

Review

Recent Advances in Path-Tracking and Motion Control for Autonomous Tractor–Trailer Systems

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Abstract

The path-tracking and motion control of autonomous tractor–trailer systems (TTSs) in unstructured off-road environments have become important research topics of intelligent equipment. Traditional control architectures face challenges due to multiple physical constraints such as time-varying soil rheology, time-varying wheel slip, multi-body nonlinear coupling, and vehicle stability constraints. This review provides an overview of advanced control technologies for autonomous TTSs in off-road environments. First, this review analyzes multi-source sensors and joint state estimation frameworks for time-varying terrain classification, all-wheel slip ratio estimation, and articulation angle. Secondly, nonholonomic kinematic, multi-body three-dimensional spatial dynamic, and tire–soil interaction mechanic models are deconstructed for on-axle and off-axle hitching configurations. On this basis, adaptive kinematic control, model predictive control (MPC), robust disturbance rejection, and distributed electric-drive control strategies are compared horizontally, and the application of active trailer steering, torque vectoring, and implemented chassis cooperative control in active safety is elaborated. Finally, emerging research directions, including online tire–soil interaction learning, embodied AI foundation models, and V2X-enabled multi-vehicle cooperative platooning, are discussed to provide insights into the development of next-generation fully autonomous off-road tractor–trailer systems.

Keywords: tractor–trailer system; path tracking; time-varying slip; tire–soil mechanics interaction; active safety control



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1. Introduction

1.1. Background and Motivation

Driven by multiple macro-environmental pressures such as sustained global population growth, increasingly scarce arable land resources, intensified climate change, and severe rural labor shortages, traditional bulk agriculture and logistics transportation models are facing unprecedented transformation challenges. In order to achieve efficient leaps in grain production under limited resources and reduce greenhouse gas and particulate matter pollution emissions, intelligent precision agriculture and unmanned off-road transportation systems based on new generation information technology have become an irreversible development trend. Among them, the evolution of heavy-duty diesel machinery towards hybrid or pure electric, fuel cell-based architectures with high flexibility, fast dynamic response, low or even zero emissions constitutes the core hardware foundation support for green and sustainable development [1–3].

Tractor–trailer systems (TTSs) are widely used in the entire process of agricultural operations such as sowing, fertilization, crop protection, harvesting, and unstructured road transportation scenarios due to their high load transport capacity, modular tool adaptability, and narrow space mobility advantages [4]. However, TTSs belong to a typical nonholonomic, underactuated, strongly coupled nonlinear multi-body system. In complex off-road scenarios such as wet rice fields, soft dry land, and hilly mountains, their operational accuracy and stability are highly dependent on the comprehensive performance of path-tracking and motion control systems [5,6]. Therefore, in-depth research on advanced path-tracking and dynamic control technology of TTSs in harsh off-road environments has important academic value and engineering significance for breaking through the bottleneck of fully autonomous landing of intelligent agricultural machinery and promoting the industrial application of precision agriculture.

1.2. Key Challenges in Off-Road Environments

Compared with structured road environments, unstructured off-road farmland and mountainous terrains are subject to complex and coupled physical disturbances, which often lead to trajectory instability and large tracking errors in conventional vehicle control systems. The core challenges focus on three aspects: soil–tire dynamic interaction, time-varying slip disturbance, and multi-body dynamic coupling.

Off-road terrain typically consists of heterogeneous, deformable, and viscoelastic soil. The repeated passage and traction operations of heavy agricultural machinery can damage the soil structure and cause persistent and spatial soil compaction problems [7–9]. Soil compaction deteriorates crop growth conditions and alters soil moisture and mechanical properties, including compressibility and shear resistance [10].

Undulating, slippery, and saline–alkali soils significantly reduce tire–ground adhesion limits. Variations in soil moisture and abrupt changes in workload induce highly nonlinear and time-varying behavior in wheel longitudinal slip ratio and lateral slip angle [11]. High-frequency slip dynamics may degrade the performance of conventional speed control algorithms, leading to chassis oscillations, inter-wheel drag, and tracking errors [12]. A TTS is a multi-degree-of-freedom coupled dynamic system that connects the tractor unit and trailer equipment through an articulated structure [13]. Frequent turning, slope operations, and road bumps in off-road scenarios can induce trailer sway and dynamic load transfer at hinge points. These effects generate unmodeled disturbance torques, which may lead to rollover and jackknifing instability, posing serious safety risks [14].

1.3. The Scope and Contributions of the Review

Extensive research has been conducted in both academia and industry on multi-source perception, state estimation, dynamic modeling, trajectory planning, and active safety control for off-road autonomous vehicles. Existing reviews mainly focus on the dynamics of highway vehicles, navigation of single unmanned tractors, or pan smart agriculture technologies. There is relatively little research specifically on the coordinated evolution of multi-body underactuated strong coupling TTSs, unstructured off-road extreme conditions, and path-tracking multi-axis collaborative control.

The main contributions of this review are summarized as follows.

- (1) A comprehensive multi-sensor perception architecture for off-road TTSs is presented, focusing on GNSS-denied and highly dynamic environments and reviewing EKF/UKF-based and data-driven state estimation methods.
- (2) The evolution of TTS modeling approaches is analyzed, from kinematic representations to high-fidelity nonlinear dynamic models incorporating brush and discrete element methods.

- (3) A unified taxonomy of path-tracking control strategies is proposed, categorizing existing methods into adaptive control, predictive optimization, robust control, and learning-based approaches.
- (4) Active safety technologies such as trailer steering and differential braking are reviewed, with emphasis on practical implementation constraints including computation delay, actuator latency, and communication constraints.

To facilitate a comprehensive understanding of this review, Figure 1 illustrates the overall technical framework covering data perception, state estimation, system modeling, control strategies, active safety execution, and prospective research directions.

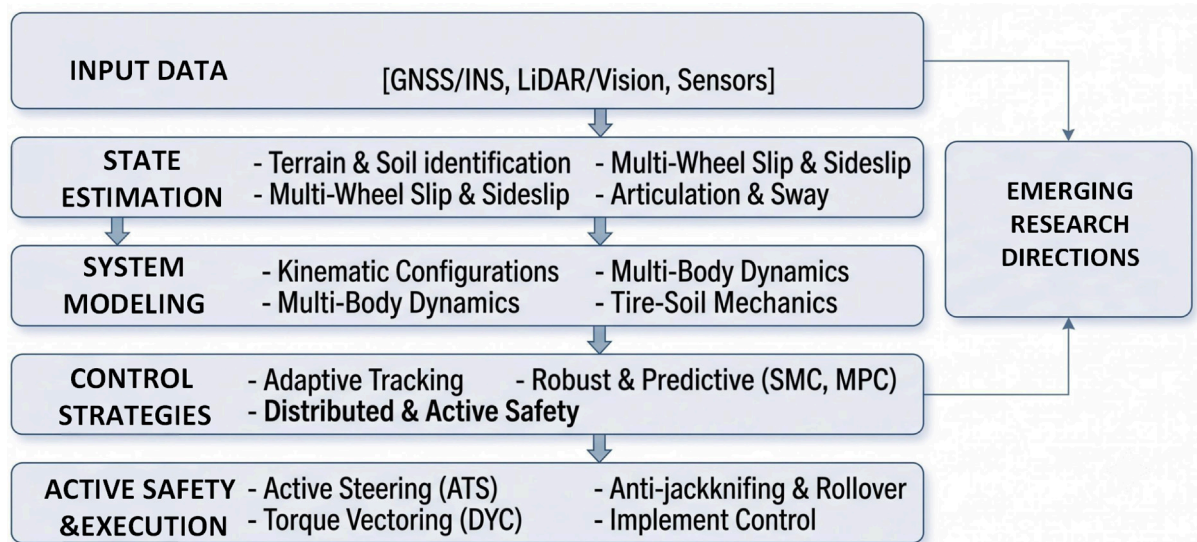


Figure 1. Framework for path-tracking and motion control of autonomous tractor-trailer systems.

2. Hardware Architecture and Multi-Source State Estimation of Intelligent TTSs

2.1. Multi-Source Sensor Architecture for Autonomous TTS Perception

In unstructured off-road agricultural environments, high redundancy, noise resistance, and all-weather perception architecture are important foundations for achieving accurate state estimation and safe control of autonomous TTSs. Existing systems typically rely on RTK-GNSS/INS integrated navigation systems to achieve a high-precision position and attitude estimation [15,16]. However, in complex environments such as forests, orchards, and greenhouses, the continuity of GNSS signals is easily affected due to factors such as crop canopy obstruction, multipath effects, and signal attenuation, leading to a decrease in positioning accuracy.

To solve the problem of reduced positioning accuracy in GNSS-denied or weak-GNSS environments, heterogeneous sensors such as 3D LiDAR, monocular/stereo vision, multispectral imaging, and millimeter-wave radar are widely used in TTS perception systems [17,18]. Among them, the fusion method of stereo vision and multispectral vision can utilize the texture differences between crop rows, vegetation canopies, and sky backgrounds to extract navigation reference features with strong resistance to illumination interference, achieving high-precision feedback of local relative poses [19,20].

Compared with traditional image processing methods, YOLO (You Only Look Once) series object detection algorithms can simultaneously perform object localization and category classification and are therefore widely used in tasks such as obstacle detection, target recognition, and crop row detection in agricultural equipment. However, traditional YOLO models still suffer from limited feature extraction capabilities in complex agricultural envi-

ronments, including significant illumination variations, complex vegetation backgrounds, and challenges in small-object obstacle detection. In response to these issues, researchers have optimized the YOLO architecture in recent years by introducing attention mechanisms and lightweight feature extraction modules. For example, the YOLOv8 model improved by integrating the Convolutional Block Attention Module (CBAM), Bidirectional Feature Pyramid Network (BiFPN), and Ghost lightweight convolution module, which enhances feature representation capabilities in complex scenarios while reducing computational redundancy and model complexity. This type of improvement can more accurately distinguish actual obstacles, such as tree trunks and pedestrians, from background interference objects, such as weeds and hanging branches, thereby reducing false detection and unnecessary obstacle avoidance behaviors and improving the perception robustness and stability of intelligent agricultural machinery in complex off-road environments [21,22].

In addition, traditional encoders and linkage-type sensing mechanisms are susceptible to the effects of field mud, vibration, and load impact, leading to frequent mechanical failures such as blockages, deformations, and line failures. The existing research adopts non-contact attitude sensors, multi-field cameras, and embedded intelligent in-tire sensors to real-time collect tire sidewall strain, tire body displacement, and ground vibration signal data, avoiding complex environmental interference on the ground and enabling accurate perception of rapidly varying wheel angles and chassis vibrations [23–26]. The multi-scale correlation established through specific designed test matrices (such as indoor bumpy simulation tables and outdoor irregular wheat ridges) with multiple physical quantity sensor inputs provides reliable real-time information for subsequent active adjustment of the whole machine's sowing depth or high-dynamic chassis balance calibration [27].

2.2. Off-Road Environment Terrain Perception and Soil–Vehicle Interaction Parameter Identification

When an autonomous tractor operates continuously on deep and deformable soil, the maximum friction force, allowable shear stress, and downward shear resistance between its tires and the surface are determined by the physical and mechanical state of the soil itself, such as shear stiffness, cohesion, internal friction angle, and volume compression coefficient. The traditional offline static table lookup or fixed parameter control schemes are unable to adapt to the spatially heterogeneous and rapidly changing unstructured soil environment and are prone to causing severe instability and hanging of the driving wheel or serious waste of power in sudden soft collapse areas [28]. The implementation of high-frequency real-time terrain classification and soil-dynamic parameter identification has become an important foundation for the adaptive tuning of modern TTS motion control algorithms.

At present, mainstream technologies mainly rely on vehicle state perception signals and multi-sensor fusion frameworks to achieve terrain recognition. Taking pure electric or distributed independent drive intelligent tractors as an example, their four-wheel drive motors can directly output high-precision dynamic-driving current and speed feedback. Researchers extracted features at the feature level from the three-dimensional high-frequency vibration response signals integrated on the vehicle's center of mass and steering axle bracket, including wheel output torque, wheel angular velocity, real-time wheel longitudinal slip characteristics, and others. After filtering using a Savitzky–Golay filter and signal segmentation, these features are fed into embedded processors or edge computing platforms, where lightweight machine learning models, including K-fold cross-validation-optimized Random Forest (RF) models and support vector machines (SVMs), are employed for real-time inference [29]. This method achieves millisecond-level terrain classification, accurately identifies working conditions such as hardened road surfaces, dry land, water-logged paddy fields, and potholed terrain, and dynamically calibrates the optimal soil slip limit zone.

To further improve control robustness in strongly nonlinear and time-varying environments, sliding mode observers and dynamic compensation theory have gradually been integrated into terrain parameter estimation methods [30,31]. The system designs a parameter estimation module based on the analytical model of tire–soil continuous interaction, based on the instantaneous load transfer and pitch attitude of the forward vehicle. By continuously capturing the marginal variation of the instantaneous longitudinal driving force of the chassis, the macroscopic mechanical characteristics of the currently deformable soil can be identified in reverse. This achievement not only provides accurate prior physical quantities for adaptive time-domain predictive decision-making and control time-domain span parameter updates in upper-level path-tracking control systems but also establishes a reliable mechanism basis for intelligent chassis active control systems to execute optimal driving torque allocation in advance.

2.3. Vehicle Motion State Estimation in Unstructured Environments

The severe longitudinal sliding caused by soft soil ground as well as the lateral sliding generated by large traction loads and long slope operations are important physical disturbance sources that affect the accuracy of autonomous TTS path tracking. If slip and lateral deviation cannot be accurately identified and actively compensated for, the upper-level path tracker will not be able to perceive the actual drift trend of the vehicle, resulting in serious trajectory divergence. It is crucial to implement low-cost and highly reliable real-time estimation of the longitudinal slip rate and sideslip angle of all-wheels based on low-level perception data without expensive professional deviation measurement equipment [32].

At present, the estimation of longitudinal slip ratios usually adopts the method of matching the difference between vehicle speed and the output speed of the four-wheel hub [33]. In pure electric all-wheel independent drive (4WID) or intelligent agricultural machinery equipped with an independent E-axle system, the current instantaneous phase current, actual voltage, battery state of charge (SOC), and high-frequency wheel angular velocity feedback of each motor inverter can be accurately read through the on-board CAN bus. By comparing the theoretical velocity derived from four-wheel kinematics and the geometric relationship of the entire vehicle with the real ground travel line velocity output from high-precision differential satellite RTK-GNSS at high speeds, the local slip rates of each discrete wheel can be independently calculated in real time [34]. By relying on low-cost IMU attitude units, a precise characterization of slip timing evolution characteristics under different field conditions can be further achieved, which is suitable for complex field operation scenarios [35].

Traditional linear models or empirical regression methods are prone to insufficient generalization ability in complex operating conditions, especially in strongly coupled sideslip angle estimation. In recent years, research has utilized machine learning methods such as BP neural networks and scale decomposition to spatially and temporally fuse crop boundary information obtained from visual perception with dynamic parameters such as vehicle longitudinal and lateral acceleration [36], predict chassis friction boundaries under low-adhesion conditions, and use lateral drift trends as control compensation inputs to improve path-tracking stability.

2.4. Articulation Angle and Trailer Sway Identification

As a typical nonlinear multi-body connection system, the essential increase in control complexity of a TTS lies in the physical connection between the trailer body and the tractor front unit through a single or multi-degree-of-freedom articulated shaft (hitch point). Rear passive trailers (or multiple implements) not only exhibit severe nonholonomic

underactuated trajectory lag on unstructured off-road surfaces but also pose unpredictable risks of trailer sway and even jackknifing when the tires undergo soft deformation, when one side encounters potholes, or during high load violent oscillations. If it is not possible to obtain the articulation angle and its time-domain derivative (i.e., the differential yaw rate between the two bodies) with high frequency and accuracy, then centimeter-level control and anti-instability adjustment of the trailer's travel trajectory cannot be discussed [37].

The currently commonly used state recognition scheme is to install solid angle sensors at the hinge points where two vehicles are connected or to use non-contact visual/LiDAR pose estimation hardware. In order to overcome measuring instantaneous distortions caused by high-frequency bumps and dust pollution obstruction in harsh off-road scenarios, researchers often integrate high-dynamic angular velocity sensors and lateral/longitudinal acceleration measurement units on the main chassis of modern agricultural tractors [38]. To reduce the sensing cost at the end of the trailer, promising technology adopts a sensorless estimation mechanism. Based on the tractor yaw state and vehicle velocity, a dynamic gain matrix is constructed to deduce the motion evolution of the trailer center of mass, reconstruct the dynamic force moment of the hinge point, and achieve passive identification of the trailer state online [39].

When facing extremely harsh saline-alkali wastelands or steep and uneven hills and mountains, the underactuated and strong nonlinear dynamic characteristics of the system will be further amplified [40]. Recent control theories typically construct dual trajectory collaborative prediction models to deconstruct the instantaneous spatial pose evolution of passive trailers under multidimensional non-uniform lateral sliding, longitudinal nonlinear tilting, and soil sliding resistance constraints. This method utilizes time series parameter estimation to dynamically transform complex vehicle body connection deviations into continuous variables defined by safety state machine boundaries. It can real-time identify and capture the amplitude and frequency upper limit of trailer swing, thereby outputting compensation constraints with predictive characteristics for the vehicle stability control system in the precursor stage of trailer over-limit swing or irreversible folding.

2.5. Multi-Source Data Fusion and State Estimation Methods

The TTS operation process in unstructured environments is affected by factors such as soil non-uniformity, wind disturbance, asynchronous sensors, and straw slip, resulting in significant nonlinear and non-Gaussian noise. Traditional observer-based methods are difficult to ensure convergence of state estimation. Therefore, Bayesian estimation frameworks represented by the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) have become the current mainstream state fusion methods [41,42].

In actual autonomous TTSs, raw measurement values collected from multiple sensors (including RTK-GNSS/INS, LiDAR, wheel speed sensors, and chassis state sensors) are typically preprocessed, coordinate-transformed, and time-synchronized before being integrated into the state estimation module. Then, the preprocessed measurement values are fused with the prediction model using the Kalman filtering framework. In this process, the prediction step estimates the vehicle state based on a dynamic model, while the measurement update step corrects the predicted state using multi-source sensor observations. Therefore, Kalman filtering provides a mathematical framework for combining heterogeneous sensor information and improving the reliability of vehicle state estimation under noise and uncertain off-road conditions. In response to the time-varying tire-soil interaction and the problem of divergence in traditional Kalman filtering under stiffness saturation conditions, improved algorithms such as the Adaptive Unscented Kalman Filter (DAUKF) and Strong Tracking Adaptive Unscented Kalman Filter (ASTUKF) have been proposed [43]. These improved methods dynamically adjust estimation parameters based

on measurement residuals and system uncertainty, achieving a reduction in the impact of time-varying noise and model mismatch. This type of method adjusts the residual covariance through dynamic attenuation factors and time-varying gain matrices, avoiding estimation bias caused by static noise assumptions and achieving the accurate estimation of vehicle motion state, soil slip resistance, and inter-axle load transfer. The overall hardware input framework of multi-source sensors is illustrated in Figure 2.

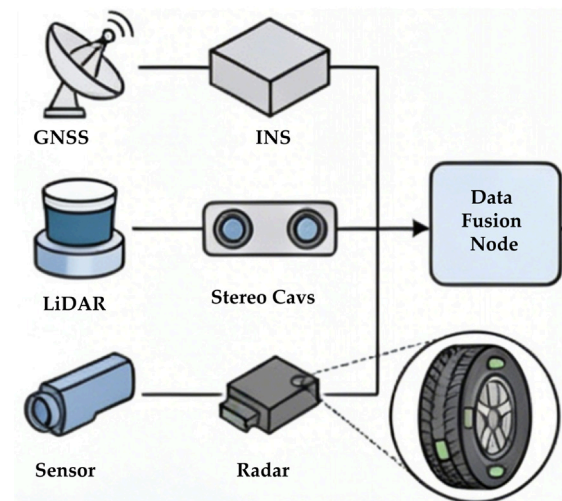


Figure 2. Raw hardware input layer of multi-source sensors.

To avoid the accuracy loss caused by the linearization of tire models, a hybrid estimation paradigm combining nonlinear filtering and lightweight neural networks has become a research frontier [44]. The bottom layer dual extended Kalman filter (DEKF) outputs the basic state and initial tire stiffness, while the upper layer adaptive radial basis function neural network (ARBFNN) takes the tracking error and heading angle deviation as inputs to fit unmodeled nonlinear terms such as soil rheology and tire–soil friction online, dynamically reconstructing steering resistance and variable stiffness parameters [45]. This dual-layer architecture provides an additional compensation mechanism for nonlinear uncertainties that traditional filtering methods cannot fully capture, thereby improving the adaptability of state estimation in complex off-road conditions.

3. Kinematic and Dynamic Modeling of Tractor–Trailer Systems

3.1. Nonholonomic Kinematic Models

3.1.1. Effects of Hitching Configurations on System Kinematics

The development of a path-tracking controller begins with a path-tracking control algorithm for the autonomous TTS, which is used to establish a nonholonomic kinematic model that can accurately describe the pose evolution under the geometric constraints between multiple bodies and the assumption of pure rolling without slip. In the traditional kinematic derivation, the topology of the system is largely determined by the physical placement of the hinge points. According to the geometric relative position of the hinge point with respect to the central axis of the rear axle of the forward tractor drive, it can be divided into two distinct classical kinematic configurations.

The kinematic configuration of on-axle hitching is that the hinge point coincides with the center of the tractor's rear drive shaft, and the tractor's lateral motion does not produce additional lateral translational components. The trailer's yaw motion exhibits first-order linear follow-up characteristics, with simple kinematic coupling and strong controllability [46]. The kinematic configuration of off-axle hitching is that there is a fixed offset distance between the hinge point and the rear axle, which is a universal

configuration for agricultural three-point suspension. When the tractor turns, the hinge point will generate lateral displacement coupled by angular velocity and offset length, causing strong nonlinear differential coupling of the system. This coupling may result in overshoot and increased deviation of the trailer trajectory, increasing the difficulty of control calculation [47]. The tractor–trailer hitching configurations are shown in Figure 3.

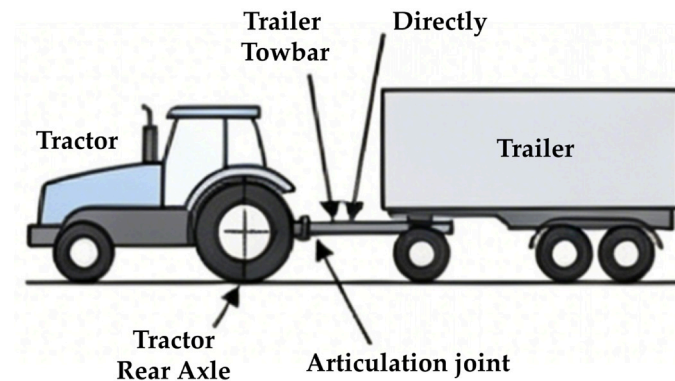


Figure 3. Axial hanging configuration.

3.1.2. Expansion of Generalized Kinematic Model for Multi-Segment Trailers

In the scenario of multiple machines and trailers, the system can be extended to a generalized N-trailer (GNT) kinematic model [48,49]. The multi-body system has serious underactuated characteristics. Relying solely on the tractor's single-end actuator to achieve vehicle control is prone to the problem of trajectory errors, accumulating step by step. Traditional single-point forward control and kinematic inversion algorithms are prone to failure due to nonlinear singularities in situations of sudden turns and reverse trajectory tracking on the ground [50,51]. Therefore, building a universal dynamic model that is adaptable to multi-link structures and that can compensate for curvature deviations is the foundation for achieving autonomous control in all scenarios [52,53].

3.2. Nonlinear Multi-Body Dynamic Models

3.2.1. Core Modeling Theory System of Multi-Body Dynamics

The pure kinematic model is only applicable to ideal working conditions of low speed, no slip, and high adhesion. In off-road scenarios such as high-speed driving and deep plowing with heavy loads, dynamic characteristics such as center-of-mass inertia, load transfer, and soil reaction force dominate. Pure kinematic models may exhibit serious prediction biases [54]. Therefore, constructing a high-fidelity multi-body nonlinear dynamic model is the core prerequisite for the development of high-performance off-road controllers.

State-of-the-art modeling methodologies frequently adopt the Lagrangian formalism or multi-body dynamic analytical theory (such as combining d'Alembert's principle and position rotation homogeneous matrix spatial transformation). These methods derive highly nonlinear spatial coupled dynamic equations with multiple degrees of freedom, including tractor longitudinal lateral yaw, trailer relative articulation motion, and vehicle roll and pitch [55,56]. In these advanced multi-body large dynamic architectures, the strong nonlinear mechanical dynamic interactions in the following three dimensions are mainly deconstructed.

3.2.2. Nonlinear Characteristics of Vehicle Vibration Transmission and Load Interaction

The random convex excitation on off-road roads can cause coupled pitch and vertical vibrations of the entire vehicle, and traditional Gaussian road models cannot adapt to the real non-stationary terrain impact characteristics [57,58]. The refined multi-rigid body vibration model can quantify the impact of road surface disturbances on steering limits

and tire ground contact loads, providing a mechanical basis for chassis stability control and anti-rollover control [59,60]. By combining real load spectrum compilation techniques, we can further break through the bottleneck of modeling input distortion and improve model fidelity [61]. In heavy-duty operations such as plowing and rotary tillage, the sudden periodic resistance generated by the cutting of soil by the machinery can cause dynamic displacement of the vehicle's center of gravity and nonlinear redistribution of axle loads through the suspension link [62,63], leading to sudden changes in tire adhesion limits, inducing trajectory oscillation and axle drag, and seriously deteriorating path-tracking accuracy. Under extreme working conditions such as hilly slopes and soft soil subsidence, the three-dimensional posture of the vehicle undergoes drastic changes. The model requires coupling of multiple boundary constraints such as soil pushing resistance, subsidence resistance, and lateral gravity slip components. Based on the joint simulation platform of RecurDyn (FunctionBay, Seongnam-si, Republic of Korea) and MATLAB (MathWorks, Natick, MA, USA), the stable envelope domain of multi-body systems can be accurately solved, providing dynamic constraint boundaries for controllers [64–66].

3.3. *Tire–Soil Interaction and Terramechanic Characterization*

3.3.1. Core Value of Tire–Soil Interaction Modeling in Off-Road Scenarios

In the whole chain calculation of an off-road autonomous TTS dynamic control system, the instantaneous microscopic force characterization between the tire and the heterogeneous deformable soil surface is a crucial physical link to determine the high fidelity and control accuracy of the model. The classic Pacejka Magic Formula tire model, used for urban paved roads, is entirely based on the assumption of a rigid pavement. Once it is directly extrapolated and applied to farmland or soft terrain with compressibility and plastic failure characteristics, its mechanical prediction deviation usually exceeds the physical allowable boundary [67]. Establishing a new tire–soil interaction model that integrates the mechanisms of Terramechanics has become an important breakthrough direction in the academic community in recent years.

3.3.2. Classification and Mechanism of Mainstream Tire–Soil Interaction Models

The current tire–soil interaction models for off-road TTS simulation and control are mainly divided into three categories, and a comparison of core characteristics is shown in Table 1. Empirical/semi-empirical ground mechanic model: Based on the classical theories of Bekker and Wong and the Janosi Hanamoto soil shear formula, the soil bearing and shear mechanic equations are constructed with soil cohesion, internal friction angle, and subsidence index as core parameters. The structure is simple and suitable for offline parameter fitting, but the prediction accuracy is limited under dynamic large-slip conditions [68]. Brush soil mechanic fusion model: Combining the theory of elastic deformation of tire bristles with soil plastic failure criteria, the grounding area is divided into an adhesive zone and a sliding zone, and the mechanical properties are characterized by tire surface stiffness and Mohr–Coulomb shear limit, respectively. This improves the accuracy of traction and settlement prediction, and the error can be controlled within 10% [69]. Tire surface structure enhancement parameter model: For specialized structures such as large agricultural pattern tires and wetland cage wheels, SVMs, particle swarm optimization (PSO), and discrete element simulation are integrated to quantify the coupling effects of tire edge shear, lug penetration, and tire pressure and accurately adapt to high-slip extreme working conditions [70,71].

Table 1. Multidimensional comparison of models of tire–soil interaction mechanics.

Model Category & References	Key Parameters & Mechanics	Real-Time Control Advantages	Refs.
Empirical/Semi-empirical Bekker–Wong	Cohesion, friction angle, sinkage exponent, and shear modulus.	Simple structure; efficient for offline fitting; and basic kinematic matching.	[72,73]
Fused Brush–Soil Model	Contact patch split (adhesion/sliding), bristle stiffness, and Mohr–Coulomb failure criteria.	Couples tread deformation with soil elastoplastic failure; net traction error <10%.	[69]
Lug-Enhanced Variable Parameter	Lug angle, edge shear area, cage wheel resistance, and carcass inflation pressure.	Accurately models pressure/track variations; highly robust in high-slip zones.	[74,75]

4. Advanced Path-Tracking and Motion Control Strategies for TTSs

4.1. Adaptive Tracking Control Based on Kinematic Models

4.1.1. Adaptive Improvement and Optimization of Classic Kinematic Algorithms

The core goal of path-tracking control is to quickly converge the lateral deviation and heading deviation of the vehicle by adjusting the steering actuator, ensuring precise trajectory tracking. Adaptive kinematic control has the advantages of a simple structure, no need for complex dynamic parameters, and strong real-time performance and is the fundamental navigation core algorithm for agricultural unmanned chassis [76]. The traditional Pure Pursuit and Stanley algorithms use a fixed forward distance and constant gain, which can lead to response lag and high-frequency oscillation in off-road conditions with bumps and sudden curvature changes. In response to this bottleneck, advanced control schemes in recent years have developed multidimensional adaptive forward-looking and evaluation function tuning mechanisms [77,78]. The system is based on the real-time online capture of the operating speed of the job, the local curvature of the reference path ahead (path curvature), and the current relative attitude deviation of the vehicle. It uses fuzzy logic or a multi-objective adaptive decision engine to dynamically find the optimal self-adjusting look-ahead mechanism within the designated area. This technology can significantly reduce the lateral path deviation of agricultural chassis when driving on bumpy roads. In addition to traditional fuzzy logic-based parameter tuning, recent research has also introduced modern artificial intelligence (AI) algorithms, including neural networks, reinforcement learning, and lightweight deep learning models, for analyzing multi-source sensor measurements. These AI-based methods can extract nonlinear features from vehicle states, such as speed changes, path curvature, heading deviation, and terrain-related disturbances to more accurately estimate tracking errors and adaptively adjust controller parameters under complex off-road conditions. The input data flow awareness framework of the upper-level multi-sensor system is shown in Figure 4.

4.1.2. Multi-Body Trajectory Precise Tracking Technology Based on Backstepping Control

To solve the problem of underactuated nonlinear tracking in TTSs, existing research integrates backstepping control with adaptive foresight and neural compensation techniques [79,80]. In response to harsh operating conditions such as high-precision rice planting and weeding, the traditional mode of using the tractor rear axle as the reference is abandoned. The error calculation reference is based on the center of the machine array or the center of mass of the trailer. A virtual control quantity is constructed through the cascading speed decomposition method, integrating angular velocity feedback and disturbance calibration on the line [81–84]. This scheme can shorten the turning adjustment time,

effectively suppress trajectory overshoot caused by slip and terrain changes, and achieve smooth and accurate tracking of multi-body systems.

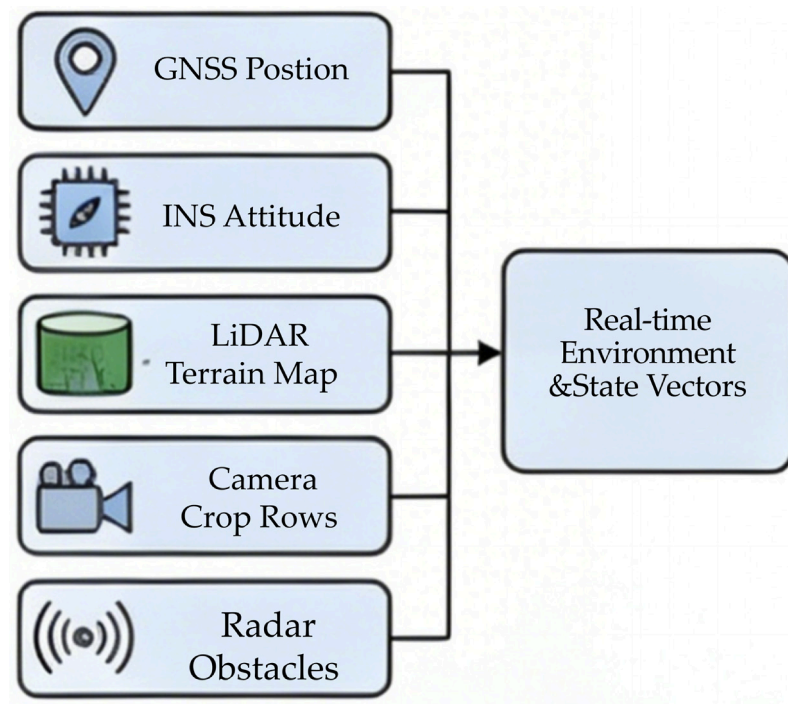


Figure 4. Real-time perception of input stream by upper-layer multi-source sensors.

4.1.3. Key Evaluation of Adaptive Motion Controller

Although adaptive motion controllers have improved the flexibility of classical algorithms, their performance is still strongly influenced by the accuracy of vehicle state estimation and the quality of reference paths. The Pure Pursuit and Stanley methods remain attractive for agricultural vehicles due to their low computational burden and ease of deployment. However, they often overlook tire slip and trailer articulation dynamics, which limits their performance in low grip soil conditions. More advanced inversion-based methods can handle nonlinear tractor–trailer coupling, but their effectiveness depends on accurate parameter identification and interference estimation.

4.2. Model-Based Robust Control Strategies

Model Predictive Control (MPC) has become a widely studied control framework for autonomous agricultural vehicles, as it can explicitly consider system dynamics and actuator constraints. Although MPC is generally considered a predictive control method, its optimized disturbance compensation mechanism has strong robustness under uncertain off-road conditions. Therefore, this review discusses MPC-based methods and robust control strategies.

4.2.1. Predictive Optimization Control Based on Vehicle Models

In order to address the shortcomings of manual trial-and-error adjustment of traditional MPC parameters, existing research has introduced meta-heuristic optimization algorithms into the MPC framework, including genetic algorithms (GAs), PSO, and differential evolution (DE). These algorithms optimize key parameters such as prediction range, control range, and weighting matrix based on vehicle speed, tracking error, and tire–soil adhesion conditions, thereby improving the adaptability of MPC controllers in different off-road environments [85,86]. Based on the vehicle speed, tracking error, and tire–soil

adhesion status, the prediction horizon, control horizon, and weight matrix are optimized online to achieve adaptive optimal matching of control parameters.

4.2.2. Hierarchical Longitudinal and Lateral Cooperative Optimization Control

The double-layer longitudinal and transverse collaborative MPC architecture has been widely used to address the risk of lateral divergence in low-adhesion muddy and long-slope off-road conditions [87,88]. The upper-level controller relies on a multi-body 8-DOF dynamic model and an adaptive LTV-MPC algorithm to solve the required front-wheel steering angle and anti-instability additional yaw moment for precise tracking. The lower-level controller allocates the optimal target torque to independent electric drive axles and active trailer bridges through quadratic programming and deep reinforcement learning (DRL) networks [89–91]. This architecture can constrain the lateral state of the entire vehicle within a safe envelope range, balancing tracking accuracy and dynamic stability.

4.2.3. Robust Disturbance-Rejection Control

In addition to predictive optimization, robust disturbance-rejection methods provide another important solution for maintaining path-tracking stability in uncertain agricultural environments. In unstructured off-road farmland and uncertain terrain operations in the wild, the controller of an autonomous TTS faces external noise and model uncertainty that do not always maintain benign and Gaussian characteristics. The sudden impact of uneven deep hard soil blocks, sudden changes in tillage depth, sudden changes in local resistance caused by the entanglement of long grass on the ground, and severe mechanical clearance wear at multi-body connections constitute typical nonholonomic matched and unmatched composite lumped disturbances. If the controller lacks anti-interference ability, even if the prediction model is constructed with high precision, its closed-loop path-tracking system may still be taken out of the stable convergence domain by high-frequency strong external shocks. The Robust and Disturbance-Rejection Control strategy, specifically designed for unknown hard boundary disturbances, remains an important approach in the field of off-road multi-body vehicles [92]. Among various robust control methods, sliding mode control (SMC) and disturbance observer-based methods have attracted the attention of many scholars due to their strong robustness to model uncertainty and external disturbances.

4.2.4. Sliding Mode Control and Disturbance Observer-Based Robust Control

Within the robust control framework, SMC and disturbance observer-based methods represent two representative approaches for improving disturbance-rejection capabilities in autonomous TTSS. Traditional first-order sliding mode control (FOSM) has inherent chattering problems, which can easily cause wear and failure of the steering actuator. Second-order and third-order sliding mode control (SOSM/TOSM) based on the super distortion algorithm can embed discontinuous control terms into high-order integral terms, which can significantly suppress mechanical chattering while ensuring finite-time convergence of errors [93,94]. This type of advanced algorithm cleverly hides the discrete switch discontinuity term of the control law in the high-order derivative of the time integral term, while ensuring that the error state variable can rigidly and smoothly converge to a small neighborhood around the desired state within a finite time, reducing the oscillation amplitude and total control gain of the steering wheel actuator by several orders of magnitude. To solve the problem of unknown disturbance boundaries, the frontier architecture adopts a high-order disturbance observer (DOB/ESO) and an adaptive sliding mode cascade structure to achieve precise disturbance compensation and smooth control [95]. Table 2 summarizes typical SMC variants and observer-assisted robust control strategies, highlighting their different mechanisms for suppressing disturbances and oscillations.

Table 2. Analytical synthesis of anti-disturbance sliding mode control (SMC) variants and observers.

Control Architecture & References	Manifold Design & Anti-Disturbance Mechanism	Tracking & Chattering Mitigation Merits	Refs.
Barrier Function Adaptive SMC (BFASM)	Nonlinear Barrier Function with adaptive gains decaying near the zero-error boundary.	Zero prior knowledge of lumped disturbance upper bounds required; ultra-smooth steady-state inputs.	[96]
Prescribed Performance SMC (PPC-SMC)	Performance envelope time-bounds; homeomorphic error mapping to unconstrained manifolds.	Guarantees transient tracking quality; enforces user-defined maximum overshoot and convergence rate limits.	[66,97]
Cascaded FTESO Super-Twisting SMC	Top-layer fixed/finite-time observer (FTESO) decouples disturbances; bottom-layer STA SMC.	Perfect decoupling of feedforward compensation and feedback loop; reduces chattering effects under specific disturbance conditions.	[98,99]

Although the mathematical paradigms summarized in Table 2 effectively address the issues of algorithm-level jitter suppression and finite-time convergence, their direct deployment on tractor–trailer systems still faces additional engineering challenges. Due to the multi-body structure, underactuated characteristics, actuator limitations, and nonlinear soil–vehicle interactions of TTs, robust controllers must consider mechanical constraints and multivariable coupling effects in practical implementation. Therefore, Table 3 further compares the integrated path-tracking and motion control framework of TTs extended from a single robust control algorithm to typical off-road conditions.

Table 3. Matrix of advanced path-tracking and motion control paradigms for tractor–trailer systems.

Control & Observation Architecture	Targeted Hazard & Disturbance	Primary Active Actuators	Core Theoretical Advantages	Refs.
ADP + Critic Neural Network (NN).	Unmodeled dynamics, unknown slip, and time-varying load.	Wheel-side drive/brake torque vectoring.	Model-free integrated path and velocity tracking; reduces energy footprint.	[100]
Leader–Follower + Asymmetric Barrier Lyapunov Function.	Actuator saturation, limited sensor FOV, and fleet conflict.	Tractor steering and driveline.	Semi-globally uniformly ultimately bounded; strictly prevents jackknifing under rigid distance limits.	[101]
Sampled-Data Feedback + High-Order State Observer.	Low GPS refresh rates and high-frequency heading offset.	Electro-hydraulic proportional steering valve.	Lyapunov stable; mitigates steering overshoots caused by slow data freshness.	[102]
Adaptive Second-Order Sliding Mode (ASOSM) + API Preview Manifold.	Unstructured farmland noises and stochastic wheel slip.	Automated electric steering wheel.	Finite-time stable; drives sliding variables smoothly to zero, suppressing chattering.	[103]
Reduced-Order Integral SMC + 3rd-Order DOB.	3D terrain slopes, multi-axial sideslip, and implemented feedback.	Active chassis leveling + implemented row followers.	Finite-time stable; strictly decouples tractor attitude leveling from implemented soil following.	[104]

Table 3. *Cont.*

Control & Observation Architecture	Targeted Hazard & Disturbance	Primary Active Actuators	Core Theoretical Advantages	Refs.
Integral SMC + Linear Quadratic Regulator (LQR).	Underactuated nonholonomic constraint and severe inner-wheel cut.	Tractor drive axle + trailer passive steering mechanism.	Asymptotic tracking convergence; utilizes trailer passive steering angles to enable jackknife-free reversing.	[105]
Layered LTV-MPC + Multi-channel RBFNN Predictor.	Adverse lateral slopes and non-Gaussian draft resistance.	Front independent brakes + rear electronic LSD.	Rolling-horizon optimization; eliminates large steering over-corrections via differential braking.	[106]
Articulation Angle Preview + Linear Predictive Model.	Nonlinear trailer reversing and severe off-tracking gaps.	Wheel-side lateral force distribution.	Optimal quadratic cost convergence; explicitly integrates articulation factors into preview steps.	[107]
GPR Draft Predictor + Discrete NMPC Supervisor.	Severe hard clod impacts and sudden yaw disturbances.	Distributed 4WD in-wheel motor system.	Implicit extremum approximation; predicts future draft variations to boost yaw tracking accuracy.	[108]

4.3. Learning-Based and Intelligent Control Strategies

With the development of artificial intelligence and electrified agricultural machinery, learning-based control strategies have received increasing attention due to their ability to handle nonlinear dynamics and unknown disturbances.

4.3.1. Development of Distributed Electric Drive Intelligent Control

Driven by rapid advancements, next-generation TTSs equipped with power-split powertrains, battery-electric or fuel-cell propulsion systems, and distributed in-wheel motors are emerging as a promising platform for intelligent agricultural robotics [109]. Due to the advantages of independently controllable wheel torque and rapid torque adjustment, distributed electric drive chassis can integrate learning-based algorithms, DRL, and neural networks to optimize four-wheel torque distribution online. These strategies improve traction efficiency and energy utilization while enhancing path-tracking performance under specific experimental conditions. This represents a promising research direction for intelligent off-road vehicles.

4.3.2. Reinforcement Learning-Based Dynamic Torque Allocation

The traditional fixed-rule torque distribution algorithm is difficult to adapt to off-road large-slip and strongly coupled nonlinear working conditions. Existing research integrates LSTM and self-attention mechanisms to optimize the architecture of SAC and TD3 reinforcement learning algorithms [110,111]. Using the wheel edge load, path curvature, and tracking error timing signals as inputs, a multi-objective Pareto reward function is constructed that integrates tracking accuracy, lateral stability, slip loss, and motor thermal constraints. The optimal slip ratio and torque distribution strategy for all four-wheels are solved online. Compared to traditional algorithms, this approach can improve tracking accuracy while reducing vehicle energy consumption by 5.6% to 9.7% [112]. The multi-objective nonlinear Pareto adaptive weight optimization layer is depicted in Figure 5. In practical applications, reinforcement learning-based controllers are usually developed us-

ing the MATLAB/Simulink reinforcement learning toolbox and ROS/Gazebo simulation (Available online: <https://www.ros.org> and <https://gazebo.org>) environment and deployed on edge computing platforms such as NVIDIA Jetson series processors. Recent research has validated these methods on electric tractors, autonomous agricultural robots, and distributed drive experimental platforms. However, large-scale on-site deployment is limited by training data requirements, security verification, and adaptation to constantly changing soil conditions.

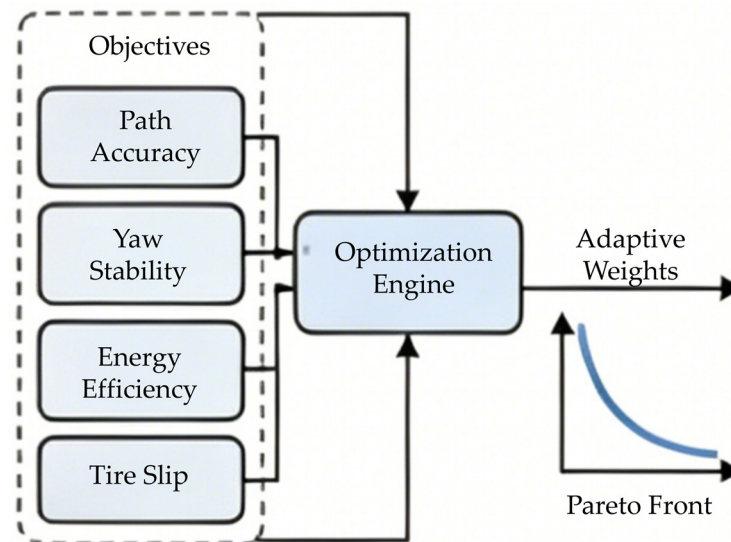


Figure 5. Multi-objective nonlinear Pareto weight optimization layer.

4.3.3. Multi-Algorithm Fusion and Meta-Heuristic Optimization for Energy Management

In the macro-optimization strategy of global energy flow allocation for the entire vehicle, multi-algorithm fusion and meta-heuristic optimization methods have shown great potential in improving energy efficiency and adaptive parameter adjustment [113]. Researchers have decoupled and woven the dynamic programming (DP) large-span global optimization perspective, PSO optimization operator, and equivalent hydrogen/oil consumption minimization theory (ECMS) with the MPC control framework through software and hardware [114,115]. BP neural networks can be used to predict soil resistance and speed changes, dynamically adjust fuel-cell output power and battery power discharge rates, optimize wheel side transmission ratios and energy flow distributions, and effectively improve the overall endurance and operational economy under heavy-duty off-road conditions [116,117]. However, multi-algorithm fusion increases the complexity of the system and requires precise parameter coordination between different optimization layers. Real-time agricultural applications still require lightweight optimization frameworks with adaptive parameter adjustments.

4.4. Comparative Analysis and Future Perspectives of Control Strategies

Different control strategies exhibit complementary characteristics in autonomous TTSS. Adaptive motion controllers have low computational costs and strong deployment feasibility, but their anti-interference ability is limited. Model-based robust controllers, including MPC and sliding mode methods, achieve higher tracking accuracy under complex conditions but require precise models and more computational resources. The learning-based approach provides powerful nonlinear adaptability. However, their reliability and interpretability remain key challenges for practical agricultural applications. Furthermore, meta-heuristic optimization methods provide an effective auxiliary strategy for controller

parameter tuning and multi-objective optimization. However, their online applications are still limited by computational burden and embedded hardware limitations.

5. Coordinated Chassis Control and Active Safety Systems

5.1. Active Trailer Steering Systems

With the development of heavy-duty agricultural TTSs towards large multi-unit formations, relying solely on the tractor's front wheel Ackermann steering mechanism is difficult to meet off-road conditions such as small radius turns, ground U-turns, and reversing, which can easily cause trailer off-tracking, tire slip, and wheel-traffic crop damage. The Active Trailer Steering (ATS) system has become the mainstream technical solution to overcome this bottleneck by adding a steering mechanism to the trailer. The current advanced ATS control architecture generally abandons the traditional passive following and turns to adopt a layered multi-body multi-axis collaborative active control design [118,119]. The ATS system hardware adopts high-precision electro-hydraulic or pure electric servo steering knuckles, and the algorithm adopts a multi-level cascade architecture of LQR and LTV-MPC. The controller relies on a recursive least squares algorithm with a forgetting factor to identify the lateral stiffness of trailer tires, solve for the optimal trailer steering angle, and achieve precise coincidence of trailer and tractor wheel tracks.

By deeply integrating the ATS mechanism with advanced rear wheel active steering (RWS) or four-wheel fully independent active steering (4WSS) control laws, the system can achieve significant motion flexibility and spatial compression efficiency [120–122]. Under standardized double-lane-change (DLC) tests and field evaluations conducted in dense forests, orchards, and saline–alkali soils, the ATS-equipped multi-body chassis demonstrated improved off-road maneuverability and path-tracking performance. Specifically, the system reduced both the swept path width and the peak lateral deviation of the trailer during turning maneuvers. Moreover, it maintained the rearward amplification (RA) of the trailer below the stability threshold of 1.0 when negotiating sharp curves, thereby mitigating trailer sway, reducing sideslip, and improving overall vehicle stability [123,124].

5.2. Distributed Electric Drive, Torque Vectoring, and Differential Braking

Under soft and heterogeneous off-road conditions, an autonomous TTS that relies solely on adjusting steering angles is prone to reaching the tire-road adhesion limit of tires when driving with high resistance and excessive sideslip. The saturation of lateral forces can cause lateral slip instability and significant yaw in path tracking, leading to traditional steering control entering a control dead zone. Under the Fifth Industrial Revolution (5IR), the distributed electric drive chassis introduced Direct Yaw Moment Control (DYC), which dynamically sets the longitudinal driving forces between the wheels on both sides of the tractor and the electric drive hub of the trailer to generate the main yaw moment, breaking free from the mechanical constraints of steering angles and achieving rapid convergence of the vehicle trajectory towards the reference path.

This control often adopts a layered cascaded chassis architecture [125]: the upper layer uses an LQR or MPC to compare the deviation between the actual yaw rate, center-of-mass lateral angle, and reference state of the vehicle in real time and solves the desired yaw moment to ensure the stability of the multi-body system. The lower-level Torque Vectoring Controller (TVC) combines tire vertical load distribution strategy with a constrained Quadratic Programming (QP) algorithm to distribute control instructions to the high-gap agricultural vehicle, which is equipped with a permanent magnet synchronous motor and brake calipers, to achieve vehicle stability control [126,127]. The multi-degree-of-freedom lateral sway real-time monitoring architecture for the upper-layer control system is shown in Figure 6.

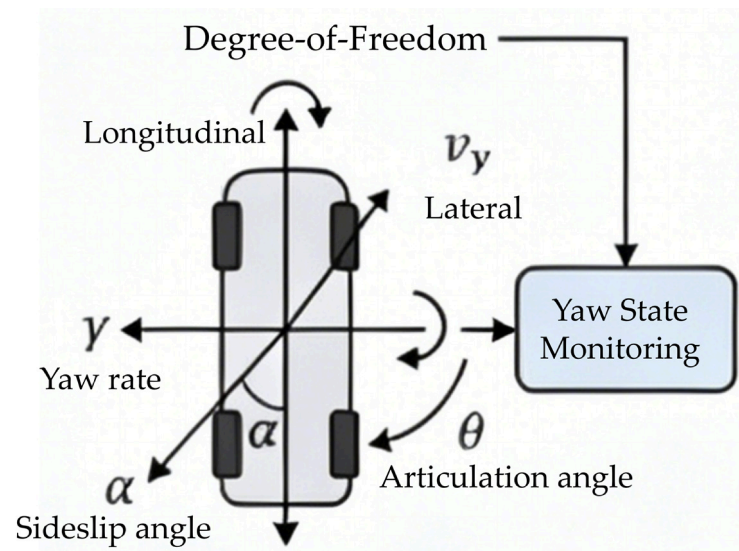


Figure 6. Monitoring layer for dynamic lateral sway state of upper layer with multiple degrees of freedom.

The control scheme of electric drive torque vectoring combined with active differential braking has outstanding advantages in low-adhesion and harsh working conditions such as muddy paddy fields and cultivated land [128,129]. When a single-sided tire experiences severe slippage due to soil collapse, the system can cut off the power of the wheel within a few milliseconds. It can then redistribute the driving force to the wheel with better adhesion conditions and generate a corrective yaw moment. Through joint testing and verification of actual vehicles and hardware in the loop (HIL) test benches, this collaborative control strategy, combined with a high-precision electro-hydraulic steering system, can reduce tire wear under zero-radius turning conditions and reduce lateral tracking errors during asymmetric off-road cornering. This strategy also contributes to improving the all-weather off-road capability of agricultural machinery [130–132].

5.3. Anti-Jackknifing and Rollover Mitigation Strategies

In unstructured heterogeneous off-road scenarios, two critical forms of instability in tractor–trailer multi-body systems are jackknifing and rollover [133]. High-speed turns, heavy-load sharp turns, and emergency obstacle avoidance operations can easily trigger jackknifing of the jackknife and colliding with the tractor. When driving on a mountain slope, centrifugal force and bump excitation can cause one side of the wheel to lift off the ground, leading to the overturning of the entire vehicle. Two types of accidents not only cause failure of the path-tracking control system but also structural damage to the transmission structure. Therefore, an active suppression strategy with predictive pre-intervention capabilities is the safety bottom line of multi-body control systems.

Regarding jackknifing, existing research has adopted a multidimensional chassis cooperative active control architecture for prevention and control [134]. A dynamic model of a heavy-duty tractor equipped with a composite electro-hydraulic steering actuator (EHCSS) was constructed. The Arithmetic Optimization Algorithm (AOA) was used to achieve offline parameter global optimization of the system's center-of-mass position and tire shear saturation angle. When the rate of change in the articulation angle exceeds the safety threshold, the system synchronously activates a triple control strategy: the use of Active Front Steering (AFS) to reconstruct the vehicle trajectory, adjusting the rear axle lateral driving force through torque vector control (TVC), and applying unilateral pulse differential braking to the trailer. Multi-actuator collaboration forms a force constraint

mechanism, significantly reducing the lateral deviation between the tractor and trailer and effectively avoiding hinge node locking faults.

Heavy-duty agricultural machinery is prone to rollover during operation on long hills and slopes. The current protection scheme has been upgraded from passive damping protection to active angular momentum compensation and a steering coordination intervention scheme. The Single-Gimbal Control Moment Gyroscope (SGCMG) system is a representative hardware innovation [135]. This scheme distinguishes between two types of critical rollover conditions before and after the wheels leave the ground, establishes a multi-body gyroscope-coupled variable-parameter dynamic model, and estimates the center-of-mass offset in real-time based on the exponential terminal non-singular SMC. When the vehicle reaches the critical boundary for rollover, the gyroscope mechanism rapidly processes to output a reverse anti-overturning moment, suppressing the amplitude of body roll. Combined with active front wheel steering (AS) coordinated regulation, the safe driving range of vehicles can be doubled, and a reliable active anti-overturning barrier can be constructed for heavy-duty off-road agricultural machinery [136].

5.4. Coordinated Control of Vehicle Chassis and Working Implements

In the context of precision agriculture, a TTS is a multi-equipment complex that couples the power chassis, adjusting linkages, and implementation tools. Relying solely on the lateral deviation of the chassis to design the controller can easily lead to trajectory instability during heavy field operations. The Coordinated Control of Vehicle Chassis and Implementation strategy can synchronously ensure the accuracy of path tracking and the quality of field operations.

Mainstream collaborative control relies on the Electro-hydraulic Hitch System (EHHS) combined with dynamic scheduling technology for powertrain operating conditions to achieve engineering applications [137,138]. During plowing operations, when the plow encounters hard soil blocks or sudden terrain changes, it will generate non-Gaussian high-frequency fluctuations in draft resistance. The impact load is transmitted through three-point suspension, causing the vehicle to slow down and load distribution between axles. A sudden drop in load on the driving wheels will cause severe slip and idle, which will damage the stability of the closed-loop path tracking.

The collaborative controller introduces a three-dimensional integrated collaborative regulation engine based on a bivariate sliding mode differential observer (SOSM), which includes throttle opening, motor speed allocation, and electro-hydraulic suspension depth limitation [108,139,140]. At the moment when the slipping tire quickly crosses over the soft and slippery area and re-enters high-stiffness soil, the lifting valve controls the implement to return to the desired target ideal working layer with a smooth response without overshoot or step. This technology ensures the heading stability and longitudinal and lateral motion of the entire chassis under complex undulating terrain and extremely low-adhesion saline-alkali slopes in the wild [141–144].

There is a strong mechanical coupling relationship between chassis active safety control and work tools, which can easily lead to power distribution conflicts, actuator torque saturation, and other problems. It is necessary to establish a comprehensive performance evaluation system. Table 4 compares and analyzes the mechanisms, safe operating ranges, and engineering implementation constraints of various collaborative controllers, providing theoretical support for the optimization of chassis and operational equipment collaborative control.

Table 4. Critical analysis of coordinated chassis control and active safety paradigms for off-road autonomous systems.

Category & Core References	Coordinated Control/Safety Mechanism	Actuator Interface & Topology	Tractive & Safety Merits	Refs.
Traction-Assist Co-Management	Tractor drawbar pull monitoring + towed implemented electric axle power injection.	Hybrid diesel generator + implemented auxiliary electric motor axle.	Reduces tractor drawbar power demands and wheel slip in soft, wet soils.	[145]
Independent E-Axle Slippage Suppression	Real-time motor speed feedback + travel speed differential slip scheduling.	Four-wheel independent driving (4WID) electric axles.	Optimizes tractive efficiency within the peak 10–20% slip ratio range.	[146]
Auxiliary Hub-Wheel Turn Enhancement	360° electro-hydraulic servo-wheel steering + active lifting control.	Front-mounted auxiliary wheel assembly + hydraulic servo.	Boosts headland turning efficiency by 50–80% via compressed space appropriation.	[147]
Omnidirectional Chassis Leveling	Disturbance observer-based ASOSM synchronized cylinder control.	“Double/Three-layer frame” + servo-electric/hydraulic cylinders.	Compensates lateral slopes up to 20–25°; maintains center-of-mass stability.	[148]
Adaptive Energy Management (FA-ECMS)	Fuzzy-PI adaptive equivalence factor regulation + battery SOC feedback.	Engine–motor dual power source + Hydro-Mechanical Continuously Variable Transmission (HMCVT).	Cuts fuel consumption by 5.04–6.71% during heavy-duty plowing cycles.	[149]
Mechanic–Electronic–Hydraulic Fusion	Economy transmission ratio matching + hybrid rule-based optimal energy management.	Integrated MEH-PS powertrain configuration.	Enforces engine operations inside the highly loaded, peak-efficiency fuel economy zone.	[150]

According to the summary analysis in Table 4, the stability control technology of autonomous multi-body systems in off-road environments has evolved from a single passive braking protection scheme to an active pre-control strategy for multi-actuator collaborative power distribution. Although omnidirectional chassis leveling technology and traction-assisted transmission systems have achieved significant improvements in anti-folding stability margin and terrain slope adaptability, there is always an irreconcilable engineering trade-off between the closed-loop control of chassis path tracking and the dynamic variations of implemented traction load. Inconsistent short-term small lifting actions and transient differential braking torque vector control often induce high-frequency oscillations in the powertrain, which not only cause abnormal changes in the compaction characteristics of the surface soil but also lead to execution delays in the control system. Therefore, in order to achieve stable and high-precision tracking of multi-body system trajectories under variable soil machinery coupling conditions, it is not only necessary to design a robust closed-loop feedback control strategy but also to build a lightweight and real-time iterative rolling optimization algorithm architecture. Overall, the above discussion summarizes the main advances and engineering trade-offs in perception, modeling, and control of autonomous TTSs. In order to provide a comprehensive overview of the characteristics, limitations, and application scenarios of representative methods, Table 5 summarizes the main sensing, modeling, and control methods discussed in this review.

Table 5. Comparison of representative sensing, modeling, and control approaches for autonomous TTSs.

Category	Method	Advantages	Limitations	Suitable Scenarios	Refs.
Sensing	RTK-GNSS/INS	High positioning accuracy	GNSS blockage	Open farmland	[151,152]
Sensing	LiDAR	3D perception	High cost	Complex terrain	[153,154]
Modeling	Kinematic model	Simple and efficient	Cannot handle slip	Low-speed operation	[40,76]
Modeling	Dynamic model	High fidelity	High computation	Heavy-duty operation	[46,155]
Control	MPC	Constraint handling	Computational burden	High-performance systems	[156,157]
Control	SMC	Strong robustness	Chattering problem	Disturbance environments	[92,158]
Control	Learning based	Adaptive capability	Data dependency	Complex scenarios	[159,160]

6. Embedded Deployment and Engineering Implementation of Intelligent Agricultural Machinery Control Algorithms

6.1. Software Implementation of Embedded Computing Architecture and Control Algorithms

The autonomous control system of agricultural machinery usually consists of a perception layer, a decision-making layer, a control layer, and an execution layer. Its engineering implementation requires comprehensive consideration of sensor acquisition frequency, control algorithm computation, actuator response speed, and real-time communication. In recent years, agricultural machinery chassis have gradually integrated electric drive, hydraulic drive, multi-sensor fusion, and automatic navigation technologies, promoting the development of embedded control systems from a single controller to a multi-module collaborative architecture [161]. In terms of software implementation, the underlying driver program usually uses C/C++ languages to complete sensor data acquisition, motor control, and communication interface development; the real-time task scheduling layer relies on RTOS or embedded Linux to achieve multi-task management; and the algorithm application layer utilizes MATLAB/Simulink for automatic code generation, C/C++ secondary development, or ROS frameworks for algorithm deployment [162,163].

Research has shown that control architectures based on microcontrollers (MCUs) can meet the low-latency control requirements of high real-time tasks such as agricultural equipment steering control. For example, the electric automatic steering system implements steering execution through brushless motors, reduction mechanisms, and embedded control units and uses digital PID algorithms to track target angles, verifying the feasibility of lightweight embedded solutions in unmanned tractors [164]. For actuators with complex nonlinear dynamic characteristics, such as electro-hydraulic proportional valves, relying solely on empirical adjustment makes it difficult to ensure control accuracy. Therefore, it is necessary to establish actuator models using simulation platforms such as AMESim and optimize control parameters through experimental data to improve the compatibility between algorithms and mechanical systems [165].

In addition, different types of agricultural machinery power platforms have different requirements for control hardware. Traditional wheeled tractors mainly focus on steering and path-tracking control, while emerging equipment such as electric orchard tractors and greenhouse-tracked electric tractors need to simultaneously meet the requirements

of power management, energy optimization, and operation control. Therefore, a more flexible embedded control architecture is required to support multi-task collaborative operations [166,167].

6.2. Control Algorithm Calculation Requirements and Real-Time Performance Analysis

The engineering deployment of control algorithms not only depends on the theoretical control performance but is also constrained by computational complexity, control cycles, and hardware resources. Different algorithms exhibit significant differences in real-time performance requirements when applied to agricultural machinery.

Fuzzy control and its combination with traditional proportional-derivative control are widely used in the motion control of mobile robots and agricultural vehicles due to their strong nonlinear adaptability and low computational complexity. Related studies have applied fuzzy PD control strategies to achieve trajectory tracking and obstacle avoidance of wheeled mobile robots, while compensating for unmeasurable variables through state observers to improve the system's motion control performance [168]. Similarly, in autonomous navigation systems of agricultural machinery, fuzzy control is commonly used to optimize PID parameters, enabling controllers to adapt to dynamic changes under different operating conditions. For example, an automatic steering system based on fuzzy control-optimized PID parameters can adjust control parameters in real time, according to different resistance conditions and complete field tests on rice transplanters, tractors, and high-clearance sprayers, achieving centimeter-level path-tracking accuracy [169].

In contrast, MPC requires the online solving of optimization problems, which imposes higher requirements on processor computing capabilities and memory resources. In visual navigation systems, MPC usually predicts future vehicle states based on vehicle dynamic models, while SMC is employed to enhance system robustness. Although the combination of MPC and SMC can improve navigation performance under complex environments, it requires higher-performance edge computing platforms to support real-time operation. Related research has addressed visual delay problems through MPC and SMC cooperative control, significantly reducing path-tracking errors in agricultural machinery navigation experiments, reflecting the development trend of complex control algorithms toward practical equipment applications [170].

For multi-degree-of-freedom agricultural machinery systems, such as tractor-trailer combination systems, the dynamic models are more complex and require advanced control methods to ensure system stability. The composite adaptive sliding mode controller improves the path-tracking accuracy of multi-trailer systems by compensating for external disturbances through an extended state observer. However, this method still mainly relies on simulation and experimental verification, and its embedded real-time deployment requires further optimization [171].

In addition, the coordinated control of longitudinal speed regulation and lateral path tracking further increases the computational burden of algorithms. To address steering delay problems in autonomous tractors, a longitudinal and lateral decoupling control strategy has been investigated, combined with improved Smith predictive control to reduce system delays and improve path-tracking performance [172]. This indicates that future agricultural machinery control systems should select appropriate computing platforms according to algorithm complexity rather than simply relying on high-performance hardware configurations.

6.3. Engineering Implementation Status from Simulation Verification to Field Application

At present, the development of agricultural machinery control algorithms presents the characteristics of "partially mature deployment, while many methods remain at the verifica-

tion stage.” Algorithms that have completed physical equipment deployment mainly focus on automatic steering, actuator control, and navigation assistance. For example, research on electro-hydraulic proportional valve control provides parameter support for the practical application of automatic steering systems by experimentally analyzing variations in valve flow rate, pressure, and power characteristics [173]. Automatic navigation, autonomous driving, and variable-rate operation systems have also been tested in field environments using tractors, sprayers, and other agricultural equipment, achieving closed-loop integration from algorithm design to mechanical execution.

However, some advanced control algorithms still mainly remain at the simulation or experimental platform stage. For example, although an automatic tractor steering system based on sliding mode predictive control can effectively compensate for external disturbances and improve anti-interference capabilities, its large-scale field application requires further validation due to complex factors such as soil disturbances, mechanical backlash, and sensor noise in practical agricultural environments [174]. Therefore, future research should focus more on algorithm lightweighting, code optimization, and real-time hardware implementation rather than solely pursuing theoretical control accuracy.

6.4. Challenges and Development Trends of Intelligent Agricultural Machinery Control System Integration

The further development of intelligent agricultural machinery control systems requires addressing the collaborative optimization of algorithms, hardware, and mechanical systems. First, although data-driven methods such as machine learning can improve state prediction capabilities under complex environments, their high computational requirements make real-time deployment dependent on edge computing and model compression technologies. For example, a machine learning-based tractor comfort prediction system collects operational status data through IoT devices and adjusts operating parameters in real time using optimization algorithms, providing a new technological approach for intelligent decision-making in agricultural equipment [175].

Second, stable control of multi-module mechanical systems remains an important challenge in engineering applications. Research on modular tractors has demonstrated that optimizing mechanical structures and coordinating control strategies can improve motion stability under complex operating conditions; however, the corresponding control algorithms still require further adaptation to embedded platforms [176]. Similarly, dual-steering tractors improve maneuverability in narrow working environments through the integration of mechanical structures and electro-hydraulic control systems, providing a new direction for future intelligent chassis control development [177].

In addition, the development of intelligent actuators will further promote closed-loop control systems in agricultural machinery. Active adjustment mechanisms, such as electronically controlled air suspension systems, can adjust vehicle posture in real time according to operating conditions, improving transportation stability and ride comfort and providing references for multi-degree-of-freedom intelligent control of agricultural equipment [178].

Furthermore, the engineering deployment of agricultural machinery control algorithms is not only limited by computing resources but is also affected by the coupling effects of multiple physical factors, including machinery, soil, and environmental conditions. Related studies have analyzed the influence of different tire parameters on soil compaction by establishing soil stress propagation models, indicating that agricultural machinery motion control should comprehensively consider the interaction between equipment structural parameters and field environmental responses [7].

Overall, the future development direction of agricultural machinery control algorithms is not simply to increase algorithm complexity but to construct an engineering system based

on collaborative optimization among perception, computation, control, and execution. By allocating embedded computing resources according to algorithm characteristics, optimizing software architectures, and strengthening long-term reliability testing under field conditions, advanced control algorithms can be effectively transformed from laboratory models into practical and scalable intelligent agricultural equipment.

7. Open Challenges and Future Perspectives

The autonomous TTS in the current unstructured off-road environment has achieved significant research progress and practical applications in path-tracking, state estimation, dynamic modeling, and active safety control. However, the system still has problems such as insufficient generalization capabilities, weak adaptability to extreme working conditions, and limited multi-vehicle collaboration capabilities, making it difficult to achieve fully autonomous operations in all-weather and all-scenario environments. Therefore, several key technical challenges remain to be addressed.

7.1. High-Fidelity Online Soil–Tire Interaction Learning

Traditional tire–soil interaction models mainly rely on classical ground mechanic analytical equations or offline-fitted semi-empirical models. Although these methods provide important theoretical foundations, their parameters are typically obtained under limited soil conditions. It may not be possible to accurately represent the dynamic changes caused by soil moisture, compaction history, and spatial heterogeneity. The soil mechanic parameters in the field will undergo irreversible nonlinear dynamic variations with spatial terrain, rainfall environment, and repeated vehicle compaction. Consequently, when vehicles are driving under rapidly changing soil conditions, the adaptability of fixed parameter models may be limited. Future research should focus on developing an online tire–soil interaction learning framework that combines physics knowledge and data-driven methods. This system integrates high-frequency current feedback of in-wheel motors, three-dimensional strain data of intelligent in-tire sensors, and surface subsidence point cloud information of LiDAR. Combined with Physics-Informed Neural Networks (PINNs), the soil shear failure mechanism and subsidence dynamic constraints are embedded in the network loss function to achieve online estimation of soil stiffness and adhesion limit, providing accurate parameter support for upper-level LTV-MPCs and other controllers and improving control stability under large-slip conditions.

7.2. Vision–Language–Action (VLA) Models and Embodied AI for Off-Road Autonomy

The existing TTS autonomous control system adopts a hierarchical perception–planning–control architecture of perception, planning, and control. There are problems of disconnection and error accumulation in information transmission between modules. In extreme operating conditions such as straw entanglement, mud pit sinking, crop lodging, and human–machine interference, parameter drift and control logic locking faults are prone to occur. Future technological development will focus on the deep integration of lightweight Vision–Language–Action (VLA) Models and off-road embodied AI. By deploying a lightweight VLA model that adapts to the edge computing power of vehicles, multimodal information fusion involving panoramic vision, infrared perception, vehicle power load signals, and agricultural domain knowledge can be achieved. Future AI-based systems can reduce reliance on manual design rules by integrating multimodal perception, domain knowledge, and adaptive decision-making mechanisms. Although the reliability, safety verification, and computational requirements of these methods need further evaluation, they have the potential to improve adaptability under complex field conditions.

7.3. Edge Computing and V2X-Enabled Multi-Vehicle Cooperative Formations/Platooning

The autonomous agricultural machinery operation mode is evolving from a single machine independent operation to multi-vehicle cooperative platooning, which integrates aerial–ground operations. The multi-vehicle fleet operation has problems such as large sensor data volume, high edge computing load, complex coupling of multi-tire–soil dynamics, and high centralized control delay pressure. In the future, a distributed collaborative control architecture based on edge computing and the Internet of Vehicles (V2X) needs to be built. High-frequency synchronization of multiple vehicle positions, angles of articulation, and implemented draft forces can be achieved by relying on the 5G Advanced/6G private network. By using Distributed Model Predictive Control (DMPC) and multi-agent reinforcement learning algorithms, rolling optimization is achieved for multi-vehicle obstacle avoidance, precise follow-the-leader tracking, job width stitching, and computing load balancing. These distributed control strategies can reduce the limitations of individual vehicle perception and computing capabilities. It can also provide potential avenues for efficient cooperative agricultural operations.

8. Conclusions

This review summarizes the core technologies of path-tracking and dynamic motion control for autonomous TTSs in unstructured off-road environments and summarizes the recent advances and technical characteristics of existing technology systems. The main conclusions are as follows. At the level of state estimation, the multi-source fusion of RTK-GNSS/INS with LiDAR and stereo vision has constructed the fundamental perception framework of off-road perception. In response to issues such as slip lateral deviation and articulation instability caused by soil deformation, adaptive Kalman filtering algorithms such as ASTUKF and DAUKF, along with ARBFNN data-driven observers, have been investigated to improve the estimation accuracy and adaptability of vehicle states and tire–soil interaction parameters under complex operating conditions.

At the level of modeling and control strategy, traditional kinematic control is difficult to adapt to extreme working conditions such as large slip, high load, and mountain cross slope. Currently, research is increasingly integrating nonlinear vehicle dynamics, terrain mechanics, and implementation-related disturbances into advanced control frameworks. It includes LTV-MPC, NMPC, and high-order sliding mode methods to improve tracking performance and stability under challenging conditions. By combining intelligent optimization algorithms, adaptive prediction-horizon adjustment technology, and ATS, torque vectoring control (TVC) and electromechanical hydraulic suspension collaborative control can effectively compensate for actuator delay, ensure path-tracking accuracy, suppress folding instability and rollover instability, and optimize the tractive efficiency and energy consumption level of the vehicle.

Although the existing hierarchical modular control architecture has matured, its generalization ability remains limited under heterogeneous soil dynamic rheology and complex extreme operating conditions. Future research on autonomous agricultural machinery is expected to further explore physics-based tire–soil interactive learning, decision and control frameworks based on artificial intelligence, and distributed multi-vehicle coordination realized by edge computing and advanced communication technology. However, significant efforts are still needed in terms of model generalization, computational efficiency, security validation, and large-scale on-site deployment.

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