

Research on Greenhouse Positioning Based on Multi-Source Information Fusion

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Abstract

With the deep penetration of modern technology into the agricultural field, greenhouses have become an indispensable part of agricultural production, and the demand for internal navigation and positioning technology is increasingly prominent. Due to the shielding nature of the internal environment of greenhouses, traditional single navigation positioning methods often fall short in pursuing high-precision positioning. Therefore, this article aims to address the navigation and positioning challenges in greenhouse environments by conducting in-depth research on multi-source information fusion positioning methods to improve positioning accuracy and stability. This article establishes a novel multi-source navigation algorithm. This algorithm integrates data from multiple sensors, including but not limited to GNSS signals, IMU data, and magnetic field information, to achieve more accurate positioning results. To verify the correctness and effectiveness of the proposed algorithm, a navigation and positioning device was designed and extensively tested through experiments. Through the experimental verification of this device, the performance and reliability of the algorithm can be more accurately evaluated. After experimental verification, the multi-source information fusion positioning method adopted in this article demonstrates higher positioning accuracy and stronger robustness in greenhouse environments, providing strong support for precise management of greenhouse agricultural production and effectively responding to complex and changing greenhouse environments. In addition, simulation testing and functional testing have been completed, further confirming the practical application effect of the algorithm. This article not only provides innovative solutions for precise navigation of greenhouses, but also brings new inspiration and methods to the research of positioning technology in related fields, promoting the further development of positioning technology.

Keywords

Multi-Source Information Fusion, Greenhouse, Navigation, Algorithm Verification, Sensor Fusion

1. Introduction

With the continuous increase of global population and the increasing scarcity of arable land resources, improving agricultural production efficiency and precision has become particularly crucial, which is of great significance for ensuring food security and sustainable development. The continuous advancement of modern agricultural technology has brought new opportunities for agricultural production, and greenhouse is one of the important technologies [1]. However, with the continuous expansion of greenhouse scale and the increasingly complex internal structure, how to accurately locate and navigate inside the greenhouse has become a key issue that urgently needs to be solved in the current agricultural production field. Many scholars have begun to focus on how to use modern technological means to improve the positioning accuracy and efficiency of greenhouses [2]. Among them, Wireless Sensor Network (WSN) technology is a widely studied direction by domestic researchers [3]. The greenhouse wireless sensor network positioning algorithm based on Received Signal Strength Indicator (RSSI) improves the positioning accuracy between nodes by optimizing the measurement method of signal strength [4]. However, WSN technology still faces problems such as high node deployment costs and significant signal interference in practical applications. In addition to WSN technology, ultrasonic positioning technology has also been favored by domestic scholars. A researcher designed a greenhouse positioning system based on ultrasound, which achieves target positioning by measuring the propagation time of ultrasound signals [5]. However, the application of ultrasonic positioning technology in greenhouse environments is still affected by factors such as multipath effects and temperature drift, which may lead to certain deviations in positioning results, affecting the accuracy and reliability of positioning. To compensate for the shortcomings of a single positioning technology, a research team proposed a multi-source information fusion positioning method based on Wireless Sensor Network (WSN) and ultrasound technology [6]. By combining the advantages of both, the accuracy and stability of positioning were effectively improved. This article focuses on the special environment inside greenhouses and develops a greenhouse positioning technology based on multi-source information fusion. Due to the shortcomings of current methods, many or all, in order to compensate for the shortcomings of a single sensor, this article develops a greenhouse positioning technology based on multi-source information fusion for the special environment inside the greenhouse. It comprehensively uses multiple sensors, including GNSS, IMU (Inertial Measurement Unit), magnetic field sensors, etc., and improves the accuracy and stability of positioning through data fusion and pro-

cessing [7].

2. Related Work

In 2022, another research team proposed a greenhouse localization algorithm based on deep learning [8]. This algorithm can accurately determine the location information inside the greenhouse by training a large number of data samples, providing important technical support for agricultural production. Johnson and Smith developed a greenhouse positioning technology based on image recognition, which achieves high-precision positioning of targets in complex environments [9]. This provides a new approach for precise management of greenhouses. This system uses cameras to capture image data inside the greenhouse and achieves precise target positioning through image processing technology, providing an effective means for greenhouse management. Robinson and Davis designed a greenhouse navigation system based on LiDAR in the field of laser navigation [10]. The system uses LiDAR to scan the surrounding environment, construct a three-dimensional map of the greenhouse, and plan and navigate the path based on the map information. In addition to single positioning technology, multi-source information fusion technology has also been widely studied abroad. Miller and Wilson proposed a multi-source information fusion positioning method based on GNSS, IMU, and LiDAR [11]. This method integrates data from multiple sensors to achieve high-precision positioning in complex environments, providing important support for precision agriculture management in greenhouses. Jackson and Anderson proposed a neural network-based greenhouse localization algorithm [12]. This algorithm learns and predicts the position of the target in the greenhouse by training a large amount of historical data.

3. Establishment of Multi-Source Information Fusion Navigation Algorithm

3.1. Data Preprocessing and Synchronization

In multi-source navigation systems, data preprocessing and synchronization play a crucial role in ensuring the accuracy and effectiveness of information fusion. The system integrates a variety of sensors, including GNSS, IMU, and magnetic field sensors [13]. These sensors have significant differences in sampling frequency, data format, and data transmission timeliness. Therefore, careful preprocessing and synchronization of data from different sources are necessary to lay a solid foundation for subsequent information fusion and accurate positioning.

For GNSS data, in order to improve this situation, methods such as Kalman filtering or extended Kalman filtering can be used to smooth GNSS signals through dynamic modeling and prediction, thereby reducing errors and improving positioning accuracy [14]. IMU data typically includes readings from accelerometers and gyroscopes, which are crucial for determining the posture and motion state of the device. When preprocessing IMU data, it is generally necessary to

calculate parameters such as velocity and displacement through integration, and to remove deviations caused by the sensor's own characteristics. This usually involves de-biasing the raw data and applying appropriate filtering techniques to reduce noise. Magnetic field sensor data also has important applications in navigation, especially indoors or in areas with poor GNSS signals. However, the readings of magnetic field sensors are easily affected by metallic objects in the surrounding environment, resulting in interference from hard and soft iron [15]. In the preprocessing stage, in order to obtain more accurate magnetic field strength and direction information, various interferences must be corrected to ensure the accuracy and reliability of the data. The calibration process may involve collecting readings from multiple locations, identifying and removing interfering components through algorithms.

Mathematically, data preprocessing can be seen as applying one or more transformation functions X_{pre} to the raw data X_{raw} , resulting in the preprocessed data $X_{raw} = X_{pre}$:

$$X_{pre} = f_{pre}(X_{raw}) \quad (3.1)$$

here, f_{pre} may represent a series of complex operations, including but not limited to filtering, denoising, normalization, and data conversion.

After completing the preprocessing of various sensor data, the next key step is to achieve synchronization of these data over time. In view of the difference in sampling frequency between different sensors, and the possible delay in data transmission and processing, these factors have an impact on the system performance, and need to be processed and optimized by corresponding technical means. The core of data synchronization is to align the data from different sensors in time to ensure that they correspond to the same measured value at the same time point or time period. This typically involves matching the timestamps of each sensor's data and using interpolation methods to estimate the data values at a given point in time.

Let t_i be the timestamp of each sensor data, and x_i be the data value under the corresponding timestamp. In order to achieve synchronization, we need to establish a common time reference. In most cases, to ensure the accuracy and reliability of the data, the sensor or system clock with the highest accuracy is usually selected as the reference. Then, for other sensors, at each reference time point t , we use interpolation methods to find the closest data value x :

$$x = \text{Interpolate}(\{(t_i, x_i)\}, t) \quad (3.2)$$

here, $\text{Interpolate}()$ represents the interpolation function, which can effectively predict and estimate data values at any time by utilizing known data points and their corresponding timestamps, thereby achieving accurate analysis and processing of data. The commonly used interpolation techniques include linear interpolation, polynomial interpolation, spline interpolation, and other methods. The specific choice of method depends on the characteristics and accuracy requirements of the data.

3.2. Multi-Source Information Fusion Strategy

Multi-source information fusion strategy is the core component of multi-source navigation system. It can effectively integrate information from different sensors to achieve accurate estimation of key parameters such as target position and attitude. This system integrates multiple information sources such as GNSS, IMU, and magnetic field sensors [16], each with its own advantages and limitations. Weighted fusion is an intuitive and practical information fusion technique [17]. In this method, we assign a corresponding weight to each sensor based on its accuracy, reliability, and historical performance. The core idea of weighted fusion method is to optimize the allocation of weights, so that the information of all sensors can be combined in the most effective way, thereby improving the accuracy of overall positioning.

Mathematically, weighted fusion can be simply represented as a weighted average of data from various sensors. Let x_i represent the data value of the i -th sensor, w_i be the weight of that sensor, and satisfy the condition that the sum of the weights is 1, that is

$$\sum_{i=1}^n w_i = 1 \quad (3.3)$$

The weighted fused data value x_{fused} can be calculated by the following equation:

$$x_{fused} = \sum_{i=1}^n w_i \cdot x_i \quad (3.4)$$

Kalman filter is an efficient recursive data processing algorithm, particularly suitable for state estimation of dynamic systems [18]. In multi-source navigation system, Kalman filter is widely used to fuse data from different sensors to provide optimal estimation of system state. The Kalman filter achieves iterative estimation of the system state through two consecutive steps of prediction and update, thereby accurately grasping the dynamic changes of the system. In the prediction stage of the estimation process, the filter uses the dynamic model of the system to predict the state at the next moment. In the update process, the filter uses the latest observation data to correct the predicted values, in order to obtain more accurate state estimation values, thereby enhancing the positioning accuracy and stability of the system.

In a multi-source navigation system, constructing a comprehensive state vector can comprehensively cover key information such as position, velocity, and attitude of the system, providing a solid data foundation for subsequent navigation and positioning. Then, the data from GNSS, IMU, and magnetic field sensors are fused using a Kalman filter to achieve optimal estimation of the state vector.

The update equation and prediction equation of the Kalman filter can be specifically expressed as:

Update equation:

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k (z_k - H_k \hat{x}_{k|k-1}) \quad (3.5)$$

Among them, \hat{x}_k is the estimated state value corresponding to time k , $\hat{x}_{k|k-1}$ is the predicted state value at time k based on the state at the previous time point and the dynamic model, K_k is the Kalman gain, which determines the degree of influence of new observation data on state estimation, z_k is the observation value at time k , H_k represents the observation matrix, which can map the state space to the observation space.

Prediction equation:

$$\hat{x}_{k+1|k} = F_k \hat{x}_k \quad (3.6)$$

Among them, $\hat{x}_{k+1|k}$ represents the estimated state value \hat{x}_k at time point k and the predicted state value at time point $k+1$ based on the dynamic model. F_k represents the state transition matrix, which can describe the evolution law of the system state change from time point k to time point $k+1$.

In practical applications, it is necessary to design and adjust the parameters required for the Kalman filter based on the specific system model and sensor characteristics, such as the corresponding state transition matrix F_k , observation matrix H_k , process noise covariance matrix, and observation noise covariance matrix. The selection of these parameters mentioned earlier will directly affect the performance of the filter and the accuracy of state estimation.

3.3. Implementation and Optimization of Positioning Algorithm

The implementation and optimization of positioning algorithms is undoubtedly a core link in the development process of multi-source navigation systems. It not only concerns the positioning accuracy of the system, but also the real-time performance is crucial for the navigation system [19]. With the continuous advancement of technology, more and more advanced positioning algorithms are being integrated into multi-source navigation systems, aiming to improve the accuracy and response speed of positioning, thereby optimizing user experience and system performance.

In GNSS positioning, the least squares method is used to estimate the precise position of the receiver. Clearly define the actual position coordinates (x, y, z) of the receiver, namely the position coordinates (x_i, y_i, z_i) of the i -th satellite and the pseudorange observation value ρ_i . The pseudorange equation can be expressed as:

$$\rho_i = \sum_{i=1}^n r_i^2 = \sum_{i=1}^n \left(\rho_i - \sqrt{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2} \right)^2 \quad (3.7)$$

Among them, c is the speed of light, and δt represents the deviation between the receiver and the satellite clock. Due to sources of error such as atmospheric interference and multipath effects, the observed ρ_i may deviate from the true value.

Using the least squares method, seek to minimize the sum of squared differences between all observed pseudoranges and calculated pseudoranges, in order to obtain the optimal position estimate for the receiver. If r is the residual between the

observed and estimated values, then the objective function corresponding to the least squares method can be expressed as:

$$J = \sum_{i=1}^n r_i^2 = \sum_{i=1}^n \left(\rho_i - \sqrt{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2} \right)^2 \quad (3.8)$$

By solving:

$$\begin{aligned} \frac{\partial J}{\partial x} &= 0 \\ \frac{\partial J}{\partial y} &= 0 \\ \frac{\partial J}{\partial z} &= 0 \end{aligned} \quad (3.9)$$

The position estimation of the receiver can be obtained.

When dealing with nonlinear systems, the extended Kalman filter has demonstrated its unique advantages, providing an efficient and accurate state estimation method [20]. The state equation and observation equation corresponding to the selected system are as follows:

$$\begin{aligned} x_k &= f(x_{k-1}) + w_{k-1} \\ z_k &= h(x_k) + v_k \end{aligned} \quad (3.10)$$

Among them, f and h are nonlinear functions, and w_{k-1} and v_k are process noise and observation noise, respectively.

The essence of extended Kalman filter lies in linearly approximating nonlinear functions at each time node to achieve more accurate state estimation. Assuming that $\hat{x}_{x|k-1}$ corresponds to the state estimation at the previous time point, the state prediction at this time point can be expressed as:

$$\hat{x}_{x|k-1} = f(\hat{x}_{k-1}) \quad (3.11)$$

The linearized system matrix and observation matrix are:

$$\begin{aligned} F_k &= \left. \frac{\partial f}{\partial x} \right|_{\hat{x}_{k-1}} \\ H_k &= \left. \frac{\partial h}{\partial x} \right|_{\hat{x}_{k|k-1}} \end{aligned} \quad (3.12)$$

Subsequently, the state estimation is performed using standard Kalman filtering update steps.

To improve positioning accuracy, optimization techniques such as gradient descent, Newton's method, and quasi-Newton's method can be used [21], which can effectively enhance the performance of navigation systems and ensure the accuracy and stability of positioning.

Gradient descent minimizes the loss function through iterative updates:

$$x_{k+1} = x_k - a \nabla f(x_k) \quad (3.13)$$

Among them, a is the learning rate, and $\nabla f(x_k)$ is the gradient of the loss function at x_k .

Newton's method relies on the second-order derivative information of the loss

function to perform update operations:

$$x_{k+1} = x_k - H_k^{-1} \nabla f(x_k) \quad (3.14)$$

Among them, H_k is a Hessian matrix.

The quasi-Newton method iteratively approximates the inverse matrix of the Hessian matrix, avoiding the complexity and computational complexity of directly calculating the Hessian matrix, thereby improving the efficiency and practicality of optimization algorithms.

4. Experimental Result

4.1. Testing Process and Algorithm Establishment

This article uses the Extended Kalman Filter (EKF) technique to process data parsed from images. Extended Kalman Filter is a Kalman filtering method designed specifically for nonlinear systems [22]. Nonlinear systems are vastly different from linear systems, and specific methods and techniques are required to ensure accuracy and effectiveness when dealing with such systems.

The principle of extended Kalman filter is based on the model of nonlinear system, and its form is:

$$\begin{aligned} x_{k+1} &= f(x_k) + w_k \\ z_k &= h(x_k) + v_k \end{aligned} \quad (4.1)$$

Among them, f and h are non-linear functions, corresponding to the system's state transition and observation model, respectively. w_k and v_k correspond to process and observation noise, respectively.

The extended Kalman filter and the classical linear Kalman filter have similarities in algorithm steps and structure, but the former exhibits unique advantages in dealing with nonlinear systems [23]. However, the main difference lies in the way they handle nonlinear system models and matrices A and H. In the extended Kalman filter, a nonlinear system model equation is used instead of the traditional linear system equation, and new matrices A and H are obtained by solving the partial derivatives of the system model. In the process of solving the partial derivatives, the estimated value obtained at the previous time point is used as a reference point to complete linearization.

The algorithm structure of Extended Kalman Filter can be summarized as follows: Firstly, the nonlinear function f is biased towards the state vector x at the estimated value x_k to obtain matrix A ; similarly, the observation function h is biased towards x at the predicted value x_k to obtain matrix H . Then, these matrices are used for filtering updates and prediction steps.

To verify the performance of the extended Kalman filter, it is planned to build a simulation environment. This environment will simulate a dynamic system with nonlinearity and generate corresponding observation data. By applying the extended Kalman filter in this simulation environment, its effectiveness in practical applications can be evaluated, including positioning accuracy, convergence speed, and stability. This will provide valuable reference information for us to further optimize

filter parameters and algorithms.

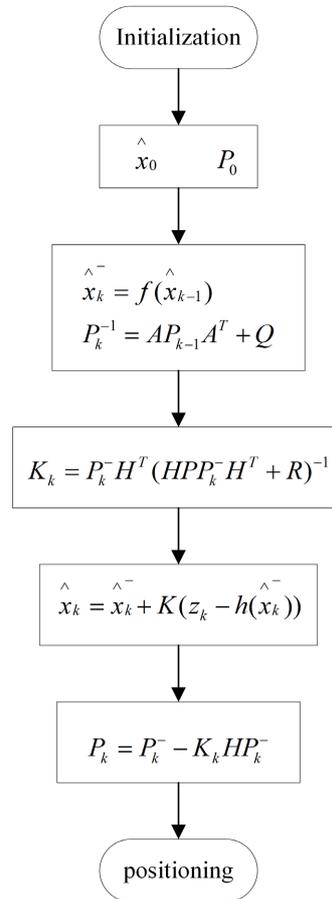


Figure 1. Test data processing flow.

As shown in **Figure 1**, importing from various sensors such as GPS odometry IMU, experimental data on image features. Initialize filter parameters, including state vector X (representing the position and orientation of the robot), error covariance matrix P (representing the uncertainty of state estimation), measurement noise covariance matrix R , process noise covariance matrix Q , etc. Filter out key information for positioning from the data, including GPS odometer data, IMU, and image feature data. Perform necessary conversions and formatting on the filtered data to ensure the efficiency and accuracy of subsequent processing. Use odometer data (*i.e.* robot's movement distance and steering angle) to predict the new position of the robot. This is usually done based on the motion model of the robot, such as the differential drive model. Use feature data obtained from images as observations. These data include the position information of the target relative to the landmark obtained by identifying specific landmarks. The above prediction and update steps are iteratively performed on the entire dataset, with each iteration using new observations to correct the robot's position estimation. Through multiple iterations, the filter can gradually reduce the uncertainty of state estimation, thereby improving the positioning accuracy.

4.2. Functional Testing and Validation

This function mainly implements a positioning algorithm based on multi-source information (GPS odometer data and image feature data), and evaluates the accuracy of the positioning algorithm by comparing it with the real path. The program finally outputs a comparison chart between two paths and the real path, as well as a comparison chart between odometer error and fusion error, as shown in **Figure 2**.

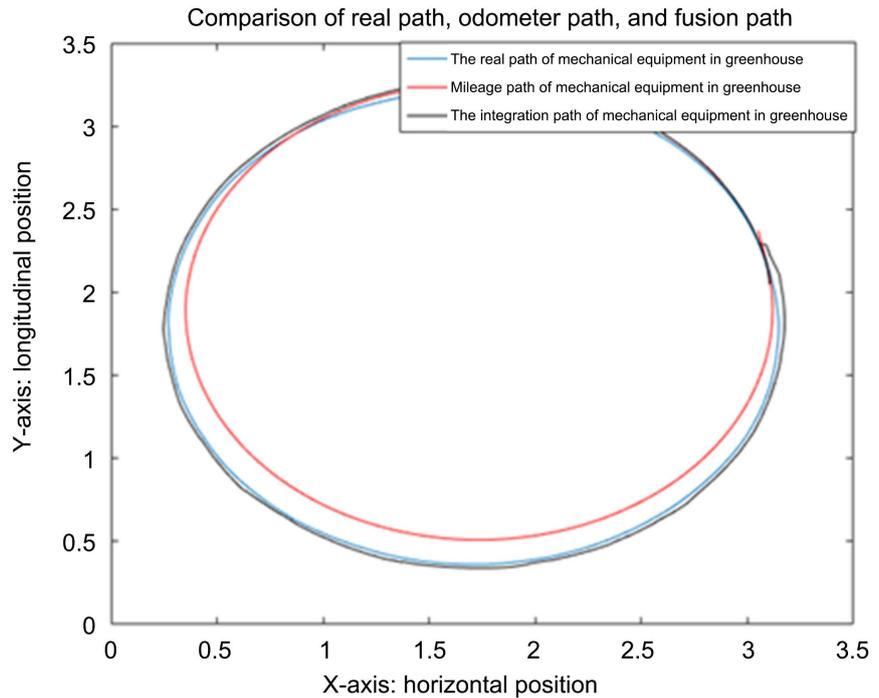


Figure 2. Path comparison diagram.

The real path is a path obtained through some high-precision method (such as GPS, motion capture system, etc.), used as a benchmark for evaluating other positioning methods. The odometer path is a path calculated solely based on GPS odometer data. Due to the cumulative error of the odometer, this path may gradually deviate from the true path. The fusion path is a path calculated through a fusion algorithm that combines GPS odometer data, IMU, and image feature point data. Ideally, this path should be closer to the real path. From the path comparison chart, the differences between the three paths can be visually observed. If the fusion path is closer to the real path than the odometer path, it indicates that the fusion algorithm effectively improves the positioning accuracy.

As shown in **Figure 3**, the error comparison chart illustrates the variation of odometer error and fusion error with the number of data points.

As the distance traveled increases, the cumulative error of the odometer may gradually increase. This usually manifests as a gradually rising curve. If the fusion algorithm is effective, this curve should be lower than the odometer error curve, indicating that the fused positioning data is more accurate than using odometer data alone. By comparing these two curves, the performance of the fusion algorithm

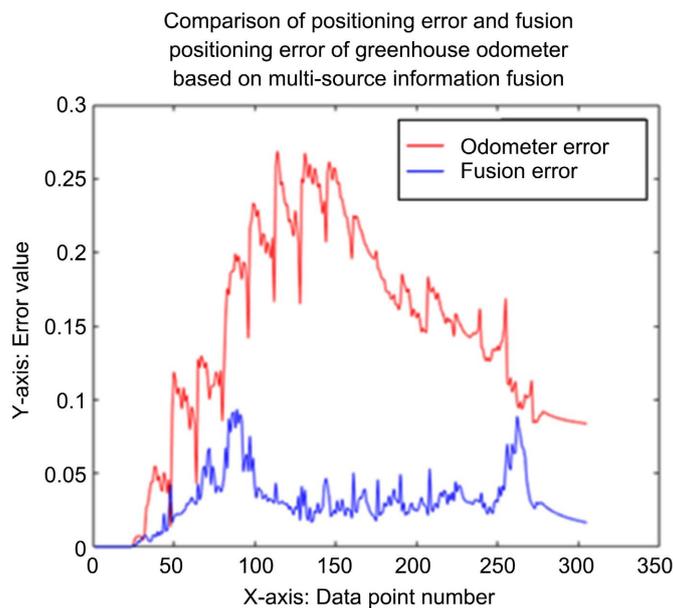


Figure 3. Error comparison chart.

in reducing positioning errors can be intuitively evaluated, thereby verifying its effectiveness.

5. Conclusion

The theme of this article is to solve the problem of navigation and positioning in greenhouses. Through in-depth exploration of multi-source information fusion positioning technology, we strive to improve the accuracy and stability of positioning. This article successfully establishes a new multi-source navigation algorithm. This algorithm achieves more accurate positioning by integrating GNSS signals, IMU data, and image feature data. The mutual compensation between IMU and GNSS signals effectively avoids their respective shortcomings and promotes their respective advantages. Experimental data shows that using multi-source information fusion positioning method can significantly improve positioning accuracy in greenhouses, while exhibiting high robustness. This method can effectively cope with the variability of greenhouse environment and provide strong support for precise management of greenhouses. In addition, simulation testing and functional testing have been completed to further confirm the practical application effect of the algorithm. These experimental results fully demonstrate the excellent performance of the multi-source information fusion navigation algorithm in practical applications, highlighting its advantageous position in the field of navigation and positioning. This article not only provides a new solution for precise navigation inside greenhouses, but also offers new ideas and methods for positioning technology research in related fields. This research achievement is expected to inject new impetus into the development of modern agricultural technology, promote its continuous advancement, and achieve higher efficiency and wider application. In future devel-

opment, laser radar can be introduced into the system to improve its positioning accuracy.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

- [1] Chen, Q., Xie, Y., Guo, S., Bai, J. and Shu, Q. (2021) Sensing System of Environmental Perception Technologies for Driverless Vehicle: A Review of State of the Art and Challenges. *Sensors and Actuators A: Physical*, **319**, Article ID: 112566. <https://doi.org/10.1016/j.sna.2021.112566>
- [2] Ma, W.F., Shi, J.Z., Ge, L.H., Dai, K., Zhong, S.R. and Wu, L. (2020) Research Progress on Monocular Visual Odometry for Autonomous Vehicles. *Journal of Jilin University (Engineering and Technology Edition)*, **50**, 765-775.
- [3] Wu, X.Y. (2018) Research on Pose Estimation of Autonomous Vehicles Based on Laser Odometry. Master's Thesis, Chang'an University.
- [4] Li, X., Li, Q., Yin, C. and Zhang, J. (2022) Autonomous Navigation Technology for Low-Speed Small Unmanned Vehicle: An Overview. *World Electric Vehicle Journal*, **13**, Article 165. <https://doi.org/10.3390/wevj13090165>
- [5] Qiao, X., Li, X.M. and Xiao, D.Y. (2019) Indoor Positioning Design Based on Ultrasonic Ranging. *Electronic Design Engineering*, **27**, 102-105.
- [6] Li, B.X., Qi, H.R., Lu, Y. and Tang, Y. (2020) Overview of Indoor Positioning Algorithms and Technologies. *Electronic Components and Information Technology*, **4**, 47-50.
- [7] Babak, E.S., Mahdi, R., Rodolfo, V., Arash, R. and Yaser, P.F. (2022) High-Definition Map Representation Techniques for Automated Vehicles. *Electronics*, **11**, Article 3374. <https://doi.org/10.3390/electronics11203374>
- [8] Peng, Y.S., Li, J.L., Xu, Z.F., He, G.H. and Jia, P. (2021) Overview and Prospect of Bluetooth Indoor Positioning Technology. *Household Appliances*, No. 12, 58-64.
- [9] Ge, M.J. and Zhao, Z.H. (2021) Indoor Positioning System for the Internet of Things Based on Bluetooth Technology. *The Internet of Things*, **11**, 52-57.
- [10] Mair, N. and Mahmoud, Q. (2012) A Collaborative Bluetooth-Based Approach to Localization of Mobile Devices. *Proceedings of the 8th IEEE International Conference on Collaborative Computing: Networking, Applications and Worksharing*, Pittsburgh, 14-17 October 2012, 1-9. <https://doi.org/10.4108/icst.collaboratecom.2012.250437>
- [11] Wang, W. and Zhu, Q.S. (2021) Research on Circular Triangle Localization Algorithm in Wireless Sensor Networks. *Modern Electronic Technology*, **44**, 47-50.
- [12] Zhang, J. and Chen, W.L. (2021) Research on Indoor Personnel Positioning System Based on ZigBee Node Technology. *Scientific and Technological Innovation*, No. 20, 173-174.
- [13] Li, H. (2018) Research on LTE Indoor Positioning Based on Regional Division. Master's Thesis, Xiangtan University.
- [14] Challa, N.S.R., Kesari, P., Ammana, S.R., Katukojwala, S. and Achanta, D.S. (2019) Design and Implementation of Bluetooth-Beacon Based Indoor Positioning System. 2019 *IEEE International WIE Conference on Electrical and Computer Engineering (WIECON-ECE)*, Bangalore, 15-16 November 2019, 1-4. <https://doi.org/10.1109/wiecon-ece48653.2019.9019997>
- [15] Shi, G.T., Wang, B.Y. and Wu, B. (2015) Overview of Indoor Positioning Methods Based on Wi-Fi and Mobile Intelligent Terminals. *Computer Engineering*, **41**, 39-44.

-
- [16] Luo, Y.F., Wang, P.F. and Chen, Y.F. (2017) Research on Wi-Fi Indoor Positioning Algorithm Based on RSSI Ranging. *Measurement and Control Technology*, **36**, 28-32.
- [17] Tang, Y., Bai, Y., Ma, Y. and Lan, Z.L. (2016) Research on the Application of Wi-Fi Based Fingerprint Matching Algorithm in Indoor Localization. *Computer Science*, **43**, 73-75.
- [18] Guo, X., Elikplim, N.R., Ansari, N., Li, L. and Wang, L. (2020) Robust Wi-Fi Localization by Fusing Derivative Fingerprints of RSS and Multiple Classifiers. *IEEE Transactions on Industrial Informatics*, **16**, 3177-3186.
<https://doi.org/10.1109/tii.2019.2910664>
- [19] Wang, H., Deng, Z., Zheng, X. and Fu, X. (2021) DOP Analysis for Indoor Hybrid TDOA/TOA Positioning Based on Mobile Communication Network. In: Yang, C. and Xie, J., Eds., *China Satellite Navigation Conference (CSNC2021) Proceedings*, Springer, 576-585. https://doi.org/10.1007/978-981-16-3142-9_55
- [20] Ma, D.J., Li, M. and Zhang, R.J. (2022) TOA Estimation of Wi-Fi Indoor Positioning Signals Based on Waveform Edge Detection. *Journal of Zhengzhou University (Engineering Edition)*, **43**, 15-20.
- [21] He, C.W., Yuan, Y.B. and Tan, B.F. (2021) An Iterative Least Squares Algorithm Based on UWB TDOA Positioning Mode. *Geodesy and Geodynamics*, **41**, 806-809.
- [22] Chen, D.L., Zhu, G.M., Huo, Y.Z. and Wang, J.B. (2021) Research on Azimuth Prediction Method Based on Terminal Sampling Data AOA. *Jiangsu Communication*, **37**, 32-36.
- [23] Zhang, B.S., Tong, Z.Y., Tang, S.F., Tong, M.L. and Xu, C.L. (2018) Overview of Indoor Positioning Technology Based on RSSI. *Computer Age*, No. 7, 1-4, 8.