Proceedings of CONF-FMCE 2026 Symposium: Smart City and Infrastructure Engineering
DOI: 10.54254/2755-2721/2026.CH38707

Research Progress on Multi-Sensor Fusion-Driven Autonomous Navigation and Obstacle Avoidance Technologies for Agricultural Machinery

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Abstract. Autonomous navigation and obstacle avoidance are key technical foundations for intelligent agricultural machinery operating in open fields, orchards, greenhouses, and mixed human-machine production environments. Single-sensor navigation is constrained by canopy occlusion, dust, vibration, illumination variation, reflective soil surfaces, GNSS multipath, terrain unevenness, and the coexistence of crops, workers, vehicles, animals, and implements. Multi-sensor fusion improves positioning continuity, environmental perception, mapping reliability, and real-time safety decisions by integrating GNSS, inertial measurement units, wheel odometry, LiDAR, RGB cameras, RGB-D cameras, stereo vision, radar, ultrasonic sensors, and crop-row perception. Recent studies have advanced from isolated perception modules toward tightly coupled localization, semantic mapping, trajectory tracking, and dynamic obstacle avoidance. Fusion strategies are becoming more adaptive and uncertainty-aware. However, field deployment still faces challenges in environmental robustness, sensor reliability, real-time computation, and perception–control integration. The review summarizes research progress in sensing foundations, calibration, synchronization, fusion architectures, autonomous navigation, obstacle detection, risk prediction, and local planning. The discussion emphasizes sensor characteristics, algorithmic robustness, agricultural scene complexity, and field-deployable autonomy.

Keywords: Agricultural machinery, Autonomous navigation, Multi-sensor fusion, Obstacle avoidance, LiDAR

1. Introduction

Agricultural mechanization is moving from operator-assisted automation toward field-deployable autonomy. Autonomous tractors, orchard sprayers, robotic weeders, harvest-assist platforms, and compact field robots are expected to perform navigation, implement control, obstacle avoidance, and task execution under variable soil, crop, and weather conditions. Navigation errors in these environments directly affect row following, spraying overlap, crop damage, safety distance, fuel consumption, and field efficiency. Recent reviews on agricultural automatic navigation describe the transition from satellite-guided steering toward integrated perception and intelligent control systems, with increasing emphasis on robustness in unstructured scenes [1, 2].

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DOI: 10.54254/2755-2721/2026.CH38707

Agricultural environments differ from structured roads and indoor robotics. Crop canopies generate GNSS multipath and signal attenuation. Tree rows and high-density crops introduce repetitive visual textures, partial occlusion, branch interference, and seasonal changes. Dust, fog, low-angle sunlight, shadows, mud, and vibration degrade camera and LiDAR measurements. Field surfaces are uneven and deformable, which changes vehicle attitude and wheel-ground interaction. Humans, animals, implements, pipes, stones, and other vehicles may appear unpredictably. These characteristics make single-sensor navigation unreliable and create a need for fusion systems that preserve perception and control when one modality becomes incomplete [3, 4].

Multi-sensor fusion combines complementary measurements across position, motion, geometry, appearance, and semantics. GNSS provides global positioning but fails near trees, terrain slopes, greenhouses, and dense canopy. Inertial measurement units and wheel encoders preserve short-term motion continuity but drift with time. LiDAR provides range geometry and row structure under weak illumination, whereas cameras provide texture, crop state, semantic categories, and color features. Radar and ultrasonic sensors can support obstacle detection under dust or poor lighting but provide coarser spatial information. Fusion methods seek to integrate these heterogeneous signals at data, feature, state, decision, or control levels [5, 6].

Recent research has moved from proof-of-concept autonomous navigation toward stable autonomy under field disturbances. Current systems increasingly combine localization, mapping, semantic perception, path planning, and trajectory tracking in a single navigation stack. Orchard-dosing robots, orchard weeding robots, under-canopy row-following robots, and collaborative harvesting robots demonstrate that multi-sensor fusion can improve operational continuity when GNSS, vision, or LiDAR alone is insufficient [7]. The following sections synthesize recent advances in multi-sensor fusion-driven agricultural navigation and obstacle avoidance, with attention to sensing foundations, calibration, fusion architectures, localization, mapping, planning, risk prediction, and deployment constraints.

2. Multi-sensor perception and fusion foundations for agricultural machinery

Autonomous agricultural machinery requires perception systems that can identify vehicle state, crop-row geometry, traversable space, obstacles, field boundaries, and implement-relevant features. The design of such systems begins with sensor selection, because each sensing modality provides a different physical measurement and a different failure mode. A deployable fusion system must consider nominal accuracy together with field robustness, mounting position, maintenance cost, computational load, environmental tolerance, and compatibility with agricultural implements.

2.1. Agricultural navigation sensors and environmental perception characteristics

GNSS remains the main source of global positioning for agricultural machinery because it supports large-scale path reproduction, georeferenced field operations, and connection with digital farm maps. Real-time kinematic correction can provide centimeter-level positioning in open fields, but the measurement quality decreases under canopy, near field margins, inside orchards, and during temporary signal interruption. BeiDou and GNSS integrated navigation systems for orchard spraying robots show that satellite navigation requires inertial and vehicle-state compensation to maintain usable pose estimates during agricultural operations.

LiDAR measures three-dimensional or two-dimensional geometry and is suitable for detecting crop rows, trunks, ridges, ditches, workers, implements, and obstacles with weak dependence on illumination. Its limitations include sensitivity to dust, rain, reflective surfaces, sparse returns from

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thin vegetation, and mounting-angle changes induced by vibration. Cameras provide dense appearance and semantic information for crop recognition, travelable-area segmentation, row extraction, and obstacle classification. Visual navigation studies in open fields and controlled environments show that cameras are powerful for crop and boundary interpretation, although performance depends on illumination, plant morphology, and training data distribution [3].

Inertial measurement units, wheel odometry, radar, ultrasonic sensors, and depth cameras complement satellite, vision, and LiDAR systems. Inertial sensors capture angular velocity and acceleration, making them essential for short-term state propagation and attitude compensation on uneven terrain. Wheel odometry provides local displacement but is affected by slip, soil deformation, and implement drag [8]. Radar can improve object detection under dust or poor visibility, whereas ultrasonic sensors are inexpensive but limited in range and angular resolution. Multi-sensor reviews show that agricultural navigation increasingly relies on redundancy rather than on any single high-performance device [9].

2.2. Multi-source sensor calibration, synchronization, and preprocessing

The reliability of multi-sensor fusion depends on accurate spatial calibration, temporal synchronization, and preprocessing. Extrinsic calibration determines the rigid transformation between the coordinate frames of cameras, LiDAR, inertial units, GNSS antennas, radar, and vehicle bodies. Intrinsic calibration corrects camera lens parameters and range-sensor characteristics. In agricultural machinery, calibration is complicated by vibration, mechanical deformation, attachment changes, and implement replacement. A sensor package calibrated in a workshop may show changed alignment after long-term operation in a field, so calibration stability needs to be treated as a deployment variable rather than a one-time laboratory step.

Temporal synchronization is equally important because navigation and avoidance decisions are made under motion. A camera frame, LiDAR scan, GNSS fix, and inertial update may represent different physical moments. When vehicle speed increases or terrain is uneven, millisecond-level offsets can produce spatial inconsistencies that appear as false obstacles, blurred rows, or unstable localization. Tightly coupled GNSS, LiDAR, and IMU approaches in orchard scenes illustrate the need to model measurement timing and uncertainty when fusing high-rate inertial propagation with lower-rate absolute or geometric observations [10].

Preprocessing transforms raw sensor streams into robust inputs for fusion. Camera images may require illumination correction, semantic segmentation, row-line extraction, or crop-background separation. LiDAR scans may require ground filtering, clustering, trunk detection, row feature extraction, and outlier removal. GNSS data need quality screening based on dilution of precision, satellite number, multipath indicators, and correction status. IMU and wheel odometry data require bias compensation and slip-aware filtering. A travelable-area boundary dataset for field robots reflects the growing recognition that robust preprocessing and annotated agricultural datasets are prerequisites for reliable visual navigation [11].

2.3. Multi-sensor information fusion architectures and methods

Fusion architectures can be arranged at several levels. Data-level fusion combines raw or nearly raw measurements, such as camera pixels and LiDAR points projected into a shared coordinate frame. Feature-level fusion integrates extracted row lines, trunks, obstacles, semantic masks, and geometric landmarks. State-level fusion estimates vehicle pose, velocity, attitude, and sensor bias through Kalman filtering, nonlinear observers, graph optimization, particle filtering, or factor graphs.

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Decision-level fusion combines independent detection or planning outputs to improve reliability under uncertain observations [10, 12].

State estimation for agricultural navigation commonly relies on extended Kalman filters, unscented Kalman filters, graph optimization, or tightly coupled observers. Extended Kalman filters remain attractive because they are computationally efficient and can integrate GNSS, IMU, wheel odometry, and LiDAR features on embedded hardware. Graph optimization offers stronger consistency when loop closure, landmark constraints, or semi-tight coupling are available. Semi-tight GNSS, LiDAR, vision, and IMU positioning has been used in GNSS-challenging environments, while embedded EKF-SLAM based on LiDAR, IMU, and GNSS fusion shows how similar estimation principles can be implemented on autonomous ground platforms [13].

A representative fusion architecture combines filtered IMU states, converted GPS coordinates, LiDAR scan matching, and learned motion prediction within a UKF estimator, as shown in Figure 1.

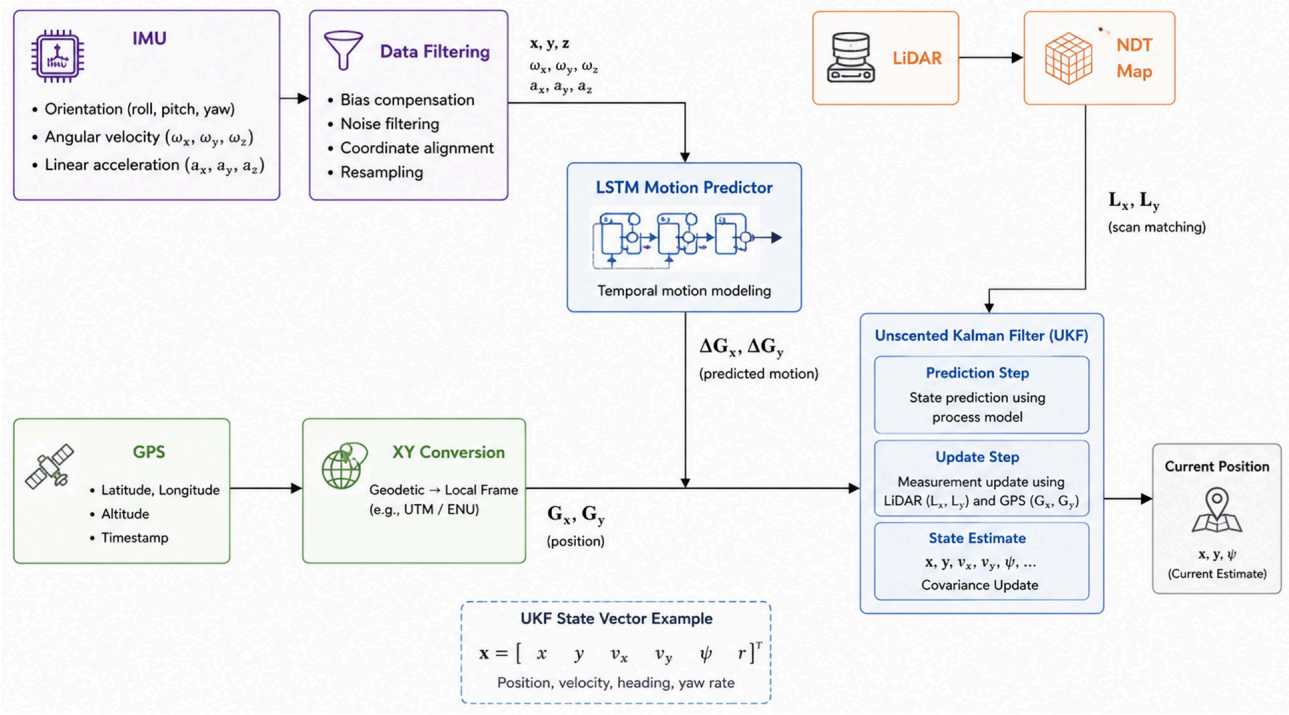

Figure 1. UKF-based integration of IMU, GPS, LiDAR, and learned motion prediction for position estimation [8]

Learning-based fusion has expanded because cameras and LiDAR produce high-dimensional data that can encode crop morphology and obstacle semantics. Deep networks support semantic segmentation, object detection, traversability estimation, and visual feature extraction. However, field deployment requires more than benchmark accuracy. Agricultural machines operate with limited onboard computation, changing light, seasonal growth, and safety constraints. Fusion models need uncertainty estimation, failure detection, and fallback behaviors. Reviews of sensor-fusion navigation and multi-sensor SLAM emphasize that reliability depends on sensor health assessment and adaptive weighting, not only on the selected algorithm class [14].

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3. Multi-sensor fusion-driven autonomous navigation of agricultural machinery

Autonomous navigation converts perception into continuous vehicle motion. In agricultural machinery, the navigation task may involve following crop rows, moving along preplanned coverage paths, traversing orchard corridors, executing headland turns, maintaining implement alignment, or coordinating with other machines. Multi-sensor fusion contributes by stabilizing pose estimation, extracting navigation features, maintaining maps, and supporting controllers that can tolerate terrain and sensing disturbances.

3.1. Multi-source fusion localization and pose estimation

Localization combines global position, local geometry, inertial propagation, and vehicle kinematics. Open-field tractors often begin from GNSS-based guidance, but row crops, orchards, and sheltered environments require additional perception. BDS/IMU integrated navigation for orchard spraying robots and LiDAR/IMU/GNSS navigation for orchard-dosing robots demonstrate how inertial data and range measurements can compensate for satellite degradation during orchard operations [15]. GNSS, LiDAR, and IMU fusion odometry based on a tightly coupled nonlinear observer further shows the value of directly incorporating geometric and inertial constraints in orchard localization [16].

LiDAR-IMU and GNSS-vision-IMU methods extend pose estimation from absolute positioning to motion continuity. LiDAR-IMU SLAM can estimate relative movement in tree rows or structured field scenes, while GNSS provides global correction when available. Camera features add semantic and geometric constraints but can fail under repetitive crop texture or changing illumination. Sensor weight balancing strategies for GNSS, vision, and IMU integration respond to this issue by adjusting the contribution of each modality according to measurement quality [17]. Such adaptive weighting is important in agricultural scenes because sensor reliability changes within a single operation.

Under-canopy row following provides a representative example of agricultural pose estimation. Compact agricultural robots may lose GNSS quality beneath crop leaves and stems, yet LiDAR rows can remain detectable. A robust row-following system based on LiDAR and IMU fusion used an extended Kalman filter and local goal generation to navigate real field conditions over long distances [5]. This type of architecture does not depend on a permanent global map, but uses local crop geometry to maintain motion in the row. The approach is suited to crop fields where the relevant navigation feature is near-field row structure rather than global localization alone.

3.2. Agricultural environment mapping and navigation feature extraction

Mapping in agricultural environments is task-specific. Unlike urban autonomous driving, field robots often need maps of rows, tree trunks, headlands, ridges, furrows, travelable boundaries, obstacles, and implement zones. LiDAR-based maps provide geometric structure, while visual maps provide semantic categories such as crop, weed, soil, obstacle, road, and boundary. Multi-sensor SLAM surveys indicate that camera, LiDAR, and IMU combinations can improve map stability by combining appearance, geometry, and motion constraints. Agricultural systems adapt these principles to vegetation-rich scenes where landmarks may be deformable, seasonal, or partially occluded.

Feature extraction must separate navigation-relevant structure from biological variability. In orchards, trunks and tree-row corridors can act as stable features, whereas leaves and branches are more variable. In field crops, row lines, canopy edges, and soil gaps can guide motion. Visual

DOI: 10.54254/2755-2721/2026.CH38707

navigation and obstacle avoidance using LiDAR and camera data has shown that geometric and visual cues can support both row alignment and obstacle handling [18]. LiDAR-IMU SLAM in orchards further indicates that stable geometric features can sustain navigation when visual texture is insufficient or lighting changes [19].

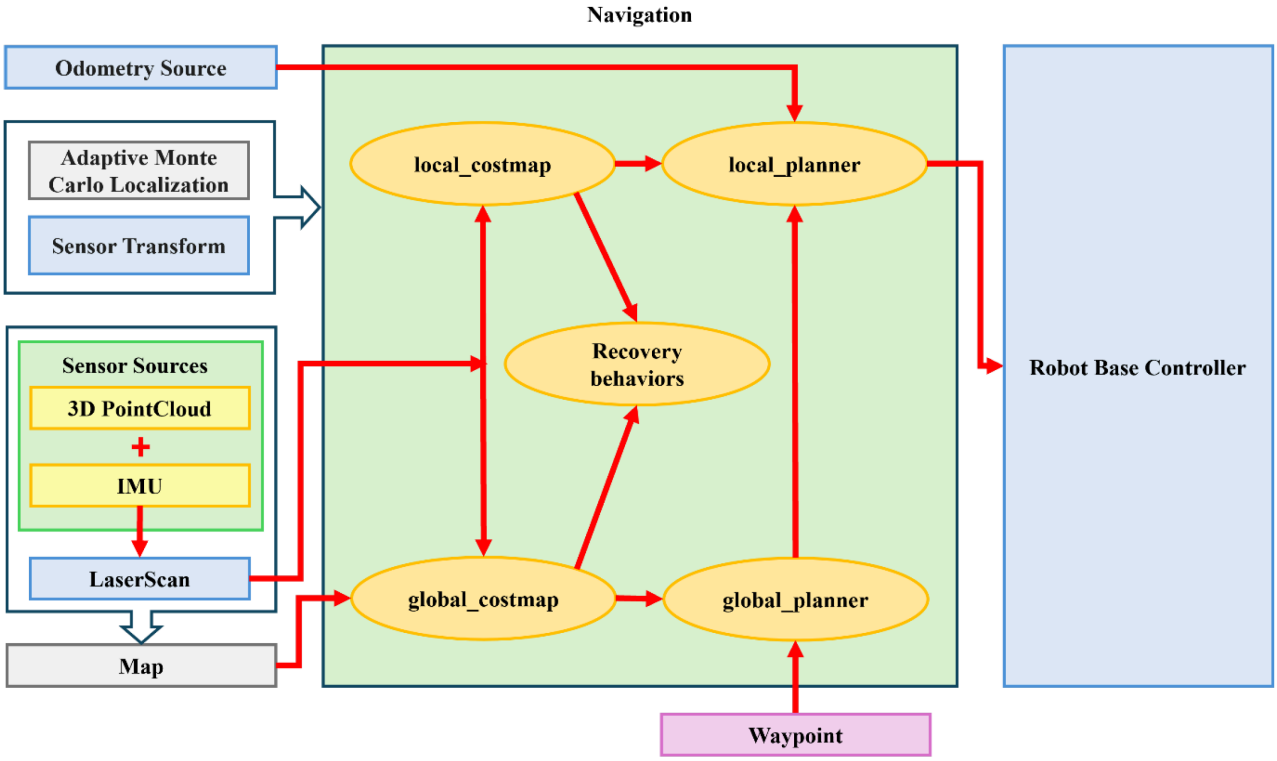

Figure 2. Integrated LiDAR-IMU navigation architecture linking sensing, mapping, planning, and robot control [19]

The corresponding navigation stack links LiDAR-IMU sensing and transformed scan data with localization, costmaps, global and local planning, recovery behavior, and robot-base control, as summarized in Figure 2.

Travelable-area extraction has become a core mapping task because agricultural robots need to distinguish navigable soil or corridor regions from crops and hazards. Boundary datasets for field robots support supervised learning and evaluation of visual navigation methods [11]. However, map reliability depends on sensor viewpoint and crop growth stage. A model trained on one crop, season, or camera height may transfer poorly to another condition. Multi-sensor fusion mitigates this limitation by allowing semantic segmentation to be checked against LiDAR geometry, inertial motion, and prior field structure.

3.3. Perception fusion-supported path planning and trajectory control

Path planning in agriculture includes global route generation, coverage planning, headland turning, row-to-row transition, and local path adjustment. Trajectory tracking then converts the path into steering, speed, and implement-control commands. Recent reviews describe the use of A*, rapidly exploring random trees, model predictive control, pure pursuit, Stanley control, dynamic window approaches, and deep reinforcement learning in agricultural robots and mobile robots [20]. The

DOI: 10.54254/2755-2721/2026.CH38707

selection of a planner depends on whether the environment is structured, whether obstacles are static or dynamic, and whether the robot must maintain crop-row alignment.

Fusion perception improves path planning by providing more stable environmental constraints. GNSS-based field boundaries can define global coverage paths, LiDAR can identify row geometry or obstacles, cameras can detect crop damage risks, and IMU data can support safe speed limits on slopes or uneven terrain. Map-constrained LiDAR-IMU localization with segmented tracking control for orchard robots illustrates the integration of localization and control under orchard constraints [21]. In such systems, a controller does not simply follow a geometric line, but adjusts vehicle motion according to localization confidence, corridor boundaries, and task-specific constraints.

Trajectory control for agricultural machinery must account for vehicle dynamics, low-speed steering behavior, soil-wheel interaction, slip, implement load, and actuator delay. A planner that is effective in simulation may produce unstable steering in a muddy field or during headland turns. Multi-sensor fusion can reduce this gap by feeding controllers with more reliable lateral deviation, heading error, velocity, and obstacle distance. Collaborative harvesting robots add another layer because inter-row following must maintain spacing and coordination among machines. This requires fusion architectures that support both individual navigation and cooperative operation.

4. Multi-sensor fusion-driven intelligent obstacle avoidance for agricultural machinery

Obstacle avoidance is a safety-critical extension of autonomous navigation. Agricultural obstacles include humans, animals, vehicles, irrigation equipment, stones, tree branches, posts, ditches, crop clusters, field margins, and temporary implements. Some obstacles are static, while others move unpredictably or appear suddenly from occluded regions. Multi-sensor fusion supports obstacle avoidance by improving detection, classification, state estimation, risk prediction, and local replanning.

4.1. Fused obstacle perception and recognition in complex agricultural scenes

Obstacle perception begins with detecting objects and separating them from crop or terrain structures. LiDAR provides direct range measurements and can identify obstacle geometry even when color contrast is weak. Cameras provide object categories and visual context, allowing the system to distinguish humans, vehicles, animals, crops, and implements. Radar and ultrasonic sensors can provide redundancy when dust, fog, or strong illumination affects optical sensors. Obstacle detection and tracking for intelligent agricultural machinery shows that tracking is inseparable from detection because machinery safety depends on object continuity and motion state rather than on isolated frames [22].

LiDAR-camera fusion is widely used because the two modalities compensate for different weaknesses. Camera-based semantic detection may misclassify objects under illumination variation, whereas LiDAR may have difficulty interpreting thin vegetation or object identity. Projecting LiDAR points into images or associating image detections with point clusters allows systems to combine category and distance information. Visual navigation and obstacle avoidance control for agricultural robots via LiDAR and camera demonstrates how fused perception can support both navigation and obstacle response in agricultural environments [6]. Augmented perception work in agricultural robot navigation also shows the importance of multi-modal ambient awareness for safe field operation.

DOI: 10.54254/2755-2721/2026.CH38707

Recognition performance must be evaluated in agricultural operating conditions rather than only in controlled datasets. Shadows, moving leaves, crop residues, and irregular terrain can produce false positives. Dense vegetation may hide workers or animals. A conservative obstacle detector can stop frequently and reduce efficiency, while an aggressive detector can endanger workers or damage crops. Multi-sensor fusion needs confidence estimation and context-aware thresholds. Reviews of obstacle avoidance for autonomous agricultural machinery identify perception reliability, real-time computation, and generalization across operations as major constraints for field deployment.

4.2. Dynamic obstacle state estimation and risk prediction

Dynamic obstacle avoidance requires estimating position, velocity, heading, acceleration, and predicted trajectory of moving objects. In agricultural scenes, dynamic obstacles may include workers crossing rows, nearby tractors, livestock, and moving implements. State estimation can use Kalman filters, interacting multiple-model filters, Bayesian tracking, optical flow, LiDAR clustering, and learning-based prediction. The challenge is that observations are intermittent and may be partially occluded by crops or machinery structures. Fusion tracking reduces uncertainty by combining range, visual category, inertial ego-motion, and temporal continuity.

Risk prediction links obstacle state to vehicle motion and task context. The same object may require different responses depending on distance, relative speed, crop-row width, vehicle mass, implement type, and available escape space. Agricultural robots also operate near high-value crops, so a safe evasive maneuver must avoid both collision and crop damage. Global navigation data, local LiDAR scans, semantic camera detections, and vehicle dynamics need joint evaluation. General sensor-fusion navigation studies emphasize uncertainty-aware fusion, and this principle is directly applicable to agricultural risk assessment because sensor confidence changes with canopy density, vibration, and lighting.

Prediction is further complicated by limited communication and computational resources. Field machines may not have stable cloud connectivity, so risk assessment must run onboard with bounded latency. The algorithm must decide when to slow down, stop, yield, steer around an obstacle, or request human supervision. These decisions require calibrated uncertainty rather than only object labels. Multi-sensor fusion provides a basis for estimating time-to-collision, lateral clearance, stopping distance, and feasible avoidance corridors, but the output must be compatible with the machine controller and safety policy.

4.3. Fusion perception-driven local planning and dynamic obstacle avoidance

Local planning converts fused perception into collision-free motion under real-time constraints. Dynamic window approaches, velocity obstacles, model predictive control, A*, DWA fusion, and reinforcement learning have been applied to mobile robot avoidance and are increasingly adapted for agricultural machinery [23]. A* and DWA fusion improves the relationship between global path search and local velocity selection, while model predictive control can include vehicle dynamics and constraints. In agricultural settings, local planning must also preserve row alignment and avoid damaging crops, so a geometrically shortest path is not necessarily an acceptable path.

A complete obstacle-avoidance loop therefore connects fused data acquisition and preprocessing with target recognition, false-target rejection, and maneuver execution, as illustrated in Figure 3.

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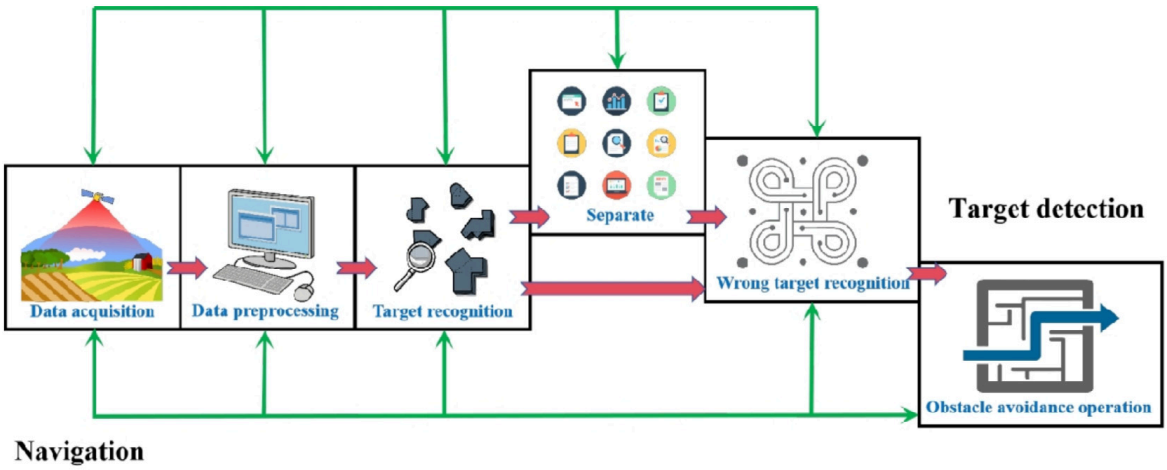

Figure 3. Perception-to-action workflow for agricultural machinery obstacle avoidance [4]

Dynamic obstacle avoidance for agricultural machinery increasingly combines learning-based decision making with classical planning. Deep reinforcement learning can learn policies for complex interaction, while DWA and model predictive methods provide interpretable constraints and local feasibility. Agricultural machinery cannot rely only on a learned policy because safety certification, rare-event behavior, and domain shift remain difficult. A practical strategy is to use learning for perception or high-level behavior selection while retaining deterministic constraints for speed limits, collision envelopes, stopping distances, and emergency braking.

Field deployment requires coordination between obstacle avoidance and task execution. An orchard sprayer may need to pause spraying while avoiding a worker. A weeding robot may need to preserve tool alignment after a detour. A harvester may need to coordinate with transport vehicles and maintain safe inter-machine spacing. Multimodal navigation frameworks for orchard weeding robots and fusion-based inter-row following systems for collaborative harvesting show that avoidance cannot be separated from the agricultural operation itself.

5. Challenges and outlook

Multi-sensor fusion has improved agricultural machinery navigation and obstacle avoidance, but several challenges still restrict broad deployment. The first challenge is scene variability. Crops change with variety, growth stage, pruning state, disease, planting density, and seasonal management. Soil texture, moisture, residue, and slope change the appearance and traversability of the field. Algorithms trained or calibrated in one location may lose accuracy elsewhere. More open datasets, cross-season validation, and benchmark protocols are needed to evaluate whether a method is robust beyond the conditions used for development.

The second challenge is reliable calibration and sensor health monitoring. Agricultural machines experience vibration, impact, dust accumulation, mud, moisture, and thermal variation. These conditions can gradually change camera focus, LiDAR alignment, GNSS antenna geometry, IMU bias, or wheel encoder reliability. Fusion systems should estimate sensor quality online, adjust weights, and trigger maintenance or fallback modes when measurements become unreliable. Robust fusion will depend on diagnosis of sensor degradation as much as on nominal fusion accuracy.

The third challenge is the integration of perception with control and safety. Accurate obstacle detection does not guarantee safe avoidance if the planner ignores braking distance, actuator delay, crop damage risk, or implement state. Similarly, precise localization may not improve operation if

DOI: 10.54254/2755-2721/2026.CH38707

the controller cannot tolerate slip or terrain-induced roll and pitch. Future research should connect perception uncertainty with control constraints, risk prediction, and agricultural task requirements.

The fourth challenge is standardization and scalability. Different manufacturers and research groups use different sensor suites, coordinate frames, datasets, test fields, and performance metrics. Reported accuracy is often difficult to compare because experiments differ in terrain, crop density, speed, weather, and obstacle definitions. A more mature field will require shared evaluation scenarios, repeatable field trials, and metrics that include navigation error, intervention distance, detection latency, false-stop rate, crop damage, energy cost, and operator workload.

Future agricultural autonomy is likely to combine GNSS, inertial sensing, LiDAR, vision, radar, semantic mapping, adaptive fusion, and constrained local planning. The most useful systems will not maximize sensor number, but will select complementary modalities that match the crop, machine, task, and safety requirement. Progress will depend on robust calibration, uncertainty-aware fusion, field-scale datasets, embedded computation, and closer coupling between perception and agronomic operation. Under these conditions, multi-sensor fusion can support agricultural machinery that navigates accurately, avoids obstacles intelligently, and maintains productivity in complex field environments.

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