Review of the field environmental sensing methods based on multi-sensor information fusion technology

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Abstract: Field environmental sensing can acquire real-time environmental information, which will be applied to field operation, through the fusion of multiple sensors. Multi-sensor fusion refers to the fusion of information obtained from multiple sensors using more advanced data processing methods. The main objective of applying this technology in field environment perception is to acquire real-time environmental information, making agricultural mechanical devices operate better in complex farmland environment with stronger sensing ability and operational accuracy. In this paper, the characteristics of sensors are studied to clarify the advantages and existing problems of each type of sensors and point out that multiple sensors can be introduced to compensate for the information loss. Secondly, the mainstream information fusion types at present are outlined. The characteristics, advantages and disadvantages of different fusion methods are analyzed. The important studies and applications related to multi-sensor information fusion technology published at home and abroad are listed. Eventually, the existing problems in the field environment sensing at present are summarized and the prospect for future of sensors precise sensing, multi-dimensional fusion strategies, discrepancies in sensor fusion and agricultural information processing are proposed in hope of providing reference for the deeper development of smart agriculture.
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1 Introduction

Environmental sensing is the foundation for timely decision-making and control of agricultural machinery path planning, operating speed, and steering by acquiring environmental information during agricultural operations, further providing timely and accurate decision-making basis for the safe operation of unmanned agricultural machinery. Due to the complexity and diversity of field information, the sensing mode using a single sensor is incompetent at providing sufficient redundant information for processing, and a more powerful sensor configuration is required to acquire the full understanding of the environment. Therefore, the integration of multiple sensors in field environment perception is essential. Multi-sensor information fusion technology is the specific method and technical means to achieve sensor fusion from multiple sources. Its basic principle is similar to that of the human brain's centralized processing of information acquired by various sensory organs. The fusion technology requires the coordination of all the sensors, which registers the data acquired in time and space and makes full use of the ability of each sensor to reasonably allocate the calculative resources of each sensor. Then, information fusion algorithm is used to seek the possible potential correlation in massive data from different sensors, remove redundant information and form a complete systematic environment so as to achieve the purpose of accurate understanding[1].

Multi-sensor information fusion technology integrates redundant information from multiple homogeneous or heterogeneous sensors to enable agricultural machinery to assess observed objects more accurately, make correct judgments and decisions, and operate in more diverse environments. This enables comprehensive, accurate, and efficient perception of agricultural field environments, providing scientific evidence and precise management methods for agricultural production. With the promotion of agricultural intelligence and technological advancement, the perception of agricultural field environments is gradually becoming a research hotspot in the field of agriculture. The application of multi-sensor information fusion technology in the perception of agricultural field environments holds great potential for application and market demand. Based on the above, this paper investigates the following aspects: elucidating the characteristics of a single type of sensor, analyzing the advantages and limitations of each type; reviewing and comparing existing sensor fusion methods; enumerating several application scenarios of multi-sensor information fusion technology in field environment perception; identifying the current issues surrounding sensor-based field environment perception. Currently,

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there are numerous application cases of multi-sensor information fusion technology in the field of environmental perception. The research conducted in this paper can provide the latest advancements and innovative ideas for researchers and technology developers in the agricultural domain.

2 Sensor characteristics and analysis

The data acquired by sensors is mainly used for acquiring the system's status or sensing the surrounding environment. In this chapter, the advantages and disadvantages of sensors of different types in field environment sensing are analyzed in details and the comparison of technical characteristics of various types of sensors is listed in Table 1. The development of sensor technology is relatively mature, providing corresponding applicable types for different demands of different environments, data types and functions. In accordance with the working principles of sensors (Figure 1), at present, the mainstream environmental sensing methods can generally be divided into two types, namely the electromagnetic wave information based method and the image information based method (Table 2).

Table 1 comparison of technical characteristics of all types of sensors

Type	Laser radar	MillimeteR WAVE RADar	Ultrasonic radar	Stereo camera
Detection Distance (up to)	30-40 m	100-150 m	15-500 cm	15-30 m
Detection Accuracy	+++	++	+	+
Ability to Resist Against Adverse Conditions	+	+++	+++	++
Night time robustness	+++	+++	+++	+
Costs	+++	+++	++	+
Advantages	High operation; can draw 3D environmental maps and radar positioning	Long detection distance; low environmental impact; all-day and all-weather availability	High detection speed and high data processing speed	High pixels, color recognition; achievement of various functions through algorithms
Disadvantages	Vulnerability to weather, high costs	Low resolution, difficult signal processing and interpretation	Low resolution and limited ranging scope	Highly affected by weather, higher requirements for algorithms, not stable enough

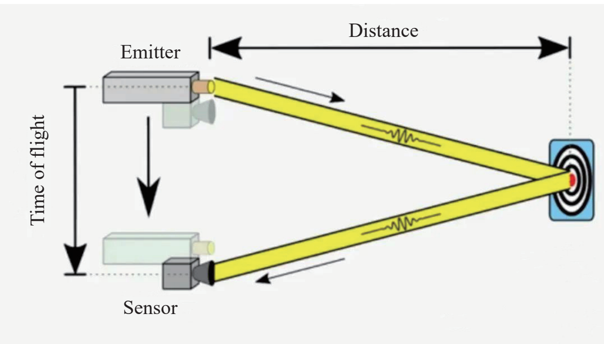


Figure 1 The basic principle of ToF distance measurement

Table 2 Classification of common sensors

Classification basis	Common sensors
Electromagnetic wave information based	Lidar Radar Sonar
Image based	Monocular camera Stereo camera Infrared sensor

2.1 Electromagnetic wave information based sensors

So far, the most commonly used sensors for ranging include lidar, radar and sonar. Among them, lidar is used for light detection and ranging, which acquires the spatial location of the target by generating 3D cloud through laser beam scanning of the target. Radar is a sensor used for radio detection and ranging, which mainly aims at detecting the range and measuring the object speed using radio frequency waves. Sonar judges the location, shape and distance of the target through emitting sound waves and receiving the echoes, which is mainly used for sound navigation and ranging.

2.1.1 Lidar

2D lidar generally only uses one set of laser sensors and a rotating device to scan on one line. Through scanning a circumference on the 2D plane, it acquires one set of distance information and updates in real time so that it can keep higher resolution and data processing ability in actual application[2]. In 1999, Kwon et al.[3] acquired the distance information using 2D lidar and judged the neglected areas or some uneven details when detected using conventional methods combined with the continuity of spatial distance. However, in terms of displaced obstacles, this method will results in greater errors. Zhang et al.[4] designed a set of auto alignment sensing system for corn harvester consisting of 2D lidar, mechanical alignment sensor, gyroscopic goniometer and other parts (Figure 2a). Lidar mainly detects the horizontal deviation before entering the plot. The experiment results show that, in lidar static detection, the mean deviation is 0.0775 m and the mean standard deviation is 0.1309 m. The average proportions of deviations within ±15 cm and ±30 cm are 80.5% and 95%, respectively. The average adjustment distance for automatic field alignment of lidar is 7.89 m and the average deviation is 0.146 m. Shang et al.[5] developed the rice-wheat harvest boundary detection system based on 2D lidar and also developed the auto alignment system for harvesters integrated with control system (Figure 2b). In the study, the whole harvest boundary auto alignment control system was experimented and the auto boundary alignment accuracy test method based on high accuracy positioning was proposed. The experiment results show that the average horizontal deviation of auto harvest boundary alignment is 9.18 cm and the standard deviation is 2.48 cm. It can be known from the aforementioned study that the prerequisite for the application of 2D lidar is that the farmland is relatively flat without significant bumpiness. However, the uneven terrain in the hilly farmland environment will result in violent bumps during vehicle operating. In addition, because the output information is 2D point, it is infeasible to monitor the size, shape and other information of obstacles in real time.

The main difference between 3D lidar and 2D lidar lies in their different dimensions of data acquired. 3D lidar can sense the information of its surrounding 3D space, showing more abundant and detailed information and providing more accurate environmental sensing and target detection ability. The Time of Flight (ToF) method is widely utilized in 3D laser radar systems, enabling the calculation of distance by measuring the time it takes for a laser beam to be emitted from the radar, reflect off the target object, and return to the radar (Figure 1). In the recent two years, with the increase in demand for unmanned driving functions of agricultural machinery and the decrease in 3D lidar costs, there have been more and more research on unmanned driving of agricultural machinery based on 3D lidar. Shang et al.[6] proposed a method for detecting obstacles in the field using 3D lidar (Figure 2c). This method adopts RANSAC algorithm to detect the farmland ground point cloud, divide the ground point cloud and the obstacle point cloud on the ground, and conduct Euclidean clustering on the obstacle point cloud on the ground. Then, through judging the quantity of clustering points and the volume of circumscribed cuboid, the obstacles will be located. In the experiment, the field machinery, haystacks, ridges, low-rise houses, roadside trees, and field pedestrians were detected. The results show that the method can detect the common obstacles in fields well and the average detection successful rate of field pedestrians within the range of 30 m is 96.11%. Yang et al.[7] proposed an extraction method for low-curvature road free space (RFS) based on line segments using 3D lidar (Figure 2d). The experiment results show that TPR, FPR and accuracy of lidar point cloud data are 98.54%, 9.27% and 97.57% on semi-structural roads, and are 97.78%, 4.57% and 97.55% on non-structural roads. The average processing speed of semi-structural roads is 57 ms/frame and the average processing speed of non-structural roads is 61 ms/frame. Affected by lighting conditions, the influence caused by vehicle bumps is relatively small, providing more support for accuracy and reliability of farmland environmental sensing. However, the costs of 3D lidar are relatively high, further proposing higher requirements for calculation resources and data processing ability.

a. Auto alignment sensing system for corn harvester

b. Ricewheat harvest boundary detection system

c. Field obstacle detection system

d. Field RFS extraction system

e. Field environmental information sensing system

f. Field obstacle detection system

Figure 2 Agricultural machineries loaded with laser radar

And therefore, for the limitations of a single type of sensors in farmland environmental sensing, Liu[8] built the environmental information sensing system containing 2D lidar, Inertial Measurement Unit (IMU) and geostationary satellite positioning instrument, and proposed a method for real-time detection of static and dynamic obstacles by agricultural robots (Figure 2e). The experiment results show that the average deviations of spacing and size detected by the system are 1.02 cm and 1.08 cm, respectively, when the obstacles deviate vertically in static experiment, while the horizontal deviation and average size deviation detected when the obstacles deviate horizontally are 1.13 cm and 1.34 cm, respectively. Through the real-time experiment, the update frequency of obstacle attitude parameters for the entire system is 5.04 Hz, proving the method's reliability and effectiveness. Ji et al.[9] combined 2D/3D lidar and Global Navigation Satellite System (GNSS)/ Attitude and Heading Reference System (AHRS) data to detect and identify the obstacles in farmland environment (Figure 2f). The experiment results show that the method proposed by the research can accurately and reliably detect the candidate obstacles and identify the interested obstacles with the average loss rate of 1.24% and the accuracy, precision and recall rates over 80%. However, when classifying the obstacles, the adopted MCB method is relatively sensitive to morphological characteristics, resulting in relatively worse classification effects on obstacles of similar shape or with mutual obstruction.

2.1.2 Radar

Millimeter wave radar detects targets by receiving and analyzing echo signals, further providing the target location and motion status (Figure 3). Due to strong robustness to brightness and harsh weather, millimeter wave radar is almost unaffected by rainy, snowy and foggy weather, showing strong environmental applicability[10]. Tan[11] used millimeter wave Doppler frequency shift characteristic detection return waveform to design the millimeter wave based obstacle detection method on obstacle changes (Figure 4a), which mainly acquires the data through calculating the relative distance and angle between the radar and obstacles. In the research, the flight scenarios of various obstacles encountered during farmland operation of plant protection unmanned vehicles were analyzed in details and the flight schemes under different obstacle scenarios were offered so as to enable plant protection unmanned vehicles to handle most obstacles in farmlands and guarantee the stability and safety of plant protection operation. Xue et al.[12] detected the farmland obstacles based on millimeter wave radar (Figure 4b) and proposed a method lowering computational volume by filtering data generated by millimeter wave radar. Through analyzing the target information output by millimeter wave radar, the information of farmland target obstacles was extracted and the invalid target filtering algorithm was developed to conduct detection judgment and filtering processing on the analyzed empty target, pseudo target and non-threatening target data. The experiment results show that the average filtering rate of the proposed algorithm is above 85% under static status. Under the driving status, though the filtering rate decreases to some extent with the increase of speed, the average filtering rate under various status can reach above 84%. Henry et al.[13] used mobile millimeter wave radar system to estimate the vineyard yield (Figure 4c) and installed the radars on the rovers moving along the ridges between vine plants. The proposed yield estimates were classified based on the radar echoes measured at different grape species, meteorological conditions and grape growing stages.

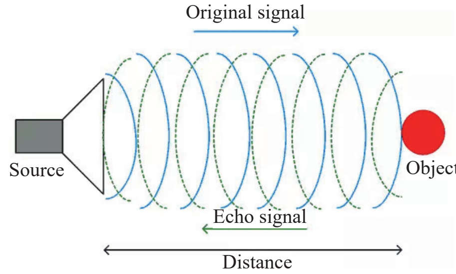
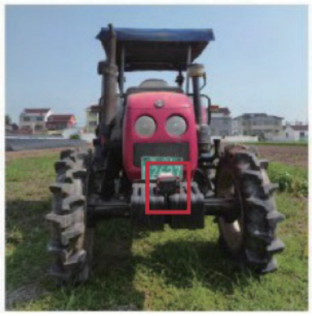
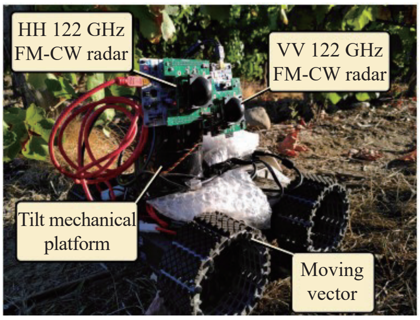


Figure 3 The basic principle of radar

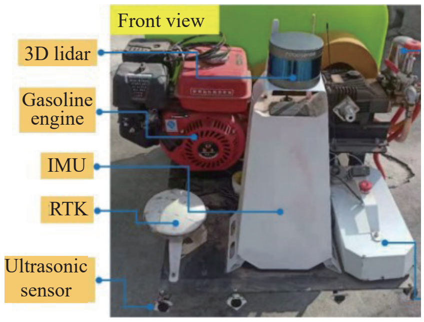
a. Obstacle avoiding system for plant protection unmanned vehicles



b. Detection system for farmland obstacles



c. Mobile millimeter wave radar system



d. Orchard auto navigation spraying system

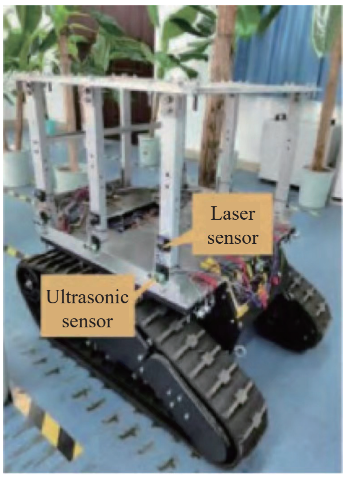
Figure 4 Agricultural machineries loaded with millimeter wave radar

Compared with laser radar, millimeter wave radar is limited in resolution, but is relative good in resolution in horizontal direction, which is able to provide the distance, angle, speed and other information of targets. However, in the vertical direction, due to relatively larger beam width, the height resolution will be relatively poor. Additionally, because millimeter wave radar mainly acquires information through measuring the micro motion between targets and radar, the relatively static targets cannot generate sufficient micro motion. And thus, it is impossible to distinguish the relatively static targets. Nevertheless, millimeter wave radar is greatly advantageous in target detection and tracking in other dynamic environments. In actual application, the ability to detect static targets can be improved combined with other sensors or algorithms. Wang et al.[14] developed an orchard auto navigation spraying system that senses the environment and builds the maps based on 3D laser radar, and further chose millimeter wave warder for multi-source information fusion to sense the obstacles (Figure 4d). The experiment results show that when the obstacles are moving persons or different slender pillars, unmanned vehicles can rapidly identify the obstacles and make emergency stops to find narrow feasible areas. Through multiple experiments, the safety obstacle avoiding distance is about 0.5 m, meeting the obstacle avoiding requirements. Zhang et al.[15] proposed the multi-sensor front ridge detection scheme combining that data acquired by cameras and millimeter wave radar, which acquires the distance and height information of ridges by assisting to filter the interference points in millimeter radar after using visual inspection to acquire the ridge shapes. The experiment results show that the average deviation of distance detection based on integrated algorithms is 0.11 m; the standard deviation of distance detection is 6.93 cm; the average deviation of height detection is 0.13 m; the standard deviation of height detection is 0.19 m.

2.1.3 Sonar

Ultrasonic radar is a type of sonar. The basic principle of ultrasonic distance detection is to generally locate the objects by calculating the time of fly (ToF) of ultrasound from ultrasound emitted by sensor and reflected by objects[16]. Vinod et al.[17] developed an auto agricultural robot system to solve the sowing on uneven land. In this system, the positioning mechanical part of robot is commanded and controlled by the signals emitted by the controller and the ultrasonic sensor placed on the robot. If any obstacle, such as stones and trees, is detected on fields, the sensor will continuously emit and receive the ultrasound so that the robot can detect and avoid obstacles with the obstacle avoiding accuracy of 95%. Li et al.[18] designed a precise evaluation system for wheat topdressing based on the cross detection method of ultrasonic sensor arrays (Figure 5a). The system consists of the operating trajectory detection part, data collection part and data analysis & evaluation part. Depending on the ultrasonic sensor installed on the topdressing machine, the wheat topdressing is cross-detected and the operating trajectory of topdressing machine is detected. The field experiment results show that, when the operating speed of topdressing machines is 3-4 km/h, the deviation misjudgment rate is 9%, and the maximum error distance is 3.15 cm. The proportion of error distance within 2 cm exceeds 90%, and the average standard deviation is 2.10 cm, which is consistent with the actual operation situations. Hao et al.[19] detected the inter-row operating attitude using agricultural machineries installed with ultrasonic ranging sensors and, through research, proposed the system using fuzzy control to output voltage signals of different speed regulations to correct the operating routes of agricultural machineries, further guaranteeing that agricultural machineries can automatically correct the operating attitude without manual intervention. The field experiment shows that when operating in the day lily experimental field with the row width of 1.3 m, agricultural machineries can basically exclude the interference from unfavorable factors. The use of auto inter-row operation of agricultural machineries in day lily harvest can improve the efficiency by about 30%.

a. Precise evaluation system for wheat topdressing



b. Tracked robot ranging system for banana plantations

Figure 5 agricultural machineries loaded with ultrasonic radar

In conclusion, ultrasound is advantageous in low costs, strong penetration and easy acquisition of concentrated sound energy. However, there are still existing problems in the application of ultrasound technology in farmland environmental sensing. For example, ultrasonic obstacle detection is based on sound, and thus it is insensitive to obstacular factors like light, dust, steam, fog, and smoke, in environment. The accuracy of spatial positions is relatively low with the error between 10-50 cm[20]. The air temperature can exert effects on the spreading speed of ultrasonic waves to some extent[21]. Thus, it is impossible to sense in complex farmland environment using the technology of ultrasonic wave only. Rather, the trend of future research is to use this technology combined with other sensor detection technologies. Fu et al.[22] proposed a laser and ultrasonic wave method for banana tree ranging based on fitting filtering (Figure 5b), which can accurately measure the minimum distance between robot and banana tree in the complex banana plantation environment where there are small shrubs and other obstacles and bumpy machinery farming roads. The experiment results show that the maximum ranging error rate of this ranging method for banana trees in ideal environments is 1.0% while the maximum ranging error rate in environments with small bushes and other obstacles or bumpy roads and outdoor natural scenarios is 2.0%. The corresponding maximum ranging error is 1.0 cm and the ranging stability is good.

2.2 Image-based sensors

Vision sensors refer to the sensors that process the images shot by cameras, output the location, speed and other data after detecting the target and make result judgments. According to the differences of camera and layout, vision sensors mainly include monocular cameras, stereo cameras and multicular cameras. Vision sensors can produce the image data of visible lights, so it is the commonly-used passive imaging sensor in obstacle avoiding tasks.

The working principle of monocular cameras is to identify the target through image matching algorithm first and then measure the distance according to the image size (Figure 6). They project the objects and scenarios in the 3D world onto 2D image planes. Though deep information may miss during this process, massive texture details can be maintained on the image planes[23]. Wang et al.[24] judged whether there were ridges according to the leap characteristics of pixel grayscale inside and outside farmland based on machine vision technology, and acquired the main extension azimuth line of the actual irregular ridge boundaries by evenly dividing the image into 8 sub processing regions along the horizontal direction. Then they moved the main extension azimuth line downward and parallel so as to acquire the boundaries for agricultural machineries to safely turn around at the current ridge. The experiment results show that this method can achieve the timely and accurate sensing of spatial location of ridges by agricultural machineries in complex farmland operating environment. During field operation, the wide attitude angle of agricultural machineries, especially the rolling angle, can influence the farming depth and compressive strength of agricultural machineries, further affecting the farming quality. And therefore, Li et al.[25] proposed a farmland surface characteristic point registration model based on monocular camera, studied to calculate the rolling angle of objects during image matching using an image registration algorithm, and used monocular camera to conduct the field test on the model performance. The field experiment suggests that the model can acquire the attitude changing trend when agricultural machineries are working in irregular farmlands relatively accurately. In order to make up for the loss of depth information and acquire the locations of surrounding obstacles from monocular images, some developed the simultaneous localization and mapping (SLAM) and structure from motion (SFM) technology[26]. The core of SLAM and SFM is to estimate the motion (rotation and translation) and build the unknown surrounding environment using multi perspective geometry. Wang et al.[27,28] used such methods to provide the positioning information of surrounding environment, but such methods show relatively worse robustness towards big scenarios or rapid motion. Monocular cameras are simple in structure, and can be used for obstacle detection in specific environment with known types of obstacles. However, only 2D information can be obtained in non-specific environment, and is now mostly applied to spraying, sowing, fertizlizing, ridge identifying and field path detecting.

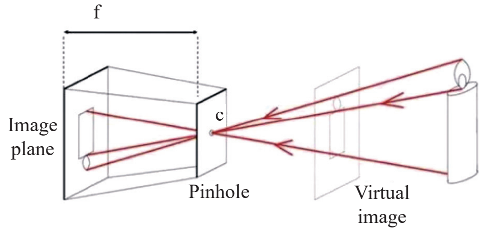


Figure 6 The basic principle of monocular camera

Multicular cameras need three cameras and more, which is complex in structure and high in costs and requirements for computational speed of computer processor[29], resulting in fewer applications in agricultural machineries. The working principle of stereo cameras acquire the images under different perspectives. They are the depth cameras that confirm the 3D spatial points through parallax calculation based on geometric principles (Figure 7). Compared to monocular cameras, stereo cameras can also acquire 3D spatial information based on the acquisition of 2D image information[16]. To sum up, stereo cameras are more conducive to the research and use, especially in environmental sensing, winning the attention of scholars at home and abroad. Hong et al.[30] proposed an identifying and ranging method for farmland ridge boundaries based on stereo vision (Figure 8a). Targeting at the great lighting changes and many repetitive textures in farmland environments, the method combining Census transform and truncated gradient is adopted to carry out cost calculation on stereo stereo matching and the segmentation tree algorithm for multiscale cost merge is adopted in the cost aggregation step to rapidly acquire good parallax maps. Meanwhile, focusing on the actual situations of uneven farmlands and crop growth height, the self-adaptive threshold point cloud extraction, interference removal and other operations are performed on the 3D point cloud constructed from parallax maps, achiving the identification of ridge boundaries. Wei et al.[31] extracted the field crop height and harvest boundary information based on stereo vision (Figure 8b). Stereo vision is used to acquire 3D data that will be converted into corresponding actual heights according to the distance from the point to the plane and the height data is classified. Through combining the height classification and color image segmentation results, the extraction of crop height information is achieved. Based on the least squares method fitted with boundary lines, the candidate scope of boundary points for the next frame of data is predicted according to the current boundary lines, providing a basis for real-time adaptive control of combined harvesters.

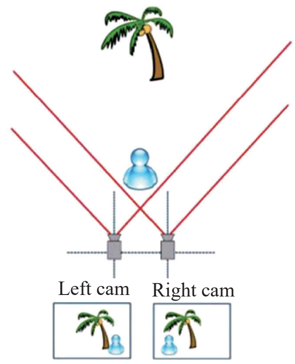
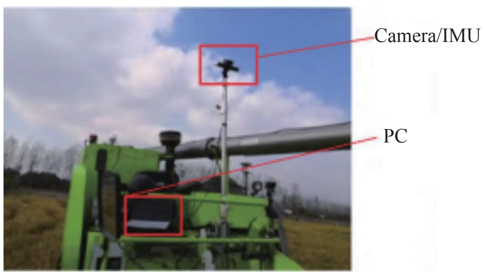
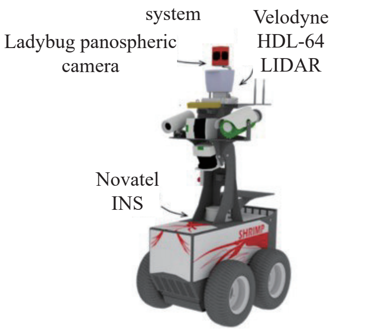


Figure 7 The basic principle of stereo camera

a. Farmland ridge boundary detection system



b. Detection system for field crop height and harvest boundaries



c. Field multimodal obstacle detection system

d. Farmland obstacle detection system

Figure 8 Agricultural machineries loaded with visual cameras

When using binolar vision for farmland environmental sensing, it does not affect the surrounding environment and can detect the objects under wider perspectives without scanning as it does not emit any signal[32, 33]. However, there also remain problems to be solved: it is difficult to detect the objects without sufficient lighting. Adverse weather conditions can greatly affect the detection. The detection distance of stereo vision is limited as the accuracy of stereo matching decreases with the increase of detection distance and some systems cannot meet the actual farmland operations. Though there lack good solutions to the aforementioned problems, machine vision technology has proved that effective sensing is available under controllable environmental conditions. With the research development, the technology will be more applied in farmland environmental sensing. Kragh et al.[34] proposed a multimodal obstacle detection method based on the fusion of conditional random field, laser radar and camera (Figure 8c). Camera and laser radar are combined in a probabilistic manner while the spatial temporal, and multimodal links between corresponding 2D and 3D regions as well as the data pairs collected in various agricultural environments by mobile ground vehicles are used. The experiment results show that the two modes complement mutually improved by 1.4% and 7.9% in 2D and 3D, respectively. Cai[35] proposed a solution with visual sensing as the main part and millimeter wave radar detection as the supplement part targeting at the problems that the detection of obstacles by a single sensor can easily be affected environmentally (Figure 8d). The temporal and spatial fusion of vision and millimeter wave radar is realized. With the effective targets selected by millimeter wave radar as seed points, the task of detecting the obstacle size is completed in the vision depth map. The experiment proves that this solution can accurately detect the spatial location and size information of obstacles in front of agricultural machineries.

3 Multi-sensor Information fusion Methods and Their Comparison

Different sensors can provide distinct types of information, yet each sensor has its own limitations. In complex agricultural environments where precision perception is required, a single sensor cannot capture all necessary information, and it may be susceptible to noise, interference, or malfunction, resulting in erroneous or biased information perception and subsequently affecting the system's performance and reliability. And therefore, Lahat et al.[36] fully studied the multi-sensor fusion, highlighted that complementarity is the main reason for using multiple sensors and putforward guidelines on how to process data fusion issues. De Silva et al.[37] proposed to actively utilize multimodes and redundance and achieve the reliable and consistent environmental sensing through sensor data fusion. By employing multiple sensors, it is possible to address the limitations of individual sensors and improve measurement accuracy and reliability. Additionally, the dependence on a single sensor can be reduced. When one sensor is subjected to interference, the presence of other sensors enables the provision of redundant information, preventing a decline in system performance, and enhancing system robustness. Based on the above, it can be concluded that the fusion-based methods mainly have two purposes: redundance and complementarity. Redundance uses the same physical measurements from heterogeneous sensors or time series from the same sensor. The purpose of redundance fusion is to update the reliability of fusion information through identifying and correlating data, further improving the measurement accuracy and uncertainty of data management. There are two types of complementary information, including the first type that uses different physical measurements (e.g. scope, color, temperature, etc.) for the same vision field and the other type is the complementarity of vision fields that uses complementary information to help enrich the manifestations of surrounding environments[23].

As such, in this section, we review and compare existing sensor fusion methods, categorizing them into four classes: statistical inference theory, signal processing and estimation theory, information theory, and artificial intelligence (Table 3). Table 4 illustrates commonly used data fusion methods and their characteristics.

Table 3 Classification of multi-sensor data fusion algorithms

Classification basis	Fusion method
Statistical inference theory	Bayes estimation Dempster-Shafter's theory
Signal processing and estimation theory	Average weighting method Kalman filter Unscented Kalman filter
Information theory	Cluster analysis Entropy method
Artificial intelligence	Neural Net Genetic algorithm

Table 4 Comparison of common data fusion methods

Fusion method	Operating environment	Information type	Fusion technology	Applicability
Bayesian Estimation	Static	Redundancy	Probability statistics	Decision-level fusion
D-S Evidence Theory	Static	Redundance and complementarity	Logical inference	Decision-level fusion
Least Squares Method	Static	Redundancy	Linear regression	Data-level fusion
Kalman Filter	Dynamic	Redundancy	Recursive filtering	Data-level fusion
Clustering Analysis	Static	Redundance and complementarity	Clustering algorithm	Data-level fusion
Entropy Method	Static/ Dynamic	Redundance and complementarity	Information entropy calculation	Data-level/Decision-level fusion
Neural Networks	Static/ Dynamic	Redundance and complementarity	Weight updating	Data-level/Decision-level fusion
Genetic Algorithm	Static	Redundance and complementarity	Genetic operations	Decision-level fusion

3.1 Statistical inference theory based

The method based on statistical inference theory is built upon Bayes Inference. Bayes Estimation provides a probabilistic framework and calculates the posterior probability distribution of target parameters for parameter estimation through combining observation data and prior information. Sun Z. D.[38] used multi-sensor data fusion algorithm to combine the measurement data of multiple nodes and reduce the uncertainty through data redundance, further acquiring highly reliably data information. As proved by experiments, using Bayes Estimation can effectively integrate the uncertain data from multiple sources and solve the inconsistency of data. However, this method requires much prior information, which is not easily accessed in actual application. Sock J.[39] et al. studied the traversibility of outdoor mobile robots on unstructured roads and built the binary probability grid map online by combining 3D laser radar and camera. When vehicles traverse terrains, the traversibility estimatin of vision cameras will automatically collect the training data and update the classifiers. 3D laser radar predicts the traversibility through measuring the slope and uses Bayes method to integrate the two independently-built probability mapping, further improving the detection ability. The experiment results show that the algorithm has better robustness towards environmental changes.

Dempster-Shafter's Theory is the generalization of Bayes Estimation, which can be used without prior probability distribution, and thus it can replace all the information fusion problems with the ability to process uncertain information using Bayes Estimation. Though Dempster-Shafter's Theory can process the information fusion tasks without taking prior probability into account, it may result in counterintuitive conclusions when processing highly conflicting evidence. In light of this defect, Zhao et al.[40] proposed a new distribution distance measuring method to measure the degree of conflict between evidence, further obtaining the credibility of the evidence, and introduced a revised information calculation method to measure the effects of the evidence itself, further generating the information volume of the evidence. Through correction using the credibility of each evidence by information volume, the weight of each evidence is acquired, which will be used to adjust the evidence before fusion. The improved combination method not only considers the evidence uncertainty, but also considers the system conflict degree, which can effectively process the contradictory evidence. Wang et al.[41] proved the relative importance of the evidence through entropy of information and acquired the evidence credibility using divergence. Then, they used the evidence credibility to optimize the evidence difference, further acquiring the difference information volume, acquired the final weights of data through calculation and used them as the basic probability distribution in Dempster-Shafer's Theory for decision-making. Compared to other methods, this method is faster in convergence and higher in accuracy in the data fusion of processing of conflicting evidence, consistent evidence, and evidence of varying amounts.

The result drawn from the algorithm based on statistical inference theory is the target-based assumption. The sensor information is described using trust interval, so it is not necessary to build models for actual objects. However, it is relatively difficult to define the prior cause, which makes it impossible to effectively process the contradictory evidence. Faced with complex conditions, the inference ability will be lowered.

3.2 Signal processing and estimation theory based

The signal processing and estimation theory mainly includes the least square method, weighted average method, Kalman filter (KF) and other linear estimation technologies, as well as the unscented Kalman filter (UKF), random sampling based particle filter (PF) and other non-linear estimation technologies.

The weighted average method is to perform weighted averaging on a set of redundant information provided by sensors and the results drawn are used as values for information fusion. This method is simple and intuitive[42]. The weighted average method is to process the data from multiple sensors according to different weights. Tan et al.[43] conducted weighted distribution on the observation values of two ultrasonic radars. As suggested by research, when the weighted observation value is proper, the optimal estimation value can be acquired and it is also of high feasibility to extend the conclusion to multiple ultrasonic radar and laser radar data fusion. However, it is not easy for the weighted average method to confirm the weight of data from each sensor, affecting the accuracy rate of information collection. And therefore, Zhen et al.[44] proposed an adaptive weighted average method, which uses different methods to process high and low frequency data and is higher in accuracy rate but harder in processing of sensor errors and environmental interference compared to traditional weighted average methods.

Kalman filter (KF) mainly integrates the redundant data of dynamic multi-sensors in real time at lower levels, which is very suitable for processing complex multi-sensor status estimation and data fusion. When the system meets the dynamics model and the sensor errors and system meet the Gaussian white noise model, the only optimal estimate can be acquired through this algorithm. Meng et al.[45] proposed a detection tracking based online multi-target tracking framework using KF as the core of multi-target tracking targeting at the vehicles with uncertain motions in dynamic road environment, so as to solve the complex operating environment and target uncertainty issues. Liu et al.[46] built the multi-sensor sensing and dynamic weight distribution and elimination system so as to remove the sensor data with poor detection results through weight setting based on Kalman tracking variance, and reduce the measurement error and uncertainty of multiple sensors, further improving the accuracy rate of integrated system in actual application. Peng et al.[47] designed based on iterated extended Kalman filter, and integrated various sensors, including IMU, GPS, camera and laser radar. Firstly, IMU is used to predict the prior vehicle status. Then the parallel fusion structure is built to conduct different information processing on the data of various sensors for updating the prior status. The experiment results show that the proposed algorithm shows relatively high accuracy of positioning and speed observations in maps, along with sufficient redundance and real-time performance.

Unscented Kalman filter (UKF) is a new filter based on unscented transformation (UT), which adopts the Kalman linear filter framework. Through selecting a set of special sampling points named UT to approximate non-linear transformation and using the sampling points to predict and update the status and observation[48], the scope of use of Kalman filter is improved. Wu et al.[49] explained that the application of UKF algorithm in the field of target tracking was improved significantly. Moreover, in actual application, the algorithm's simple realization and small calculation volume improve the usability. Nevertheless, UFK is worse in robustness and tracking ability in case of inaccurate models or sudden status changes.

The algorithms based on signal processing and estimation theory use the principles of statistics and directly calculate the characteristics of physical objects according to models. The calculation results can be used to approximate the theoretical optimal solution, further improving the sensing and estimation accuracy of targets or environments. However, as actual models are very complex, the building process is extremely difficult.

3.3 Information-based theory

In some occasions, multi-sensor data fusion target identification identifies the targets through the mapping relationship between observation parameters and target identities rather than using statistical methods for the random forms of direct simulated data observation[50]. Such methods are named as information theory based fusion identification algorithm, mainly including entropy method, voting method and cluster analysis.

Entropy method reflects the information volume using the probability of event occurrence. In view of its principles, the entropy of frequent events is the lowest while the entropy of infrequent events is the highest. Its application in the sensor data fusion process aims at drawing the conclusion of maximizing entropy. Wei et al.[51] discussed the application of reliability theory of maximum entropy method in engineering, and studied and discussed the influence of sample mean and standard deviation on convergence, as well as the influence of sample size and maximum entropy method order on probability density function, transcendental probability, and reliability index accuracy. At present, entropy method has been applied to the integrated multimedia observation data classification by researchers. Magalha et al.[52] applied entropy method to semantic multimedia index, which retrieves images through combining text and image based characteristics. It is found out that the fusion by this method is better in effects than Bayes method. As for the systems with high requirements for real-time performance, when the accurate prior design is unavailable, or from the overall perspective of cost-effectiveness, entropy method is of high application values.

Cluster analysis is a heuristic algorithm that can classify based on a certain degree of similarity between samples and divide the datasets into several subsets according to the structure or similarity of sensor data. The similar datasets are integrated to produce some identifiable sets and be separated from datasets[53]. Such method is commonly used in information fusion systems with undefined target type amount. Liu et al.[54] proposed a multiple base radar method based on cluster analysis to identify the false targets with sources. Using the differences in correlation between signal vectors received by true and false targets, with correlation coefficient as measurement, the false targets generated by the same interference sources are classified as one type while each true target is classified as one type through cluster analysis, further archiving the effective identification of the false targets with sources. This method is suitable for the application scenarios with distributive interference of multiple interference sources. Liu et al.[55] proposed a method using the vibration information of the robot itself for terrain cluster analysis and adaptively adjust the motion speed based on the cluster results. The experiment results show that this method can make robots accurately conduct cluster analysis on different terrains and realize the adaptive speed adjustment under different terrain environments, effectively enhancing the terrain adaptability of robots.

Information theory based algorithm achieves the effective fusion of multi-sensor data and improves the system performance and result accuracy through maximizing the information complementarity, reducing uncertainty, and optimizing decision-making in the data fusion process. However, as a heuristic algorithm, cluster analysis will produce more prominent effects in unknown environments.

3.4 AI-based algorithm

AI based algorithm acquires the optimal integrated weight by inputting a large amount of information into the neural network and generating fixed logic through training. The main methods include neural network method, fuzzy logic method and genetic algorithm. At present, the method commonly used in multi-sensor fusion is neural network method.

Based on the modern neuroscience research achievements, neural network is advantageous in the strong self-learning, adaptive, self-organizing, and fault-tolerant abilities, as well as the ability to simulate the complex non-linear mappings. This method achieves performance on the weight distribution of the network. Lu et al.[56] proposed a neural network based reliability evaluation model, which uses dynamically updating reliability to intelligently integrate the navigation results, further reducing the data fusion errors and improving the navigation reliability. The results of loading this algorithm onto plant phenotype detection robots for field experiments show that, under multiple interferences, the navigation error of mulsi-sensor information fusion is 2.7 cm, which can effectively solve the navigation reliability issues of plant phenotype detection robots in complex farmland environments. Bai et al.[57] proposed a multi-sensor integrated neural network, which adds the prior information of millimeter wave radar into convolutional neural network to acquire the new attention module that is later combined with SSD target detection network. This integrated algorithm based on deep learning improves the stability and reliability of target detection. Weber et al.[58] found out that the use of neural network can effective solve the inherent problems in multi-sensor fusion. However, in order to achieve the optimal fusion results, it is necessary to collect the data of all the possible events. In addition, the self-learning algorithm specified by the neural network can acquire knowledge to obtain the uncertain inference mechanism. Then, neural network automatic inference and signal processing function are used to achieve the information fusion of multiple sensors.

Genetic algorithm is a group optimization process, during which a set of initial values re optimized. The optimization process is the process that this group keeps reproducing, competing and inheriting and mutating[59]. In actual operation, in order to control the group optimization process, the genetic evolution process is planned, commonly using the method combining genetic algorithm and other algorithms. Typically, the current evolutionary characteristics are judged and controlled through combining with neural network target classifier. Niu et al.[60] combined genetic algorithm and neural network target classifier. Through the feedback information of identification results, the genetic evolutionary directions of genetic algorithm are controlled to realize the characteristic optimization. In order to solve the immature convergence problem of genetic algorithm, the improved genetic algorithm combining correlation selection and adaptive genetic operators is proposed. The experiment results have verified the effectiveness of the method. Liu[61] proposed a multi-source data fusion model based on GA-PSP-BP neural network., exquisitely combining genetic algorithm and particle swarm algorithm, which can not only overcome the difficulty of inaccurate estimation in traditional fusion models, but can also make up for the deficiencies of traditional BP algorithm.

4 Application of multi-sensor information fusion technology in farmland environmental Sensing

4.1 Real-time positioning

In the field of autonomous positioning for unmanned agricultural machinery, the utilization of multi-sensor fusion is common. This technology combines visual sensors with IMUs and other sensors to enhance the completeness of received information, addressing some of the limitations associated with single-sensor use. By combining the characteristics of data obtained from various sensors with corresponding information fusion algorithms, multi-sensor fusion reduces positioning errors caused by sensor measurements, increases the amount of available information, and enhances positioning accuracy[62]. Yang[63] utilized GNSS, IMU, and stereo visual sensors to form the foundation of multi-sensor fusion algorithm. This approach enabled the completion of attitude tracking tasks and positioning. GNSS provided global positioning information for calibration, IMU offered carrier motion data for supplementary positioning, and the stereo camera captured image data for visual pose tracking. These sensors complemented each other's limitations and leveraged their respective strengths, effectively addressing problems like position drift, image distortion, and distance estimation errors. To tackle the problem of visible light cameras failure to provide real-time positioning in low-light and dark environments, Zheng et al.[64] proposed an algorithm for target recognition and positioning based on the fusion of infrared vision and laser radar, which enhanced the generalization performance of infrared target recognition algorithms. By integrating visual images with laser radar point cloud data, this algorithm achieved estimates of target positions based on dense depth maps. Experimental results demonstrated that this method significantly improved the accuracy of target positioning for unmanned vehicles in low-light and dark environments. Huang et al.[65] aimed to enhance the positioning accuracy and reliability of autonomous navigation in agricultural machinery. They designed a combination navigation system based on a real-time kinematic BeiDou Navigation Satellite System (RTK-

BDS) and an Inertial Navigation System (INS). In this system, they developed an autonomous navigation control board that integrated a high-precision BeiDou analysis module, an IMU module, and a radio module. They also implemented integrated navigation algorithms on the control board. Experimental results showed that the system achieved position errors within 3 cm, azimuth errors within 0.6°, and errors of tilt within 1° on open roads. Moreover, it rapidly converged when encountering challenging road conditions.

4.2 Target identification and tracking

In the process of agricultural machinery operations, it is necessary for the machinery to perceive the presence of obstacles in its surrounding environment, identify and track them, and take timely actions to avoid them[66]. In complex field environments, using a single sensor for target identification may result in limited perceptual capabilities and increased perceptual errors. Therefore, the application of multi-sensor information fusion in target identification is essential to improve accuracy. Lv et al.[67] proposed a method for identifying agricultural obstacles based on integrating information from millimeter-wave radar and visual cameras. By combining the advantages of millimeter-wave radar in distance and speed measurements with the advantages of cameras in type recognition and lateral positioning, a decision-level algorithm was designed to integrate millimeter-wave radar and camera information. Global nearest neighbor method was used for data association. Weighted outputs were obtained for effective target sequence of successfully associated millimeter-wave radar and camera data to achieve more accurate target azimuth, longitudinal velocity, and type. Experimental results showed that the correct identification rate of obstacles reached 86.18%, surpassing the 62.47% achieved with a single camera. Yang et al.[68] aimed to improve obstacle avoidance in drones when approaching objects like cables and poles. They employed a multi-sensor fusion algorithm that integrated data from various sensors, including machine vision, millimeter-wave radar, and GPS navigation systems. The approach involved the use of a Virtual Force Field (VFF) method to evaluate obstacles around the drone. He et al.[69] integrated machine vision and 2D laser radar to identify and track rows of rice, allowing for navigation control to avoid crushing the rows of rice with agricultural machinery. The research utilized machine vision and 2D laser radar to extract the center points of the rice rows and unify spatial coordinates and target areas. A robust regression algorithm was applied to fit the centerline of the rice rows, derive the navigation reference line, and calculate the navigation parameters. A predictive tracking PID controller was designed, and a rice-row tracking navigation test platform was established for experimental research. Precise crop detection is essential for intelligent agricultural machinery to function effectively. Therefore, Wang et al.[70] fused the advantages of LiDAR and cameras to detect maize seedlings. Experimental results indicated that the standard deviations of 1.4 cm for maximum distance error and 1.1° for maximum angle error, respectively, which are acceptable under current technical requirements. Due to the varied environment of farmland, which is dominated by primary crops and subject to changing conditions, the fusion of images and LiDAR points can provide more precise information, resulting in smarter agricultural machinery.

4.3 Path planning

Global path planning is a method that operates under the premise of having prior complete information about the working environment[71]. This information includes the positions, shapes, and sizes of the working area and obstacles. Depending on the working scenarios, global path planning can be categorized into two types: global coverage path planning and global point-to-point path planning[72]. Both aim to optimize the working path, enhance quality, and reduce costs. Li et al.[73] utilized extended Kalman Filter to integrate environmental information from laser radar and depth cameras and obtained attitude and acceleration data from attitude sensors. Global path planning was carried out by improved Ant Colony Algorithm. Simultaneously, the dynamic window method was employed for local planning and obstacle avoidance. Experimental results revealed that the use of the improved Ant Colony Algorithm for smoothing path angles and the dynamic window method for real-time obstacle avoidance increased path planning efficiency, enabling automatic feedback control for intelligent vehicles. Jiang et al.[74] employed ultrasonic sensors for real-time road obstacle identification and updated position coordinates in real time through RTK-GPS. They devised a steering control strategy for transplanters to navigate around obstacles. The method dynamically adjusted the size of the potential field by incorporating the relative distance between the transplanters' real-time position and the target working point as a judgement condition. Additionally, virtual local target points were introduced to address the algorithmic limitations of traditional artificial potential field methods, such as inaccessible target points and local minima. Experimental results demonstrated that the obstacle avoidance strategy could meet the requirements for obstacle avoidance during the transplanters' agricultural operations and exhibited feasibility and robustness.

5 Discussion and prospect

Multi-sensor information fusion is an advanced, interdisciplinary technology, and its development in agriculture needs to align with the requirements of contemporary agricultural machinery. Whether it is used in practical farmland or scientific research, it can play its role. This paper provides an overview from two aspects: sensor characteristics and multi-sensor fusion. It introduces commonly used sensor types in agriculture, such as laser radar, millimeter-wave radar, ultrasonic radar, and vision cameras. The paper also outlines types of current mainstream information fusion. As the level of modernization in agriculture increases, the application of science and technology in agriculture becomes more widespread, thereby promoting the transformation and renewal of farmland data acquisition. However, it also poses certain challenges that require ongoing innovation to adapt to the new normal of agricultural development.

5.1 Existing problems

5.1.1 Challenges in precise sensing of farmland environment

The level of sensor development directly influences the information perception capability, and continuous innovation in sensing technology is essential for improving the reliability and quality of agricultural environmental information acquisition. Currently, the application of agricultural sensors faces several challenges, including: In large-scale agricultural environments, issues such as weak signals and unstable data transmission may arise, leading to inevitably involves errors in sensor information acquisition; Adverse weather conditions such as rain, fog, and snow can result in a reduction in the sensing range and a decrease in detection accuracy; In rugged terrains characterized by variable topography and uneven landscape features, maintaining image stability poses difficulties; Moreover, the presence of obstacles of various sizes in the field can obstruct the sensor's field of view, making the perception and detection of the environment difficult.

5.1.2 Insufficiency of uni-dimensional data fusion in complex scenarios

The emergence of multi-sensor information fusion technology has addressed the issues of incomplete data collection, large observation errors, and susceptibility to environmental influences in single sensors. However, in complex agricultural machinery operation scenarios, the content of perception becomes more diverse, and uni-dimensional sensors have limitations. For instance, in agricultural field perception, uni-dimensional sensors can only provide data on certain specific physical quantities, such as temperature and humidity. While these data can offer some information, they do not fully reflect the overall picture of the agricultural environment. Besides the physical quantities like temperature and humidity, agricultural fields also involve other factors that need to be considered comprehensively, such as soil pH value and land use conditions.

5.1.3 Diversity in sensor fusion

Agricultural machinery often needs to perform various tasks, and during the process of agricultural machinery working in farmland, numerous unknown, dynamic, and variable environmental factors must be considered, including different crops, light intensity, road conditions, weather, various dynamic and static obstacles. This implies the need for flexible addition or replacement of sensors to provide data perception and decision support tailored to different crops and environmental requirements. However, different sensors exhibit variations in characteristics and performance, such as measurement range, sensitivity, and response speed, which may lead to difficulties in accurately comparing and integrating data from different sensors during the data fusion process, thereby affecting data integrity and consistency.

5.1.4 Innovative approaches to agricultural information processing

With the continuous advancement of precision agriculture, modern information technology has been applied to traditional agriculture, leveraging various sensors and wireless communication technology deployed in the fields, in conjunction with agricultural IoT, cloud computing, and new internet technologies. The vast area of farmland imposes high requirements on the coverage and stability of wireless communication, and the massive amount of agricultural information data also demands high processing capabilities. Therefore, the integration of advanced technologies should be accelerated to apply the Internet of Things (IoT) and communication technology to the field of agricultural information sensing. This will keep agricultural information up-to-date, continuously improve the data chain, and populate databases, fostering resource sharing and mutual utilization.

5.2 Prospect

5.2.1 Novel sensors

Currently, there have been many low-cost, high-performance novel sensors developed, such as the Intel D435 stereo camera and the StereoLabs ZED stereo camera. These cameras, consisting of two camera modules, mimic human stereo vision, providing possibility for depth and stereo vision-based agricultural machinery target identification. Additionally, the TF01 LiDAR developed by Benewake Company maintains high performance while keeping costs low, addressing the limitations of high cost associated with LiDAR in agricultural applications. Despite some improvements made to the novel sensors, further research and validation are needed to ensure their stability and reliability in actual field conditions, particularly in agricultural environments.

5.2.2 Strategies for multi-dimensional fusion

The main development direction of multi-sensor information fusion is multidimensional fusion and multi-strategy fusion, integrating and fusing data from different types of sensors to obtain more accurate environmental states or feature descriptions. To effectively utilize data from multiple sensors, it is necessary to develop applicable data fusion algorithms, which should be capable of integrating and analyzing data from different sensors and extracting agricultural indicator information. By selecting appropriate data fusion algorithms, the integration and processing of multi-sensor data by agricultural machinery can be optimized, thereby improving the efficiency of field management and harvesting. Additionally, constructing different models for data from different sensors and considering the strengths of different models can enhance decision accuracy in agricultural environments.

5.2.3 Scalability and compatibility of fusion systems

The design of a sensor fusion system should possess modular characteristics, where different types of sensors are separated into independent modules, allowing the system to dynamically add or remove sensor modules as needed to achieve scalability. Simultaneously, the system should utilize unified interfaces and communication protocols, enabling different types of sensors to connect and communicate with the system, maintaining compatibility with devices or platforms. The scalability and compatibility of the fusion system can meet various agricultural needs, provide comprehensive agricultural information, enhance system interoperability, and reduce costs while increasing efficiency. This will drive the intelligence and modernization of agricultural machinery, providing greater flexibility and sustainability for agricultural production.

5.2.4 Establishing agricultural field monitoring network

The establishment of an agricultural field environment monitoring network involves connecting multiple sensor nodes to achieve real-time monitoring and data sharing of the agricultural environment, promoting intensive management and sustainable development of agricultural production. This network can help monitor and assess the impact of agricultural activities on the environment, as well as provide timely warnings and control of potential environmental issues. Integrating and sharing multi-domain agricultural environmental data, and analyzing new and historical data in conjunction with smart agricultural machinery and agricultural robots, can facilitate precise sowing, precise pesticide application, precise harvesting, and other operations. This provides accurate and comprehensive agricultural field environment information for relevant decision-makers and research institutions.

6 Conclusions

With the advancements in computer technology, sensor functionality, and information fusion technology, multi-sensor information fusion has been vital for intelligent machines in the field of artificial intelligence. In the realization of environmental perception in farmland, the design and construction of environmental perception systems using multi-sensor information fusion can compensate for the limitations of single-sensor use. This approach enhances environmental perception accuracy and optimizes the performance of agricultural machinery environmental perception systems. It effectively ensures the stability and safety of unmanned agricultural machinery during operation, thereby promoting the development of intelligence and informatization within the agricultural machinery industry. However, the current research is still in its infancy, and further in-depth research into agricultural environmental perception is required. Building a system tailored for environmental perception in farmland also needs more time for development.

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