Sugarcane Stem Node Detection Based on Wavelet Analysis

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ABSTRACT The article discusses a wavelet-based approach for recognizing sugarcane stem nodes in order to improve pre-cut sugarcane planting technology, beginning with sugarcane form characteristics that permit automated sugarcane seed production. The location signal is collected by the acceleration and thin-film piezoelectric sensors and then decomposed into the tenth, eleventh, and twelfth layers using the Daubechies tight-branch wavelet. After capturing the signal, it is reconstructed and superimposed to capture the stem node region's features using the default threshold technique. A multi-sensor fusion approach is developed based on a weighted average and a Kalman filter to confirm the experiment's validity. The weighted average process produces an average value that is 0.3512mm off from the experimentally observed data average. The discrepancy between the Kalman filter method's anticipated average value and the empirically determined average error is 0.5778mm. To facilitate the investigation, 175 sugarcane samples with intermediate length processing are used. The detecting position system is determined experimentally after extensive experimental research and diligent examination. On average, the standard deviation is 0.494mm, while the maximum value is 9.99mm. 99.63 percent of cane seed samples are detected, with an error rate of 0.37 percent and a response time of 0.25 seconds. The proposed technology is conceptually feasible and achievable, and it can provide a reference for the development of automated cane seed pre-cutting machinery to give its contribution to agricultural production.

KEYWORD Automation, multi-sensor redundancy, pre-cutting, sugarcane stem section, wavelet analysis.

I. INTRODUCTION

Sugarcane is a vital tropical economic crop used as a raw material in China and other nations for sugar manufacture. Its planting area exceeds 85% of China's perennial sugar crop planting area, and its sugar production exceeds 90% of overall sugar production. Sugarcane is a critical pillar of economic development and the primary source of income for farmers in southern China's central sugarcane producing districts. Sugarcane reproduces asexually by stem buds, cylindrical stems that are erect, tillering, tufted, and jointed, and nodes with buds must leave nodes for planting good kinds. Real-time cutting is a technique used in traditional sugarcane planting that entails placing the entire sugarcane seed into the planting ditch and then cutting it into several segments, each about 30-40cm in length, ensuring that each segment has at least two buds, and then covering each segment with soil entirely by hand. Apart from mechanized plowing and road transit, practically all other links are manually performed, requiring significant personnel and material resources for seed storage and selection. Sugarcane seed selection and seed value efficiency can be considerably increased by automated production.

The real-time seed-cutting sugarcane planting machine has been created to boost planting efficiency both domestically and abroad. It cuts seeds in real-time with the aid of a motorized planting double knife, a technique that generally requires four to six humans to undertake high-intensity operations. Additionally, the length of the chopped
sugarcane stems is predetermined, resulting in harm to the buds and an inability to precisely detect the sugarcane stems. At the moment, agricultural machinery equipped with automatic planting and a recognition algorithm for sugarcane stem nodes is incapable of achieving intelligent and robotic planting of sugarcane seed cuttings. Agricultural planting requires the ability to detect and find characteristics such as sugarcane stem nodes rapidly and to output the results in a short period to automate the production of sugarcane species. As a result, the technology for detecting sugarcane stem nodes is crucial in sugarcane mechanical automated production. To establish the stem and node position, this research develops a device for identifying sugarcane stem nodes that can be used to pre-cut sugarcane stem nodes with less effort and a higher budding rate.

Sugarcane node identification and localization are additional non-destructive examinations for agricultural products. There are numerous non-destructive testing methods available for agricultural products at the moment. Iran Moshashai et al. (2008) [1] using the grayscale image threshold segmentation method to identify sugarcane stem nodes, has done a preliminary study, which is still in the initial stage. Lihai Wang et al. (2009) [2] proposed wood pattern recognition and size measurement based on a wavelet neural network, using wood defect-recognition with an accuracy of 80%. Al-Mallahi et al. (2010) [3] online monitoring of potato stalks using a linear CCD industrial camera. B.J. Stray et al. (2012) [4] proposed a decision support system for optimal season sugarcane harvest scheduling. The decision system needs a series of regressions in the uniform area of sugarcane harvest scheduling. R. Confalonieri et al. (2013) [5] proposed that the study of leaf area index based on sensors' use and processing ability has low accuracy and requires many repetitions to provide reliable estimates. Lu et al. (2010) [6] discussed the sugarcane stem node feature extraction and recognition based on machine vision. The S component and H component images in the HSV color space of sugarcane images were processed differently. The two images were combined, the composite image was segmented, and several features were retrieved. Then the sugarcane nodes and internodes were then processed by a support vector machine to obtain the position of sugarcane nodes. The average recognition rate of stem node number and position is 94.11% and 91.52%, respectively, and the execution time of a single image algorithm is 0.76s. This method still does not deal with the whole sugarcane, Zhang w et al. (2016) [7] the sugarcane of a single node is identified by image processing, and the position of the stem node is obtained by the method of image segmentation and image flipping, and the time is 0.3s. FelipeF.Boccaetal. (2016) [8], the sugarcane yield is modeled by data mining, and a feature algorithm extracts the feature information. Still, the sample size model needs to be increased to optimize better. Sheng, W et al. (2017) [9] carry on the sugarcane research of the computer vision recognition technology and carries on the stem node's recognition and location through the fuzzy clustering algorithm. The request to the environment is relatively high, and the recognition rate is 80%. Carlos Henrique Wachholz de Souza et al. (2017) [10] carries out UAV image analysis and recognition based on sugarcane crops. L.M.Griffel et al. (2018) [11] used support vector machines to classify and distinguish the spectral characteristics of potato plants. When near-infrared and short-wave infrared bands were applied, the categorization accuracy of plant spectral reflectance curves increased to 89.8 percent. Dong Chen et al. (2017) [12] employed a micro-displacement sensor to measure the beat of the detection frame, which can provide a signal for the upper computer to determine the stem node. The displacement sensor signal produces waveform spikes. The detection rate of sugarcane stem node was 95.4%. Li Shangping et al. (2019) [13] adopted improved YOLOv3 network to improve the recognition rate of sugarcane stem nodes, with an accuracy reached 90.38%. Deqiang Zhou et al. (2020) [14] proposed a new sugarcane seed cutting system based on machine vision. The sugarcane seed cutting system includes mechanical parts, electrical parts, and visual processing parts. The offline recognition rate of sugarcane stems is 93%. Brajesh Nare et al. (2019) [15] designed an autonomous seed and analysis algorithm to identify sugarcane stem nodes using a real-time flower bud recognition algorithm. Chen,jiqing et al. (2021)[16] based on machine vision system, this paper proposed a sugarcane nodes identification algorithm, a double nodes identification rate of 98.5 %, with an average time consumption of 0.21 s. Chen, JQ et al. (2020) [17] In order to solve the problem that the stem nodes are difficult to identify in the process of sugarcane seed automatic cutting, a method of identifying the stem nodes of sugarcane-based on the extreme points of vertical projection function is proposed in this paper, The accuracy of simultaneous identification of the three stem nodes is 95%. Zhou, DQ et al. (2019) [18] realize automatic cutting of sugarcane seeds in single bud segment, machine vision technology was used to identify sugarcane nodes. The experimental results show that the recognition rate is 93%, and the average time is 0.539 seconds. Liu Zhiqiang et al.(2021) [19] The sugarcane seed node identification cutting device was designed based on the physical characteristics of sugarcane nodes and stems, and the experiments showed that the accuracy of cane bud identification was 91.76% and the average chopping time was 1.06s. Chen Jinjian et al. (2021) [20] the real-time dynamic recognition of sugarcane stem nodes was carried out by extracting the information of sugarcane stem nodes and constructing the YOLOv3 network structure to improve the efficiency and accuracy of recognition, recognition rate of 93%, average consumption time of 0.87s. Fan Yunlei et al.(2020) [21] The equipment uses rubber roller to grip the transportation of sugarcane. The image of sugarcane is collected by the camera and the stem node is identified, recognition accur
of 95.5%, cut seed error of 8mm. Yanmei Meng et al. (2019) [22] used laser sensors for stem node recognition, and Gaussian membership function multi-sensory fusion algorithm is used for accurate recognition.

The outstanding contributions and studies to the sugarcane industry through Moshashai et al. (2008), Dong, Z et al. (2017), Zhou, DQ et al. (2019), Chen, JQ et al. (2020), Chen, JQ et al. (2021) and Li, S et al. (2019), Meng, Yanmei et al. (2019) have enhanced the sugarcane pre-cut seed mechanization of planting, improve the efficiency of sugarcane identification, reduce the rate of cane bud loss, and reduce the manual labor intensity. We thank these authors for their research on sugarcane stem node identification in various fields and for arguing the reliability of the experiments, which provided the theoretical and applied technical basis for our subsequent research. We thank the majority of related researchers for their independent study research on sugarcane mechanical automation. Most of the current schemes use image processing methods, which significantly promote the recognition of stem nodes. However, there are still the following problems in varying degrees, the contradiction between the speed of stem node detection and complex image processing algorithm is difficult to reconcile. The high-definition high-speed camera will significantly increase the system's cost because detecting sugarcane seed stem nodes is related to positioning speed. The image processing algorithm needs to extract as many features as possible to ensure accuracy, undoubtedly hindering real-time performance improvement. The industrial field production environment is harsh, and the sundry covered on the surface of sugarcane seeds will also bring unpredictable interference to the image processing. A large amount of black powder and white frost is attached to the surface of cut sugarcane, which has a lot of trouble for machine vision to identify stem nodes. There are still some problems such as slow speed, poor real-time performance, low-performance identification efficiency, and high cost. It isn't easy to be applied in the actual production environment.

Because detection of sugarcane seed stem nodes is time-dependent, the image processing algorithm must extract as many features as possible to achieve the required accuracy. The high-definition high-speed camera would undoubtedly impede real-time performance enhancement. The device in this paper has a high recognition rate and accuracy, and low cost. It does not harm the stem node, and the performance is superior.

II. GUIDELINES FOR MANUSCRIPT PREPARATION
There are usually contact measurements (Lysenko et al., 2016) [23] and non-contact measurements (Tomioka, Kota, et al.,2020) [24], such as optical measurement (Kim, Kook Young, et al.,2020) [25]. This paper discusses the concept of contour detection, the function of a cane stem node recognition device, and the development of an accurate sugarcane stem node identification device for contact measurement. The device was designed using an acceleration sensor and a piezoelectric film sensor to collect signals, and the methods of prototype evaluation and performance were discussed.

A. APPEARANCE CHARACTERISTICS OF SUGARCANE STEM NODE
As illustrated in Figure 1, sugarcane stems are separated into internodes and nodes. Internodes in sugarcane extend from the growth zone to the leaf scar (the remnant of the leaf sheath that has fallen off the stem). Generally, the number of internodes in the stalk varies from 10 to 30, and the length of internodes ranges from 5 to 22 cm. As shown in Figure 1, the range of the section starts from the leaf scar to the growth zone, and the section includes the leaf scar, root zone, bud, and growth zone. The growth zone is a narrow region located at the junction of nodes and internodes. Between the growth zone and the leaf scar is the root zone. The root zone contains numerous rows of root points. The implantation site of the side buds is the leaf scar or the middle of the root zone.

FIGURE 1. Overall appearance diagrams of sugarcane contour.

B. SECTION LOCATION INFORMATION ACQUISITION
Considering that there are many contact measurement sensors, the acceleration sensor is used as the primary sensor. The thin-film piezoelectric sensor is used as the auxiliary method to obtain the contour signal of sugarcane. Figure 2 shows the physical map of sugarcane, and Figure 3 shows the physical map of the sugarcane node area, which can be divided into growth zone, root zone, and leaf scar.

FIGURE 2. Physical map of sugarcane.
Assume the node already has the sensor attached. The acceleration sensor and thin-film piezoelectric sensor on the device are employed in this situation to generate a signal indicating the form attributes of the sugarcane knot. The fundamental reason for the obtained signal’s drop or increase in amplitude is a change in the diameter of the sugarcane. Alternatively, it could be the result of the acquisition point deviating due to the bending of the sugarcane stem or a combination of the two.

C. ACCELERATION SENSOR UNIT

Figure 4 illustrates the waveform diagram produced when the acceleration sensor detects four sugarcane stem nodes. When the acceleration sensor’s contact device passes through the leaf scar protrusion, the leaf scar protrusion's length is between (13mm to 25mm). The signal waveform amplitude gathered by the sensor increases as the diameter of the section grows due to the abrupt increase in the cross-sectional diameter. As the voltage rises, the slope increases with it. Since the section diameter is suddenly reduced, the signal waveform amplitude collected by the sensor also decreases, the slope decreases with the decrease of the voltage, and the voltage remains at about 1.5V when the contact device reaches the growth zone, the length of the growth zone is approximately (10mm to 18mm).

Because the width of the node’s leaf scar is more significant than the diameter of the growth zone, the waveform and voltage variation range generated by the protrusion of the leaf scar is significantly greater than the waveform and voltage variation range induced by the growth zone. The voltage range generated by the growth zone is (2V to 2.4V), its length is (1.2mm to 1.8mm), and the signal waveform and voltage change amplitude in the growth zone are much greater than those of sugarcane internodes. The waveform pattern in Figure 5 shows the acceleration sensor detecting a single sugarcane stem node.

D. THIN-FILM PIEZOELECTRIC SENSOR UNIT

The thin-film piezoelectric sensor's waveform when six sugarcane stem nodes are detected is depicted in Figure 6. The PDVF piezoelectric film is thin, soft, low density, sensitive, and has a high degree of mechanical toughness, among other characteristics. When the contact device of the piezoelectric film sensor makes contact with the stem node (the average time required to pass a node is between 1s and 5s), a greater amplitude voltage is generated due to the significant change in the form of the sugarcane stem node.
excise, and the size of the area of the sensor. The greater the cross-sectional area of the cross-section, the greater the longitudinal force created. A modest longitudinal force can exert significant stress on a material. The waveform will rise strongly at the peak acquisition node, the output voltage will become more prominent, and then it will decline and become steady.

To gain more precise information about the position of the sugarcane stem node, we analyze the signal using wavelet analysis and obtain the sugarcane stem node position information by evaluating the signal characteristics of the sugarcane node.

FIGURE 7. Waveform diagram of a single sugarcane stem node is in a thin film piezoelectric sensor unit.

III. STEM NODE RECOGNITION BASED ON WAVELET ANALYSIS

A. WAVELET ANALYSIS

Wavelet analysis is a rapidly emerging new technique for data analysis in applied mathematics and engineering. A critical formalized mathematical framework has been constructed after over two decades of investigation and research. In comparison to the Fourier and Gabor transforms, the wavelet transform is a local transformation of space (time) and frequency that effectively extracts information from a signal. It is the apex of functional analysis, Fourier analysis, sample tone analysis, and numerical analysis. Wavelet analysis is a new technology of time-scale analysis and multiresolution analysis. It is used in the signal analysis (Baldazzi, Giulia, et al., 2020) [26], speech synthesis (M Kiran Reddy et al., 2017) [27], and image recognition (Komin Kaewphaluk. et al., 2017) [28], computer vision (Saradha Rani Sabbavarapu et al., 2020) [29], data compression (Jesmin Khan, Member, et al., 2015) [30], seismic exploration (Wang, Zhiguo, et al., 2017) [31], atmospheric (Hai Qiang Fu et al., 2018) [32] and ocean wave analysis (Jiaqi An et al., 2014) [33] have achieved scientific significance and application value. This article adopts the local analysis of the signal in time (space) and frequency. It gradually refines the signal (function) in multiple scales through the expansion and translation operation. Finally, it achieves the time subdivision at the high frequency and the frequency subdivision at the low frequency, which can automatically adapt to the time-frequency signal Analysis (Prieto, José Antonio González, et al., 2013) [34] requirements, so that you can focus on any details of the signal.

Wavelet signal (Yajie Li, Xiaoli Meng, et al., 2016) [35] is a fluctuating signal with fast attenuation, and its energy is limited and relatively concentrated in a local area.

Basic features of wavelet function:

$$\int_{-\infty}^{\infty} \psi(t) \, dt = 0 \quad (1)$$

The wavelet function $\psi(t)$ is formed by the extension and displacement of the wavelet function $\psi_{j,k}(t)$. And the wavelet function $\psi_{j,k}(t)$ is defined as:

$$\psi_{j,k}(t) = 2^{j/2} \psi(2^j t - k), \quad j, k \in \mathbb{Z} \quad (2)$$

The scale function $\phi(t)$ is defined by the scales function $\phi_{j,k}(t)$. And the scale function $\phi_{j,k}(t)$ is defined as:

$$\phi_{j,k}(t) = 2^{j/2} \psi(2^j t - k), \quad j, k \in \mathbb{Z} \quad (3)$$

The characteristic wavelet expansion of the wavelet function. The wavelet expansion of the wavelet function, the family of scale functions, and the signal can be stated as follows:

$$x(t) = \sum_k c_0[k] \phi_{0,k}(t) + \sum_k d_0[k] \psi_{0,k}(t) + \sum_k d_1[k] \psi_{1,k}(t) \ldots \quad (4)$$

The above is called the discrete wavelet inverse transform, the inverse discrete wavelet transform (IDWT). The discrete wavelet transform is obtained by the signal solving unfolding coefficient expanding the coefficients of signal solutions.

B. SELECTION OF FEMALE WAVELET FUNCTION
In signal processing, it is essential to make the processing effect achieve optimally, it is vital to achieving the best processing effect, and the choice of small wavelet is necessary. From the definition of wavelet function (Kahili, Kheira, et al., 2020) [36], the wavelet transform coefficient represents the similarity between the signal waveforms near the wavelet center and the waveform function waveform.

There are many commonly used wavelet basis functions, such as haar, dbN, mexh, and Meyer wavelets. After many experimental data analyses, we finally decided to choose the dbN wavelet series. Daubechies tight assembly wavelet is a wavelet function constructed by the Dao Becxi, and the abbreviation is dbN, N is the order of the wavelet. The scale functions and wavelet functions that relate to them are recorded:

\begin{align*}
N \phi(t) &= \sqrt{2} \sum_{n=0}^{2N-1} \varphi_n \phi(2t - n) \\
N \psi(t) &= \sqrt{2} \sum_{n=0}^{2N-1} g_n \phi(2t - n) \\
g_n &= (-1)^n h_{2N-1}, n = 0, 1, 2, ..., 2N - 1
\end{align*}

Where \( \varphi_n \) is the scaling function, \( g_n \) is the wavelet coefficient. Figure 8 shows the time-domain waveform of the db5 wavelet base. The prominent peak in the waveform can correspond to the leaf scar detection waveform at the sugarcane node. The signal on the left side of the main peak is a small amplitude peak first, corresponding to the sugarcane growth zone, and then entering the trough. The width of the trough is greater than the width of the main peak of the wavelet. The trough corresponds to the root zone, and the main peak represents the leaf scar. A peak to the right of the main peak corresponds to the node stem behind the leaf scar.

The features of sugarcane nodes are recovered in this article using wavelet decomposition. According to wavelet multiresolution analysis theory, the ideal wavelet decomposition level is proportional to the signal's sampling frequency. Because the final decomposition level map is required for stem node location, it is necessary to first calculate the appropriate wavelet decomposition level.

After decomposing the signal gathered by sugarcane stem nodes into 12 layers, the waveforms of the 10th, 11th, and 12th layers are picked, and the resulting breakdown is presented in Figure 9. Under normal circumstances, the wavelet decomposition signal will have a mix of interference components of varying degrees. By processing the wavelet coefficients of each layer using the default threshold approach, interference to the decomposed signal is reduced, and the node feature information is highlighted.
When the contact device makes contact with the sugarcane but not with the stem section, a minor amplitude fluctuation is unavoidable. The amplitude value is kept close to a predetermined value. When sugarcane stem nodes are encountered, the diameter of the sugarcane rapidly increases, increasing the amplitude of the waveform. Generally, the projecting portion of the waveform corresponds to the sugarcane stem section. Given the great sensitivity of the acceleration and piezoelectric sensors, as well as the modest vibration output signal, it is necessary to combine many sets of waveforms to determine the sugarcane stem section.

When the dynamic frequency of the sugarcane node's sampling signal is within the detail range of the wavelet decomposition layer, the bigger the wavelet transform coefficient, the less distortion is recovered. Experiments have established that this is true when the sampling frequency is fixed. The scale factor increases rapidly as the number of layers increases. The signals from the tenth, eleventh, and twelfth layers were reconstructed, and the result is displayed in Figure 10. In general, the larger the scale factor, the greater the node reconstruction's wavelet amplitude. As the number of layers and scale factors rise, the frequency band of the wavelet decreases, resulting in an increase in the wave width of the reconstructed signal in each layer, allowing the node to alter dramatically in terms of signal frequency and reconstruction. Because the wavelet frequency is blended, the reconstruction signal accurately captures the stem node area's properties.

FIGURE 9. Decomposition Node Surface signal under layers 10, 11, and 12.
The overlaid signal can be used to precisely evaluate and locate the sugarcane stem node. The waveform has a minor amplitude fluctuation due to the power supply voltage and external interference, but this does not affect the experiment. The reconstructed signals from many layers are layered to emphasize and identify the sugarcane node more precisely, as illustrated in Figure 11 for the reconstructed signals from the tenth, eleventh, and twelfth decomposition layers.

**FIGURE 10.** Surface signals of reconstructed nodes under layers 10, 11, and 12.
Through the observation of sugarcane objects and the waveform analysis of the signal, it is found that the width of the node, the contour of the leaf scar, and the size of the protrusion of the leaf scar are different, and the position of the sugarcane stem node can be accurately located by superimposing the signal.

![FIGURE 11. Superimposed signals on the 10th, 11th, and 12th layers.](image1)

C. VERIFY THE RELIABILITY OF THE EXPERIMENT

To ensure the experiment's reliability, we used the mean and standard deviation of sugarcane internode length (the distance between consecutive nodes) as the mean and standard deviation, respectively. Following that, we did statistical analysis on 175 sugarcane internodes and created a relationship graph between the length of the sugarcane internode and the standard deviation, as shown in Figure 12. As can be observed, the relationship between internode length and standard deviation in sugarcane follows a normal distribution, with a mean of 25.49mm and a standard deviation of 105.93mm, respectively.

![FIGURE 12. Internode length probability distribution.](image2)

![FIGURE 13. Gaussian distribution map of sugarcane stem segment length.](image3)

By observing the graph, it is known that the mode of the sugarcane segment is 100mm, and \( \mu \) and \( \sigma \) are introduced into the Gaussian membership function:

\[
f(x, \sigma, \mu) = e^{-\frac{(x-\mu)^2}{2\sigma^2}}
\]

The confidence of the sensor (the distance between adjacent nodes of sugarcane) is set to \( t(k) \) at \( t(k) \), and the Gaussian membership function determines the value of the confidence. When the speed of sugarcane transportation is \( v \), the time of the sugarcane stem node detected by the sensor is recorded as \( t(k) \), and the last recorded time is \( t(k-1) \). The sugarcane segment \( x \) is obtained by using the difference between two time points and the transportation speed. The membership curve of sugarcane internode length is shown in Figure 13.
D. MULTI-SENSOR FUSION ALGORITHM

Multi-sensor fusion (Geng, Hang, et al., 2015) [37] is analogous to the human brain’s information processing. When we identify sugarcane stem nodes because nodes cannot be detected simultaneously by each sensor, we will perform multi-level information processing on multiple complementary and optimized combinations. Finally, we will produce a consistent interpretation of the experimental environment. We make extensive use of multi-source data in this process to ensure adequate management and use. The ultimate goal of information fusion is to precisely locate sugarcane stem nodes using many sensors and derive stem node information from various information levels. Each sensor is incapable of detecting nodes simultaneously. A multi-sensor fusion technique is presented to determine optimal values through tests to identify sugarcane stem nodes’ position information reliably.

The advantage of the weighted average algorithm is its simplicity of calculation, which aids in comprehending the data processing process. The average length of sugarcane nodes can be determined using this approach. In comparison to the bar graph’s plurality, the system adjustment enables the acquisition of features of sugarcane stems and nodes in consecutive sections of the same sample.

Because the experimental data include noise and disturbances in the system, data processing is required before data analysis. Kalman filtering is capable of removing noise and disturbances from data. The Kalman filter algorithm is highly efficient at data processing. It is more efficient to gather information about the characteristics of sugarcane stem nodes and then establish their position.

1) WEIGHTED AVERAGE METHOD

The weighted average of the sensed values is calculated using many observations of the same variable sorted in time and order in the past. This value is used to forecast the variable’s value in the future. It is a trend forecasting method, and the formula is as follows:

$$\bar{x} = \frac{x_1w_1 + x_2w_2 + \cdots + x_nw_n}{w_1 + w_2 + \cdots + w_n}$$ (9)

Where $x_1, x_2, \ldots, x_n$ is the length of the sugarcane stem node, and $w_1, w_2, \ldots, w_n$ is the weight corresponding to the length. According to the weighted average method, the collected data is first observed and analyzed, and then the data is processed and optimized. The frequency of the segment is obtained, and the frequency is converted into a percentage. The predicted average value is calculated from the formula to be 104.6488mm, which is compared with the actual sensor. The average value (105mm) of the obtained data differs by
0.3512mm, which proves that the principle is feasible and the technology is reliable.

2) KALMAN FILTER METHOD
Kalman filter (Zhang Wanxin, Zhu Jihong., 2020) [38] is used to extract information from measurement data with unanticipated error and estimate some system parameter state variables. It is based on the idea that a particular performance index is optimal.

State equation is:

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}$$

The purpose of the equation of state is to hypothesize the state of the instant based on the previous moment's state and control factors. $w_{k-1}$ is the noise that obeys the Gaussian distribution and the noise of the prediction process. It corresponds to the noise of each component in $x_k$. $w_{k-1}\sim N(0,Q)$ is Gaussian white noise with expectation 0 and covariance $Q$. $Q$ is the process excitation noise. This parameter is used to represent the error between the state transition matrix and the actual process.

The observation equation is:

$$Z_k = Hx_{k-1} + v_k$$

$v_k$ is the observed noise, which obeys the Gaussian distribution. $v_k\sim N(0,R)$ and $R$ is the measurement of noise covariance. The length of the nth sugarcane segment is predicted from the length of the n-1 sugarcane segment and the error value. Comparing the predicted value with the value measured by the sensor, B in the state equation is set to 1, which is convenient for processing and calculation. The difference between the predicted value of sugarcane and the measured length value of the sensor is recorded, and the average value is 105.9313mm. According to the calculation of variance and average, the error between the analytical and experimental values is 0.5778mm.

Each sensor will invariably exhibit some variation throughout the installation process. It is impossible to align it entirely on the same measurement plane, and the sugarcane node section's perimeter distribution is uneven. As a result, we must combine all sensors' reliability and determine when the total surpasses a predefined threshold. At the time, the node is deemed to be detected.

In summary, the sugarcane node signal extraction and analysis flow chart proposed in this paper is shown in Figure 14.

IV. EXPERIMENTAL ANALYSIS

A. EXPERIMENTAL PLATFORM
The experimental platform comprises an operation control board, sugarcane conveying mechanism, sensor system, signal, and data acquisition (Miron, Sebastian, et al., 2020) [39] method, and experimental analysis system. Among them, the control board mainly includes the operation switches of the sugarcane conveying mechanism, such as the start/close switch of the sugarcane conveying mechanism, the forward/reverse switch of conveying mechanism, and the speed regulating switch other switches of conveying mechanism. The sugarcane describing mechanism includes a stepping motor, gear, slide rail, belt rack, conveyor belt, and H-shaped fixed groove. The sensor system consists of an acceleration sensor, piezoelectric film sensor, signal amplifier, and other sensors for operation during the experiment. The signal and data acquisition system comprise an oscilloscope, PC, regulated power supply, and voltage converter module. By adjusting the power supply voltage or stepper motor speed, different sugarcane conveying rates can be changed. The experimental analysis system is used to collect and analyze signals to determine the position of the stem node.

B. EXPERIMENTAL CONDITIONS AND PROCEDURES
Under normal circumstances, we contact the sugarcane by contacting the contact and combine the sensor, sugarcane transportation speed, sampling frequency, multi-sensor fusion algorithm, mathematical model, PC, and other conditions to detect the position of the sugarcane stem node. At the same time, three VTI single-axis analog acceleration sensors, one LDTM-028K piezoelectric film sensor with mass, and a magnification adjustment potentiometer are needed to detect the surface profile of sugarcane. The sensitivity of the acceleration sensor is 1200mv/g, the output voltage is (0V-3.9V), the signal frequency band of the piezoelectric film sensor and the magnification adjustment potentiometer is between (0.0003kHz -30kHz). The 5V voltage is used for the power supply. The speed of the sugarcane conveying mechanism is about 3.58cm/s, and the sampling frequency is 100 kHz. The sugarcane sample variety used in this experiment is Zhongzhe 9, which was not subjected to any surface treatments, and some impurities like soil were attached to the surface. However, these did not seriously influence the test results. The sugarcane sample comes from Fusui Experimental Base and has not undergone any surface treatment. There are a total of 175 knots on the 36 sugarcane samples we randomly selected, so we need to test these 175-knot samples. The sample used in the experiment is shown in Figure 15.

The sugarcane stem node detection system is shown in Figure 16. First of all, we feed 36 canes from the left side of the conveyor (the length of the canes is unlimited) and move them to the right through the conveyor. The acceleration sensor, piezoelectric film sensor, arch bridge contact acquisition device, and acquisition contact device on the stepping motor are used to collect experimental data in real-time and show the contour signal on the sugarcane surface through an oscilloscope. After processing the waveforms with a PC detection system, a multi-sensor fusion method was utilized to create a multi-level information complementary and optimal combination of numerous sensors to compute the precise position of the sugarcane stem node. Finally, the distance between the leaf scar and the margin of the growth zone was measured and recorded for
each sugarcane using a vernier caliper and tape. To ensure the experiment's reliability, the value measured by the acceleration sensor was compared to the value measured by the accelerometer.

**FIGURE 15.** Experimental sample.

### C. EXPERIMENTAL RESULTS AND ANALYSIS

Since 175 sugarcanes were used in the experiment and the experimental data were difficult to observe in the publication, the raw data are contained in a separate file titled Experimental Data. Table 1 contains the statistical results for 175 sections of position data acquired using an oscilloscope and a signal acquisition card. The identification system has an average error of 0.494mm, a maximum error of 9.99mm, an error rate of 0.37 percent, a recognition rate of 99.63 percent, and a response time of 0.25s. The inaccuracy is mainly caused by the sensor installation process, variations in the diameter of the cane, and the system's slight vibration, among other variables.

**TABLE 1. TICAL TABLE OF EXPERIMENTAL DATA.**

| Average error(mm) | Maximum error(mm) | Error rate(%) | Recognition rate(%) | Response time(s) |
|-------------------|-------------------|---------------|---------------------|-----------------|
| 0.494             | 9.99              | 0.37          | 99.63               | 0.25            |

### D. COMPARATIVE ANALYSIS

After comparing the experimental results of this paper with those of researchers Moshashai et al. (2008), Dong, Z et al. (2017), Zhou, DQ et al. (2019), Chen, JQ et al. (2020), Chen, JQ et al. (2021) and Li, S et al. (2019), Meng, Yanmei et al. (2019), the results are shown in Table 2.

From the 36 sets of data in the attached table and the above comparison results, it is obvious that we have done a lot of experiments to verify the reliability of the experiments and the correctness of the theory. Our system has a significant advantage over machine vision in the last five years of papers because it can quickly identify the sugar cane stem nodes faster and more accurately to help farmers select sugar cane seeds at a low cost, short identification time, and recognition rate up to 99.63%. We will cooperate with factories to further optimize the system and mass production to make our small contribution to agricultural mechanization and agricultural production.

**TABLE 2. COMPARISON OF WAVELET ANALYSIS RESULTS OF MULTI-SENSOR FUSION.**

| Algorithm         | Number of recognitions | Mean absolute error (mm) | Average time (s) | Recognition rate (%) |
|-------------------|------------------------|--------------------------|------------------|----------------------|
| Moshashai         | \                       | 2.08mm                   | 0.50            | 80                   |
| Dong, Z           | 280                    | \                        | \               | 95.4                 |
| Zhou, DQ          | 1                      | \                        | 0.539           | 93                   |
| Chen, JQ          | double nodes           | 0.42                     | \               | 98.5                 |
| Chen, JQ          | three nodes            | 2.2                      | \               | 95                   |
| Li,S              | 1                      | \                        | 0.028           | 90.38                |
| Liu Zhiqiang      | 89                     | \                        | 1.06            | 91.76                |
| Chen Jinjian      | 10                     | \                        | 0.87            | 93                   |
V. CONCLUSION

A multi-sensor fusion recognition method based on wavelet analysis is developed to determine the sugarcane stem node's position. The signal is collected using both the acceleration sensor and the piezoelectric film sensor. The precise position of the sugarcane node is determined using wavelet analysis decomposition, reconstruction, and superposition signals. The weighted average algorithm and the Kalman filter algorithm of multi-sensor fusion are utilized to detect nodes and calculate errors. The approach optimizes the mathematical model of sugarcane nodes, increases the program's robustness and accuracy, and allows the system to exit local optimization and attain global optimization. The experimental results show that the improved new algorithm has better solution quality and convergence speed through the test. The average error of this method is 0.494mm, the recognition rate is 99.63%, the error rate is 0.37%, and the response time is 0.25s. To sum up, the main contribution of this paper is to develop a new sugarcane stem node recognition system, which can save time, reduce labor intensity, and is safe and stable, which can provide a reference for the development of sugarcane stem node recognition system.

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