

# A compact intelligent system for online yarn quality evaluation

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## Abstract

Yarn quality control is a crucial step in producing high quality textile end products. Online yarn testing can reduce latency in necessary process control by providing rapid insights into yarn quality, leading to production of superior quality yarns. However, both widely used capacitance based evenness testers and emerging imaging based evenness testing systems are largely offline in operation (i.e. a posteriori). A suitable online system that could be employed to test quality of a variety of yarns in normal industrial processing conditions does not yet exist. In this study, we propose an online evenness testing system for measurement of a certain type of yarn defect called nep by using imaging and computer vision techniques. The developed system directly captures yarn images on a spinning frame and uses Viola-Jones object detection algorithm for real time detection of nep defects. The validation of nep detection algorithms and comparison of the new method with an existing evenness tester in terms of nep count demonstrated its reasonable defect detection accuracy and promising potential for application in wider yarn spinning industry.

## 1 Introduction

Natural fabrics are made of plant-based fibres, such as cotton, or animal fibres, such as wool or silk. The yarn production process involves several steps such as carding and spinning of the fibres, for providing the original material the strength required for producing robust fabrics. Due to organic and climatic conditions, the natural fibers intrinsically possess high degree of variations. Similarly, also synthetic fibers, although produced in controlled industrial settings, are far from being perfectly uniform. During the spinning process, this variation in the raw material translates to the yarn in form of unevenness. An additional source of yarn irregularities is the variation related to the yarn spinning process. Such variations include but are not limited to inadequate machine settings, faulty components and mechanical variations. For example, a worn out or damaged roller in a drafting system would not be able to evenly draft the fibrous strand to achieve required fineness, resulting in a periodic occurrence of unwanted thick or

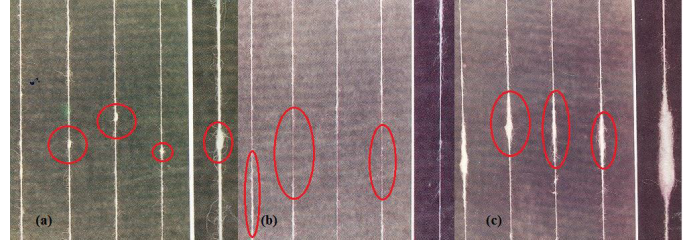


Figura 1: Different types of yarn defects a) neps b) thin place and c) thick places [Shaikat, 2014].

thin places. Similar type of issues arise from inadequate machine settings (i.e. speeds and gauges) and slippage among the moving components.

Yarn evenness represents the uniformity in fiber mass distribution along yarn length. A yarn that exhibits lower frequency and amplitude of mass related variations is classified as an even yarn and vice versa. Yarn irregularities or defects related to its evenness profile are generally categorized into three categories, depending on their thickness with respect to the base yarn diameter and their length. These three categories are neps (appearing as ‘small knots’ tied within a yarn), thick places (also called slubs) and thin places [Kretschmar e Furter, 2008], as shown in Fig. 1. A significant variation in fibre mass appears as a noticeable defect on yarn surface deteriorating its appearance [Srinivasan *et al.*, 1992; Shamey e Hussein, 2005] and undermining its mechanical performance [Haleem *et al.*, 2021]. The undesired variations in shades often lead to fabric rejection by the customer and consequent loss of economic value of the production.

Overall produced yarn quality can be improved when the cause of the defects is promptly intercepted. In particular, the process related variations could be substantially minimized, if not fully eradicated, by exerting effective process control and timely maintenances of the critical mechanical components.

The yarn quality is assessed using capacitive laboratory scale evenness testers, which provides an overall picture of the production quality testing a limited yarn sample from few randomly selected bobbins. However, these post-production tests cannot provide the live insights that are fundamental for addressing the cause of the defects.

Recently, several studies have reported the application of imaging methods to evaluate the evenness of yarns [Carva-

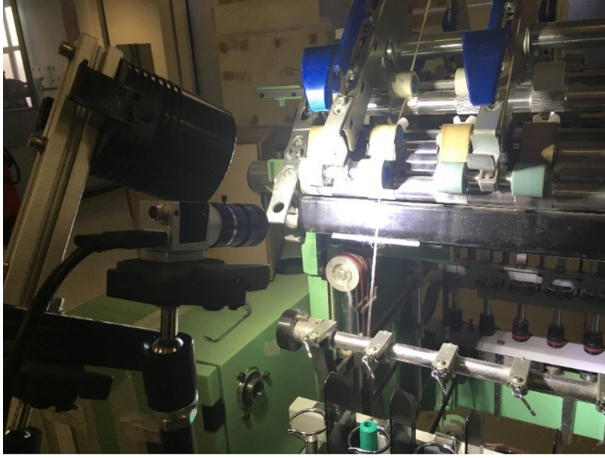


Figura 2: Image acquisition system for online yarn imaging is mounted on a ring spinning frame.

lho *et al.*, 2009; Ling *et al.*, 2010; Eldessouki *et al.*, 2014; Roy *et al.*, 2017; Li *et al.*, 2018; Pinto *et al.*, 2019]. Even if these studies proposed multiple imaging based yarn evenness testing methods as an alternative to the traditional approaches, none of these were focused on online yarn evenness testing as they used images that were either taken from static yarn samples or from yarns moving on laboratory scale transport devices. Hence, to the best of our knowledge, a suitable online yarn evenness tester remained non-existent.

In this study, we propose a new system for online measurement of yarn evenness to address the above described gap. An optimal image acquisition setup was developed to directly capture high quality yarn images in real time yarn production. The images were used to train and validate computer vision algorithms to identify a certain type of yarn defect called neps. The new system was then employed in regular industrial production for online testing of different yarn varieties and the outcomes were validated through comparison with an existing evenness tester.

## 2 Yarn image acquisition system

A Basler 1440–220um digital camera (Basler, Germany) fitted with a 50 mm lens (Tamron, Japan) and two extension rings of 5 mm thickness each, was deployed on a Marzoli MST Spin Tester ring frame (Marzoli, Italy). The camera was connected to a Dell Precision 7510 laptop (Dell, USA) through a USB 3 connection and imaging was controlled using Basler Pylon camera software suite (version 5.2.0). The physical distance between the camera and yarn specimen was 21 cm, which resulted in a vertical field of view of 1.2 cm length, along yarn axis. The digital resolution of the camera was set up at  $1100 \times 1080$  pixels and its exposure time was set to 3  $\mu$ s. The imaging speed (i.e. frames per second or FPS) was calculated for yarn specimens based on their delivery speed. A LED type light source GES-6 K-20-T (Genesi Lux, Italy) of 3600 lumens flux was applied to provide ample amount of illumination. Both camera and light source were mounted on two separate Manfrotto 244RC mounting arms (Manfrotto, Italy). This experimental setup is shown in Fig. 2.

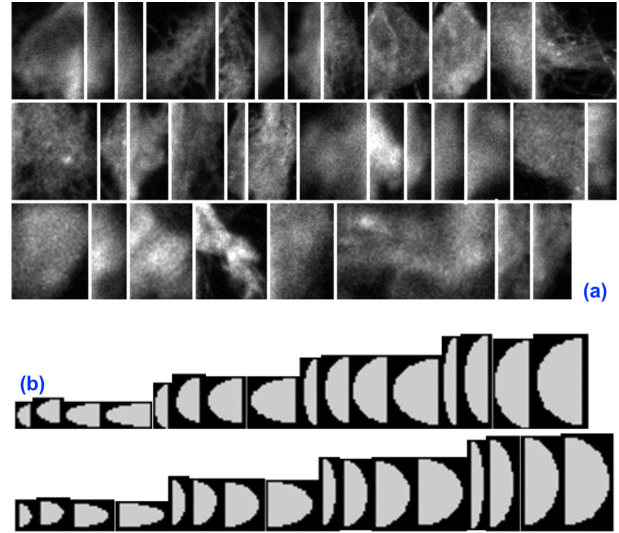


Figure 3: Cropped (a) original and (b) synthetic nep images.

## 3 Computer Vision models for nep detection

Three different image classifiers (termed as A, B and C) based on Viola-Jones algorithm have been developed. The three models vary in terms of the input data used in their training phase. We have chosen to use Viola-Jones algorithm because of its execution speed, low computational hardware requirements and good generalization capabilities also when a low number of training samples is available. Performance comparison with convolutional network based approaches is under investigation. The training data comprised of positive and negative images in 2:1 and these images were scaled with a ratio of 0.2 and 0.1, respectively to optimise training time. The number of training epochs were 10 for each model.

In order to train Model A, 33 images of original neps were cropped out of positive images from training set, as shown in Fig. 3(a). Due to imbalanced dataset and lower number of nep images, data augmentation techniques based on linear image transformations i.e. scaling, translating and rotating were applied to produce 5000 nep images. These were combined with 2500 negative yarn images, also taken from the training set, and fed to the algorithm to train model A. For model B, similar augmentation strategy was applied on 32 ‘synthetic nep’ images instead, which are computer generated images of half ellipses and vary in terms of major and minor axes length, as shown in Fig. 3(b). Lastly, a combination of both 33 original and 32 synthetic nep images was used to augment 5000 positive images to train model C.

## 4 Preliminary results

The three nep detection models i.e. A, B and C were validated using a validation dataset, which consisted of 100 positive (with neps) and 100 negative (without neps) yarn images. The classifications achieved by each model were categorised as true positive (TP), true negative (TN), false positive (FP) and false negative (FN). These parameters are provided for all three models in form of confusion matrices, as shown in Fig. 4, which suggest superior accuracy of Model C compared to both models A and B as it correctly classified 86% neps

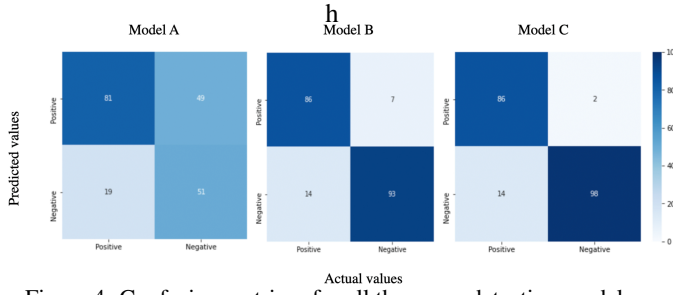


Figura 4: Confusion matrices for all three nep detection models.

and 98% negative yarn images. In addition, its false positives and negatives rate were 2% and 14% respectively.

In order to quantify the performance and facilitate inter-model comparison, four evaluation metrics, namely detection success rate (DSR), sensitivity, specificity and F-score, were calculated. The values of these metrics are provided in Table 1.

Model	DSR	Sensitivity	Specificity	F-score
A	0.66	0.81	0.51	0.62
B	0.9	0.86	0.93	0.89
C	0.92	0.86	0.98	0.91

Tabella 1: Four valuation metrics as calculated for each nep detection model.

The DSR characterises the ability of a classifier to accurately identify both positive and negative image classes. The Sensitivity of a classifier is a ratio of correctly identified positive images to the total number of positive image detections while the specificity is a ratio of correctly identified negative images to the total number of negative identified images. The F-score is a cumulative representation of both sensitivity and specificity. A comparison of these metrics for all three models also suggest higher detection score, sensitivity, specificity and F-score value for Model C, making it a clear choice for online nep detection application.

Out of all three models, model A which was trained using original nep images showed most inferior performance metrics while model B, which was trained using synthetic nep images showed significantly superior results compared to model A but slightly lesser performance than model C. A closer look into inferior performance of model A points out a close resemblance between textures of neps and yarns as a potential reason for their underperformance. The similarity of textures is due to the fact that neps and yarns are made from the same fibrous materials and imaged exactly in the same way, hence, resulting in similar grayscale intensities of their constituting pixels. The Haar-like features calculated by the computer vision algorithm from both neps and yarns would be essentially similar, which limited the ability of Model A to effectively differentiate between neps and yarns resulting in both higher number of false positives and false negatives. Moreover, the shape of neps were highly irregular and did not serve as a differential metric for nep identification either. On the other hand, models B and C, both of which used synthetic nep images, were able to differentiate between neps and yarns

as the grayscale intensity values of pixels lying within synthetic neps were uniform and clearly different than the normal yarns. In addition, their shape was also highly regular, which improved differentiation criteria between both groups.

A comparison of online nep detection system (O) with Uster Tester 3 (U) is provided in Table 2, where each data point represents an average of 3 observations.

Yarn linear density (tex)	140% neps		200% neps		400% neps		Total neps	
	U	O	U	O	U	O	U	O
59.05	5	146	3	11	3	0	11	157
29.5	26	256	5	45	0	2	31	303
14.76	220	193	56	132	3	20	278	346

Tabella 2: Four valuation metrics as calculated for each nep detection model.

The results show a substantial difference between both methods in terms of total number of neps and within nep sub classes. As a general trend, the number of neps detected by the online measurement technique are almost always higher than the number of neps reported by Uster tester in respective categories, except for + 140% neps category. However, the extent of this difference is particularly higher for coarser yarns (i.e. 59.05 tex) compared to finer yarns (i.e. 14.76 tex). The difference between total number of neps measured using both methods is also statistically significant as evaluated using Student's T-test (P-values: 59.05 tex yarn = 0.0002, 29.5 tex yarn = 0.0026, 14.76 tex yarn = 0.0032). The contradictions in the nep measurements from both methods in terms of substantiality and statistical significance is particularly interesting because the results achieved from online evenness measurement system comes with an imagery evidence as all nep containing images were stored as a part of testing. On the other hand, Uster Tester is a well established industrial technique for measurement of yarn evenness and defects. We expected a close agreement between measurements from both methods, which is clearly not the case. However, this discrepancy cannot be verified in current study as Uster Tester does not store images of yarn defects that could be directly compared with the online evenness testing system. We do not intend to undermine the accuracy of Uster Tester but the noted discrepancy essentially requires further controlled investigations as these differences could be attributed to two entirely different testing principles or a more complex issue, which remains unclear at this point. Other than this difference, the results achieved from imaging based evenness testing system indicates that our proposed system could be effectively used for online yarn testing and providing live insights into its quality for necessary process intervention and control, leading to production of superior quality yarns.

## 5 Conclusions

- An online yarn evenness testing system based on a combination of an image acquisition setup and Viola-Jones object detection algorithm is successfully developed to detect nep like defects during yarn production.

- The optimal quality online images of yarn could be acquired using an ultra-low exposure time imaging system combined with external illumination and suitable optical configuration.
- Viola-Jones algorithm effectively detected nep like defects in online yarn images with detection success rate of 92%, which may improve further with refinement of training strategy, size of training dataset or through experimenting with other object detection approaches to improve detection success rate.
- The count of nep defects achieved by online yarn evenness testing system was substantially higher than Uster Tester, although the trends of nep count were generally similar i.e. higher number of neps for finer yarns and vice versa.
- The substantial unexpected difference between nep count reported by online system and Uster tester may be attributed to two different testing principles but will essentially benefit from further careful investigations.
- In the future, the online yarn evenness measurement system can be used for detecting other types of yarn defects as well with necessary additions in image processing module to produce a complete yarn quality testing solution for wider yarn spinning industry.

## 6 Publications

The mentioned activities have been discussed in more depth in the paper published in "*Computers in Industry*" [Haleem *et al.*, 2021].

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