Hindawi
Journal of Robotics
Volume 2023, Article ID 9768015, 1 page
https://doi.org/10.1155/2023/9768015

Retraction

Retracted: Designing and Manufacturing of Industrial Robots with Dual-Angle Sensors Taking into Account Vibration Signal Fusion

Journal of Robotics

Received 19 December 2023; Accepted 19 December 2023; Published 20 December 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] J. Yan and H. Cheng, "Designing and Manufacturing of Industrial Robots with Dual-Angle Sensors Taking into Account Vibration Signal Fusion," *Journal of Robotics*, vol. 2023, Article ID 1855226, 11 pages, 2023.

Hindawi
Journal of Robotics
Volume 2023, Article ID 1855226, 11 pages
https://doi.org/10.1155/2023/1855226

Research Article

Designing and Manufacturing of Industrial Robots with Dual-Angle Sensors Taking into Account Vibration Signal Fusion

Jinshun Yan [1] and Haiqing Cheng [2]

[1] *Department of Mining Engineering, Lyuliang University, Lyuliang, 033001, China*
[2] *China Railway Hohhot Bureau Group Co. Ltd., Hohhot, Nei Monggol 010000, China*

Correspondence should be addressed to Jinshun Yan; 20131065@llu.edu.cn

Received 4 September 2022; Revised 17 October 2022; Accepted 24 November 2022; Published 4 May 2023

Academic Editor: Iqbal Ahmad

Industrial robots are an important way to realize the development of industrial industry intelligence and automation, an important driving force to accelerate the construction of Industry 4.0, and an important basic force to improve the professional level of industrial industry. The development of industrial robot technology has enhanced the requirements of its detection quality and the demand for data comprehensiveness. Most of the previous robots obtain the corresponding data through a single sensor system, which has a large error and a high limitation of the range of data obtained. The detection method of industrial robots has the problems of high cost and high professionalism. Therefore, this paper constructs a dual-angle sensor industrial robot detection system based on the fusion of multisource vibration signals and achieves the fusion of multisensor signals through Kalman filtering to provide reliable analysis data for the dual-angle sensor detection system. The experimental results show that Kalman filtering can effectively remove noise while preserving the original vibration signal characteristics and structure and improve the reliability and validity of the vibration signal. In addition, the dual-angle sensor detection system can realize the position detection of industrial robots according to the command standard and obtain the corresponding residual and standard values through system data analysis. The overall optimization of the system algorithm enhances the accuracy and reliability of the measurement.

1. Introduction

The application of modern intelligent technology has driven the development of Industry 4.0, raising the demand for industrial specialization and intelligence. At the same time, industrial robots have become an important direction for the future development of industrial industry as labor costs increase and the population ages. The in-depth research of intelligent technology has provided the technical guarantee for the intelligence of industrial robots and expanded the performance and usage of industrial robots, enabling them to develop from completing basic and simple task instructions to completing assembly lines according to industrial needs [1]. The application of a large number of intelligent industrial robots can effectively liberate labor and promote productivity improvement. In addition, with the enhancement of industrial robot technology, the classification of robots is becoming more specialized and refined, and the requirements for their performance testing are also increasing [2]. For example, intelligent robots applied in high-risk industries not only need to be able to adapt to special terrain and complex environments, etc., but also need to be able to achieve a high degree of accuracy in positioning. In the past, industrial robots used a single vibration signal source, which was not able to obtain comprehensive and accurate data from the surrounding environment and feedback on the robot's operating status due to the limitation of space and time conditions when positioning the robot [3]. The multisource vibration signals of industrial robots, i.e., the multidimensional spatial data information of the environment obtained by multisensors, provide a reliable data basis for the robot to identify the environment, transmit data, capture and extract dynamic features, etc. [4]. The key aspect of multisensor applications in industrial robots is the fusion of different sensor data information, i.e., the multisource vibration signals are processed in a uniform manner and are able to describe the observed target jointly according to the corresponding rules [5]. Therefore, vibration signal fusion technology has a great impact on the development of industrial automation and robot intelligence and is an important element of research.

The application of intelligent sensors to the detection field of industrial robots is a new field of robot detection technology research at present. It faces many key technical problems, which can be summarized in two aspects. On the one hand, it is the practicality of sensor systems. The research focus is on the modeling, planning, and fusion technology of multi intelligent sensor systems and the control strategy of group behavior. This includes the following items: multiagent group architecture, mutual communication and negotiation mechanism, perception principle, and learning method. The other is a stable and reliable multi intelligent sensor fusion algorithm 7, which involves the capture, recognition, extraction, analysis, and evaluation of static and dynamic features of multisensor data, especially in the case of nonlinear, nonstationary, non-normal distribution, and multisensor system fusion algorithm. In addition, it also includes the noise interference of the external environment on the system, the accuracy evaluation of the multisensor system, the principle of data communication, the error compensation mechanism, and the calibration performance evaluation. Therefore, it is of great significance to study the fusion technology of multiple intelligent sensors to improve the level of industrial automation in China. With the expansion of industrial robots' applications, their detection problems are gradually highlighted. Some common detection methods currently have high costs, difficult operation, technical condition restrictions, and large error variations, and many robots applied in special working environments are relatively difficult to detect, which require the safety and reliability of their detection to be considered in robot design. The application of intelligent sensors in industrial robots has expanded the development direction for their detection field, and the fusion of vibration signals has become an important part of the key technologies to be solved for their application. Therefore, this paper designs a dual-angle sensor industrial robot performance detection system and introduces Kalman filtering in the detection module to achieve vibration signal fusion, reduce the original data noise, improve the accuracy of data analysis, and conduct the corresponding performance analysis through experiments. The vibration signal fusion technology reduces the residual vibration at the end of motion and the vibration caused by high-frequency torque in the process of motion by optimizing the acceleration waveform. The optimized velocity waveform and acceleration waveform are obtained from the optimized acceleration waveform and boundary conditions. The optimal joint torque is obtained. The vibration reduction effect of inverse dynamics is simulated by the modal analysis method.

2. Status of Vibration Signal Fusion Technology and Industrial Robot Research

The research and application of industrial robotics is an important element to promote the development of industrial automation and intelligence, and the in-depth research of sensor technology provides strong data and information basis for robot development. In the past, robots obtained information by means of a monolithic sensor measurement system, and the verification index of the robot performance was relatively monolithic, with relatively low data comprehensiveness, which was not conducive to the analysis of robot systems and the detection and diagnosis of their performance [6]. Cruz Miguel et al. pointed out that single-source vibration signals not only have noise signal interference but also may generate more redundant information due to system reasons, which add burden to the system transmission data, and at the same time, the single system data transmission path is largely affected by external influences, and the data accuracy and authenticity are relatively low [7]. Based on this, Fu et al. proposed to achieve multidirectional diversified access to the corresponding environmental data through different sensor systems, but their existence of multiple sensor systems with different time standards and a certain amount of repetition in the data transmitted by each independent sensor system increases the energy consumption of the whole robot system [8]. Multisource vibration signal fusion, i.e., multisensor information fusion, can achieve a uniform representation of the data information obtained from different sensors through comprehensive technical processing, and the redundant data transmitted by different sensors can complement each other to improve the comprehensiveness and integrity of the overall system information. Among them, the estimation algorithm is one of the common and widely used methods, which includes the weighted average method and the Kalman filter. Wei et al. proposed to combine multivariate statistics and the artificial intelligence algorithm to achieve the fusion of multisource vibration signals. They propose to combine multivariate statistical methods and fusion accuracy to derive the optimal assignment of weighted averaging [9]. Other scholars have reconstructed for vibration signal combustion information combined with multichannel vibration acceleration signal, and the signal with high correlation of combustion information is obtained in a new way, while the fusion of its vibration acceleration signal is achieved by weighting coefficients [10]. With the development of artificial intelligence technology, the application of the Kalman filter has been gradually expanded, and Li et al. have used the extended Kalman filter method to achieve the fusion of position and acceleration signals in vibration sensors to achieve the prediction of dynamic displacement of the infrastructure [11]. Other scholars have incorporated Kalman filtering in intelligent vehicle location systems to reduce the risk probability of failure in vehicle health maintenance systems through the fusion of fuzzy sensor data [12].

The artificial intelligence technology method is to extract the feature information of multisource vibration signals through neural networks and obtain the best vibration signal fusion processing results after model training, whose advantage is that neural networks have good autonomous learning ability and self-organization ability and can process and store large-scale data effectively [13]. Its disadvantage is that it requires model training of a large amount of data to be able to reduce the error rate of data fusion, the stability of data fusion is low, and the generalization ability needs to be improved. Li et al. introduced convolutional neural networks for multisensor data fusion in rotating machinery fault identification and achieved optimization of neural networks through bottleneck layers, which can be effective in improving the richness of information obtained by the sensors [14]. Zhang et al. introduced dynamic integrated convolutional neural networks in fault diagnosis, which constructed a multilevel wavelet coefficient matrix based on wavelet packets for the description of nonsmooth vibration signals, and the fusion of its dynamic ensemble layer and multilevel wavelet packets enhanced the effectiveness of diagnosis [15]. In addition to neural networks, Ikuta et al. introduced the fuzzy theory into the field of signal processing and combined it with other algorithms to achieve the fusion of vibration signals and enhance their effectiveness and accuracy [16]. Other scholars have combined multisensor technology and fuzzy information fusion algorithms to improve the accuracy and reliability of chemical enterprise safety assessment systems in the analysis of chemical enterprise accidents and related casualty probabilities [17]. Other scholars have combined the fuzzy theory and neural networks to build a system that can extract signal features according to the principle of adaptive fuzzy control and establish a system for diagnosing energy dissipation information of mechanical equipment faults [18].

In addition to the fault diagnosis of industrial machinery and robots, intelligent sensor technology is widely used in the field of industrial robot inspection. With the improvement of industrial robot technology and the expansion of its uses, Bai et al. have proposed higher and more comprehensive performance testing standards and a performance evaluation model incorporating neural networks [19]. It has also been proposed for wheeled robots to build a ground classification system based on convolutional neural networks, combining feature-level and decision-level data fusion [20]. Thus, it can be seen that sensor technology has an important role in promoting future research in industrial robotics, and multisensor data fusion is a key aspect and technology for its development.

3. Construction of the Kalman Filter-Based Measurement Module for Industrial Robots with Dual-Angle Sensors

3.1. Multivibration Signal Fusion Technology. The design of industrial robots involves various disciplines and technologies such as computers, mechanical electronics, and artificial intelligence. They often need to have good mobility and stability and cooperate with each other through multiple joints in the range of motion to complete the command tasks, and this process requires data information obtained through different types of sensors as the basis for analysis and decision making. The information obtained from single-source vibration signals is redundant and limited by the environmental space and sensor location, which cannot meet the environmental information needs of industrial robots. In addition, multisource vibration signal fusion can reasonably and effectively utilize the redundant information in various sensors, redistribute the redundant information from the perspective of the system as a whole, supplement the uncertainty in the information obtained by other sensors, and improve the accuracy and integrity of the information of the whole system. Multisource vibration signal fusion is also beneficial to optimize the system structure of industrial robots, avoiding the corresponding costs due to the increase of individual sensor systems.

Artificial intelligence technology is widely used in industrial robot design, which can improve the intelligence level of robots and achieve the goal of industrial intelligence and automation. One of the common methods of multisource vibration signal fusion in artificial intelligence is Kalman filtering, which can predict the data afterwards based on the data obtained from the vibration sensors at the moment, and it can also effectively reduce the impact of noise in multisource vibration signal data. The Kalman filter can be understood as a way to perceive a noisy world. When we want to locate the robot, it depends on two conditions. We know how the robot moves from one moment to the next because we command it to move in a certain way. This is called state transition (that is, how a robot moves from one state to another), and we can use various sensors such as cameras, lidars, or echo detectors to measure the robot's environment. The problem is that both types of information are affected by noise. We cannot accurately know the accuracy of the robot's transition from one state to the next because the executive parts are not perfect. And we cannot measure the distance between objects with infinite precision. This is where the Kalman filter comes into play.

Different types of sensors collect and transmit data according to different time series; so, industrial robots need to synchronize the time-stamped relationship of multisource vibration signals and transform the coordinate systems of different sensors into a unified world coordinate system, as shown in Figure 1.

Let the state at time t be denoted as $M(t)$ and its filtered value be denoted as $\widehat{M}(t/t)$, then the prediction of the next state is shown in the following equation:

$$\widehat{M}\left(\frac{t+1}{t}\right) = \alpha(t)\widehat{M}\left(\frac{t}{t}\right) + \beta(t)U(t), \tag{1}$$

where $t+1$ indicates the next moment, the state description is $\widehat{M}(t+1/t)$, the system parameters are described as $\alpha(t), \beta(t)$, and the state control quantity is noted as $U(t)$.

Let the covariance matrix at time t be denoted as (t/t), whose prediction matrix is shown in the following equation:

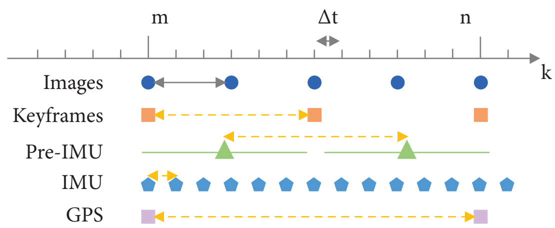

Figure 1: Time-stamped relational synchronization condition of multisource vibration signals.

$$P\left(\frac{t+1}{t}\right) = \alpha(t)P\left(\frac{t}{t}\right)\alpha^{T}(t) + Q(t), \tag{2}$$

where $\alpha^{T}(t)$ represents the transpose matrix of $\alpha(t)$.

The predicted values of the measurements are calculated as shown in the following equation:

$$\widehat{S}\left(\frac{t+1}{t}\right) = H(t+1)\widehat{M}\left(\frac{t+1}{t}\right). \tag{3}$$

The new information covariance matrix is described as shown in the following equation:

$$X(t+1) = H(t+1)P\left(\frac{t+1}{t}\right)H^{T}(t+1) + R(t+1). \tag{4}$$

The gain matrix is represented as shown in the following equation:

$$Kg(t+1) = P\left(\frac{t+1}{t}\right)H^{T}(t+1)X^{-1}(t+1). \tag{5}$$

The state filter values are calculated as shown in the following equation:

$$\widehat{M}\left(\frac{t+1}{t+1}\right) = \widehat{M}\left(\frac{t+1}{t}\right) + Kg(t+1)\left[S(t+1) - \widehat{S}\left(\frac{t+1}{t}\right)\right]. \tag{6}$$

The filtering covariance matrix is described as shown in the following equation:

$$P\left(\frac{t+1}{t+1}\right) = P\left(\frac{t+1}{t}\right) - Kg(t+1)S(t+1)Kg^{T}(t+1). \tag{7}$$

3.2. Dual-Angle Sensor-Based Measurement System for Industrial Robots. In order to improve the operability of the industrial robot measurement, this paper selects a dual-angle sensor measurement system consisting of two sensors and a microprocessor module, one of which has a detection function and the other a calibration function, and each of which contains a three-axis gyroscope and accelerometer and a digital motion processor, both of which maintain a cooperative communication state with the microprocessor module. The measurement system is embedded in the industrial robot in a simple way, and its corresponding position needs to be adjusted and determined as a basis for adjusting and optimizing the circuit layout to enhance its safety and stability. Before carrying out the detection group to initialize the operation of the two sensors, that is, the calibration results determined according to the dynamic and static characteristics of the response, we also need to detect the two parts of the sensor and the composition of the system accuracy and the corresponding requirements for comparison through continuous adjustment and threshold information feedback to achieve the results and industrial robot position command data comparison analysis. The microprocessor module is responsible for the control of the operating state of the system, data communication, and the corresponding processing of the received real-time data. At present, based on multisensor signal fusion, data registration is mainly used to realize mutual estimation of state and parameters. State information fusion is suitable for target tracking, while feature information fusion is suitable for combined classification, which is mainly based on traditional pattern recognition technology to achieve classification fusion. Feature-level fusion can automatically extract information sources with representative features from the original data, integrate them, and retain important information, so as to provide data support for later decisions. This mode has low requirements for communication broadband.

The system works on the principle that the two sensors take the angular velocity data of each axis obtained by gyroscope and accelerometer and derive the corresponding position analog signal according to the difference method; then, the data are transformed by the data motion processor and the industrial robot attitude data are derived according to the calibration sensor. The data are then transferred to the microprocessor module for the next step of data processing and analysis. In order to improve the accuracy and reliability of the data analysis results, Kalman filtering is used in the microprocessor module to remove noise from the raw data transmitted by the sensors. Based on the existing input and output laws, the system adjusts the data acquisition frequency in the form of iterative approximation to obtain the optimal value in the characteristic threshold, maintain the input and output correspondence, and avoid the distortion problem. The dynamic response characteristics obtained in this process will be smoothened by error compensation to reduce the errors generated by the system due to installation operations, gyroscope angle integration accumulation, and other problems, so as to obtain better static response characteristics.

The key of initialization lies in the calibration of detection sensor and calibration sensor. The calibration results are divided into static characteristic response and dynamic characteristic response. The dual-angle sensor measurement system is composed of STM32 microprocessor module and two MPU6050 modules. The system is simple in structure, easy to install, and realize. Fix the sensor MPU6050 for detection at the center point (TCP) of the industrial robot tool with screws. Ensure that the MPU6050 does not vibrate significantly during the high-speed movement of the robot. The other MPU6050- and STM32-embedded modules are fixed close to the zero point of the robot base coordinate system, and this sensor is used as the reference, that is, the sensor for calibration. In the accuracy analysis, the system needs to analyze the accuracy, sensitivity, stability, and other changes in state and amplitude, according to the response situation to select the response compensation factor so that it meets the corresponding requirements. After the accuracy meets the standard is the correction of zero point drift, that is, according to the principle of the minimum error, the distance between the predicted value and the target point of the system is driven to the minimum through the adjustment of the static and dynamic characteristics weights. A flowchart of the Kalman filter-based measurement system for industrial robots with dual-angle sensors is shown in Figure 2.

The original data of the system are filtered by low-pass filter to remove noise interference, especially white noise generated by mechanical vibration. Observe the law of input and output, and adopt the iterative approximation method to adjust the sampling frequency and optimize the characteristic threshold. The method of multiple iterations is used for error compensation, referring to Dr. Zhang Xiaoping's MDH kinematic error model. Optimize the compensation coefficient, reduce the process error of system installation and drift error accumulated by gyro angular velocity integral, and obtain good static response characteristics. Continue error compensation. It is required to redistribute the weight, modify the weight proportion of static and dynamic characteristics, and refer to the principle of the least square method. According to the principle of the minimum error, adjust the zero position to make the estimated value approach the sample point. If the standard is met, the final result will be the output; otherwise, the second step will be returned, starting from adjusting the characteristic threshold, and the dynamic characteristic response will be repeated until the standard is met. Let the commanded and actual measured positions of the industrial robot be described as $Z(x_i, y_i, z_i, \alpha_i, \beta_i, \lambda_i)$ and $(x_i, y_i, z_i, \alpha_i, \beta_i, \lambda_i)$, respectively, and the deviation results between the actual measured and estimated values can be analyzed by the position residuals; the settlement process of which is shown in the following equation:

$$R = \sqrt{\left(\sum_{i=1}^{N} x_{M,i} - x_{Z,i}\right)^2 + \left(y_{M,i} - y_{Z,i}\right)^2 + \left(z_{M,i} - z_{Z,i}\right)^2}. \tag{8}$$

The dynamical observations of the entire system that have been calibrated, after removing the noise disturbances, show a nonlinear relationship between the measured values, and the minimum value of the total squared error between the actual and commanded values is determined by combining regression analysis and the least squares theory. The results of the next stage of calibration are then estimated by the minimum distance between the input data points and the straight line.

Let the point A_1, A_2, A_3, A_4, A_5 be the position point in the determined working range, and the industrial robot moves according to the number of point sequences. Let the attitude O, P, Q denote the direction of the corresponding industrial robot's working surface, and its corresponding commanded position is (x_l, y_l, z_l), and the accuracy is calculated according to equations (9) and (10).

$$W_i = \sqrt{(\overline{x} - x_l)^2 + (\overline{y} - y_l)^2 + (\overline{z} - z_l)^2}, \tag{9}$$

$$\begin{cases} \overline{x} = \dfrac{1}{N}\displaystyle\sum_{i=1}^{N} x_i, \\ \overline{y} = \dfrac{1}{N}\displaystyle\sum_{i=1}^{N} y_i, \\ \overline{z} = \dfrac{1}{N}\displaystyle\sum_{i=1}^{N} z_i. \end{cases} \tag{10}$$

The attitude command is $(\alpha_l, \beta_l, \lambda_l)$, and its accuracy is calculated as shown in (11) and (12).

$$\begin{cases} T_\alpha = (\overline{\alpha} - \alpha_l), \\ T_\beta = (\overline{\beta} - \beta_l), \\ T_\lambda = (\overline{\lambda} - \lambda_l), \end{cases} \tag{11}$$

$$\begin{cases} \overline{\alpha} = \dfrac{1}{N}\displaystyle\sum_{i=1}^{N} \alpha_i, \\ \overline{\beta} = \dfrac{1}{N}\displaystyle\sum_{i=1}^{N} \beta_i, \\ \overline{\lambda} = \dfrac{1}{N}\displaystyle\sum_{i=1}^{N} \lambda_i. \end{cases} \tag{12}$$

The corresponding positional repeatability can be calculated according to equations (13)–(16).

$$R_d = \overline{d} + 3S_d, \tag{13}$$

$$\overline{d} = \frac{1}{N-1}\sum_{i=1}^{N} d_i, \tag{14}$$

$$d_i = \sqrt{(x_i - \overline{x})^2 + (y_i - \overline{y})^2 + (z_i - \overline{z})^2}, \tag{15}$$

$$S_d = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} \left(d_i - \overline{d}\right)^2}. \tag{16}$$

The attitude repeatability can be calculated according to the following equation:

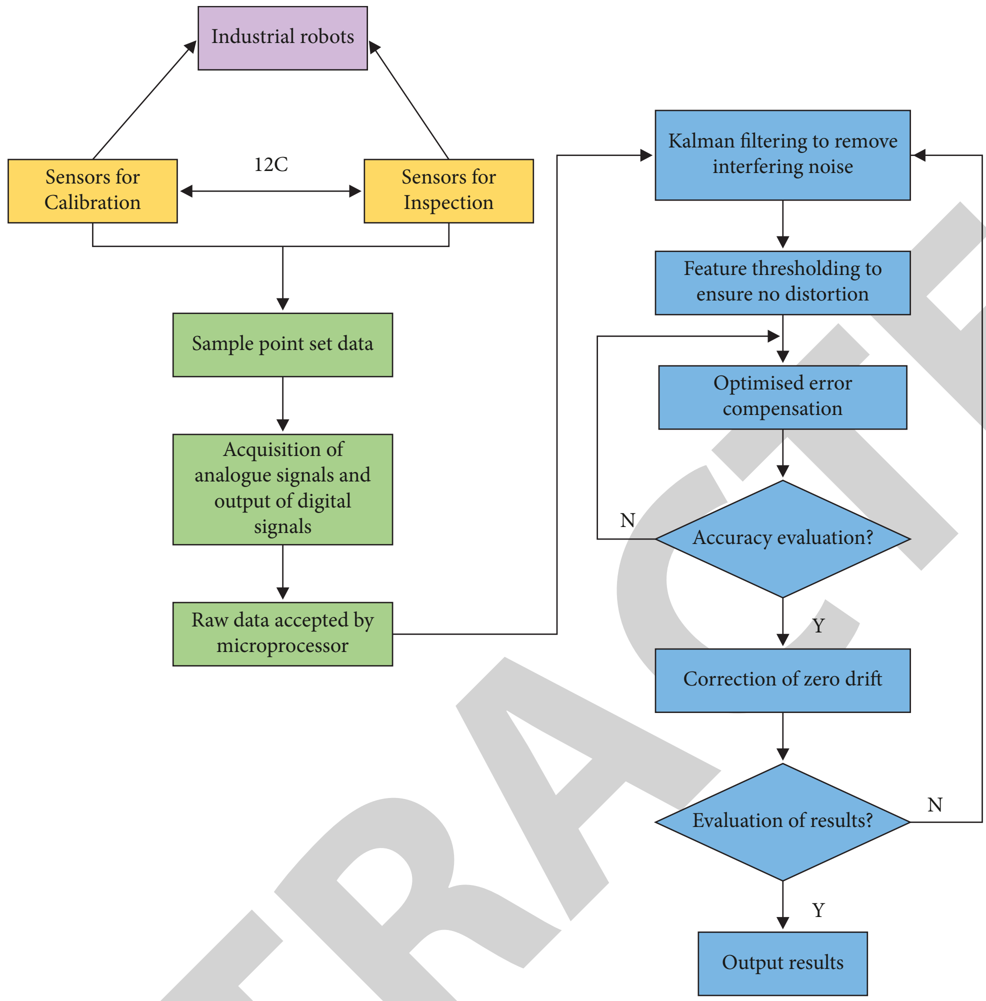

FIGURE 2: Flowchart of the Kalman filter-based dual-angle sensor industrial robot measurement system.

$$\begin{cases} R_\alpha = \pm 3S_\alpha = \pm 3\sqrt{\dfrac{1}{N-1}\sum_{i=1}^{N}(\alpha_i-\overline{\alpha})^2}, \\ R_\beta = \pm 3S_\beta = \pm 3\sqrt{\dfrac{1}{N-1}\sum_{i=1}^{N}(\beta_i-\overline{\beta})^2}, \\ R_\lambda = \pm 3S_\lambda = \pm 3\sqrt{\dfrac{1}{N-1}\sum_{i=1}^{N}(\lambda_i-\overline{\lambda})^2}. \end{cases} \tag{17}$$

The root mean square is able to provide a measure of the degree of dispersion of a group of points with discrete characteristics, and it reflects the degree of offset between the measured and commanded values of the robot, which is calculated as shown in the following equation:

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_{M,i}-x_{Z,i}\right)^2}. \tag{18}$$

The standard deviation can reflect the relationship between the sample data with your own and the mean self-test, which is calculated as shown in (19) and (20).

$$B_{StdDev} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\delta)^2}, \tag{19}$$

$$\delta = \frac{1}{N}\sum_{i=1}^{N}x_i. \tag{20}$$

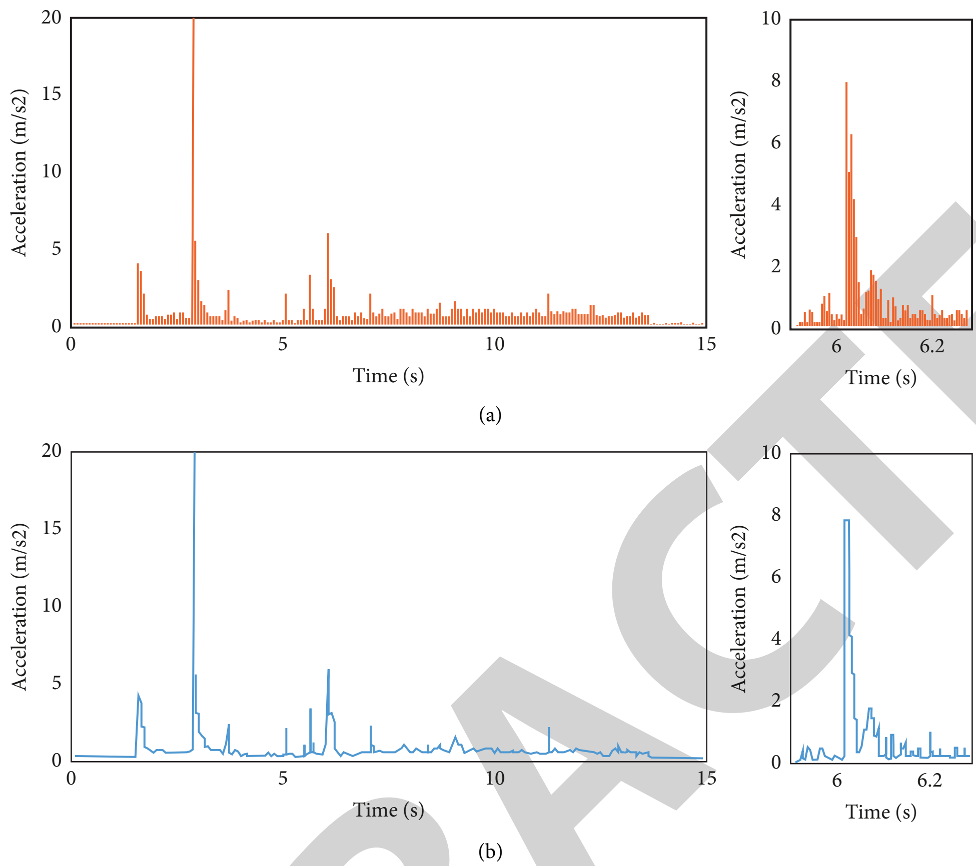

FIGURE 3: Original signal and filtered effect of multisource vibration signal of industrial robot. (a) Raw data. (b) Filtered data.

4. Experimental Results of the Kalman Filter-Based Measurement Model for Industrial Robots with Dual-Angle Sensors

The Kalman filter algorithm implementation steps are as follows: first measurement. The filter receives the pose and velocity of the robot in the coordinates from the radar or laser radar as the initial measurement and next the inverse initialization, state, and covariance matrix. The filter will initialize the position of the robot based on the first measurement. The filter receives a new sensor measurement after the time period. The predicted position and the measured position are combined to give an updated position. The Kalman filter will assign different weights to the predicted position or the measured position according to the uncertainty of each value. The filter will then receive a new sensor measurement. The algorithm then performs another prediction and updates the step. In the actual detection system, the working environment of the sensor is complex and harsh, the amplitude of the output electrical signal is small, and there is a certain distance between the sensor and the circuit. The noise generated by the cable resistance that needs to transmit signals, the internal resistance of the sensor, and the amplifier circuit will affect the amplifier circuit and its normal operation. Therefore, targeted measures must be taken to improve the anti-interference ability of the sensor circuit. Remote transmission of analog quantity shall be avoided as far as possible when selecting sensors and designing equipment interfaces, and digital communication interfaces can be selected. This kind of communication interface has a long transmission distance and less interference and can be extended by adding relay. Before conducting experiments on industrial robots with dual-angle sensors, the raw data need to be filtered. The raw and filtered signals of the multisource vibration signal of the industrial robot are shown in Figure 3. The results show that there are many noise signals in the local part of the original vibration signal of the robot, and the overall signal waveform has many small-amplitude peaks. After filtering, the overall signal is smoother, and the small-amplitude peaks in the local signal effectively reduce the interference noise, especially the white noise. At the same time, the filtering process maintains the waveform structure of the original vibration signal as much as possible, avoiding its distortion problem and ensuring the authenticity and validity of the multisource vibration signal.

The industrial robots involved in the experiments are six-axis robots with handling functions, and the appropriate joint motion range, corresponding speed limit, working space, and center position are set according to the experimental requirements to ensure that the handling robots can bypass the singularities to the maximum extent. Thirty points were randomly selected from the sample data set for calibration and none of the selected points had singularities.

The actual and average values of the position residuals and attitude residuals of the robot after reaching the calibration points through various postures are shown in Figures 4 and 5, respectively. The results in Figure 4 shows that the residual values of each random position point of the handling robot are identical, but the overall fluctuation is within a certain range, and there are individual sample data points whose position residual values fluctuate more compared with others. However, the average of the residual values of all sample data points in the experiment is very low, less than 0.1 mm, and the overall fluctuation condition also gradually stabilizes. This indicates that although there is a certain error between the actual data and the command data of the handling robot, the degree of closeness between them is high, the fluctuation is small, the error is small, and the reliability and validity of the calibration results are high.

The results of the analysis of the actual and mean values of the robot's posture residuals are shown in Figure 5. The results show that most of the actual measured residuals of the robot fluctuate in the range of 0.00018°–0.00065°, and there are a few sample data points where the actual measured residuals are too high or too low. The mean values of the posture residuals of the sample data points in the experiment are very small, i.e., they reflect that the actual results of the robot posture and the calibration results are highly accurate, relatively stable, and in good agreement with the command data.

In the process of signal acquisition and transmission, it is bound to be interfered by the surrounding environment and internal noise; so, we need to process the signal correctly to eliminate the influence of interference and try to obtain the required signal, which requires filtering the received signal. Filtering is the process of extracting signals from noisy observation data. Kalman introduced the concept of state space into the theory of random estimation and regarded the signal as the output of a linear system excited by white noise. This input-output relationship is described by state equation. Because the signal information used is the time domain, it can estimate not only the one-dimensional stationary random process but also the multidimensional, nonstationary random process. This overcomes various limitations encountered in the design of Wiener filtering in the frequency domain and has a wide range of applications.

As shown in Figure 6, the measured results of the position of the handling robot are in the A_1 points, the number of cycles of the process of approaching each position in each experimental direction is 20, and some of the measured data results are shown in the figure.

The calculated results of the robot's posture at A_1 are shown in Figure 7. The combination of the results with Figure 6 shows that the accuracy of the robot's posture in different directions is high, and the effective mean value of the dispersion of the point group is small, which indicates that the actual measured value and the commanded value are in good agreement and the position of the measured point is basically in the range close to the commanded point. The smaller average value of the standard deviation value reflects the higher concentration of the distribution of the actual data measurement points in space, and the high degree of fit with the mean value, and the high stability of the system.

In summary, the Kalman filter-based dual-angle sensor industrial robot measurement model can effectively fuse the multisource vibration signal and reduce the noise interference in the signal, providing a more accurate data information basis for subsequent analysis while maintaining its authenticity and reliability. The dual-angle sensor system in the model can improve the performance of the system algorithm, increase the validity and accuracy of the measurement data, and has good efficiency and practicality.

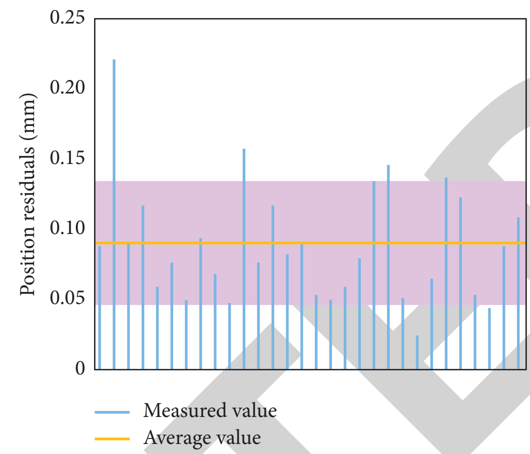

Figure 4: Actual and mean value analysis results of the position residuals of the handling robot.

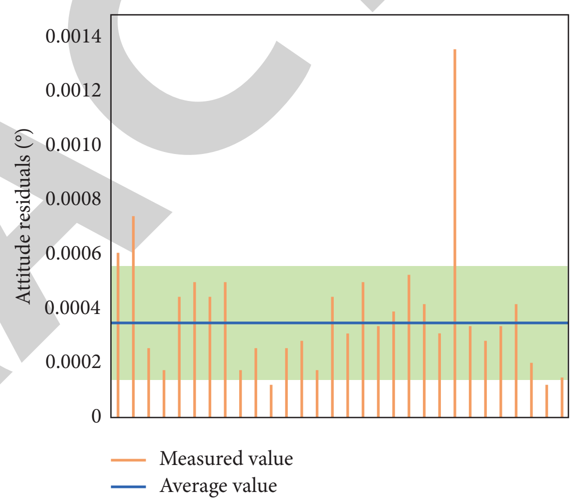

Figure 5: Actual and mean value analysis results of the pose residuals of the handling robot.

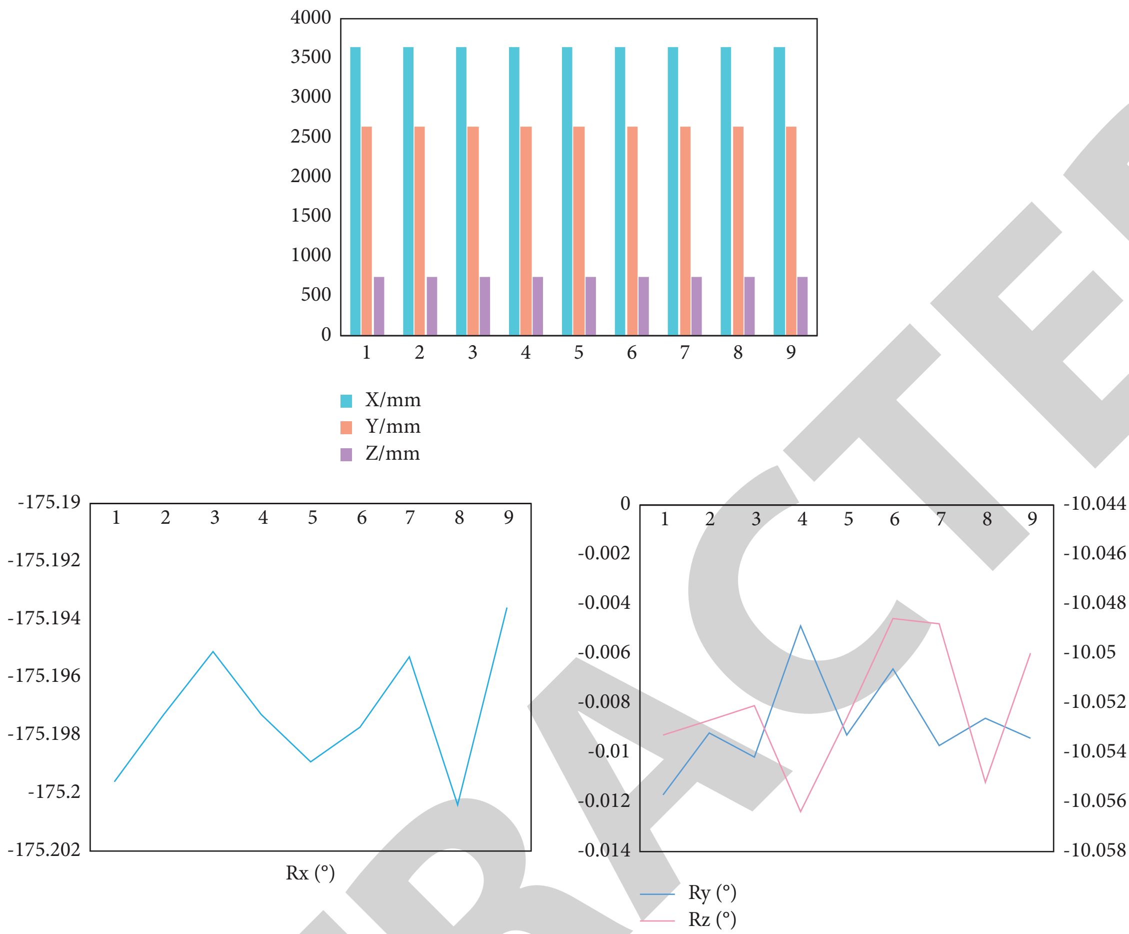

FIGURE 6: Position measurement results of the handling robot in A_1 points.

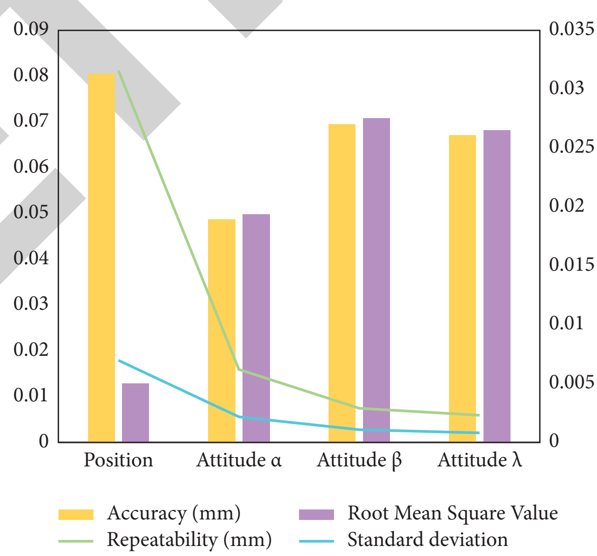

FIGURE 7: Calculated results of the position pose of the handling robot at A_1.

5. Conclusion

The advent of Industry 4.0 era has promoted the optimization process of industrial structure and opened a new period of high-quality development of industrial industry, and the traditional industrial model to improve automation, intelligence, and specialization standards has become the inevitable development direction. Industrial robots can not only liberate part of the labor force and improve production efficiency but also enhance the degree of intelligence and automation of industrial industries. In addition, the working environment of some industrial industries is complex, and it is difficult to obtain corresponding spatial information data artificially. Obtaining data through individual sensors will be restricted by time and space, and the accuracy of single-source vibration signals is relatively low. Industrial robots are able to obtain multidirectional spatial information through multiple sensors, providing a more reliable data base for robot measurement and analysis. Therefore, this paper introduces the Kalman filter algorithm to achieve the fusion of multisource vibration signals in the industrial robot design and builds a measurement system based on dual-angle sensors in the industrial robot detection module. The experimental results show that the data information obtained by the handling robot through multiple sensors can effectively reduce the noise signal interference and improve the accuracy and validity of the original signal after Kalman filtering processing, while maintaining its basic signal characteristics and structure. In addition, the dual-angle sensor-based industrial robot measurement system can detect the corresponding robot position data according to any command and standard and obtain the corresponding data analysis results through the system calculation. The results show that the system can reduce the error rate of the industrial robot, enhance its reliability, improve the system algorithm, and show good practicality and efficiency. However, the design of the industrial robot in this paper needs further improvement, its measurement of itself is still inadequate, and there is a gap between the complexity of the experimental environment and the actual environment, which needs further verification of its performance in the actual environment.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant no. 52165035) and the Postgraduate Research and Innovation Funding Project of Inner Mongolia Autonomous Region of China (Grant no. BZ2020037).

References

[1] Z. Zheng, X. W. Dai, and Z. W. Gao, "Pick-and-place robot sensor fault detection based on unknown input observer," *Control Engineering*, vol. 27, no. 12, pp. 2063–2069, 2020.

[2] R. Liu, F. Wang, B. Yang, and S. J. Qin, "Multiscale kernel based residual convolutional neural network for motor fault diagnosis under nonstationary conditions," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 6, pp. 3797–3806, 2020.

[3] R. N. A. Algburi and H. Gao, "Health assessment and fault detection system for an industrial robot using the rotary encoder signal," *Energies*, vol. 12, no. 14, p. 2816, 2019.

[4] H. Kolvenbach, C. Bartschi, L. Wellhausen, R. Grandia, and M. Hutter, "Haptic inspection of planetary soils with legged robots," *IEEE Robotics and Automation Letters*, vol. 4, no. 2, pp. 1626–1632, 2019.

[5] V. Bijalwan, V. B. Semwal, and T. K. Mandal, "Fusion of multi-sensor-based biomechanical gait analysis using vision and wearable sensor," *IEEE Sensors Journal*, vol. 21, no. 13, pp. 14213–14220, 2021.

[6] G. Li, S. Liu, L. Wang, and R. Zhu, "Skin-inspired quadruple tactile sensors integrated on a robot hand enable object recognition," *Science Robotics*, vol. 5, no. 49, Article ID eabc8134, 2020.

[7] E. E. Cruz-Miguel, J. R. García-Martínez, J. Rodríguez-Reséndiz, and R. V. Carrillo-Serrano, "A new methodology for a retrofitted self-tuned controller with open-source fpga," *Sensors*, vol. 20, no. 21, p. 6155, 2020.

[8] Y. Fu, X. Chen, Y. Liu, C. Son, and Y. Yang, "Multi-source information fusion fault diagnosis for gearboxes based on SDP and VGG," *Applied Sciences*, vol. 12, no. 13, p. 6323, 2022.

[9] J. Wei, F. Zhang, J. Lu, X. Yang, and Y. Yan, "Fault diagnosis method for machinery based on multi-source conflict information fusion," *Measurement Science and Technology*, vol. 33, no. 11, Article ID 115007, 2022.

[10] A. Aria, E. Lopez Droguett, S. Azarm, and M. Modarres, "Estimating damage size and remaining useful life in degraded structures using deep learning-based multi-source data fusion," *Structural Health Monitoring*, vol. 19, no. 5, pp. 1542–1559, 2020.

[11] C. I. Li, G. D. Chen, T. Y. Sung, and H. F. Tsai, "Novel adaptive Kalman filter with fuzzy neural network for trajectory estimation system," *International Journal of Fuzzy Systems*, vol. 21, no. 6, pp. 1649–1660, 2019.

[12] X. Liu, Z. Ren, H. Lyu, Z. Jiang, P. Ren, and B. Chen, "Linear and nonlinear regression-based maximum correntropy extended Kalman filtering," *IEEE transactions on systems, man, and cybernetics: Systems*, vol. 51, no. 5, pp. 3093–3102, 2021.

[13] M. Ma, C. Sun, X. Chen, X. Zhang, and R. Yan, "A deep coupled network for health state assessment of cutting tools based on fusion of multisensory signals," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 12, pp. 6415–6424, 2019.

[14] Z. Li, J. Li, Y. Wang, and K. Wang, "A deep learning approach for anomaly detection based on SAE and LSTM in mechanical equipment," *The International Journal of Advanced Manufacturing Technology*, vol. 103, no. 1–4, pp. 499–510, 2019.

[15] X. Zhang, Z. Zhao, Z. Wang, and X. Wang, "Fault detection and identification method for quadcopter based on airframe vibration signals," *Sensors*, vol. 21, no. 2, p. 581, 2021.

[16] A. Ikuta, H. Orimoto, and K. Hasegawa, "A noise suppression method for speech signal by jointly using bayesian estimation and fuzzy theory," *Journal of Software Engineering and Applications*, vol. 14, no. 12, pp. 631–645, 2021.

[17] M. I. Tariq, S. Ahmed, N. A. Memon et al., "Prioritization of information security controls through fuzzy AHP for cloud computing networks and wireless sensor networks," *Sensors*, vol. 20, no. 5, p. 1310, 2020.

[18] G. Menga, “The spherical inverted pendulum: exact solutions of gait and foot place-ment estimation based on symbolic computation,” *Applied Sciences*, vol. 11, no. 4, pp. 1588–1604, 2021.
[19] C. C. Bai, J. F. Guo, and H. X. Zheng, “Three dimensional vibration-based terrain classification for mobile robots,” *IEEE Access*, vol. 7, no. 7, pp. 63485–63492, 2019.
[20] K. Yamamoto, T. Kamioka, and T. Sugihara, “Surveyon model-based bipedmotion control for humanoid robots,” *Advanced Robotics*, vol. 34, no. 21-22, pp. 1353–1369, 2020.