

Research on the Application of Multi-Sensor Networks

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Abstract: Single sensor sensing has insufficient coverage, poor anti-interference and limited detection accuracy, which is difficult to ensure the stable operation of intelligent sensing. This paper explores the multi-sensor fusion technology, and respectively builds the Carla vehicle obstacle avoidance system and the improved yolov5 strawberry disease recognition platform. The on-board system integrates millimeter wave radar, vision, differential positioning and can bus, and is developed based on Linux and python. It can avoid fixed obstacles, cross targets, front vehicle sudden braking and opposite vehicles, adapt to various road conditions in urban areas, high-speed and suburban areas, and help the automatic driving landing. Aiming at the pain points of low efficiency of strawberry artificial disease screening, frequent misdiagnosis and blind drug use, the system embedded CBAM attention to optimize small lesion extraction in yolov5, combined with manipulator and Jetson nano edge hardware, built agricultural equipment integrating disease identification, result display, prevention and control guidance, scientifically controlled pesticide consumption, and stabilized fruit output. The two systems rely on multi-source information complementation to make up for the short board of a single sensor, and customize the fusion scheme according to the application scenario, which is more cost-effective than general products. The experimental verification scheme is feasible, which can provide engineering reference for multi-sensor fusion in the field of intelligent transportation and modern agricultural detection.

Keywords: Multi-sensor Fusion; Intelligent Driving; Intelligent Agriculture; CARLA Simulation; YOLOv5; Object Detection

1. Introduction

With the rapid development of Internet of things, artificial intelligence and embedded hardware, intelligent perception is an important cornerstone of the development of intelligent transportation and intelligent agriculture industrialization. The performance of a single sensor is limited in complex operating environment. Relying on the fusion technology of multi-sensor information complementation has become the mainstream means to optimize the system performance. The existing vehicle assisted driving and agricultural disease detection equipment have their own short boards, which are difficult to adapt to the landing requirements of the subdivided scenes. Therefore, based on the theory of multi-sensor fusion, this paper developed two sets of systems for vehicle obstacle avoidance and strawberry disease recognition, and compared the design ideas of fusion schemes in different scenarios, providing practical basis for the research and development of similar intelligent equipment.

2. Multi-Sensor Networks and Information Fusion Technologies

2.1 Overview of Multi-Sensor Networks

Multi sensor networks integrate sensing, processing, communication and control units to achieve environmental information collection, fusion and analysis. Compared with single sensor, the advantages are as follows:

- a. Multi dimensional acquisition, covering distance, image, position, speed and other information;
- b. Multi device mutual inspection and calibration, excellent anti-interference performance;

- c. Relying on the fusion algorithm, effectively improve the accuracy of detection and decision-making;
- d. Good environmental compatibility, stable operation under complex lighting and weather conditions.

2.2 Levels of Multi-Sensor Information Fusion

The fusion is divided into three layers: the data layer integrates the original data and the most complete information, but the amount of computation is large; After feature layer fusion and feature extraction, the accuracy and efficiency are balanced and the application is the most; The sensors at the decision-making level are identified separately and summarized, and the real-time performance is the best. In engineering, the hybrid fusion scheme is adopted in combination with hardware and task requirements.

2.3 Integration Strategies and Mathematical Models

To achieve precise integration of multi-source information, this paper adopts a strategy combining weighted fusion and feature stitching, and establishes the following mathematical model.

Multi-sensor weighted fusion formula:

$$F = \sum_{i=1}^n w_i O_i$$

$$\sum_{i=1}^n w_i = 1$$

In the formula: F represents the fusion output value at time k ; w_i denotes the adaptive weight of sensor i ; O_i is the sampled output from that sensor; and the weights are dynamically updated based on the sensor's real-time error.

Feature Layer Fusion Vector Formula:

$$H = [f_{\text{radar}}; f_{\text{image}}; f_{\text{gps}}]$$

In the formula: H is the fusion feature vector; f_{radar} is the radar range-velocity feature; f_{image} is the image semantic feature; and f_{gps} is the positioning coordinate feature.

3. Design and Implementation of a Multi-Sensor Fusion System

3.1 Overall System Architecture

The two systems adopt a four-tier closed-loop architecture and rely on multi-source fusion to optimize the perception performance. Based on Carla, the vehicle system integrates multi-sensor, can communication, decision and control modules; Strawberry system takes edge equipment as the core to realize visual acquisition, mechanical inspection, model reasoning and result display. The design follows the principle of information complementarity, stability and efficiency.

3.2 Intelligent Driving Scenarios: Vehicle Intelligent Obstacle Avoidance System Based on CARLA

3.2.1 System Composition and Working Principle

This system is a dedicated obstacle avoidance system, focusing on obstacle avoidance in complex road conditions, focusing on safety and real-time. The system integrates millimeter wave radar, camera and differential positioning to form a heterogeneous perception network, collects obstacle location, speed, image and positioning information, outputs obstacle avoidance instructions through fusion operation and executes them in Carla simulation. The module interaction diagram is shown in Fig.1.

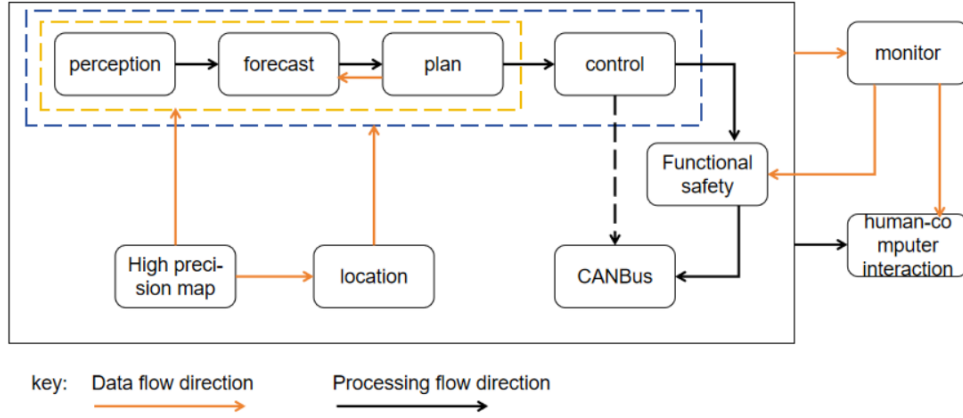


Fig.1: Interaction Relationship Diagram of Core Modules in the Autonomous Vehicle System

The sensors are reasonably arranged: the front bumper radar realizes 150° detection, the windshield camera coincides with the radar field of view, and the positioning antenna is arranged on the roof. Radar ranging and speed measurement, camera recognition of targets and lanes, and positioning provide global coordinates. The hardware architecture is shown in Fig.2.

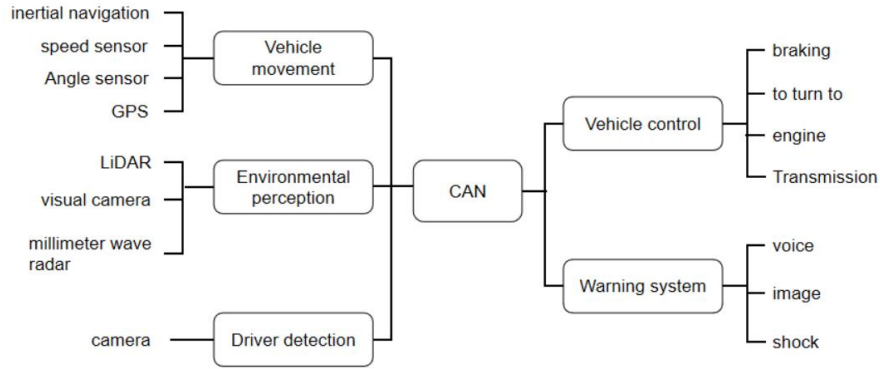


Fig.2: Hardware architecture diagram of the vehicle autonomous driving system

3.2.2 Multi-Sensor Fusion and Communication Implementation

The system is composed of four modules: perception fusion, decision planning, control execution and safety monitoring. Perceptual fusion is used for spatio-temporal registration of radar, image and positioning data. The feature+decision-making level hybrid weighted fusion is used to build a unified environment model. The relevant calculation formula is as follows.

Multi-sensor weighted fusion formula:

$$F(k) = w_1 S_1(k) + w_2 S_2(k) + w_3 S_3(k)$$

$$w_1 + w_2 + w_3 = 1$$

In the formula: $F(k)$ represents the fusion result at discrete time instant k , S_1, S_2, S_3 denote radar, visual, and positioning sampling data respectively; w_1, w_2, w_3 represent sensor weights.

Obstacle avoidance safety distance formula:

$$D(k) = v(k)\tau + \frac{1}{2}a\tau^2 + D_{\text{offset}}$$

In the formula: $D(k)$ is the real-time safety distance, $v(k)$ is the instantaneous vehicle speed, τ is the system delay, a is the braking deceleration, and D_{offset} is the safety margin.

The decision-making planning module determines a safe trajectory based on obstacle type, distance, and vehicle speed, prioritizing both timeliness and stability in avoidance operations.

The CAN bus serves as the core of system communication. The project utilizes the CANoe development environment to implement message parsing, node simulation, and data acquisition—as illustrated

ed in Fig.3(CANoe Traffic Data Acquisition Diagram)—enabling data exchange between sensors and the decision-making module within the simulation environment.

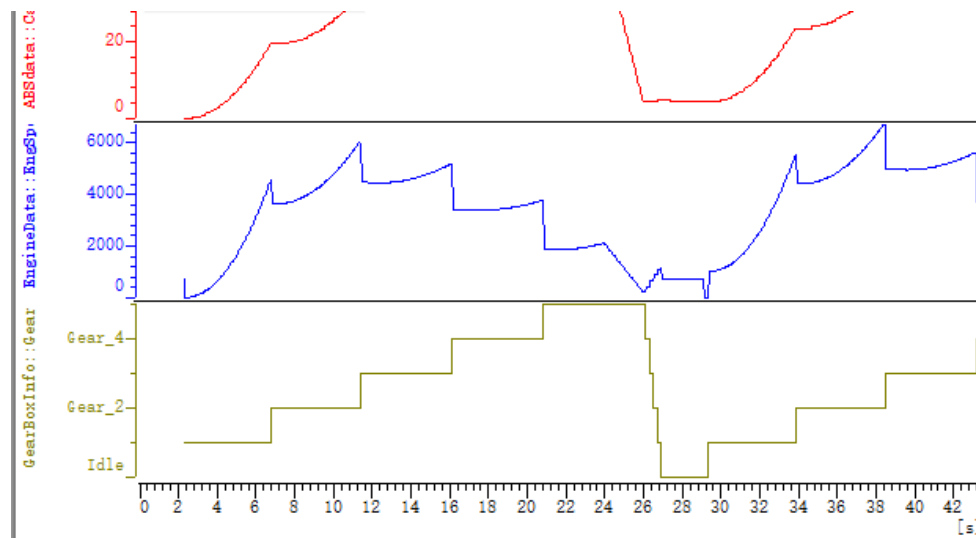


Fig.3: CANoe traffic data acquisition diagram

3.2.3 System Simulation and Testing

The system is developed and debugged based on Carla platform, and can customize road conditions, meteorology and obstacle environment. The test covers such working conditions as fixed obstacles, crossing pedestrians, front vehicle emergency braking, and opposite vehicle meeting. The 3D simulation test diagram is shown in Fig4, and the test effect of high-precision map is shown in Fig.5. The system is suitable for urban, high-speed and suburban roads, with fast response, stable driving trajectory, and can effectively avoid collision, which verifies the reliability of the multi-sensor fusion scheme.

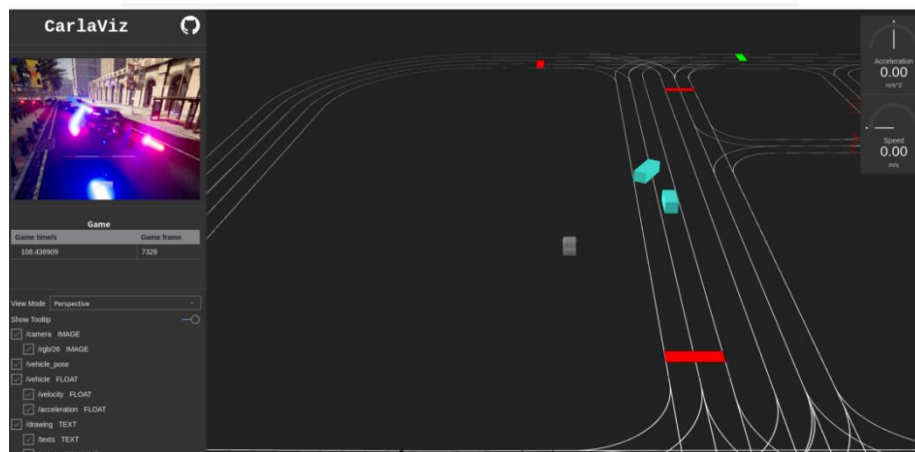


Fig.4: CarlaViz automatic avoidance function 3D simulation test



Fig.5: high-precision map test rendering of the vehicle's automatic obstacle avoidance system

3.3 Smart Agriculture Scenario:A Strawberry Disease Recognition System Based on Improved YOLOv5

3.3.1 System Requirements and Composition

Aiming at the problems of low detection efficiency,high false detection rate and pesticide abuse of strawberry artificial diseases,an integrated system of collection,identification and prevention suggestions was built,and the batch accurate detection of diseases was achieved by improving yolov5,Jetson nano and sliding rail manipulator.

3.3.2 Hardware System Design

The cost of the whole set of hardware is less than 12000 yuan.The Jetson nano low-power main control is used.The six degree of freedom robot arm is equipped with a high-definition camera to complete image acquisition.The LCD screen is equipped to display disease information.The equipment is easy to operate.The hardware composition of strawberry disease identification system is shown in Fig.6 below.

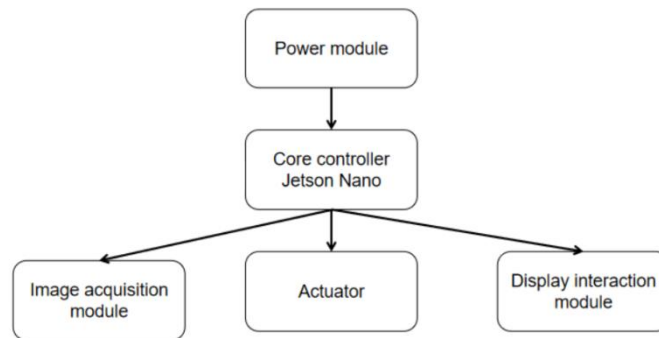


Fig.6: Hardware configuration diagram of the strawberry disease identification system

The inspection manipulator structure is shown in Fig.7 two dimensional diagram of robot hardware.The whole machine includes slide rail base,connecting rod,actuator,camera module,pneumatic parts and PCB substrate.There are 14 components in the icon,which are divided into transmission,acquisition and control modules to provide hardware support for hand eye coordinate conversion.

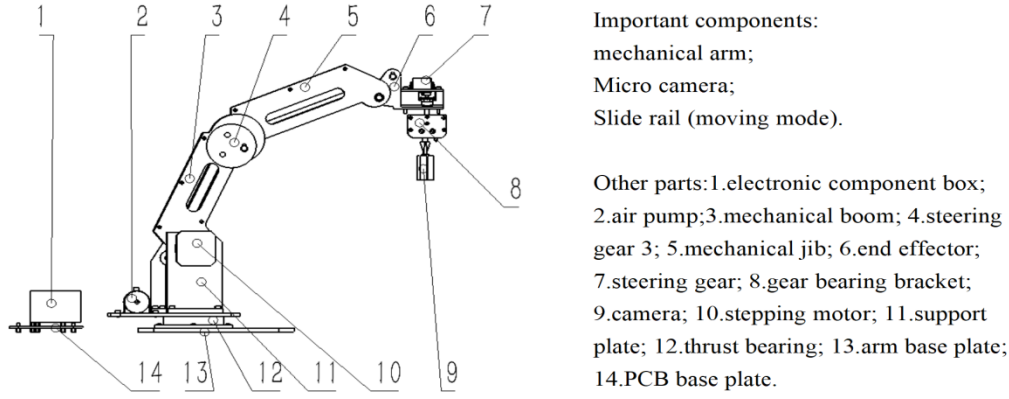


Fig.7: 2D diagram of robot hardware

3.3.3 Software System Design

Build a multi light and multi category labeled disease data set to improve the generalization performance of the model.Yoyov5 relies on focus,CSP and spp modules to build a backbone network. The network topology is shown in Fig.8.Structure diagram of yoyov5 core modules;CBAM was embedded in the network to enhance the feature extraction of small lesions.After pruning and quantification,the model volume was<5MB,the edge reasoning was ≥ 15 fps,and the recognition accuracy was $\geq 95\%$.Three sets of mathematical models are used to complete parameter constraints:

$$L_{total} = \lambda_{box} L_{box} + \lambda_{obj} L_{obj} + \lambda_{cls} L_{cls}$$

Where: L_{total} is the total loss of the model, L_{box} , L_{obj} , L_{cls} are the positioning, confidence, classification loss respectively, λ_{box} , λ_{obj} , λ_{cls} are the loss weight coefficients to optimize the convergence effect of small lesions.

$$P_{arm} = R \cdot P_{cam} + T$$

Where: P_{arm} is the base coordinate of the manipulator, R is the rotation matrix, P_{cam} is the camera coordinate,and T is the translation vector.Real time coordinate conversion is realized by hand eye calibration.

$$w' = \sigma(\text{MLP}(\text{AvgPool}(F)) + \text{MLP}(\text{MaxPool}(F)))$$

Where: w' is the feature attention weight, σ is the sigmoid activation function,MLP is the multi-layer perceptron,AvgPool is the average pooling,MaxPool is the maximum pooling, F is the input feature map,which can adaptively enhance the lesion characteristics and suppress the field clutter interference.

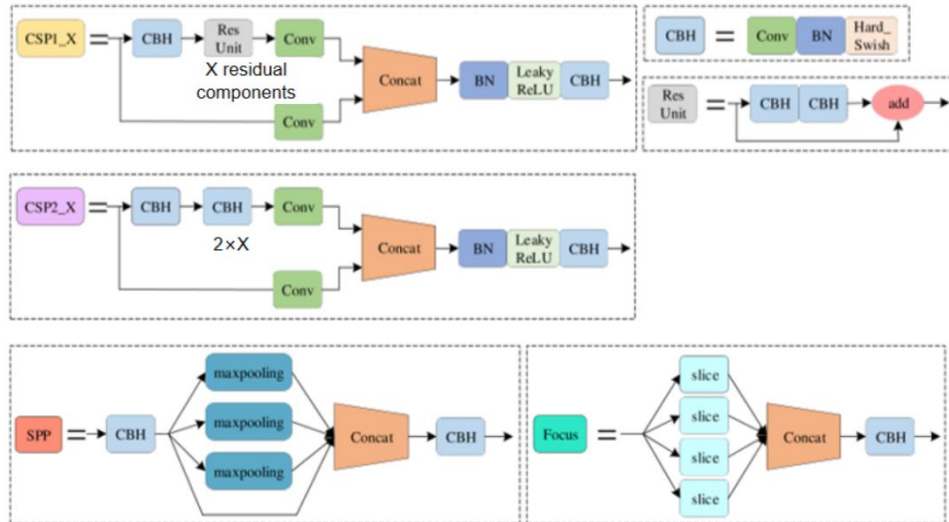


Fig.8: yolov5 core module structure diagram

The hand eye coordination algorithm is optimized, and the inspection path planning program is provided to realize the joint inspection between the manipulator and the camera.

3.3.4 System Innovation and Advantages

The system integrates deep learning, manipulator and edge calculation, and can detect off-line in real time; Relying on the improved algorithm to optimize the identification of small disease spots, the hardware selection is cost-effective and the equipment cost is low, which is convenient for the popularization in the field, as shown in Fig.9 below.

Work steps of disease identification system

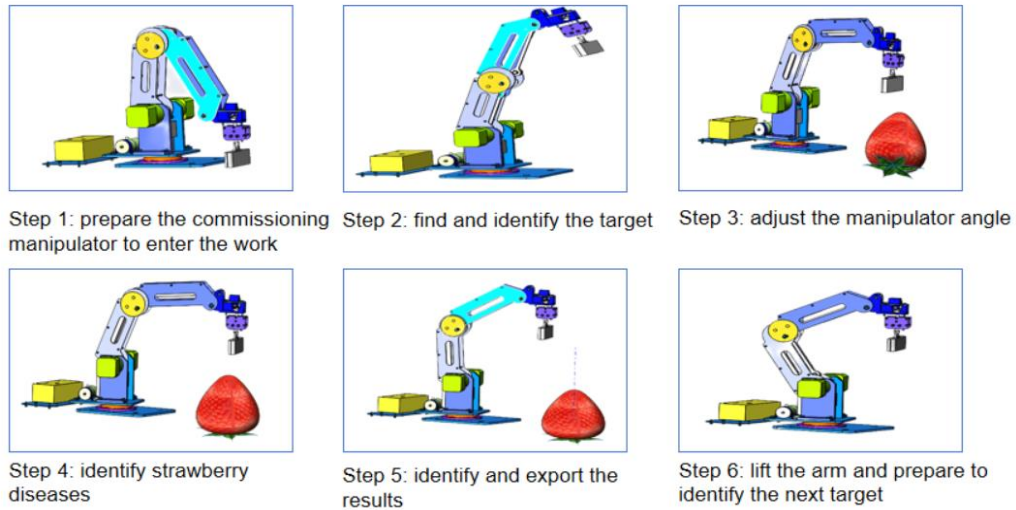


Fig.9: Working steps of disease identification system

4. Testing and Effect Analysis

4.1 Testing of Intelligent Vehicle Obstacle Avoidance Systems

Relying on Carla, a variety of road condition simulation scenarios were built to carry out the test. The system can accurately identify five types of obstacles, and can smoothly complete various obstacle avoidance actions on urban, high-speed and suburban low-speed roads, without missed detection and false triggering, and meet the safe operation indicators.

4.2 Testing of the Strawberry Disease Identification System

The accuracy of the original yolov5 is 88%, and the accuracy is improved to more than 95% after being embedded in the CBAM attention module. The hardware joint debugging shows that the robot arm inspection, image acquisition and edge end reasoning are up to standard, and the whole set of equipment is easy to operate, which can reduce pesticide application and improve strawberry output.

4.3 Analysis and Summary

The actual measurement shows that multi-sensor fusion can make up for the defect of single sensor, cross modal fusion can optimize the stability of vehicle perception, and multi-sensor vision can improve the detection of small disease spots of crops; The fusion scheme needs to be customized according to the scene, cost and computing power, and there is no general optimal scheme.

5. Conclusion and Prospects

This paper focuses on the research of multi-sensor fusion technology for intelligent driving and intelligent agriculture. Based on Carla simulation and improvement of yolov5, two systems of vehicle

obstacle avoidance and strawberry disease identification are built. Experiments show that multi-sensor fusion can effectively make up for the defects of limited detection range, weak anti-interference and insufficient recognition accuracy of a single sensor; Combined with the lightweight model, the hybrid fusion architecture can achieve low delay and high stability detection at the edge terminal, and the scenario customization scheme has lower cost and stronger landing performance than the general product. Subsequently, the lightweight fusion algorithm and migration learning performance will be optimized, the vehicle decision logic and agricultural inspection equipment will be improved iteratively, the industrialization of disease identification equipment will be promoted, and the application space of multi-sensor fusion in intelligent transportation and modern agriculture will be expanded combined with agricultural big data.

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References

- [1]Fu Guangming,Lu Ziao,Ma Lei,etc.Summary of end-to-end automatic driving algorithm based on Carla simulation.Journal of Zhejiang University (SCIENCE EDITION),2025
- [2]Xujiqian,xiaoyufeng.Modeling and Simulation of driverless scene in open pit mine based on Carla and unreal engine.open pit mining technology,2025,40(04):50-54
- [3]Li runlin,Yin Mingxu,Liu Rui,et al.Research on virtual simulation experiment design of intelligent vehicle perception technology based on Carla simulation platform.science and technology information, 2025,23(09):210-213+218
- [4]Yang Cheng Application analysis of wireless sensor networks in smart agriculture. smart agriculture guide, 2025,5 (17):13-16.
- [5]Jocher G,et al.ultralytics/yolov5:v7.0-YOLOv5 SOTA Realtime Instance Segmentation.Zenodo,2022.
- [6]Weiyianli Application of deep learning in image recognition and intelligent monitoring system. information and computer, 2026,38 (10):42-44