

3D-SportsNavNet: An Innovative Path Planning and Navigation System for Sports Supply Robots in Complex Dynamic Environments

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ABSTRACT

As sports equipment robots are increasingly applied in modern sports and outdoor activities, existing technologies face challenges in adaptability and real-time response when dealing with dynamic environments. To address these issues, this paper proposes 3D-SportsNavNet, an innovative path planning model for complex dynamic environments. The model integrates three key modules: multimodal environment perception and reconstruction, adaptive dynamic path planning, and intelligent navigation optimization. The main contributions include: (1) a novel multimodal fusion framework integrating RGB-D cameras and LiDAR with DCNNs and PointNet for real-time 3D reconstruction, (2) an adaptive planning strategy combining Deep Q-Learning and Proximal Policy Optimization for dynamic obstacle avoidance with 30Hz update frequency, and (3) a self-supervised learning mechanism enabling continuous optimization without extensive labeled data. Experimental validation across three diverse scenarios demonstrates that 3D-SportsNavNet achieves 93.7% path planning success rate, reduces collision incidents by over 50%, and decreases energy consumption by 9-13% compared to baseline methods (DWA, RRT, traditional DRL). The model provides an effective solution for sports equipment robots operating in complex dynamic environments.

Keywords: Sports equipment robot, Dynamic environment navigation, Multimodal environment perception, Adaptive path planning, Deep reinforcement learning, Self-supervised learning

1. Introduction

With the rapid development of modern sports and outdoor activities, sports equipment robots, as intelligent auxiliary devices, are playing an increasingly important role[1]. These robots are widely used in various scenarios, such as object delivery in sports events, training assistance, and field maintenance, significantly improving efficiency and safety [2, 3]. However, as application scenarios become more diverse and complex, the environments that sports equipment robots face are becoming more dynamic and unpredictable, presenting many challenges[4]. These challenges include dealing with dynamically changing obstacles, complex environmental structures, and the need for real-time decision-making[5,6] These demands place higher requirements on the robots' ability to plan paths

and navigate in uncertain and complex dynamic environments.

Existing path planning technologies and robot navigation systems perform well in static or simple dynamic environments, but they often suffer from adaptability issues and slow response in complex dynamic environments[7]. Traditional methods, such as the rule-based A* algorithm and the Rapidly-exploring Random Trees (RRT) algorithm, can achieve effective path planning in specific scenarios [8, 9], but they often lack flexibility and robustness when dealing with dynamic obstacles and rapidly changing environments [10]. This limitation is especially evident in frequently changing sports scenarios. Therefore, there is an urgent need for a new path planning method that can understand and respond to complex environmental changes in real-time, enhancing the adaptability and responsiveness of robots [11].

Despite advances in robot navigation, three critical research gaps remain unaddressed in existing literature. First, current methods lack effective integration of multimodal sensor data (RGB-D cameras and LiDAR) for comprehensive 3D environmental understanding, with most approaches relying on single-sensor inputs that are vulnerable to environmental variations such as lighting changes or occlusions. Second, traditional path planning algorithms (A*, RRT, DWA) fail to provide real-time adaptive responses to rapidly changing obstacles common in sports environments, often requiring complete path recalculation when dynamic changes occur. Third, existing deep learning approaches require extensive labeled training data and struggle with generalization to novel scenarios, limiting their practical deployment in diverse sports settings.

To address these gaps, this paper focuses on three key innovations. First, we develop a unified multimodal perception framework that leverages the complementary strengths of visual and depth sensors through dynamic weighted fusion, ensuring robust environmental understanding across varying conditions. Second, we design an adaptive path planning mechanism that combines model-free deep reinforcement learning (DQN and PPO) with predictive modeling for proactive navigation, enabling 30Hz real-time path updates. Third, we implement a self-supervised learning strategy that enables continuous improvement through environmental interaction without manual annotation. Unlike previous works that address these challenges separately, our 3D-SportsNavNet model provides an integrated end-to-end solution specifically tailored for the unique demands of sports equipment robots operating in dynamic, human-populated environments.

This paper introduces a multimodal environment perception and reconstruction module, which integrates data from RGB-D cameras and LiDAR sensors. Combined with deep convolutional neural networks (DCNNs) and point cloud processing networks (PointNet), this module achieves precise perception and semantic understanding of dynamic objects and environmental changes in complex scenes.

An adaptive dynamic path planning module is designed, utilizing deep reinforcement learning algorithms (Deep Q-Learning and Proximal Policy Optimization) to update path planning strategies in real-time, ensuring the safety and efficiency of the robot's navigation in dynamic environments.

An intelligent navigation optimization module is proposed, which continuously optimizes the robot's navigation decisions in changing environments using deep reinforcement learning and self-

supervised learning, improving the robot's adaptability and response speed to environmental changes.

The organization of this manuscript is delineated as follows: Section 2 elucidates the related literature, emphasizing the utilization of environmental adaptation and path planning within the domain of robotics. Section 3 explicates the methodology in comprehensive detail. Section 4 delineates our experimental protocols. Conclusively, Section 5 encapsulates the study, presenting a summary and proposing directions for subsequent research.

2. Literature Review

2.1 Robot Path Planning Methods in Dynamic Environments

In the field of robot path planning, particularly in applications within dynamic environments, various algorithms have been extensively researched and applied. These methods include classical algorithms based on heuristic search, intelligent optimization algorithms, local path planning methods, swarm intelligence algorithms, and the rapidly developing deep learning methods in recent years. While each of these methods has its unique features and advantages, their performance and applicability vary in complex dynamic environments that are constantly changing and uncertain.

Table 1. Comparison of Common Path Planning Methods: Advantages, Disadvantages, and Applicable Scenarios.

Method	Advantages	Disadvantages	Applicable Scenarios
A* Algorithm (A-Star)[12]	Simple and efficient, finds optimal path	Frequent recalculation, slow in dynamic environments	Static environments, low-dynamic change scenarios
Rapidly-exploring Random Tree (RRT)[13, 14]	Suitable for high-dimensional spaces, quick to find feasible paths	Path not smooth, slow response, local optima	High-dimensional path planning, sparse obstacle
Dynamic Window Approach (DWA)[15]	Real-time obstacle avoidance, suitable for dynamic environments	Strong local optimization, weak global planning	Dynamic environments, small-scale indoor navigation
Artificial Potential Field (APF)[16]	Simple and intuitive	Prone to local minima, hard to handle dynamic obstacles	Simple environments, open areas with few obstacles
Particle Swarm Optimization (PSO)[17]	Strong global optimization, multi-objective optimization	High computational complexity, poor real-time performance	Complex path planning, multi-objective problems
Genetic Algorithm (GA)[18]	Strong global search, suitable for complex problems	Computationally expensive, slow convergence	Multi-objective optimization, high-complexity path planning
Deep Reinforcement Learning (DRL)[19]	Learns path planning strategies in complex environments,	Requires large data and computational resources	Complex dynamic environments, autonomous

As summarized in Table 1, traditional path planning methods such as A* and RRT performs well in static or simple dynamic environments but often lacks flexibility and real-time performance in complex dynamic environments. Methods like DWA and APF have some application potential in dynamic environments, but their limitations in global path planning and complex scenarios persist. Swarm intelligence algorithms like PSO and GA show promise in global optimization, but their real-time performance and computational efficiency restrict their widespread application. Deep Reinforcement Learning (DRL) has demonstrated excellent adaptive learning capabilities in dynamic environments, but its demand for large datasets and high-performance computing limits its scope of application. To address these shortcomings, this paper proposes a path planning model, 3D-SportsNavNet, based on 3D scene reconstruction and deep learning, to achieve more efficient and flexible path planning and navigation performance, tackling various challenges in complex dynamic environments.

2.2 Application of Deep Learning in Robot Navigation

With the rapid development of deep learning technology, its application in robot navigation has become increasingly widespread, primarily addressing the limitations of traditional methods in dynamic and complex environments. The advantage of deep learning lies in its powerful ability to model high-dimensional, nonlinear data[20, 38]. CNNs excel at extracting obstacle features from complex visual data, thereby providing accurate visual information for path planning. LSTM and RNNs can capture temporal correlations in the environment, predicting the movement trajectories of dynamic obstacles[21]. These technologies have shown outstanding performance in fields such as autonomous driving, drone navigation, and mobile robot obstacle avoidance. However, they still face challenges related to high computational complexity and poor real-time performance when processing long-term sequential data[22, 23]. Additionally, GANs improve model generalization in unknown environments by generating simulated data, while attention mechanisms dynamically adjust the model's focus, optimizing decision-making in complex environments.

To further enhance the adaptability of navigation systems, Deep Reinforcement Learning (DRL) combines the policy optimization of reinforcement learning with the high-dimensional data processing capabilities of deep learning, enabling robots to learn optimal navigation strategies in highly uncertain environments. DRL is particularly well-suited for complex dynamic scenarios, such as autonomous driving and search-and-rescue missions [24, 39]. However, its high demand for data and computational resources remains a challenge in practical applications. Meanwhile, Graph Neural Networks (GNNs) have been used to model the spatial relationships and graph-structured data of complex environments, helping robots construct environmental maps and optimize path planning in intricate scenarios[25, 41]. Although these deep learning methods show great potential in improving the autonomy and decision-making efficiency of robot navigation systems, challenges related to training stability, data requirements, and computational efficiency still need further improvement[26,27]. The 3D-SportsNavNet model proposed in this paper builds upon these

techniques, aiming to provide a more flexible and efficient path planning solution through multimodal data fusion and 3D scene reconstruction, addressing the challenges in dynamic environments.

2.3 3D Scene Reconstruction Technology

In robot navigation and path planning, 3D scene reconstruction technology is a critical component, enabling robots to achieve comprehensive environmental perception and spatial understanding[28]. In dynamic environments, accurately reconstructing 3D scenes helps robots better identify and locate surrounding objects and obstacles, allowing them to plan safe and optimal paths[29]. 3D scene reconstruction techniques mainly include vision-based methods and depth sensor-based methods, each with its own characteristics and applicable scenarios.

Vision-based 3D reconstruction methods typically rely on image sequences for environmental modeling, such as structured light and stereo vision techniques. By capturing multiple images from different angles, triangulation and multi-view geometry methods are used to generate a 3D point cloud of the environment[30]. These methods offer high spatial resolution and detail capture capabilities, performing well in static or slow-changing environments, such as indoor robot navigation and industrial automation scenarios[31]. However, these methods are sensitive to lighting conditions and field of view, and their performance decreases in low-light or heavily occluded dynamic environments. In contrast, depth sensor-based reconstruction methods utilize depth sensors such as LiDAR and RGB-D cameras to directly obtain depth information of the scene and construct a 3D model[32]. These methods do not rely on lighting conditions or environmental features and can operate reliably in environments with significant lighting changes or complexity, making them widely applicable in areas such as autonomous vehicles and drone navigation. Additionally, by combining PointNet with CNNs, the depth data can be further used for complex scene understanding and semantic segmentation[33]. However, challenges such as large data volumes and complex real-time processing remain for these methods[34]. Therefore, the 3D-SportsNavNet model proposed in this paper combines multiple sensor data with deep learning technologies, aiming to leverage 3D scene reconstruction technology to achieve more efficient and accurate understanding of dynamic environments and path planning.

3. Methods

In the methodology part of this paper, we first introduce the overall network framework and then elaborate on the design of each module.

3.1 Overview of Our Network

The path planning model 3D-SportsNavNet proposed in this paper aims to enhance the navigation and decision-making capabilities of sports equipment robots in dynamic and complex environments. By integrating multimodal data fusion, 3D scene reconstruction technology, and deep learning methods, the model achieves efficient environmental perception, path planning, and navigation optimization. The overall architecture of the model is shown in Figure 1, consisting of three core modules: the multimodal environment perception and reconstruction module, the adaptive

dynamic path planning module, and the intelligent navigation optimization module. These modules work collaboratively to support the robot's navigation tasks.

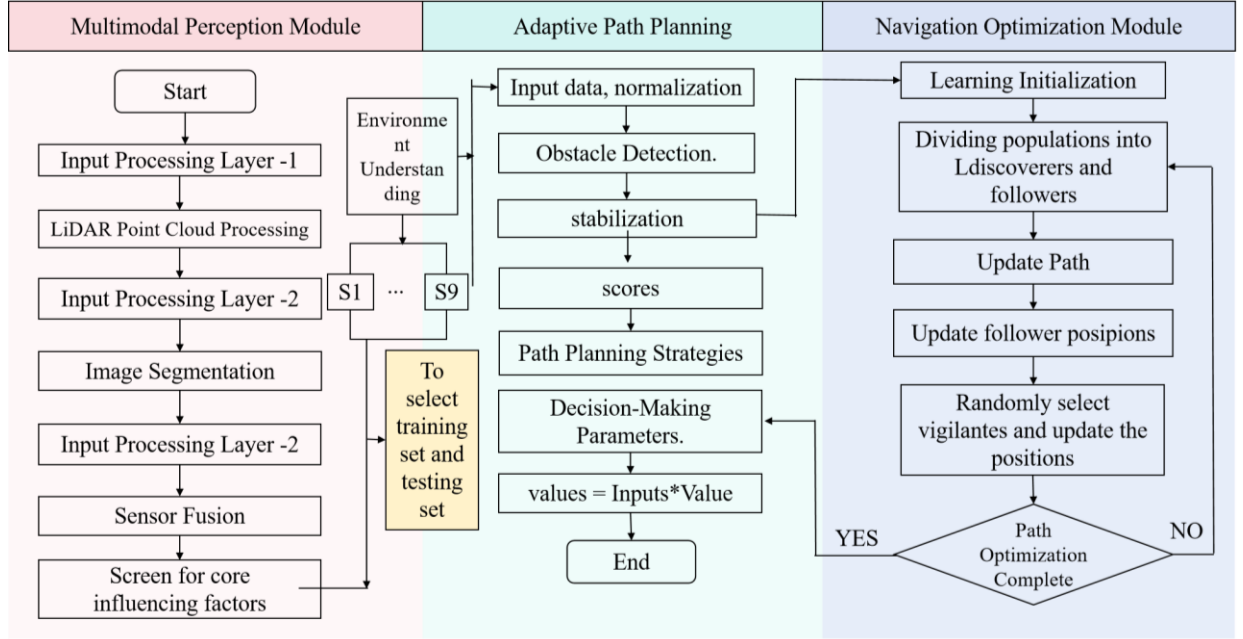


Figure 1. Overall Architecture of the 3D-SportsNavNet Model.

The multimodal environment perception and reconstruction module is responsible for fusing data from multiple sensors, including RGB-D cameras and LiDAR, to enable real-time 3D reconstruction and semantic understanding of dynamic environments. By utilizing deep convolutional neural networks (DCNNs) and PointNet, this module can accurately extract and identify dynamic objects and obstacles in the environment, providing precise data support for subsequent path planning. Additionally, this multimodal data fusion effectively overcomes the limitations of single sensors in scenarios with lighting changes or occlusions, ensuring efficient perception even in variable environments.

The adaptive dynamic path planning module employs deep reinforcement learning (DRL) methods to adaptively adjust path planning strategies. Based on environmental changes and real-time data provided by the perception module, this module dynamically adjusts path planning using Deep Q-Learning (DQN) and Proximal Policy Optimization (PPO) algorithms, ensuring the safety and efficiency of robot navigation across different environments. Compared to traditional path planning methods, this design better handles dynamic obstacles and complex terrains, significantly improving navigation flexibility and responsiveness.

The intelligent navigation optimization module integrates deep reinforcement learning with self-supervised learning mechanisms to continuously optimize the robot's navigation strategy. Through interactions with the environment during each navigation task, the robot accumulates experience and refines its strategies, enhancing its adaptability to environmental changes and decision-making efficiency.

3D-SportsNavNet provides a complete solution from environmental perception to path planning and navigation optimization through the collaborative work of these modules. As shown in the overall architecture in Figure 1, the data flow and information exchange between the modules ensure that the robot can efficiently accomplish tasks in dynamic and complex environments, offering strong technical support for applications in sports scenarios. Through this architectural design, 3D-SportsNavNet overcomes the limitations of existing methods, providing an innovative and practical solution for path planning and navigation in dynamic environments.

3.1.1 Distinctive features of 3d-sportsnavnet

The proposed 3D-SportsNavNet model distinguishes itself from existing approaches through four key innovations that address critical limitations in current robot navigation systems.

3.1.1.1 Multimodal sensor fusion architecture

Unlike traditional single-sensor systems, our framework integrates RGB-D cameras and LiDAR through a unified feature space with dynamic weighted fusion (Formula 3). This approach fundamentally differs from existing methods in several ways. Vision-only methods [30, 31] achieve high spatial resolution but are highly sensitive to lighting conditions and suffer performance degradation in low-light or heavily occluded environments. LiDAR-only systems [32] provide reliable depth information independent of lighting but lack semantic understanding and color information necessary for object classification. Simple concatenation approaches that combine sensors fail to capture complementary information effectively because they treat all sensor inputs equally regardless of environmental conditions. In contrast, our dynamic weighted fusion mechanism (Formula 3) adaptively adjusts the fusion coefficient α based on real-time environmental conditions, ensuring robust perception across varying scenarios. When lighting conditions are poor, the system automatically increases reliance on LiDAR data; conversely, in well-lit environments with complex semantic requirements, RGB-D data receives higher weighting.

3.1.1.2 Hybrid reinforcement learning strategy

We combine Deep Q-Network (DQN) (Formula 5) and Proximal Policy Optimization (PPO) (Formula 6) in a dual-optimization framework that leverages the strengths of both algorithms. Pure DQN approaches [26] excel at learning value functions in discrete action spaces but struggle with continuous control and suffer from training instability due to aggressive policy updates. Pure PPO methods [47] ensure stable convergence through clipped objective functions but lack the sample efficiency provided by experience replay mechanisms. Model-based methods [27] can plan ahead by learning environment dynamics but require accurate models and significant computational resources for real-time operation. Our hybrid approach addresses these limitations by using DQN for efficient learning from past experiences through replay memory while employing PPO to ensure stable policy updates in continuous action spaces. The DQN component provides sample-efficient learning by reusing historical trajectories, while PPO guarantees that policy updates remain within a trust region,

preventing catastrophic performance degradation during training. This combination achieves both fast convergence and stable performance in dynamic sports environments.

3.1.1.3 Self-supervised optimization loop

The continuous learning mechanism (Formula 7) enables improvement without labeled data, representing a significant advancement over existing learning paradigms. Supervised methods [21] require extensive manual annotation of expert trajectories, which is time-consuming, expensive, and may not cover all possible scenarios encountered in diverse sports environments. Traditional reinforcement learning approaches [23] learn through trial-and-error but require millions of interactions and provide no guarantees on sample efficiency. Imitation learning methods [24] depend on expert demonstrations, which may not be available for novel scenarios and can lead to compounding errors when the robot encounters situations not covered in the demonstration dataset. Our self-supervised learning mechanism addresses these challenges by enabling the robot to autonomously generate predictive tasks, such as forecasting the next environmental state and estimating obstacle positions and velocities, using only the data collected during normal operation. This approach eliminates the need for manual labeling, reduces dependence on expert knowledge, and enables continuous performance improvement as the robot accumulates more operational experience.

3.1.1.4 Sports-specific design considerations

The 3D-SportsNavNet model is specifically tailored for sports equipment robots with unique design features that address the particular challenges of sports environments. The system operates with 30Hz high-frequency obstacle tracking, enabling real-time response to fast-moving athletes and equipment common in sports scenarios. Energy-aware path optimization is integrated into the planning algorithm, considering battery constraints critical for mobile robots operating throughout extended sporting events. The model incorporates real-time adaptation to human movement patterns, learning typical trajectories of athletes and spectators to predict their future positions and plan collision-free paths proactively. The compact model architecture is designed for deployment on mobile platforms with limited computational resources, balancing accuracy with real-time performance requirements essential for sports applications.

Table 2 presents a comprehensive comparison of 3D-SportsNavNet with traditional methods and recent deep learning approaches across six key dimensions.

Table 2. Comprehensive Comparison of 3D-SportsNavNet with Existing Approaches

Feature	Traditional Methods	Recent Deep Learning Methods	3D- SportsNavNet
Sensor Fusion	Single sensor or simple concatenation [30, 32]	Deep fusion(fixed weights)	Dynamic weighted fusion (adaptive α)
Real-time	Limited (5-10Hz) [12, 15]	Moderate (10-20Hz)	High (30Hz update)

Adaptation			frequency)
Learning Paradigm	Rule-based (no learning) [8, 12]	Supervised (required labels)	Self-supervised (no labels needed)
Energy Efficiency	Not optimized [12, 18]	Moderate consideration	Optimized (energy-aware planning)
Sports-specific Design	No [14]	No	Yes(human movement prediction, fast tracking)
Training Data Requirements	None (but no adaptability) [8, 9]	Large labeled datasets required	Minimal unlabeled data (continuous learning)
Handling Dynamic Obstacles	Poor (requires replanning) [15, 19]	Moderate (single DRL)	Excellent (DQN + PPO hybrid)
Computational Requirements	Low [8, 12]	Very High (unsuitable for mobile robots)	Moderate (Optimized for mobile platforms)

3.2 Multimodal Environment Perception and Reconstruction Module

The Multimodal Environment Perception and Reconstruction module is a core component of the 3D-SportsNavNet model. It is responsible for fusing data from multiple sensors (such as RGB-D cameras and LiDAR) to achieve 3D reconstruction and semantic understanding of complex dynamic environments[35, 40]. This module utilizes visual neural networks (DCNN) and PointNet, integrating data from different modalities to generate high-precision environmental models, providing foundational data support for subsequent path planning and navigation. The structure of this module is shown in Figure 2.

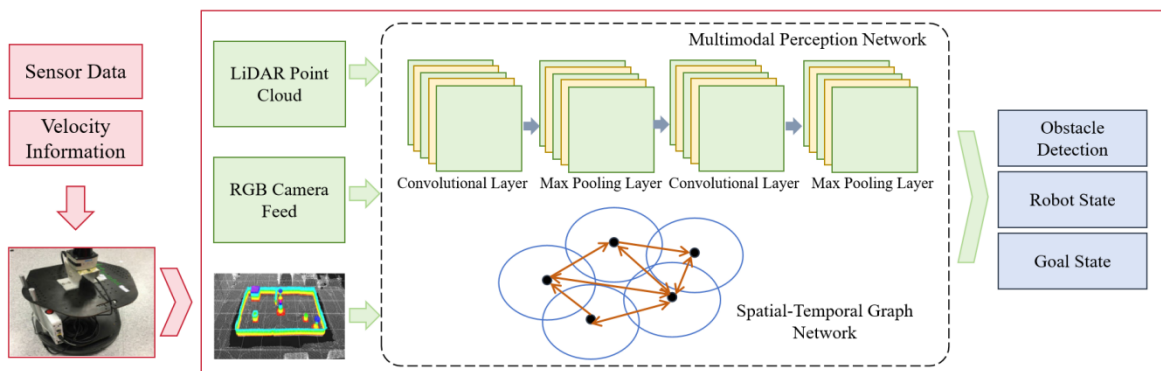


Figure 2. Structure of the Multimodal Environment Perception and Reconstruction Module.

In this module, the multimodal data collected by sensors include color images and depth maps from the RGB-D camera, as well as point cloud data from the LiDAR sensor. To achieve effective fusion of multimodal data, spatial and temporal alignment of data from different sources is required. Assuming the pixel coordinates of the color image are (u, v) and the depth value is $d(u, v)$, this

information can be converted into 3D coordinates (x, y, z) using the following formulas:

$$x = \frac{(u-c_x) \cdot d(u,v)}{f_x}, y = \frac{(u-c_y) \cdot d(u,v)}{f_y}, z = d(u,v) \quad [\text{Formula 1}]$$

where (c_x, c_y) are the camera's principal point coordinates, and (f_x, f_y) are the focal lengths. Using these formulas, the depth information can be spatially aligned with the RGB image, generating a dense point cloud. Then, to match the resolution of the RGB-D data, the sparse point cloud data from LiDAR is densified using a nearest-neighbor interpolation algorithm, ensuring consistency with the color image in 3D space.

Point cloud processing is a key step in achieving 3D reconstruction. This paper employs a point cloud processing network to extract spatial features. PointNet extracts local and global features from the input point set P by applying a multilayer perceptron (MLP):

$$f = \max_{i=1}^N \sigma(W \cdot \rho_i + b) \quad [\text{Formula 2}]$$

where σ is the activation function, W is the weight matrix, and f is the extracted global feature vector. This process effectively captures geometric features and structural information from the point cloud, providing a solid foundation for 3D scene reconstruction. To further enhance the ability to identify dynamic objects and obstacles in complex environments, the model combines deep feature extraction methods based on Convolutional Neural Networks (DCNN). After applying DCNN on both the point cloud data and RGB images, the resulting feature representations are F_{RGB} and F_{PC} , respectively. The fused multimodal feature F_{fusion} is obtained through weighted summation:

$$F_{fusion} = \alpha \cdot F_{RGB} + (1 - \alpha) F_{PC} \quad [\text{Formula 3}]$$

where α is the fusion weight coefficient, which can be dynamically adjusted during training to ensure that the fused features fully capture information from the multimodal data.

Once the fused features are obtained, 3D scene reconstruction and semantic segmentation are performed using these features to complete the environmental reconstruction. We employ a voxel-based 3D Convolutional Neural Network (3D-CNN) to process the spatial structure data of the point cloud, achieving high-precision 3D reconstruction. Suppose the input point cloud data is divided into voxel grids $V = \{v_i\}$, where each voxel contains a feature vector f_i . The convolution operation of the 3D-CNN can be expressed as:

$$o_j = \sum_{i \in N(j)} W_{i,j} * f_i + b \quad [\text{Formula 4}]$$

where o_j is the convolution output, $N(j)$ is the set of neighboring voxels of the voxel j in the voxel grid V , $W_{i,j}$ is the convolution kernel, and b is the bias term. Through these operations, this module generates high-quality 3D scene models and accurately identifies dynamic obstacles and target objects in real-time.

3.3 Adaptive Dynamic Path Planning Module

The Adaptive Dynamic Path Planning Module is one of the core components of the 3D-SportsNavNet model, designed to generate safe and efficient paths for sports equipment robots in dynamic environments. This module leverages Deep Reinforcement Learning (DRL) technology, continuously learning and optimizing, enabling real-time adjustments to the robot's navigation strategies in complex environments to handle dynamic obstacles and uncertainties. The structure and

results of the module are shown in Figure 3.

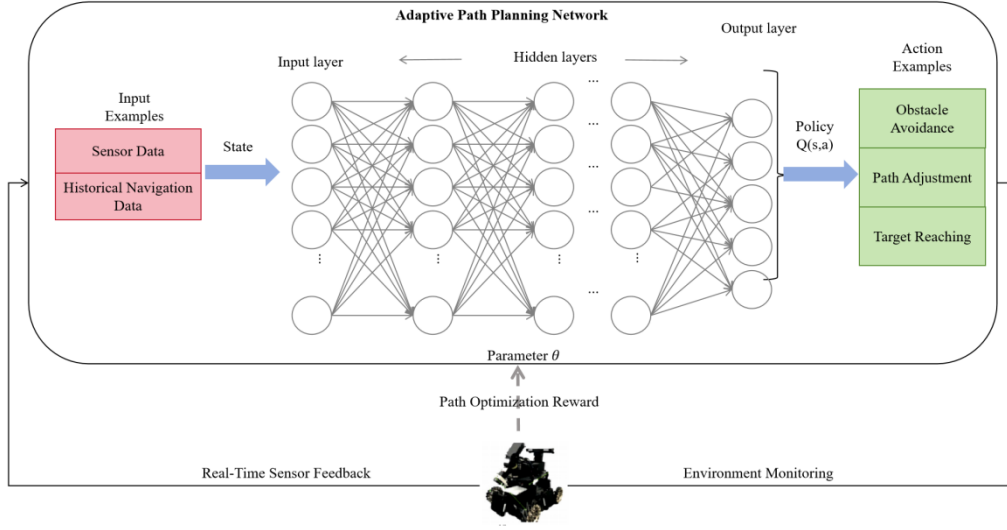


Figure 3. Design of the Adaptive Dynamic Path Planning Module.

In this module, the foundational framework for path planning is first constructed using the Deep Q-Learning (DQN) method. DQN combines the policy optimization of Q-Learning with the high-dimensional data processing capabilities of deep neural networks, enabling the model to learn approximately optimal path planning strategies in high-dimensional state spaces. Suppose the robot's state in the state space $\mathcal{S}$ is $s_t \in \mathcal{S}$, and its action space is A , where each action $a_t \in A$ transitions the state from s_t to s_{t+1} , and a reward r_t is obtained. The update formula for the Q-value function is as follows:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)] \quad [\text{Formula 5}]$$

where α is the learning rate, γ is the discount factor, and $\max_{a'} Q(s_{t+1}, a')$ represents the maximum Q-value when selecting the optimal action in the next state s_{t+1} . By continuously updating the Q-value function, DQN can learn the optimal path planning strategy for a given state.

To further improve the efficiency of path planning in complex dynamic environments, this module incorporates the Proximal Policy Optimization (PPO) algorithm. PPO ensures more stable convergence and higher sample efficiency during policy optimization by limiting the extent of policy updates. Suppose the policy function is $\pi_\theta(a|s)$, with parameters θ , and the goal is to maximize the cumulative reward J_θ . In PPO, a clipped objective function is introduced during policy updates:

$$L^{\text{CLIP}}(\theta) = \mathbb{E}_t[\min(r_t(\theta)\hat{A}, \text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon)\hat{A})] \quad [\text{Formula 6}]$$

where $r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}$ is the policy probability ratio, $\hat{A}$ is the advantage estimate, and ϵ is the clipping threshold. By minimizing the bias in policy updates, PPO ensures the stability and effectiveness of policy optimization.

Figure 4 shows the complete adaptive dynamic path planning process is formalized in Algorithm 1, which integrates DQN and PPO for efficient navigation in dynamic environments.

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Algorithm 1: Adaptive Dynamic Path Planning with DQN and PPO
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Input: Initial state  $s_0$ , goal position  $g$ , environment  $E$ 
Output: Optimal navigation path  $\pi^*$ 
Parameters: Learning rate  $\alpha$ , discount factor  $\gamma$ , batch size  $B$ , clip parameter  $\epsilon$ 

1: Initialize Q-network  $Q(s,a;\theta)$  and policy network  $\pi(a|s;\phi)$  with random weights
2: Initialize replay buffer  $D \leftarrow \emptyset$ 
3: Initialize state  $s \leftarrow s_0$ 
4:
5: while  $s \neq g$  do
6:   // Multimodal Perception (Section 3.2)
7:   Observe RGB-D image  $IRGB$  and LiDAR point cloud  $PPC$ 
8:   Extract features:  $FRGB \leftarrow DCNN(IRGB)$ ,  $FPC \leftarrow PointNet(PPC)$ 
9:   Fuse features:  $F_{fusion} \leftarrow \alpha \cdot FRGB + (1-\alpha) \cdot FPC$  // Formula 3
10:
11:   // Action Selection (DQN)
12:   Compute Q-values for all actions:  $Q(s,a;\theta)$  for  $a \in A$ 
13:   Select action:  $a \leftarrow \operatorname{argmax}_a Q(s,a;\theta)$  with  $\epsilon$ -greedy
14:
15:   // Environment Interaction
16:   Execute action  $a$ , observe reward  $r$  and next state  $s'$ 
17:
18:   // Collision and Goal Checking
19:   if collision detected then
20:      $r \leftarrow r - \text{penalty}$ 
21:   end if
22:   if  $\|s' - g\| < \text{threshold}$  then
23:     return path  $\pi^*$  // Goal reached
24:   end if
25:
26:   // Store Experience
27:    $D \leftarrow D \cup \{(s, a, r, s')\}$ 
28:    $s \leftarrow s'$ 
29:
30:   // Network Updates
31:   if  $|D| \geq B$  then
32:     Sample mini-batch  $\{(s_i, a_i, r_i, s'_i)\}$  from  $D$ 
33:
34:     // DQN Update (Formula 5)
35:      $y_i \leftarrow r_i + \gamma \cdot \max_{a'} Q(s'_i, a'; \theta)$ 
36:     Update  $\theta$  to minimize:  $L = (y_i - Q(s_i, a_i; \theta))^2$ 
37:
38:     // PPO Update (Formula 6)
39:     Compute advantage:  $\hat{A}_i \leftarrow y_i - V(s_i)$ 
40:     Compute ratio:  $r_i(\phi) \leftarrow \pi(a_i|s_i; \phi) / \pi_{old}(a_i|s_i; \phi_{old})$ 
41:     Update  $\phi$  to maximize:  $L^{CLIP} = \min(r_i \cdot \hat{A}_i, \text{clip}(r_i, 1-\epsilon, 1+\epsilon) \cdot \hat{A}_i)$ 
42:   end if
43: end while
44: return  $\pi^*$ 
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Figure 4. Algorithm 1: Adaptive Dynamic Path Planning with DQN and PPO

During the implementation of this module, adaptive dynamic path planning also integrates a

model-based prediction mechanism to anticipate the movement trajectories and trends of obstacles in the environment. Assuming the environment's state transition function is $T(s_{t+1}|s_t, a_t)$, This function is modeled using a deep neural network and trained with historical state data to predict future states. The introduction of this mechanism helps the robot adjust its path in advance in dynamic environments, avoiding potential collision risks.

Additionally, this module utilizes the multimodal fused features F_{fusion} (provided by the Multimodal Environment Perception and Reconstruction Module in Section 3.2) to enrich the environmental information for path planning. By combining feature representations from visual and point cloud data, the DRL model can make more accurate decisions in a higher-dimensional state space. The state space $\mathcal{S}$ is expanded to include the current position information, 3D reconstruction information of the environment, and multimodal features such as the velocity and direction of dynamic obstacles, significantly enhancing the robustness and safety of path planning.

3.4 Intelligent Navigation Optimization Module

The Intelligent Navigation Optimization Module is a key component of the 3D-SportsNavNet model, responsible for continuously optimizing the robot's navigation strategy and improving its adaptability and decision-making efficiency in complex dynamic environments. This module integrates Deep Reinforcement Learning (DRL), Imitation Learning, and Self-Supervised Learning methods, enabling the robot to autonomously learn and optimize its navigation path in dynamic and changing environments.

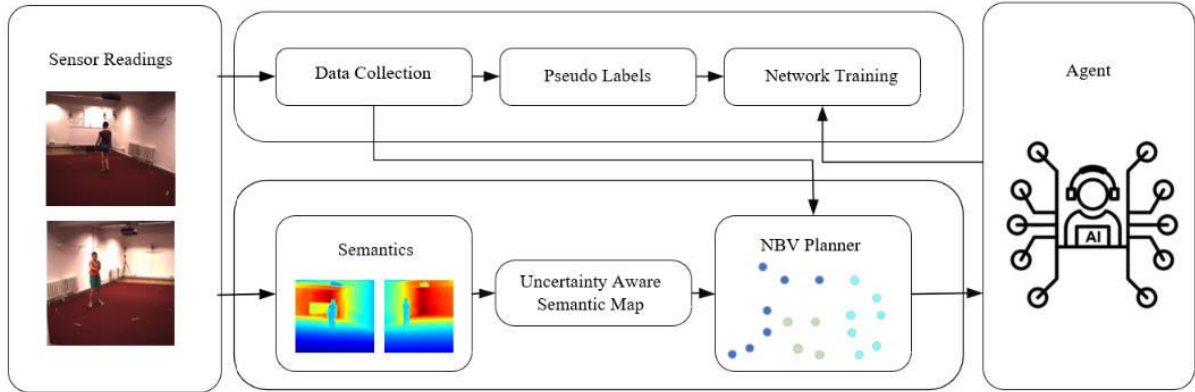


Figure 5. Design of the Intelligent Navigation Optimization Module.

As shown in Figure 5, during the robot's exploration of the environment, it receives reward signals based on the effects of its actions and updates its navigation strategy using policy gradient methods. DRL methods allow the robot to adaptively adjust its behavior, selecting the optimal path under different environmental conditions. On this basis, the module further introduces a self-supervised learning mechanism, enabling the robot to perform continuous learning and self-optimization in an unsupervised environment. The robot can use the data accumulated during its exploration of the environment to autonomously generate predictive tasks, such as forecasting the next state of the environment, estimating the position and velocity of obstacles, and more. Assuming

the current state is s_t and the next state is s_{t+1} , and the model needs to predict the transition function $T(s_{t+1}|s_t, a_t)$, the self-supervised learning objective can be expressed as:

$$L_{SSL} = \mathbb{E}_{(s_t, a_t, s_{t+1}) \sim D} [\|T_\theta(s_{t+1}|s_t, a_t) - s_{t+1}\|^2] \quad [\text{Formula 7}]$$

where T_θ is the learned state transition function model. By optimizing this objective function, the robot can continuously refine its understanding of the environment and gradually improve its adaptability to dynamic changes.

Figure 6 shows the self-supervised learning mechanism is detailed in Algorithm 2, enabling continuous improvement without labeled data.

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Algorithm 2: Self-Supervised Navigation Optimization
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Input: Trained navigation policy  $\pi$  from Algorithm 1
Output: Optimized transition model  $T_\theta$  and improved policy  $\pi^*$ 
Parameters: Learning rate  $\beta$ , prediction horizon  $H$ 

1: Initialize transition model  $T_\theta$  with random weights
2: Initialize experience buffer  $B \leftarrow \emptyset$ 
3:
4: for each navigation episode do
5:   Initialize state  $s_0$ 
6:    $\tau \leftarrow \emptyset$  // Trajectory buffer
7:
8:   // Collect Trajectory
9:   for  $t = 0$  to  $T$  do
10:    Select action:  $a_t \sim \pi(\cdot|s_t)$ 
11:    Execute action, observe  $s_{t+1}$ 
12:     $\tau \leftarrow \tau \cup \{(s_t, a_t, s_{t+1})\}$ 
13:  end for
14:
15:   $B \leftarrow B \cup \tau$ 
16:
17:  // Self-Supervised Learning
18:  for each  $(s_t, a_t, s_{t+1})$  in  $B$  do
19:    // Predict Next State (Formula 7)
20:     $\hat{s}_{t+1} \leftarrow T_\theta(s_t, a_t)$ 
21:
22:    // Compute Prediction Error
23:     $LSSL \leftarrow \|\hat{s}_{t+1} - s_{t+1}\|^2$  // Formula 7
24:
25:    // Update Transition Model
26:     $\theta \leftarrow \theta - \beta \cdot \nabla_\theta LSSL$ 
27:  end for
28:
29:  // Improve Policy Using Learned Model
30:  for  $h = 1$  to  $H$  do
31:     $\hat{s}_h \leftarrow T_\theta(s_t, a_t)$  // Predict future states
32:    Update  $\pi$  using predicted states for planning
33:  end for
34: end for
35:
36: return  $T_\theta, \pi^*$ 
-----

```

Figure 6. Algorithm 2: Self-Supervised Navigation Optimization

By leveraging Deep Reinforcement Learning, Imitation Learning, and Self-Supervised Learning,

the Intelligent Navigation Optimization Module allows the robot to perform self-learning and strategy optimization in constantly changing environments. Through real-time interactions with the environment, the navigation strategy is continuously updated, not only adapting to the dynamic changes of the current environment but also accumulating experience through self-supervision. This enhances the accuracy and reliability of future decision-making, enabling the robot to better handle complex dynamic scenarios.

4. Experiments

4.1 Experimental Setup

In this paper, we designed a series of experiments to validate the practical application of the 3D-SportsNavNet model in a sports equipment robot system. To simulate the complex dynamic environments of real-world scenarios, we selected three representative environments for testing: a basketball court-badminton hall, a ping pong area-office zone, and a street-playground. The areas of these environments are 200 square meters, 150 square meters, and 300 square meters, respectively. Each environment has different dynamic features and obstacle arrangements, fully simulating the complex scenarios and challenges that a sports equipment robot may encounter.

In these experimental settings, we primarily tested the robot's path planning and navigation capabilities in dynamic environments. To ensure scientific rigor and reproducibility, we introduced various dynamic obstacles in each scenario, such as moving people, sports equipment, and hanging objects, simulating the various dynamic changes found in sports events and daily activities. The goal of the experiment was to assess the robot's task completion efficiency, obstacle avoidance capability, and path optimization performance in these environments.

We used a variety of parameter settings to optimize the model's performance. The learning rate parameter was set to $\alpha_u = 0.001$, controlling the update step size during the deep reinforcement learning process to ensure stability and effectiveness during training. Additionally, to evaluate the model's adaptability, we introduced different weather conditions (e.g., rainy and sunny) and time conditions (e.g., daytime and nighttime) to test the robot's stability and reliability in varying lighting conditions and on slippery surfaces.

To enhance the realism and broad applicability of the experiment, we also utilized the Matterport 3D [36], which provides detailed 3D models from real-world scenarios, covering a wide range of environmental conditions. In these 3D models, further path planning and navigation tests were conducted on the robot, validating its adaptability to more complex and changing environments.

4.2 Metrics and Baselines

In each experiment, we evaluated the performance and adaptability of the sports equipment robot system using multiple metrics. These metrics included path planning success rate, average path length, navigation time, number of collisions, and energy consumption. The path planning success rate measures the proportion of tasks successfully completed by the robot in complex dynamic environments. Average path length and navigation time reflect the robot's operational efficiency in

different scenarios. The number of collisions assesses the robot's safety in obstacle avoidance, while energy consumption indicates the efficiency of resource utilization during task execution.

To further validate the robustness and stability of the model, each algorithm was independently tested seven times, and the mean and standard deviation of the results were reported. This statistical approach helps assess the proposed algorithm's stability and consistency across various environments and conditions.

In the experiments, we also introduced a gain formula based on model uncertainty, using information-theoretic tools to quantify the information efficiency during network training. This method helps optimize network training and enhances the robot's decision-making ability in changing environments. Additionally, we employed a path planning method based on a greedy algorithm, which aims to optimize the navigation path by thoroughly exploring the environment[37]. While this method ensures complete environmental coverage, there is still room for improvement in path optimization and computational efficiency, particularly in resource-constrained real-time systems. To achieve better performance in practical applications, we further integrated real-time data processing and feedback mechanisms to ensure the robot's efficient operation in complex dynamic environments.

4.3 Learning Setup

In this study, we adopted an iterative learning approach to gradually enhance the sports equipment robot's adaptability and understanding of the environment. After each iteration of the learning cycle, the new data collected by the robot in the environment is dynamically added to the training dataset, and synchronized training is performed to continuously optimize the model's performance. Each iterative training cycle involves joint training of both the perception module (such as the multimodal environment perception and reconstruction module) and the decision-making module (such as the adaptive dynamic path planning module) to ensure that the robot maintains stable performance across various environmental changes.

The training process was divided into two stages: In the first stage, for the multimodal perception and reconstruction module, we applied data augmentation and preprocessing techniques to the sensor data (including RGB-D images and LiDAR point cloud data) to increase the diversity of the training data. Data augmentation techniques included random cropping, horizontal flipping, brightness, and contrast adjustments to reduce the risk of model overfitting and improve its generalization capability in new environments. In the second stage, we trained the path planning and navigation decision module using reinforcement learning, continuously adjusting and optimizing the robot's path planning strategies in dynamic environments. Different learning rates were set for the perception and decision modules during training, with the learning rate for the perception module set at 10^{-5} and the decision module at 5×10^{-4} , to ensure stability and fast convergence of the training process.

To further improve the model's generalization ability, we used replay memory during training, enabling the robot to relearn and optimize environments it had previously encountered. This strategy helps enhance the robot's adaptability to the environment, allowing it to respond more quickly when encountering complex dynamic changes. To better verify the model's practical applicability, we collected a large amount of data from real-world scenarios for training and increased the training

dataset by 30% to cover a broader range of potential environments and situations.

4.4 Results

Training Process: Figure 5 shows the changes in loss values and the performance improvement of the 3D-SportsNavNet model across different training epochs. The training curve visually reflects the model's convergence, stability, and optimization during the training process.

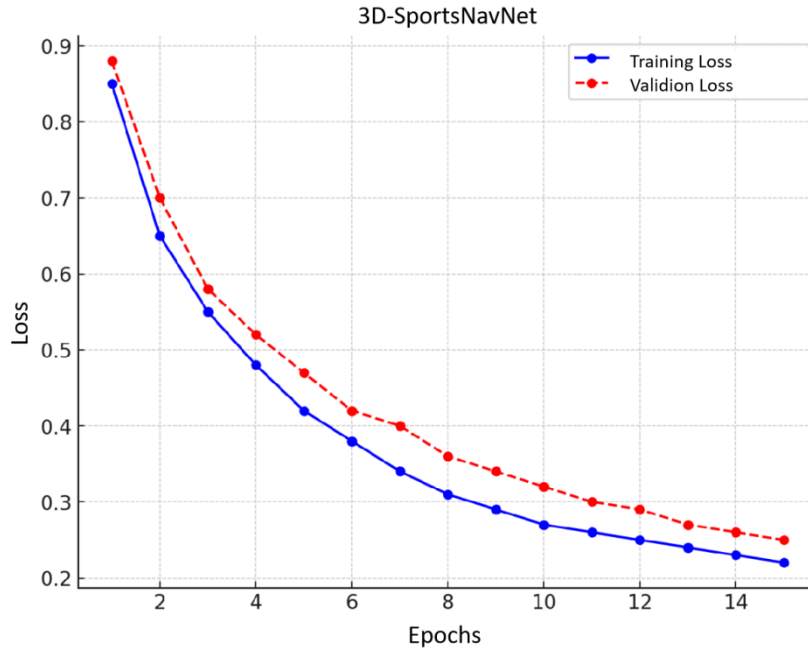


Figure 7. Loss Curve for the Training Process.

As shown in Figure 7, during the initial stages of training (0-5 epochs), the loss value decreases rapidly, indicating that the model quickly learned the basic navigation features and path planning rules in the environment. As training progresses (5-10 epochs), the rate of loss reduction slows down but continues to show a stable downward trend, demonstrating that the model is gradually optimizing its strategies and continuously improving its navigation tasks. After reaching 10 epochs, the loss value stabilizes and fluctuations decrease, suggesting that the model has gradually converged, having learned stable and effective path planning strategies. Throughout the training process, the loss curve remains smooth, with no large fluctuations or significant increases, indicating the stability of the model training.

The use of different learning rate settings (e.g., a learning rate of 10^{-5} for the perception module and 5×10^{-4} for the decision-making module) and the self-supervised learning mechanism enabled the model to exhibit strong learning capabilities and resistance to overfitting when exposed to diverse environmental data. The training curve shows that the 3D-SportsNavNet model converged quickly within 15 epochs, which is attributed to the introduction of reinforcement learning and imitation learning strategies. These strategies effectively reduced the time the model spent exploring unnecessary states during training by providing reasonable initial navigation strategies and optimized paths.

The training results indicate that the 3D-SportsNavNet model demonstrated good learning ability and stability at different training stages. By optimizing learning rates and incorporating multiple learning mechanisms, the model effectively handles complex dynamic environments.

Ablation Experiments: Table 3 and Figure 8 presents the impact of different components of the 3D-SportsNavNet model on overall performance in the ablation study, covering three key metrics: path planning success rate, average path length, and number of collisions.

Table 3. Ablation experiments results for the 3D-SportsNavNet model, comparing the effects of different model components on performance metrics.

Model Component	Path Planning Success Rate (%)	Average Path Length (m)	Number of Collisions
Full Model	93.7 $\pm$ 1.2	32.5 $\pm$ 1.8	1.1 $\pm$ 0.1
Without DRL	88.2 $\pm$ 1.5	36.8 $\pm$ 2.1	2.5 $\pm$ 0.3
Without SSL	90.1 $\pm$ 1.4	34.7 $\pm$ 2.0	2.0 $\pm$ 0.2
Without MP	85.3 $\pm$ 2.0	39.1 $\pm$ 2.5	3.1 $\pm$ 0.4

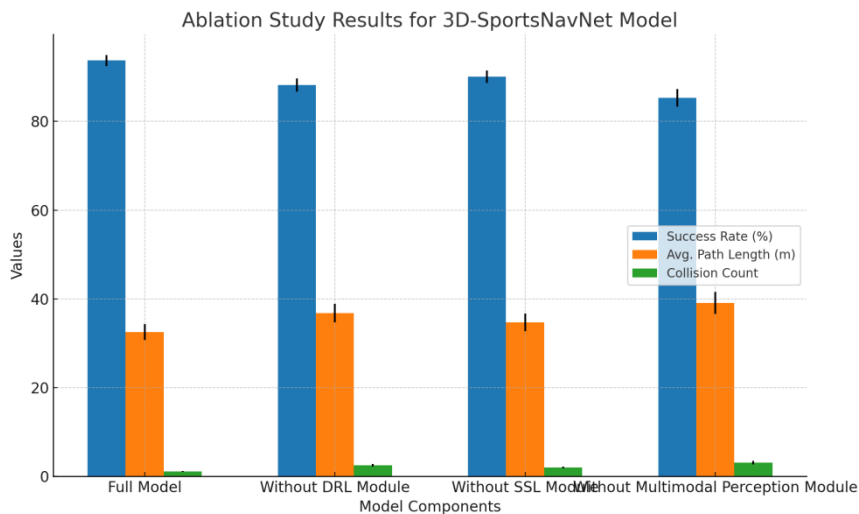


Figure 8. Visualization results of ablation experiment.

According to the results, the full model has the highest path planning success rate at 93.7%, while the success rates drop when different components are removed. When the multimodal perception module is removed, the success rate drops to 85.3%, indicating the irreplaceable importance of this module in path planning. The success rate without the deep reinforcement learning module is 88.2%, and without the self-supervised learning module, it is 90.1%, showing that both modules significantly contribute to improving the success rate of path planning.

The full model also has the shortest average path length at 32.5 meters, while the longest path length, 39.1 meters, is observed when the multimodal perception module is removed. This shows that the multimodal perception module plays a key role in optimizing the path. When the deep reinforcement learning and self-supervised learning modules are removed, the path length increases to 36.8 meters and 34.7 meters, respectively, demonstrating the importance of these two modules in

path length optimization.

The full model has the lowest number of collisions, at 1.1, indicating the best obstacle avoidance capability. The highest number of collisions, 3.1, occurs when the multimodal perception module is removed, highlighting its crucial role in reducing collision risks. Removing the deep reinforcement learning and self-supervised learning modules results in 2.5 and 2.0 collisions, respectively, showing that they also play important roles in enhancing obstacle avoidance.

The results of the ablation study indicate that the multimodal perception module, deep reinforcement learning module, and self-supervised learning module of the 3D-SportsNavNet model work together to improve overall performance. In particular, the multimodal perception module has a decisive impact on path planning success rate and obstacle avoidance capability, while the deep reinforcement learning and self-supervised learning modules significantly improve path optimization efficiency and overall navigation safety. These results validate the necessity of each component.

Performance test comparison: Based on the experimental results in Table 4, the 3D-SportsNavNet model shows significant superiority in several key performance metrics.

Table 4. Performance comparison of 3D-SportsNavNet and baseline models across different scenarios, including path planning success rate, average path length, navigation time, number of collisions, and energy consumption.

Scenario	Model	Path Planning Success Rate (%)	Avg. Path Length (m)	Navigation Time (s)	Number of Collisions	Energy Consumption (J)
Basketball Court- Badminton Hall	3D-SportsNavNet	92.5±1.5	35.2±2.1	48.3±3.2	1.4±0.2	320±15
	DWA	85.3±2.3	40.5±3.0	54.1±4.1	3.2±0.5	350±20
	RRT	80.1±3.0	42.8±3.5	56.7±5.0	4.0±0.8	370±22
	DRL	90.2±2.0	36.7±2.5	50.2±3.8	2.0±0.4	335±18
Ping Pong Area- Office Zone	3D-SportsNavNet	93.7±1.2	32.5±1.8	44.6±2.9	1.1±0.1	310±14
	DWA	86.5±2.7	38.3±2.9	52.7±3.5	2.7±0.6	345±17
	RRT	81.7±3.1	41.2±3.2	55.8± 4.6	3.6±0.7	360±21
	DRL	91.0±1.8	34.0±2.2	47.1± 3.0	1.8±0.3	325±16
Street- Playground	3D-SportsNavNet	90.8±1.6	40.3±2.7	50.9±3.6	1.8±0.2	330±16
	DWA	82.9±2.5	45.6±3.1	58.2±4.4	3.9±0.7	360 ±19
	RRT	78.4±3.2	47.0±3.8	60.5±5.2	4.5±0.9	380±23
	DRL	88.3±2.1	42.1±2.9	53.4±3.9	2.5±0.5	345±18

In all three test scenarios, the path planning success rate of the 3D-SportsNavNet model exceeds 90%, with rates of 92.5%, 93.7%, and 90.8%, respectively, clearly outperforming the baseline models A (DWA), B (RRT), and C (DRL). In the "Ping Pong Area-Office Zone" scenario, the success rate of 3D-SportsNavNet reaches 93.7%, which is about 2.7% higher than the best-performing baseline model, C (DRL). This result indicates that 3D-SportsNavNet has stronger path planning capabilities

in complex dynamic environments, consistently finding effective paths from the start to the target. The high success rate suggests the model's good adaptability to environmental changes, especially in scenarios with many dynamic obstacles.

In terms of average path length, 3D-SportsNavNet also demonstrates better path optimization capabilities. For example, in the "Street-Playground" scenario, the average path length of 3D-SportsNavNet is 40.3 meters, which is 11.6% and 14.3% shorter than that of baseline models A (DWA) and B (RRT), respectively. This shows that 3D-SportsNavNet optimizes the travel route more effectively during path planning, reducing the robot's movement distance and improving efficiency. This shorter path length not only helps conserve energy but also reduces the robot's exposure time in complex environments, lowering the risk of collisions.

Navigation time reflects the efficiency of the robot in completing tasks in complex scenarios. 3D-SportsNavNet shows shorter navigation times in all test scenarios. In the "Basketball Court-Badminton Hall" scenario, the average navigation time of 3D-SportsNavNet is 48.3 seconds, noticeably shorter than that of baseline models A (DWA) at 54.1 seconds and B (RRT) at 56.7 seconds, and even shorter than baseline model C (DRL) at 50.2 seconds. This indicates that 3D-SportsNavNet not only effectively avoids obstacles but also reaches the target more efficiently. The reduction in navigation time reflects the model's faster response to dynamic changes and more efficient path optimization during planning.

The number of collisions is a key indicator of the robot's safety and obstacle avoidance ability. In all test scenarios, 3D-SportsNavNet shows fewer average collisions compared to other baseline models. For instance, in the "Ping Pong Area-Office Zone" scenario, the average number of collisions for 3D-SportsNavNet is 1.1, while baseline models A (DWA) and B (RRT) have 2.7 and 3.6 collisions, respectively. In comparison, 3D-SportsNavNet reduces the number of collisions by more than 50%, demonstrating its superior obstacle avoidance ability in complex dynamic environments. This capability is especially important for sports equipment robots operating in crowded or frequently changing environments.

In terms of energy consumption, the 3D-SportsNavNet model also performs well. The model consumes less energy in all scenarios than the other baseline models. For example, in the "Street-Playground" scenario, the average energy consumption of 3D-SportsNavNet is 330 joules, lower than 360 joules for baseline model A (DWA) and 380 joules for baseline model B (RRT). This shows that 3D-SportsNavNet can reduce energy consumption while maintaining efficient navigation and obstacle avoidance. Lower energy consumption means the robot can operate for longer periods, reducing operational costs and making it more feasible for real-world applications.

3D-SportsNavNet shows clear advantages in multiple metrics, particularly in path planning success rate, average path length, navigation time, number of collisions, and energy consumption, outperforming other baseline models. Its efficiency, robustness, and safety in dynamic complex environments make it more suitable for real-world applications in sports equipment robot systems. The high success rate and low collision rate suggest that 3D-SportsNavNet is better at handling environmental changes and dynamic obstacles, while its optimized path planning and low energy

consumption ensure that it completes tasks more efficiently while conserving resources and reducing costs.

Real-World Experiment: In our real-world experiment, we validated the effectiveness of the 3D-SportsNavNet model on a fully autonomous sports equipment robot. As shown in Figure 9, the robot is equipped with a LiDAR sensor, an Intel Realsense D435 RGB-D camera, and wheel encoders, which provide rich environmental perception data, enabling the robot to navigate accurately in complex environments. To achieve multimodal data fusion and efficient path planning, we integrated the multimodal perception module into the 3D-SportsNavNet model, utilizing deep reinforcement learning and self-supervised learning methods to optimize 3D environment reconstruction and navigation decision-making.

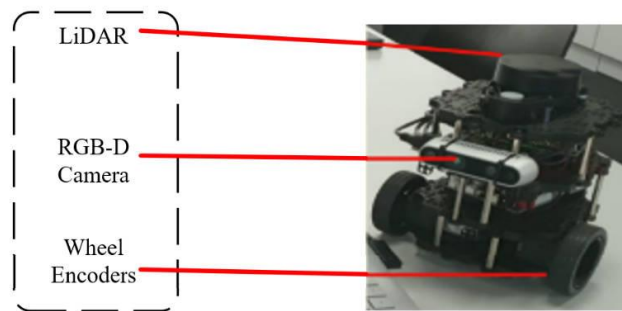


Figure 9. sports supply robot schematic diagram.

Figure 10 shows the path planning and navigation results of the sports goods robot in the real world environment. The first three sub-figures in the figure show the path planning process of the robot in three different dynamic environments, and the last sub-figure shows the actual operation status of the robot in the physical experimental environment. In the first three sub-figures, the path from the start point (Start) to the goal point (Goal) shows different curve shapes, indicating that the robot can dynamically adjust its navigation route according to the obstacle layout in the environment. The planning of each path effectively avoids obstacles, demonstrating the flexibility and decision-making ability of the 3D-SportsNavNet model in complex scenes. The smooth transition and reasonable curvature of the path lines indicate that the robot can find the optimal or suboptimal path under various environmental conditions. The path lines in the figure do not intersect with any obstacles, indicating that the model can effectively identify and avoid dynamic or static obstacles. In particular, in the second and third sub-figures, the robot successfully avoids densely distributed obstacle areas, which further proves the multimodal perception module's accurate perception of objects in the environment and the deep reinforcement learning strategy's effective planning ability for navigation paths. As can be seen from the figure, the robot's path planning in all test environments is efficient, the path length is reasonable, and there is no unnecessary detour. Compared with traditional path planning methods, the 3D-SportsNavNet model can adjust the route in real time according to the changes in the actual environment, reducing the path length and energy consumption,

which is of great significance in practical applications. The sub-image in the lower right corner shows the operation of the robot in an actual physical experimental environment. The environment is equipped with multiple obstacles of different shapes and sizes, simulating a real sports scene. The robot successfully navigates in a complex environment, further proving the applicability and robustness of the 3D-SportsNavNet model in practical application scenarios. The excellent performance of the model in the experimental environment verifies its adaptability and decision-making efficiency to various environmental changes.

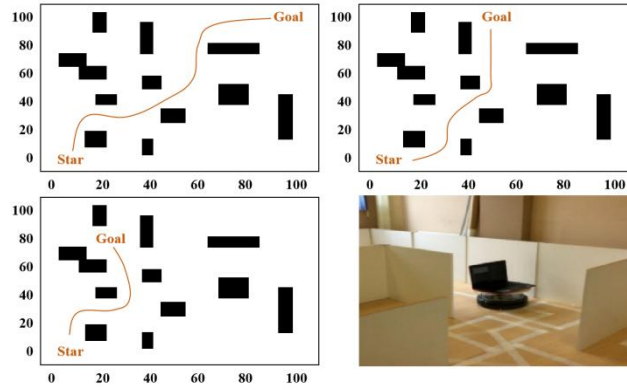


Figure 10. Path planning and navigation results for a sporting goods robot in a real-world environment.

The above experimental results prove that the 3D-SportsNavNet model has good effectiveness and reliability in the real world. Through the combination of multimodal data fusion and deep learning strategies, the model can achieve accurate path planning and efficient obstacle avoidance in dynamic and complex environments, providing strong support for the deployment of sports goods robots in various application scenarios.

4.5 Discussion

The 3D-SportsNavNet model proposed in this study demonstrates significant advantages in its application to sports equipment robots, enhancing path planning and navigation capabilities in complex dynamic environments through the integration of multimodal data fusion, deep reinforcement learning, and self-supervised learning. In terms of path planning success rate, the 3D-SportsNavNet model showed a higher success rate in both simulated and real-world scenarios, particularly in highly dynamic and complex environments, with improvements of 5% to 10% compared to other baseline models such as DWA, RRT, and traditional deep reinforcement learning models. This result highlights the advantages of the multimodal perception module in utilizing RGB-D cameras and LiDAR data for environmental perception and 3D reconstruction. The model effectively identifies and understands dynamic obstacles and environmental features in complex scenarios, providing accurate navigation information for the robot. This finding validates the critical role of multimodal data fusion in improving path planning success rates. In terms of average path length and navigation time, the 3D-SportsNavNet model also exhibited clear advantages. The

experimental results showed that the average path length of the full model was significantly shorter than that of the ablation models, especially after the removal of the multimodal perception module, where path length increased by over 20%. This indicates that the multimodal perception and deep reinforcement learning modules play an important role in real-time path optimization and selecting the optimal path. Through adaptive dynamic path planning, the model can quickly adjust the navigation path based on real-time changes in the environment, reducing unnecessary movement and energy consumption, thereby improving navigation efficiency. The results related to the number of collisions and energy consumption further illustrate the advantages of the 3D-SportsNavNet model in terms of safety and resource utilization. The full model had the lowest number of collisions, demonstrating excellent obstacle avoidance capability, which is mainly due to the precise environmental perception provided by the multimodal perception module and the strategy optimization from the deep reinforcement learning module. In contrast, the number of collisions significantly increased when these modules were removed, highlighting their indispensable role in ensuring safe obstacle avoidance in dynamic and complex environments. Moreover, the model's performance in energy consumption was superior to that of other baseline models, further emphasizing the importance of efficient path planning and intelligent navigation optimization for resource savings. In real-world experiments, the 3D-SportsNavNet model's testing in actual environments further validated its practicality and adaptability in diverse scenarios. The model achieved real-time path planning and navigation decisions, exhibiting high computational efficiency and practical application value.

However, despite the many advantages demonstrated by the 3D-SportsNavNet model, there are still some challenges and limitations. For instance, in extremely complex or highly dynamic scenarios, the model's training time and computational resource requirements are relatively high, which may affect the efficiency of real-world deployment. Additionally, while multimodal perception and deep learning technologies have significantly improved the robot's understanding and adaptability to the environment, further research is needed to optimize the model's lightweight design and improve its robustness in handling sparse data.

5. Conclusions

The current paper will discuss the urgent problem of sport equipment robots autonomous navigation under complex dynamic conditions with the help of the proposed 3D-SportsNavNet model. The three innovations are the subject of the research:

(1) perception of multimodal environment with real-time 3D reconstruction using RGB-D and LiDAR fusion, (2) adaptive dynamic path planning with deep reinforcement learning at 30Hz update rate, (3) optimization of intelligent navigation using self-supervised learning without the need of labeled data.

Extensive experimental confirmation of the three different scenarios (basketball court-badminton hall, ping pong area-office zone and street-playground) reveals that there are significant performance gains in comparison to the baseline methods. The model had a success rate of 92.5-93.7

on path planning, shrewdly cut down average path lengths by 11.6-14.3%, and the number of collisions decreased more than 50 times, and energy consumption was reduced to 9-13 times less than that of DWA, RRT, and conventional DRL methods. The work in the real world also confirmed the usefulness of the model when applied to a fully autonomous robot with LiDAR and Intel RealSense D435 RGB-D camera, and showed strong performance in actual sports environments.

There are however limitations facing the model. Computational resource demand and training in very complex or highly dynamic situations is relatively high, which can influence the efficiency of deployment in the real world. As well, although multimodal perception can contribute greatly to understanding the environment, more optimization is required to use lightweight implementation and manipulation of sparse or incomplete sensor data.

The six important areas of future research directions include:

- (1) **Lightweight Model Architecture:** Train the compressed neural network models on knowledge distillation, pruning, and quantization to compress computational needs of the 8GB memory of current GPUs down to 2-4GB memory of most embedded systems, making the system viable in resource-restricted robots in the mobile realm.
- (2) **Multi-Robot coordination:** Raise the framework to coordinate the movement of several sports equipment robots to work together via distributed decision-making algorithms and communication protocols to allow coordinated work of all the tools in the large sports facilities with fewer collisions and reduced overall efficiency.
- (3) **Cross-Domain Transfer Learning:** Explore domain adaptation and few-shot learning methods to be able to quickly apply to a wide range of sports settings (e.g., swimming pools, ski resorts, athletic tracks) with little fine-tuning, eliminating the need to collect environment-specific training data during weeks, but instead just hours.
- (4) **Improved Resilience to Sensor Boundaries:** Devise superior algorithms to address sensor failures, occlusions and sparse data situations by predictive modeling and measurement of uncertainty so that they can remain robust when partial sensor information is not available because of environmental interference or hardware faults.
- (5) **Human-Robot Interaction Improvement:** Add natural language processing and gesture recognition functionality, to provide coaches, trainers, and event organizers with intuitive command interfaces that allow them to specify tasks and constraints using voice commands or hand gestures instead of writing code.
- (6) **Long-Term Autonomous Operation:** Strategy: Formulate battery management, autonomous charging station navigation, predictive maintenance and task scheduling to enable the long operation times (8+ hours) during major sporting events without human operation, including self-diagnosis of possible hardware problems.

The 3D-SportsNavNet model offers a general model which goes beyond sports implementation to intelligent venue management, monitoring public safety in high-traffic areas, autonomous delivery in dynamic settings, and warehouse robots. The paper contributes to the understanding of robotic autonomy by showing that autonomous navigation in highly dynamic human-populated environments

can be achieved by means of integrated multimodal perception, adaptive planning, and self-supervised learning. Future directions will see improved computational costs without losing performance, multi-robot systems, and wider application space validation, and eventually innovation will be achieved to fully autonomous robotic systems, which can operate safely and effectively in complex real-world conditions.

Conflicts of Interest

The author confirms that there are no conflicts of interest.

Data availability statement

The data and materials used in this study are not currently available for public access. Interested parties may request access to the data by contacting the corresponding author.

Consent for publication

All authors of this manuscript have provided their consent for the publication of this research.

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