

# Development of an online detection system for ring-spun fine yarns using capacitive sensors

## Abstract

An online yarn evenness detection system for ring-spun yarns using capacitive sensors was developed. Appropriate mounting brackets were designed for the sensors to ensure stable acquisition of yarn evenness data from the spinning frame during operation. In addition, algorithms were used to process the acquired yarn signals; thermal drift correction and signal filtering were essential for maintaining signal stability. The accuracy of the online evenness data output by the system was verified by comparison with measurements from a Uster evenness tester. The results showed that the piecewise linear representation method with 10 segments effectively reduced thermal drift in the yarn signals; after correction, the measurement accuracy improved by 12.01%, and the error decreased by 1.28%. For signal filtering, Gaussian filtering with  $\sigma = 2.1$  was applied and performed well in processing yarn signals. Compared with the CV% obtained from the Uster evenness tester, the CV% obtained by the online system showed an average accuracy of 92.46% and an average error of 1.04%, indicating an overall improvement in the precision of the online evenness data.

**Keywords:** yarn evenness CV%, capacitive sensor, online detection, process optimization

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## Introduction

Currently, most research on fine yarn quality testing is conducted in offline laboratory settings. This conventional approach has several limitations, including raw material waste, limited data timeliness, and delayed process adjustment.<sup>1</sup>

Existing studies on yarn evenness testing mainly rely on three approaches. The first approach is capacitive testing. Pinto et al.<sup>2</sup> introduced parallel capacitive sensors combined with signal processing to detect periodic errors and developed a measurement system capable of assessing yarn mass with 1 mm length samples. Experimental results indicated that electromagnetic interference affected both detection regions similarly. Wang et al.<sup>3</sup> employed a semi-supervised sequential Gaussian mixture variational autoencoder (VAE) to classify and predict filament yarn CV values. They also upgraded the capacitive tester to enable long-term continuous measurements, achieving an overall classification accuracy of 85%. However, yarn samples were still tested offline using conventional instruments. The second approach is photoelectric testing. Roy et al.<sup>4</sup> developed a low-cost, high-resolution optical sensor system in which yarns were illuminated by LEDs, and yarn property variations were detected by phototransistors. The system, with a resolution of 1 mm, accurately detected short-term defects and remained largely insensitive to environmental factors, thereby enabling stable monitoring of diameter and quality fluctuations. However, measurements still required finished yarn packages. The third approach is image-based testing. Mohamed et al.<sup>5</sup> proposed an algorithm based on microscopic digital images of yarns. Through preprocessing steps including binarization and morphological operations, automated and accurate diameter measurement was achieved, and the Hough transform was used to quantify individual fiber diameters and fiber counts in the yarn cross-section. The algorithm achieved an average diameter deviation of only 0.05 mm from the true value; however, its application was limited to partial yarn segments. Zhang et al.<sup>6</sup> proposed a method based on an improved Canny edge-detection algorithm to analyze acquired yarn images and extract yarn edge profiles, from which the yarn evenness CV value was calculated. Li et al.<sup>7</sup> proposed a novel

machine-vision-based method for yarn evenness measurement. The method continuously captured yarn images with a dedicated device and calculated the coefficient of variation (CV) of yarn diameter. Liu et al.<sup>8</sup> processed fabric images to segment warp and weft yarns and isolate individual yarns, and then calculated yarn uniformity within the fabric by analyzing the standard deviation of yarn thickness. To date, few studies have reported the real-time acquisition of yarn evenness directly during spinning.

To address these limitations, an online yarn evenness detection system was developed in this study to acquire real-time yarn evenness data during production. This reduces yarn waste and facilitates the collection of real-time training data for predictive modeling. In the experiments, a capacitive sensor was employed as the measurement device and installed between the front roller and the yarn guide hook of the spinning machine. As the yarn passed through the sensor head, signals corresponding to variations in yarn thickness were acquired. Following data acquisition, the signals were subjected to thermal drift compensation and filtering, after which the yarn evenness CV values were calculated. Finally, an online data-driven yarn process optimization model was established to support spinning process design and enhance yarn quality.

## Instruments and methods

### Experimental instruments

The experiments were performed using a capacitive online yarn evenness detection system. The system primarily consisted of a capacitive sensor, a control unit, and data transmission cables, as illustrated in Figure 1. During testing, the yarn was guided through the sensor port. Variations in yarn thickness induced changes in the sensor capacitance, thereby generating signals that were transmitted to the control unit.<sup>9</sup> The control unit converted the capacitance variations into electrical signals, which were subsequently transmitted to a computer through a communication interface for data acquisition and storage. After testing, the recorded signals were exported as CSV files for subsequent analysis.

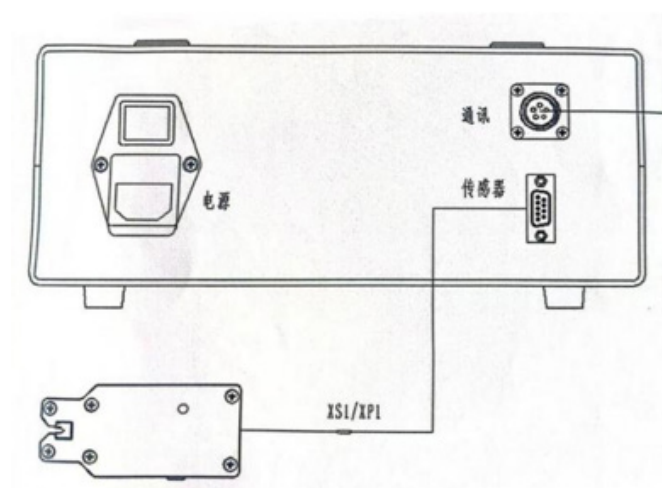


**Figure 1** Basic components of the online detection instrument.

### Experimental yarn data design

To validate the system, 200 m yarn samples with different linear densities (12 tex, 14.5 tex, 16.5 tex, 18 tex, 23.5 tex, 29 tex, and 36 tex) were spun. The yarn CV values were measured under different back-zone draft ratios (1.15, 1.35, 1.50, and 1.65) and front-zone apron spacing block settings (2.5 mm, 3.5 mm, and 4.5 mm) to assess the measurement accuracy of the proposed capacitive yarn detection system. The corresponding data are summarized in Table 1. The results showed that the yarn evenness CV (%) increased with increasing back-zone draft ratio, whereas it decreased with increasing yarn linear density. The optimal front-zone apron spacing block was identified as 3.5 mm.

**Table 1** Yarn evenness records obtained from online measurements under different process conditions

| Yarn ID | Yarn count (tex) | Spacing block (mm) | Back-zone draft (ratio) | Yarn evenness CV (%) |
|---------|------------------|--------------------|-------------------------|----------------------|
| 1       | 12               | 3.5                | 1.5                     | 16.64                |
| 2       | 14.5             | 3.5                | 1.5                     | 15.69                |
| 3       | 16.5             | 3.5                | 1.5                     | 15.23                |
| 4       | 18               | 3.5                | 1.5                     | 15.04                |
| 5       | 23.5             | 3.5                | 1.5                     | 14.31                |
| 6       | 29               | 3.5                | 1.5                     | 13.97                |
| 7       | 36               | 3.5                | 1.5                     | 13.33                |
| 8       | 12               | 3.5                | 1.35                    | 14.48                |
| ...     | ...              | ...                | ...                     | ...                  |
| 51      | 36               | 4.5                | 1.5                     | 13.02                |
| 52      | 36               | 4.5                | 1.65                    | 16.99                |

### Online yarn evenness detection system

Prior to the experiments, the online yarn evenness detection system was powered on and warmed up for 30 min. The system was connected to a laptop computer (Legion Y7000P, Lenovo) and operated through a dedicated software interface, as shown in Figure 2.

In Figure 2, CK<sub>1</sub> represents the pre-amplified voltage, Y(t) denotes the actual yarn signal voltage, and CK0 corresponds to the post-amplified voltage. During the warm-up process, the filtered output signal CK<sub>1</sub> was continuously monitored to evaluate system stability. Once CK<sub>1</sub> reached a stable state and no longer exhibited significant

fluctuations, typically after approximately 30 min, the system was regarded as fully stabilized, and subsequent online yarn evenness measurements were performed.

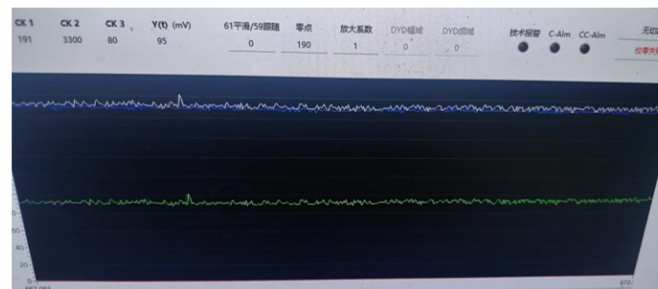


**Figure 2** Warm-up of the online yarn evenness detection system.

### Installation of the yarn evenness detection system

After the warm-up process of the online yarn evenness detection system had been completed, the sample spinning machine (DSSp-01A) was started. After the preset yarn process parameters had been entered, the capacitive sensor head was installed between the front roller and the yarn guide hook, as shown in Figure 3. The acquired yarn evenness signals were recorded and stored in CSV format for subsequent analysis.

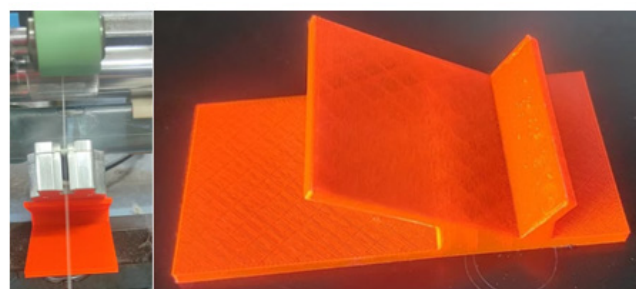


**Figure 3** Mounting bracket for the capacitive sensor head.

During online measurement, the yarn had to pass vertically through the sensor head without contacting the sensor; otherwise, measurement accuracy could be compromised and abnormal data could be introduced.

### Processing of thermal drift in yarn evenness signals

The CSV files obtained from the tests in Section (Processing of thermal drift in yarn evenness signals) were imported into the online yarn evenness detection system for signal analysis. Thermal drift analysis was first conducted on the acquired signal data to ensure that the original measurements were not influenced by inadequate sensor warm-up. Since the raw yarn signal data were recorded sequentially as CSV files following online measurement, the resulting dataset had time-series characteristics.

A piecewise linear representation method was employed for thermal drift correction.<sup>10</sup> The method involved dividing the signal into multiple time segments, subtracting the mean value of each segment to achieve zero-mean normalization, and subsequently applying an overall offset to maintain non-negative signal values. This procedure enabled progressive correction of thermal drift throughout the entire signal.

Specifically, let the original yarn signal be denoted as S(t) with a total length of N, divided into M time segments. For the i-th segment (i = 1, 2, ..., M):

$$\text{Mean of the segment signal: } \bar{S}_i = \frac{1}{n_i} \sum_{t=t_i-1}^{t_i-1} S(t) \quad (1)$$

$$\text{Corrected signal: } S'(t) = S(t) - \bar{S}_i \quad (2)$$

Where:  $t \in [t_{i-1}, t_i)$

The waveforms of the original data and the corrected yarn signal after thermal drift removal are shown in Figure 4.

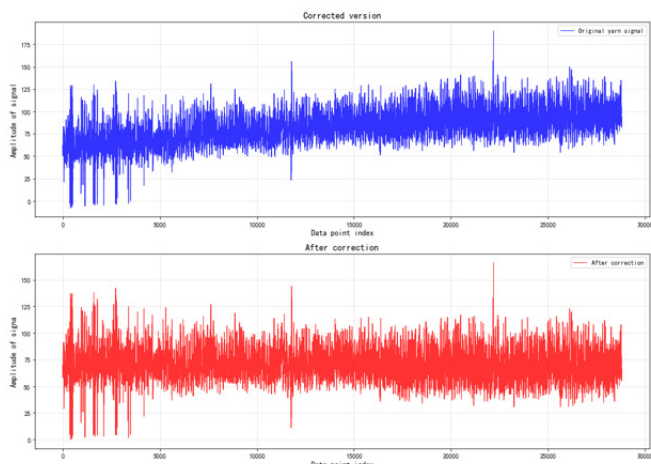


**Figure 4** Yarn signal waveforms before and after thermal drift correction using the piecewise linear method.

#### Gaussian filtering method

After preliminary thermal drift correction, the yarn signal data were further filtered to suppress low-frequency noise arising from sensor electrical interference and short-term random fluctuations in the yarn during online evenness measurement. This procedure improved the accuracy of the online detection system in determining the CV values of yarn segments.

Gaussian filtering is a widely adopted linear smoothing technique in image and signal processing. Its primary purpose is to reduce noise and smooth signal variations.<sup>11</sup> The main mathematical expressions for Gaussian filtering are presented below:

The initial estimated state  $\hat{x}_0$  and its associated error covariance matrix  $P_0$  are given as follows:

$$\hat{x}_0 = E[x_0] \quad (3)$$

$$P_0 = \text{cov}(x_0, x_0^T) = E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T] \quad (4)$$

where  $E[x_0]$  denotes the expected value of the random variable  $x_0$

$N(x; \hat{x}, P)$  denotes a Gaussian distribution with mean  $\hat{x}$  and covariance matrix  $P$ .

$$N(x; \hat{x}, p) = \frac{\exp\left(-\frac{1}{2}(x - \hat{x})^T P^{-1}(x - \hat{x})\right)}{(2\pi)^n \det P} \quad (5)$$

#### Calculation of yarn evenness CV and U values

After the yarn signal data had been processed using the filtering method described in Section (Gaussian filtering method), the online detection system calculated the yarn evenness CV values and generated

the corresponding evenness spectrograms. The yarn evenness CV values were calculated according to the following equation<sup>12</sup>:

$$CV(\%) = \frac{\sigma}{\bar{x}} \times 100\% \quad (6)$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n}} \quad (7)$$

where  $\sigma$  represents the standard deviation of the yarn signal data, and  $\bar{x}$  denotes the arithmetic mean of the yarn signal data.

#### Output of yarn evenness spectra

The core principle underlying the construction of yarn evenness spectra is the decomposition of yarn signal data into periodic components with different wavelengths by Fourier transform.<sup>13</sup> According to Fourier series theory,<sup>14</sup> a periodic function can be expressed as a sum of trigonometric components, as follows:

$$f(x) \approx \frac{a_0}{2} + \sum_{k=1}^{+\infty} [a_k \cos kx + b_k \sin kx] \quad (8)$$

$$\text{Where } a_k = \frac{1}{\pi} \int_0^{\pi} f(x) \cos kx \, dx, \quad b_k = \frac{1}{\pi} \int_0^{\pi} f(x) \sin kx \, dx$$

By extending this into the complex domain, the Fourier transform of a signal  $f(t)$  can be expressed as: (8)

$$F(\omega) = \int_{-\infty}^{+\infty} e^{-i\omega t} f(t) dt \quad (9)$$

For a 52-count yarn, Figure 5 presents the yarn evenness spectrum generated by the online detection system after signal analysis, together with the corresponding spectrum obtained from a conventional yarn evenness tester. In both spectra, a distinct mechanical wave was observed at a wavelength of approximately 40 cm, thereby confirming the validity of the yarn evenness spectrum generated by the online detection system.

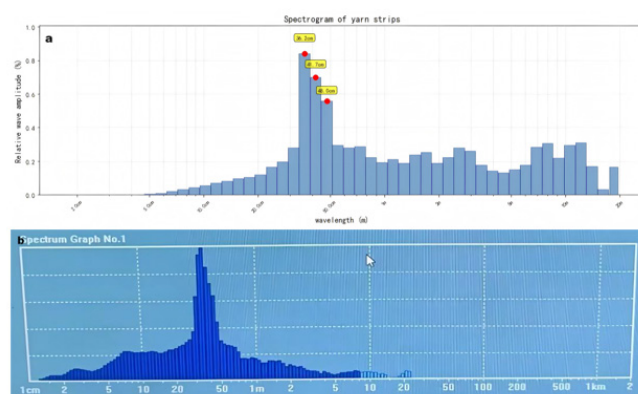


**Figure 5** Comparison of spectra: output evenness spectrum (a) and yarn evenness spectrum (b).

## Results and discussion

#### Raw signal data

The raw yarn evenness signals were acquired using the online yarn evenness detection system and corresponded to yarn segments of a specified measurement length. For a 37-count (14 tex) yarn, Figure 6 illustrates the complete waveform of the yarn evenness signal.

After online sampling had been completed, the yarn evenness CV values were calculated. As shown in Figure 7, the CV values obtained from the online detection system were consistently higher than those

measured using the conventional yarn evenness tester. The average CV error after sampling was 3.404%, and the average measurement accuracy was only 75.81%. These results indicated that the data collected by the online detection system still contained substantial noise, which may have originated from electromagnetic interference in the circuitry, sensor vibrations, ambient light fluctuations, or quantization noise. Consequently, the system was unable to accurately estimate yarn evenness CV values directly from the raw signal data. Therefore, additional signal analysis and filtering were required to improve the accuracy of the yarn evenness CV values generated by the online detection system.

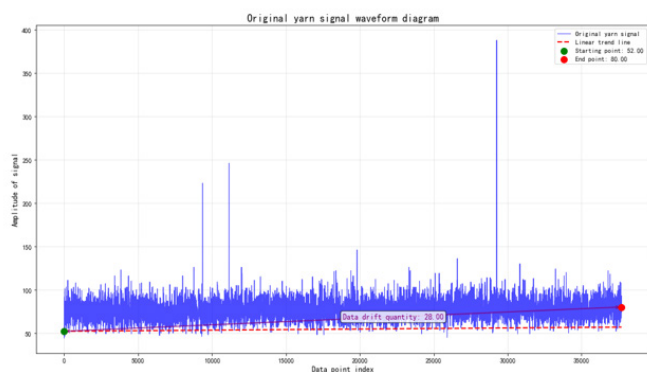


Figure 6 Yarn signal waveform of count 37 (14 tex).

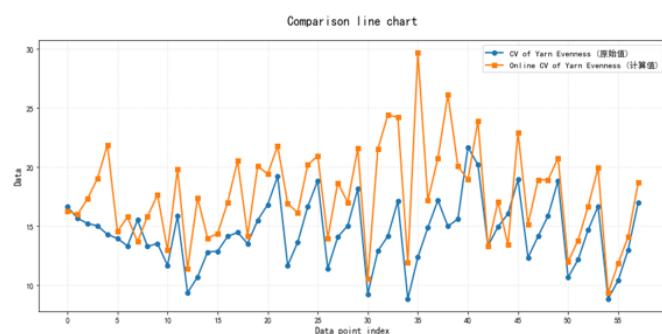


Figure 7 Yarn evenness CV values calculated from the raw signals.

Table 2 Thermal drift correction results

| Yarn ID | Thermal drift correction method        | Filtering method   | Yarn evenness CV value | Calculated yarn evenness CV value | Error (%) | Accuracy (%) |
|---------|----------------------------------------|--------------------|------------------------|-----------------------------------|-----------|--------------|
| 3       | None                                   | Gaussian filtering | 15.23                  | 14.11                             | 1.11      | 92.68        |
| 3       | Piecewise linear representation method | Gaussian filtering | 15.23                  | 14.43                             | 0.79      | 94.8         |
| 5       | None                                   | Gaussian filtering | 14.31                  | 19.06                             | 4.75      | 66.74        |
| 5       | Piecewise linear representation method | Gaussian filtering | 14.31                  | 14.71                             | 0.4       | 97.14        |
| 11      | None                                   | Gaussian filtering | 12.82                  | 12.89                             | 0.07      | 99.4         |
| 11      | Piecewise linear representation method | Gaussian filtering | 12.82                  | 28.52                             | 15.7      | -22.5        |
| 12      | None                                   | Gaussian filtering | 10.72                  | 12.15                             | 1.43      | 86.57        |
| 3       | None                                   | Gaussian filtering | 15.23                  | 14.11                             | 1.11      | 92.68        |
| 3       | Piecewise linear representation method | Gaussian filtering | 15.23                  | 14.43                             | 0.79      | 94.8         |
| 5       | None                                   | Gaussian filtering | 14.31                  | 19.06                             | 4.75      | 66.74        |
| 5       | Piecewise linear representation method | Gaussian filtering | 14.31                  | 14.71                             | 0.4       | 97.14        |
| 12      | Piecewise linear representation method | Gaussian filtering | 10.72                  | 10.87                             | 0.15      | 98.58        |

## Thermal drift experiment

Thermal drift correction was first performed on the raw yarn signals. This phenomenon mainly occurred in the yarn signal data of the first batch of yarns tested after the online detection instrument had been warmed up. Taking yarn 12 (36 tex) and yarn 11 (29 tex) as examples, Figure 8 shows the raw and corrected signals of yarns 12 and 11 as examples. Figure 8a presents the result for yarn 12 after processing by the piecewise linear representation method. The corrected waveform of yarn 12 improved significantly compared with the uncorrected waveform. Figure 8b shows the waveform of yarn 11 after correction, indicating that its raw signal had no obvious thermal drift. When the piecewise linear representation method was used, the yarn waveform did not change significantly. Figure 8c and Figure 8d show that the initial signals exhibited a trend, which disappeared after correction. For example, the yarn evenness CV values calculated before and after filtering are listed in Table 2.

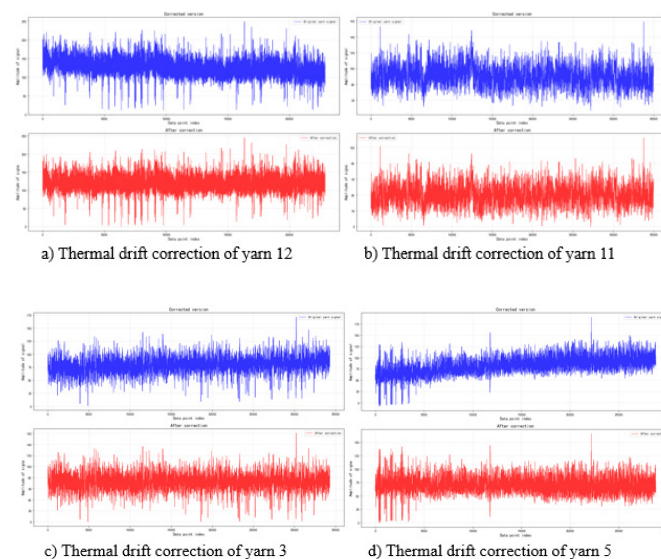


Figure 8 Yarn waveforms before and after thermal drift correction.

It can be seen from Table 2 that for yarn 12, which exhibited obvious thermal drift, the overall upward trend of the yarn signal before correction led to an accuracy of only 86.57% for the final calculated yarn evenness CV value, and the error relative to the true value was 1.43. After thermal drift correction was performed to remove the trend, the output yarn evenness CV value was significantly improved, with an accuracy of 98.58% and an error reduced to 0.15. Meanwhile, after thermal drift correction of yarn 3 and yarn 5, the trends in the waveforms disappeared, and the calculated yarn evenness CV accuracy increased by 2.12% and 30.4%, respectively. However, for yarn 11, whose raw signal showed no obvious trend, thermal drift correction produced a calculated yarn evenness CV value significantly different from that obtained without correction, even though no trend change was observed in the waveform after correction. Without thermal drift correction, the calculated yarn evenness CV value of yarn 11 was 12.89, with an error of only 0.07 relative to the true value and an accuracy of 99.40%. In contrast, after thermal drift correction, the accuracy relative to the true value was -22.50%. This may be because, although no difference was visible in the output waveform, the piecewise correction method still processed the original yarn evenness data, thereby altering the data and affecting the final calculation result. Therefore, for yarn signals that show no trend variation in the raw signal waveform, applying thermal drift correction may instead significantly reduce the accuracy of the final yarn evenness CV calculation.

Therefore, when a trend variation is observed in the raw yarn signal output by the system, the application of thermal drift correction can effectively improve the quality of the yarn signal and enhance the accuracy of the output yarn evenness CV value.

### Gaussian filtering experiment

After thermal drift correction, the yarn signal data were filtered to suppress noise originating from electromagnetic interference in the circuitry, sensor vibrations, and quantization effects. This procedure further improved signal quality and enhanced the accuracy of the calculated yarn evenness CV values.

In the experiments, yarn samples exhibiting significant thermal drift or obvious abnormalities during raw signal acquisition were excluded from further analysis, and Gaussian filtering was subsequently applied to a total of 40 sets of yarn signal data. Table 3 summarizes the average accuracy and error of the yarn evenness CV

values before and after Gaussian filtering for the 40 yarn sets, and Figure 9 presents a comparison of the evenness CV values of each yarn set before and after Gaussian filtering with those measured by the Uster evenness tester.

As shown in Table 3 and Figure 9, after Gaussian filtering was applied to the 40 sets of online yarn signals, the accuracy of the yarn evenness CV% improved compared with that of the unprocessed signals. The average accuracy reached 92.46%, corresponding to an increase of 10.49 percentage points, whereas the average error decreased to 1.04%, representing a reduction of 1.52 percentage points. Additionally, the evenness CV curve after Gaussian filtering more closely matched the values measured by the Uster evenness tester. Therefore, Gaussian filtering effectively enhanced the accuracy of the calculated yarn evenness CV% during signal processing.

**Table 3** Effect of filtering

| Filtering method       | Accuracy (%) | Error (%) |
|------------------------|--------------|-----------|
| Raw value (unfiltered) | 81.97        | 2.56      |
| Gaussian filtering     | 92.46        | 1.04      |

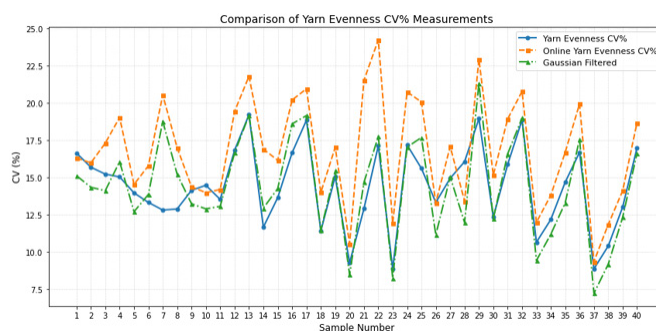


**Figure 9** Comparison of results before and after Gaussian filtering.

### Gaussian filtering parameter tuning experiment

In Gaussian filtering, the sigma parameter is of critical importance. A small sigma value results in insufficient smoothing and cannot effectively remove noise; conversely, a large sigma value leads to over-smoothing, which may erase some of the yarn thickness variations in the signal. Parameter tuning was performed using 40 sets of yarn signal data. The original hyperparameters and the optimization range are presented in Table 4.

**Table 4** Hyperparameter optimization for different filtering methods

|                    | Hyperparameter type | Original hyperparameter | Parameter optimization range      |
|--------------------|---------------------|-------------------------|-----------------------------------|
| Gaussian filtering | sigma               | 2                       | (0.5-5.0) with a step size of 0.1 |

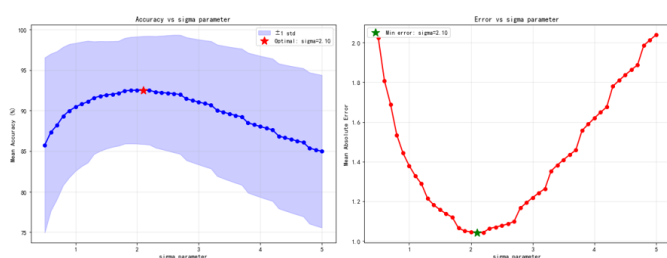
Based on the optimization strategy summarized in Table 4, the preset hyperparameters of the Gaussian filter were refined. The yarn evenness CV values were subsequently calculated under different settings, and the corresponding accuracy and mean error were evaluated. The optimized hyperparameters and the corresponding filtering performance are presented in Table 5 and Figure 10, respectively.

As shown in Table 5 and Figure 10, optimal filtering performance was achieved at  $\sigma = 2.1$ , yielding an average accuracy of 92.53% and a minimum mean error of 1.04%. When  $\sigma < 1.6$ , increasing  $\sigma$  led to a

noticeable improvement in average accuracy and a rapid reduction in mean error, indicating effective suppression of high-frequency noise. Within the range of  $\sigma = 1.6-2.2$ , the average accuracy remained above 90%, and the mean error remained below 1.1%. Within this interval, the filtering performance was optimal, effectively reducing high-frequency noise while preserving yarn thickness variations. However, when  $\sigma > 2.2$ , the accuracy declined noticeably, accompanied by an increase in error. This phenomenon can be attributed to excessive smoothing at high  $\sigma$  values, which attenuated not only high-frequency noise but also genuine yarn thickness variations, thereby reducing accuracy and increasing error.

**Table 5** Optimal hyperparameters for different filtering methods

| Filtering method   | Parameter      | Average accuracy (%) | Mean absolute error (%) |
|--------------------|----------------|----------------------|-------------------------|
| Gaussian filtering | {'sigma': 0.5} | 85.75                | 2.02                    |
| Gaussian filtering | {'sigma': 1.0} | 90.44                | 1.38                    |
| Gaussian filtering | {'sigma': 1.5} | 91.93                | 1.16                    |
| Gaussian filtering | {'sigma': 2.1} | 92.53                | 1.04                    |
| Gaussian filtering | {'sigma': 2.5} | 92.16                | 1.08                    |
| Gaussian filtering | {'sigma': 3}   | 91.06                | 1.22                    |
| Gaussian filtering | {'sigma': 4}   | 88.04                | 1.62                    |
| Gaussian filtering | {'sigma': 5}   | 84.98                | 2.04                    |

**Figure 10** Sigma optimization flowchart for gaussian filtering.

Overall, Gaussian filtering achieved optimal performance at  $\sigma = 2.1$ , effectively suppressing noise while preserving yarn thickness variations in the signal.

## Conclusion

In this study, a capacitive online yarn evenness detection system was developed and applied to investigate and optimize online detection of fine yarns. The study investigated the installation and operation of the yarn evenness detection system, together with thermal drift correction and filtering optimization of raw yarn signals. Furthermore, the preset hyperparameters for thermal drift correction and filtering were optimized to more effectively suppress thermal drift and noise in raw signals. The main conclusions are summarized as follows:

- 1) The online yarn detection system equipped with a capacitive sensor head was capable of acquiring yarn evenness CV and U values in real time during spinning.
- 2) When thermal drift correction is performed on the raw yarn signal data, it is necessary to first examine whether the raw signal waveform shows a trend in the raw yarn signal waveform. A piecewise linear representation method with 10 segments was used for thermal drift correction. After correction, the accuracy increased by 12.01%, and the error decreased by 1.28 %.
- 3) For yarn signal noise filtering, Gaussian filtering ( $\sigma = 2.1$ ) demonstrated the best overall performance. The average accuracy of the yarn evenness CV values calculated from the filtered signals reached 92.53%, with a mean error of 1.04%.

## Acknowledgments

None.

## Data availability

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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## Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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