*, 15, 4726. https://doi.org/10.3390/ma15144726

Balci Kilic, G., & Okur, A. (2019). Effect of yarn characteristics on surface properties of knitted fabrics. *Textile Research Journal*, *89*(12), 2476–2489. https://doi.org/10.1177/0040517518797337

Baloch, A., Memon, T. D., Memon, F. A., Harijan, B. L., Viyas, V., & Jan, T. (2021). Hardware synthesize and performance analysis of intelligent transportation using Canny edge detection algorithm. *International Journal of Engineering and Manufacturing*, *11*, 22–32. https://doi.org/10.5815/ijem.2021.04.03

Baştan, M., Bukhari, S. S., & Breuel, T. M. (2017). Active Canny: Edge detection and recovery with open active

contour models. *IET Image Process*, *11*(12), 1325–1332. https://doi.org/10.1049/iet-ipr.2017.0336
Basu, A., Doraiswamy, I., & Gotipamul, R. L. (2003). Measurement of yarn diameter and twist by image analysis. *Journal of the Textile Institute*, *94*(1-2), 37–48. https://doi.org/10.1080/00405000308630592
Canny, J. (1986). A computational approach to edge detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *8*(6), 679–698. https://doi.org/10.1109/TPAMI.1986.4767851
Carvalho, V., Cardoso, P., Belsley, M., Vasconcelos, R., & Soares, F. (2008). Yarn hairiness parameterization using a coherent signal processing technique. *Sensors and Actuators A: Physical*, *142*(1), 217–224. https://doi.org/10.1016/j.sna.2007.02.019
Carvalho, V., Gonçalves, N., Soares, F., Belsley, M., & Vasconcelos, R. M. (2011). An overview over yarn mass parameterization methods. In *The Second International Conference on Sensor Device Technologies and Applications* (pp. 18–24).
Carvalho, V., Soares, F., & Vasconcelos, R. (2009, September). Artificial intelligence and image processing based techniques: A tool for yarns parameterization and fabrics prediction. In *2009 IEEE Conference on Emerging Technologies & Factory Automation* (pp. 1–4). IEEE. https://doi.org/10.1109/ETFA.2009.5347255
Carvalho, V., Vasconcelos, R., Soares, F., & Belsley, M. (2009). Yarn diameter and linear mass correlation. *Journal of Nondestructive Evaluation*, *28*(2), 49–54. https://doi.org/10.1007/s10921-009-0046-8
Cybulska, M. (1999). Assessing yarn structure with image analysis methods. *Textile Research Journal*, *69*(5), 369–373. https://doi.org/10.1177/004051759906900511
Duda, R. O., & Hart, P. E. (1972). Use of the Hough transformation to detect lines and curves in pictures. *Communications of the ACM*, *15*(1), 11–15. https://doi.org/10.1145/361237.361242
Eldessouki, M., Ibrahim, S., & Militky, J. (2014). A dynamic and robust image processing based method for measuring the yarn diameter and its variation. *Textile Research Journal*, *84*(18), 1948–1960. https://doi.org/10.1177/0040517514530032
Fabijańska, A., & Jackowska-Strumiłło, L. (2012). Image processing and analysis algorithms for yarn hairiness determination. *Machine Vision and Applications*, *23*(3), 527–540. https://doi.org/10.1007/s00138-012-0411-y
Fabijanska, A., Kuzanski, M., Sankowski, D., & Jackowska-Strumillo, L. (2008). Application of image processing and analysis in selected industrial computer vision systems. In *2008 International Conference on Perspective Technologies and Methods in MEMS Design* (pp. 27–31). IEEE. https://doi.org/10.1109/MEMSTECH.2008.4558728
Fang, H., Xin, B., & Liu, X. (2013). A review of yarn appearance evaluation based on image analysis technology. *Research Journal of Textile and Apparel*, *17*(4), 1–11. https://doi.org/10.1108/RJTA-17-04-2013-B001
Frosio, I., & Borghese, N. A. (2008). Real-time accurate circle fitting with occlusions. *Pattern Recognition*, *41*(3), 1041–1055. https://doi.org/10.1016/j.patcog.2007.08.011
Guha, A., Amarnath, C., Pateria, S., & Mittal, R. (2010). Measurement of yarn hairiness by digital image processing. *Journal of the Textile Institute*, *101*(3), 214–222. https://doi.org/10.1080/00405000802346412
Guo, M., Gao, W., & Wang, J. (2023). Online measurement of sizing yarn hairiness based on computer vision. *Fibers and Polymers*, *24*(4), 1539–1552. https://doi.org/10.1007/s12221-023-00136-5
Guo, Y., Tao, X. M., Xu, B. G., Choi, K. F., Hua, T., & Wang, S. Y. (2010). A continuous measurement system for yarn structures by an optical method. *Measurement Science and Technology*, *21*(11), 115706. https://doi.org/10.1088/0957-0233/21/11/115706
Haleem, N., & Wang, X. (2015). Recent research and developments on yarn hairiness. *Textile Research Journal*, *85*(2), 211–224. https://doi.org/10.1177/0040517514538692
Haleem, N., Bustreo, M., & Del Bue, A. (2021). A computer vision based online quality control system for textile yarns. *Computers in Industry*, *133*, 103550. https://doi.org/10.1016/j.compind.2021.103550
Haleem, N., Bustreo, M., & Del Bue, A. (2023). Online evaluation of textile yarn evenness using fast exposure imaging and image processing techniques. In *2023 7th International Conference on Automation, Control and Robots (ICACR)* (pp. 68–72). IEEE. https://doi.org/10.1109/ICACR59381.2023.10314594
Haleem, N., Liu, X., Hurren, C., Gordon, S. G., Najar, S. S., & Wang, X. (2019). Investigating the cotton ring spun yarn structure using micro computerized tomography and digital image processing techniques. *Textile Research Journal*, *89*(15), 3007–3023. https://doi.org/10.1177/0040517518805387
Hough, J. F. (1969). *The soviet prefects*. Harvard University Press. https://doi.org/10.4159/harvard.9780674498891
Hu, R., Fu, Z., Zhu, S., Liu, X., & Jia, F. (2021, March). Detection of residual yarn in bobbin based on Hough transform and BP neural network. In *2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)* (pp. 68–74). IEEE. https://doi.org/10.1109/IAEAC50856.2021.9390622
Ibrahim, S., Militky, J., Kremenakova, D., & Mishra, R. (2014). Characterization of yarn diameter measured on different. In *The 4th RMUTP International Conference: Textiles and Fashion* (pp. 33–47).
Idzik, M., Idzik, M., & Design, T. (2022). Image analysis as a method of the assessment of yarn for making. *22*, 4–10. https://doi.org/10.2478/aut-2020-0021
Jošth, R., Dubská, M., Herout, A., & Havel, J. (2011). Real-time line detection using accelerated high-resolution Hough transform. https://doi.org/10.1007/978-3-642-21227-7_73
Karaca, E., Kahraman, N., Omeroglu, S., & Becerir, B. (2012). Effects of fiber cross sectional shape and weave pattern on thermal comfort properties of polyester woven fabrics. *Fibres & Textiles in Eastern Europe*, *92*(3), 67–72. https://www.researchgate.net/publication/265426453_Effects_of_Fiber_Cross_Sectional_Shape_and_Weave_Pattern_on_Thermal_Comfort_Properties_of_Polyester_Woven_Fabrics
Khaddam, H. S., & Ahmad, G. G. (2022). A method to evaluate the diameter of carded cotton yarn using image processing and artificial neural networks. *Journal of the*

Textile Institute, *113*(8), 1648–1657. https://doi.org/10.1080/00405000.2021.1943259

Kieu, S. T. H., Bade, A., & Hijazi, M. H. A. (2022). Modified Canny Edge Detection Technique for Identifying Endpoints. *Journal of Physics: Conference Series*, *2314*(1), 012023. https://doi.org/10.1088/1742-6596/2314/1/012023

Kuo, C.-F. J., Shih, C.-Y., Ho, C.-E., & Peng, K.-C. (2010). Application of computer vision in the automatic identification and classification of woven fabric weave patterns. *Textile Research Journal*, *80*(20), 2144–2157. https://doi.org/10.1177/0040517510373630

Kuzanski, M. (2006). Measurement Methods for Yarn Hairiness Analysis - the idea and construction of research standing. In *Proceedings of the 2nd International Conference on Perspective Technologies and Methods in MEMS Design* (pp. 87–90). IEEE. https://doi.org/10.1109/MEMSTECH.2006.288672

Lei, W., Lu, Y., Pan, R., & Gao, W. (2021). Evaluation of yarn appearance on a blackboard based on image processing. *Textile Research Journal*, *91*(19-20), 2263–2271. https://doi.org/10.1177/00405175211002863

Li, J. J., Wang, C., Tu, W. X., & Zuo, B. Q. (2014). A new measurement system of yarn appearance based on machine vision. *Advanced Materials Research*, *945-949*, 1810–1814. https://doi.org/10.4028/www.scientific.net/AMR.945-949.1810

Li, S. Y., & Fu, H. (2021). Image analysis and evaluation for internal structural properties of cellulosic yarn. *Cellulose*, *28*(10), 6739–6756. https://doi.org/10.1007/s10570-021-03900-z

Li, S. Y., Xu, B. G., Fu, H., Tao, X. M., & Chi, Z. R. (2018). A two-scale attention model for intelligent evaluation of yarn surface qualities with computer vision. *Journal of the Textile Institute*, *109*(6), 798–812. https://doi.org/10.1080/00405000.2017.1371870

Li, S. Y., Xu, B., Tao, X., & Ru, Z. (2015). An intelligent computer method for automatic mosaic and segmentation of tracer fiber images for yarn structure analysis. *Textile Research Journal*, *85*(7), 733–750. https://doi.org/10.1177/0040517514551459

Li, Z., Pan, R., Wang, J., Wang, Z., Li, B., & Gao, W. (2016). Real-time segmentation of yarn images based on an FCM algorithm and intensity gradient analysis. *Fibres and Textiles in Eastern Europe*, *24*(4(118), 45–50. https://doi.org/10.5604/12303666.1201130

Li, Z., Pan, R., Zhang, J., Li, B., Gao, W., & Bao, W. (2016). Measuring the unevenness of yarn apparent diameter from yarn sequence images. *Measurement Science and Technology*, *27*(1), 015404. https://doi.org/10.1088/0957-0233/27/1/015404

Li, Z., Xiang, J., Wang, L., Zhang, N., Wang, J-a., Pan, R., & Gao, W. (2019). Measuring the geometrical parameters of slub yarn using a computer vision based image sequencing technique. *Fibres & Textiles in Eastern Europe*, *27*(3(135), 26–35. https://doi.org/10.5604/01.3001.0013.0739

Li, Z., Zhong, P., Tang, X., Chen, Y., Su, S., & Zhai, T. (2020). A new method to evaluate yarn appearance qualities based on machine vision and image processing. *IEEE Access*, *8*, 30928–30937. https://doi.org/10.1109/ACCESS.2020.2972967

Lifeng Pan, D. C., & Liu, F. (2017). Image correction scheme based on improved Hough transform. *Revista Técnica de la Facultad de Ingeniería de la Universidad del Zulia*, *39*, 392–400. https://doi.org/10.21311/001.39.10.46

Liu, C. W., & Li, L. (2011). Automatic inspection of silk spinning yarn fineness. *Advanced Materials Research*, *175-176*, 360–365. https://doi.org/10.4028/www.scientific.net/AMR.175-176.360

Liu, J., Jiang, H., Pan, R., Gao, W., & Xu, M. (2012). Evaluation of yarn evenness in fabric based on image processing. *Textile Research Journal*, *82*(10), 1026–1037. https://doi.org/10.1177/0040517511431320

Liu, K., Kang, X., & Xiong, H. (2017). An image edge detection algorithm based on improved Canny. https://doi.org/10.2991/icmmct-17.2017.114

Lu, Y., & Zhou, H. H. (2016). Statistical and computational guarantees of Lloyd's algorithm and its variants. https://doi.org/10.48550/arXiv.1612.02099

Luo, L., Shen, H. L., Shao, S. J., & Xin, J. H. (2015a). A multispectral imaging approach to colour measurement and colour matching of single yarns without winding. *Coloration Technology*, *131*(4), 342–351. https://doi.org/10.1111/cote.12162

Luo, L., Shen, H. L., Shao, S. J., & Xin, J. H. (2015b). A novel method for weft and warp yarn segmentation in multicolour yarn-dyed fabric images. *Coloration Technology*, *131*(2), 165–171. https://doi.org/10.1111/cote.12130

Majumdar, A. (2010). Comparative analysis of regression and artificial neural network models for the prediction of yarn hairiness. *Research Journal of Textile and Apparel*, *14*(3), 85–93. https://doi.org/10.1108/RJTA-14-03-2010-B009

Maroš, T., Vladimír, B., & Caner, T. M. (2011). Monitoring chenille yarn defects using image processing with control charts. *Textile Research Journal*, *81*(13), 1344–1353. https://doi.org/10.1177/0040517511402123

Meng, S., Pan, R., Gao, W., Zhou, J., Wang, J., & He, W. (2019). Woven fabric density measurement by using multi-scale convolutional neural networks. *IEEE Access*, *7*, 75810–75821. https://doi.org/10.1109/ACCESS.2019.2922502

Mirzaei, M., Gharehaghaji, A. A., & Zarrebini, M. (2012). A new method of yarn hairiness reduction by air suction during carding. *Textile Research Journal*, *82*(20), 2128–2136. https://doi.org/10.1177/0040517512447586

Orcid, A. T. (2023). The evaluation of uster hairiness results with an image analysis approach [Bir Görüntü Analiz Yaklaşımı ile Uster Tüylülük Sonuçlarının Değerlendirilmesi]. *Çukurova Üniversitesi Mühendislik Fakültesi Dergisi 38*, 899–905.

Ozkaya, Y. A., Acar, M., & Jackson, M. R. (2010). Yarn twist measurement using digital imaging. *Journal of the Textile Institute*, *101*(2), 91–100. https://doi.org/10.1080/00405000802263476

Pan, R., Gao, W., Liu, J., & Wang, H. (2010). Automatic inspection of woven fabric density of solid colour fabric density by the Hough transform. *Fibres & Textiles in Eastern Europe*, *18*, 81.

Pan, R., Gao, W., Liu, J., & Wang, H. (2011). Recognition the parameters of slub-yarn based on image analysis. *Journal of Engineered Fibers and Fabrics*, *6*(1),

155892501100600104. https://doi.org/10.1177/155892501100600104
Pei, Z., & Tao, X. (2015). Measurement of yarn twist based on backward light scattering and small-angle far-field diffraction. *Measurement Science and Technology*, *26*(12), 125005. https://doi.org/10.1088/0957-0233/26/12/125005
Pereira, F., Carvalho, V., Soares, F., Vasconcelos, R., & Machado, J. (2018). Computer vision techniques for detecting yarn defects. In *Applications of computer vision in fashion and textiles* (pp. 123–145). Elsevier. https://doi.org/10.1016/B978-0-08-101217-8.00006-3
Pereira, F., Macedo, A., Pinto, L., Soares, F., Vasconcelos, R., Machado, J., & Carvalho, V. (2023). Intelligent computer vision system for analysis and characterization of yarn quality. *Electronics*, *12*(1), 236. https://doi.org/10.3390/electronics12010236
Rashmi, Kumar, M., & Saxena, R. 2013. Algorithm and technique on various edge detection: A survey. *Signal & Image Processing: An International Journal*, *4*(3), 65, 75. https://doi.org/10.5121/sipij.2013.4306
Roy, S., Sengupta, A., & Sengupta, S. (2014). Yarn hairiness evaluation using image processing. https://doi.org/10.1109/ciec.2014.6959157
Roy, S., Sengupta, A., & Sengupta, S. (2018). Quality testing of staple yarn by an instrument with dual sensing and its comparative study with capacitive sensing. *43*, 269–276.
Saimon, A. S. M., Mintoo, A. A., & Islam, M. M. (2024). Enhancing textile quality control with iot sensors: a case study of automated defect detection. *Global Mainstream Journal*, *1*(1), 19–30. https://doi.org/10.62304/ijmisds.v1i1.113
Semnani, D., Latifi, M., Tehran, M. A., Pourdeyhimi, B., & Merati, A. A. (2005). Development of appearance grading method of cotton yarns for various types of yarns. *Research Journal of Textile and Apparel*, *9*(4), 86–93. https://doi.org/10.1108/RJTA-09-04-2005-B009
Sengupta, A., Roy, S., & Sengupta, S. (2015). Development of a low cost yarn parameterisation unit by image processing. *Measurement*, *59*, 96–109. https://doi.org/10.1016/j.measurement.2014.09.028
Shin, S., Park, J., Shin, D.-H., Song, C.-G., & Kim, K.-S. (2015). Real-time photoacoustic tomograpghy using linear array probe and detection of line structure using Hough transform. *Bio-Medical Materials and Engineering*, *26 Suppl 1*, S1483–S1490. https://doi.org/10.3233/bme-151447
Siddiqui, M., & Sun, D. (2014). Porosity prediction of plain weft knitted fabrics. *Fibers*, *3*(1), 1–11. https://doi.org/10.3390/fib3010001
Sundani, D., Widiyanto, S., Karyanti, Y., & Wardani, D. T. (2019). Identification of image edge using quantum Canny edge detection algorithm. *Journal of ICT Research and Applications*, *13*(2), 133–144. https://doi.org/10.5614/itbj.ict.res.appl.2019.13.2.4
Suvari, F. (2021). Image processing based drape measurement of fabrics using circular Hough transformation. *Journal of the Textile Institute*, *112*(5), 846–854. https://doi.org/10.1080/00405000.2020.1782553
Tang, I., & Xin, J. H. (2015). Yarn color measurement and reproduction by a multispectral imaging system. *Journal of Imaging Science and Technology*, *59*(3), 030401-1–030401-8. https://doi.org/10.2352/J.ImagingSci.Technol.2015.59.3.030401
Telli, A. (2021). The comparison of the edge detection methods in the determination of yarn hairiness through image processing. *Tekstil Ve KonfeksiYon*, *31*, 91–98. https://doi.org/10.32710/tekstilvekonfeksiyon.770366
Trung, T. D. U. C., Dieu, H. C. H. U., & Anh, T. D. A. O. (2023). Influence of some winding parameters on hairiness of yarn after winding process. *Fibres and Textiles*, *29*, 2022. https://doi.org/10.15240/tul/008/2022-4-004
Turan, R. B., Okur, A., Deveci, R., & Açikel, M. (2012). Predicting the intra-yarn porosity by image analysis method. *Textile Research Journal*, *82*(16), 1720–1728. https://doi.org/10.1177/0040517511427971
Ulku, E., Demir, O., Yildiz, K., & Yildiz, Z. (2015). Fiber thickness measurement using image processing. In *2015 23nd Signal Processing and Communications Applications Conference (SIU)* (pp. 1166–1166). IEEE. https://doi.org/10.1109/SIU.2015.7130043
Wang, R., Zhou, J., Yu, L., & Xu, B. (2014). Fusing multifocus images for yarn hairiness measurement. *Optical Engineering*, *53*(12), 123101. https://doi.org/10.1117/1.OE.53.12.123101
Wang, X., Hou, R.-M., Gao, X.-Y., & Xin, B.-J. (2020). Research on yarn diameter and unevenness based on an adaptive median filter denoising algorithm. *Fibres & Textiles in Eastern Europe*, *28*(1(139), 36–41. https://doi.org/10.5604/01.3001.0013.5856
Wang, X.-H., Wang, J.-Y., Zhang, J.-L., Liang, H.-W., & Kou, P.-M. (2010). Study on the detection of yarn hairiness morphology based on image processing technique. In *2010 International Conference on Machine Learning and Cybernetics* (pp. 2332–2336). IEEE. https://doi.org/10.1109/ICMLC.2010.5580660
Weigang, Q., Qilan, H., & Gongyuan, Y. (2010). Application of on-line yarn evenness measurement through CCD image sensors. In *2010 International Conference on Computer Application and System Modeling (ICCASM 2010)* (pp. V6-115). IEEE. https://doi.org/10.1109/ICCASM.2010.5618988
Xu, B., Tao, X., & Murrells, C. M. 2010. Evaluation of a digital image-signal approach on the automatic measurement of cotton yarn snarls. *Textiles Research Journal*, *80*(12), 1151. https://doi.org/10.1177/0040517509352526
Xu, B., Wang, L., & Gao, W. (2018). 3D measurement of yarn hairiness via multi-perspective images. In P. Schelkens, T. Ebrahimi, & G. Cristóbal (Eds.), *Optics, photonics, and digital technologies for imaging applications V* (p. 39). SPIE. https://doi.org/10.1117/12.2307844
Yang, L., Li, M., Tongxin, W., Youfeng, B., Li, J., & Jiang, Y. (2023). Geo-information mapping improves Canny edge detection method. *IET Image Processing*, *17*, 1893–1904. https://doi.org/10.1049/ipr2.12764
Yang, W. X., & Huang, Z. C. (2014). Fast circular object detection using multiscale grayscale Hough transform. *Applied Mechanics and Materials*, *490–491*, 1542–1547. https://doi.org/10.4028/www.scientific.net/AMM.490-491.1542
Yilmaz, D., & Usal, M. R. (2012). Effect of nozzle structural parameters on hairiness of compact-jet yarns. *Journal of Engineered Fibers and Fabrics*, *7*(2),

155892501200700209. https://doi.org/10.1177/155892501200700209

Yu, X., & Sun, P. (2014). Effect of carding plate gauge under the licker-in of carding machine on polyester yarn hairiness. *Advanced Materials Research*, *937*, 400–403. https://doi.org/10.4028/www.scientific.net/AMR.937.400

Zhang, G., & Xin, B. (2016). An overview of the application of image processing technology for yarn hairiness evaluation. *Research Journal of Textile and Apparel*, *20*(1), 24–36. https://doi.org/10.1108/RJTA-09-2015-0027

Zhang, H., Cheng, S., Zhao, Y., Jing, J., Su, Z., & Li, P. (2024). Measurement of yarn apparent evenness based on modified Canny edge detection. *Journal of the Textile Institute*, *115*(4), 600–606. https://doi.org/10.1080/00405000.2023.2201997

Zhang, H., Qiao, G., Lu, S., Yao, L., & Chen, X. (2023). Attention-based feature fusion generative adversarial network for yarn-dyed fabric defect detection. *Textile Research Journal*, *93*(5-6), 1178–1195. https://doi.org/10.1177/00405175221129654

Zhang, J., Pan, R., Gao, W., Xu, B., & Li, W. (2015). Automatic detection of layout of color yarns of yarn-dyed fabric. Part 1: Single-system-mélange color fabrics. *Color Research & Application*, *40*(6), 626–636. https://doi.org/10.1002/col.21927

Zhang, J., Xin, B., & Wu, X. (2014). Density measurement of yarn dyed woven fabrics based on dual-side scanning and the FFT technique. *Measurement Science and Technology*, *25*(11), 115007. https://doi.org/10.1088/0957-0233/25/11/115007

Zhang, J., Zhang, K., Wu, J., & Hu, X. (2020). Color segmentation and extraction of yarn-dyed fabric based on a hyperspectral imaging system. *Textile Research Journal*, *91*, 729–742. https://doi.org/10.1177/0040517520957401

Zhang, W., Iype, C., & Oxenham, W. (1998). The analysis of yarn thin places and unevenness with an image-analysis system and program design. *Journal of the Textile Institute*, *89*(1), 44–58. https://doi.org/10.1080/00405009808658596

Zhang, Y., Chen, G., Zhang, L., Li, H., & Wang, D. (2015). Research on method of character recognition based on Hough transform and RBF neural network. *MATEC Web of Conferences*, *31*, 16001. https://doi.org/10.1051/matecconf/20153116001

Zhong, P., Kang, Z., Han, S., Hu, R., Pang, J., Zhang, X., & Huang, F. (2015). Evaluation method for yarn diameter unevenness based on image sequence processing. *Textile Research Journal*, *85*(4), 369–379. https://doi.org/10.1177/0040517514547211