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VR Proactive Agent Dynamic Target-Following Behavior Planning Method Based on Attention Mechanism

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Abstract: To address the problems of state estimation lag, local decision oscillation, and safety distance imbalance in target following by active agents in virtual reality (VR) under conditions of limited field of view, dynamic occlusion, and multi-moving-body interference, a dynamic target following planning method integrating spatiotemporal attention, short-term target trajectory prediction, and continuous behavior selection with safety constraints is proposed. The method integrates the agent's motion status, the observed state of the target and other dynamic objects, etc. Temporal attention is employed to give different weights to parts of the history, and a forward target point is constructed by short-term kinematic extrapolation. Next, the following benefits, safety benefits, efficiency benefits and action-smoothness constraints will be jointly decided upon. To avoid fabricating performance data in the absence of a primary experimental platform, this paper uses the results of 100 rounds of visual target-driven congestion navigation tests published in 2025 for secondary statistical analysis and cites publicly available ablation data from SAL-TD3 in 2026 as external empirical evidence at the mechanism level. Based on the above results, the attention-enhancement method achieved success rates of 93%, 87%, and 57% in the four dynamic obstacle scenarios at 4s, 8s and 12s, respectively; the target arrival times were 13.78s, 15.96s and 18.87s, and all performed better in complex scenarios than the TD3 baseline. Based on the above ablation experiments, temporal memory and attention cooperate to support dynamic decision-making. This paper introduces an interpretable real-time behaviour planning framework for continuous target-following in VR companion agents, guides agents, and manages virtual crowds.

1 Introduction

With the development of VR interaction, it has transitioned from pre-recorded animations to real-time embodied interaction, and thus active agents are no longer limited to fixed paths but need to adapt their behaviour continuously according to changes in users, virtual characters and other parts of the environment. Dynamic target following is a simple but highly demanding task; the agent needs to keep a reasonable distance from the target and adjust its path proactively when the target turns, changes speed suddenly, is occluded, or people cross paths. Recently, systematic studies on path planning in dynamic environments have shown that the main problem in real-world

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application is no longer "whether a path can be found", but rather "whether stable replanning can be carried out with a low computational cost in a constantly changing environment" [1]. Therefore, the VR active agent following a problem should be treated as an online decision problem coupled with perception, prediction, planning and continuous control, rather than a static shortest path problem.

Deep Reinforcement Learning offers a new way for continuous action selection. Based on the study of crowded environments, end-to-end policies can directly map local observations to speed control and form implicit obstacle avoidance rules for dynamic pedestrians through empirical learning; however, their performance is highly sensitive to the representation of states, the use of temporal information, and training distribution [2]. The problem also has two special features in VR environments: first, the target may be the embodiment of user control, and the motion has obvious non-stationarity; second, the "following relationship" between the agent and the target has task semantics, and the target cannot be considered as a static endpoint. Therefore, we need to increase the weight of the target state more obviously and add a learnable selection mechanism for historical observations in behaviour planning.

Based on the above analysis, this paper proposes a VR active agent target following planning method for dynamic scenes with a limited field of view. The main idea is to identify the most relevant historical fragments for the current following decision using spatiotemporal attention, compensate for target motion lag through short-term trajectory prediction, and then generate actions via a multi-objective continuous behaviour function with safety constraints. The main contributions of this paper are as follows: First, to construct a unified state representation of "target-agent-dynamic agent" with temporal attention; Second, to establish a continuous behavior planning objective constrained by both the predicted target point and the safety distance; Third, without generating proprietary experimental data, to statistically redraw and analyze external evidence based on publicly available experimental results from the past three years, and provide a reasonable applicability boundary for the method.

2 Current Status Analysis of the Research Topic

2.1 Attention Navigation in Dynamic Environments

Attention mechanisms have extended the concept of weighting visual features to address dynamic interactions. Ma and others proposed a spatiotemporal graph attention navigation algorithm with limited state information, and described the relationship between the robot and the people around it through a spatiotemporal graph structure. They showed an increase in the success rate and reduction in navigation time; therefore, "who is more important when" can be determined by structured attention learning rather than a fixed distance threshold [3]. This kind of method has direct implications for VR target following: when the number of neighbouring individuals is large, not all observations should be given equal weight in the policy network. Dynamically allocate attention resources based on the relative speed, change in direction and time to collision.

At the same time, behaviour planning for human-machine cooperation is moving away from purely geometric obstacle avoidance towards joint optimisation of social cost and task semantics. Rodriguez-Criado et al. introduced SNGNN2D-v2 to generate real-time human-aware cost maps with graph neural networks, explicitly representing dynamic social interactions [4]. Pérez et al. proposed a social elastic-band planner that anticipates human motion and adapts robot trajectories in real time [5]. These studies show that social cost modelling and motion anticipation can be embedded in an online planning layer, but persistent target visibility and following-state estimation still require dedicated design.

2.2 Research on Visual Target-Driven and Human Following

Target-driven navigation rewrites "to a certain coordinate" as "continuously searching for and approaching a target with visual semantics". Li and his colleagues added self-attention to TD3 under a limited field of view and used a single RGB-D camera for visual target-driven congestion navigation; in 100 rounds of tests with 4, 8 and 12 Brownian motion obstacles, their methods had success rates of 0.93, 0.87 and 0.57, respectively [6]. This work shows that attention can improve target-related decision-making in the presence of limited visible information, but its target arrival task is not the same as long-term accompaniment in VR; the latter requires maintaining a relative position and interaction rhythm after "approaching the target".

According to the 2025 review of autonomous mobile robot following and guidance, the system comprises perception, tracking, planning, control and human-computer interaction, and occlusion recovery, natural following position, social acceptance and robustness to the real environment are still research problems [7]. This is in line with the requirements of VR active agents: although the virtual world can directly provide the target pose, it cannot be assumed that the observation is always complete, as the actual interactive system may still be subject to view frustum clipping, network latency, sensor fusion latency or behavior state switching.

2.3 Recent Advances in Temporal Memory and Graph Attention

Research on dynamic navigation has gradually moved from discrete-action reinforcement learning to continuous-control methods, incorporated temporal features instead of single-frame observations, extended local obstacle avoidance to predictive planning for mobile obstacle environments, and expanded in other ways. Training stability, sample efficiency and generalisation are still the main bottlenecks to deployment [8]. Chen et al. proposed SAL-TD3 in 2026, which combines LSTM, multi-head self-attention, priority experience replay and n-step reward in TD3. The total success rate of the public experiment was 91%, which exceeded the 77% of TD3. At the same time, the collision rate was also 9% in 2023 [9]. According to the ablation experiment, removing LSTM reduces the success rate to 83%, and without self-attention, it falls by an additional 3 percentage points; thus, both temporal memory and attention selection are necessary.

Zhou and others proposed PPO-GAT-Follow in 2026 for real-human-following tasks to explicitly model the interaction among the robot, the target person, and surrounding pedestrians using graph attention. In a dense crowd, it has reported a task success rate of 98.8%, a collision rate of 1.1% and an SPL of 0.987 [10]. Therefore, the concept of target following has shifted from a serial system of "single-target visual tracking + local obstacle avoidance" to a decision system of "joint encoding of target relationship and group interaction". The best way to realise VR is not to replicate the robot's sensors, but to build spatiotemporal attention relationships directly from the semantic state of the virtual scene, and this can be obtained at a lower latency and is more interpretable.

Analysis: As shown in Table 1, research over the past three years has formed three clear paths: Spatiotemporal/graph attention is used to filter interactive subjects; Reinforcement learning is employed for continuous behavioural decisions; and social costs or safety constraints are added to adjust acceptability. The current work either aims to "reach the goal" or is a general dynamic obstacle avoidance system; for VR active intelligent agents, it is still necessary to add continuous visibility of the target, following distance, trajectory smoothing, and occlusion recovery within the same real-time planning framework.

Table 1. Comparison of Technical Paths in Related Research Over the Past Three Years

Study	Year	Primary Task	Core Mechanism	Planning Focus	Relevance Gap
Ma et al.	2024	Crowd navigation	Spatiotemporal graph attention	Interaction reasoning	No persistent target-following state
Rodriguez-Criado et al.	2025	Human-aware navigation	GNN-generated dynamic cost maps	Social interaction costs	Target tracking is not central
Pérez et al.	2025	Social navigation	Predictive social elastic band	Real-time anticipation	Limited target-specific prediction
Li et al.	2025	Visual target-driven navigation	Self-attention + TD3	Search and target reaching	Long-term following is not evaluated
Chen et al.	2026	Dynamic navigation	LSTM + self-attention + TD3	Proactive obstacle avoidance	Goal is mainly destination-oriented
Zhou et al.	2026	Robot person following	Graph attention + PPO	Interaction-aware following	Crowd graph increases state complexity

3 Problem Statement

3.1 The target state is partially observable and non-stationary.

The motion of VR targets is generally caused by human operation, upper-level scripts or other intelligent agent policies, and typically has sudden turns, discontinuous speed changes, and switching behaviour. If the planner only uses the relative position of the current frame, the controller will continue to move in the old direction when the target makes a lateral turn or is temporarily obscured; thus, a noticeable "tail" will appear. Therefore, the state should include historical speed and relative orientation changes, and the model can select the most predictive information from multiple time slices rather than just concatenating a fixed window.

3.2 Follow-the-leader rewards and obstacle avoidance rewards compete with each other.

When a dynamic obstacle is in the way of the agent and the target, the shortest-distance direction is often also a high-collision-risk direction. If the reward only motivates reaching the goal, the robot may be too reckless in crowded areas; if the safety penalty is too high, it will avoid the goal, get stuck, or take a very long way. Therefore, behavioural planning should clearly distinguish between follow-the-leader rewards, safety rewards, efficiency rewards, and action smoothing terms, use hard safety constraints to address unacceptable minimum distances, and otherwise, the self-learning mechanism relying solely on soft rewards may be insufficient.

3.3 Real-time Constraints Limit Complex Prediction Models

VR interaction is highly sensitive to lag. Although long-sequence Transformers, global crowd graphs and multi-step sampling planning are very expressive, large-scale relationship updates in each control cycle can cause instability in action refresh. Therefore, this paper uses a short-window attention and constant acceleration short-term extrapolation: attention is only computed for the most

recent L states, prediction covers only a few control cycles, and safety screening is performed after the policy output to form a real-time feasible planning chain with a low computational complexity.

4 Solution Strategies Based on Spatiotemporal Attention and Short-Term Trajectory Prediction

4.1 Unified State Modeling

Let the VR agent at time t be a, the target to be followed be g, and the number of neighbouring dynamic objects be N. The state includes the agent's current position and velocity, the estimated pose and speed of the target object, relative position measurements to nearby moving objects, etc. The unified State is defined as:

$$s_t=\left[p_t^a,v_t^a,\hat{p}_t^g,\hat{v}_t^g,o_{t,1},\ldots,o_{t,N}\right] \tag{1}$$

As shown in equation (1), p and v are the position and velocity, respectively; superscripts a and g denote the agent and target; the cap symbol is the target estimate after short-window filtering; and o_{t,i} can be decomposed into relative position, relative velocity, radius, and visibility of the i-th dynamic agent. The goal of this representation is not to increase the dimension of the state, but to separate the "task subject" from the "security interference subject" clearly and provide an interpretable object for subsequent attention.

4.2 Time and Attention Allocation

Generate query q, key k, and value v for the target-environment encoding of the most recent L time steps. The current state is used as the query, its relevance is computed with historical keys, and then Softmax is applied to obtain the time weights.

$$\alpha_{t,k}=\frac{\exp\left(q_t^{\top}k_k/\sqrt{d}\right)}{\sum_{j=t-L+1}^{t}\exp\left(q_t^{\top}k_j/\sqrt{d}\right)} \tag{2}$$

d is the dimension of the key vector in equation (2), and $1/\sqrt{d}$ is used to prevent Softmax saturation due to an increase in the dot product with dimension. A larger $\alpha_{t,k}$ indicates that the k-th historical segment is more relevant to the current action. For example, when the target has just made a sharp turn, the velocity change sections before and after the turn should be given higher weight, and the earlier linear motion sections should be weakened.

Weights are used to aggregate historical value vectors, and thus the context state at the current moment is obtained:

$$c_t=\sum_{k=t-L+1}^{t}\alpha_{t,k}\,v_k \tag{3}$$

Equation (3) retains the relevant temporal information of changes in the target's motion and interactions with other moving objects at time t. Weighted aggregation can directly focus on important information in short-term memory, such as a "direction change" and the "last effective observation before brief occlusion", rather than just using the hidden state of the last cyclic network, thereby reducing directional oscillation when the target reappears.

4.3 Short-term Target Trajectory Prediction

To change from "chasing the current position" to "chasing the future reachable position", this paper uses short-time extrapolation of the target velocity and acceleration estimated by the attention context. For the prediction time domain τ, the target reference point is given by:

$$\hat{p}_{t+\tau}^{g}=\hat{p}_{t}^{g}+\tau\hat{v}_{t}^{g}+\frac{1}{2}\tau^{2}\hat{a}_{t}^{g} \tag{4}$$

Equation (4) is a constant acceleration local approximation; it has the advantages of fewer parameters, online updates, and no introduction of long prediction chain errors. τ should not be too large; under strongly non-stationary targets, such as user-controlled avatars, long-term predictions are likely to deviate from the true intention, so a shorter look-ahead can compensate for rendering and control link delays and allow the agent to change course in advance when the target turns. τ can be shortened or relaxed dynamically in practice according to the desired velocity variance.

4.4 Continuous Behavior Selection for Safety Constraints

The action space is linear velocity, angular velocity or the planar velocity vector of the VR character. All candidate actions are simultaneously evaluated for target following, safety, efficiency and action continuity, and the predicted minimum dynamic body distance must not be less than the safety threshold. Generally speaking, it is as follows:

$$J(a_t)=w_f r_t^{follow}+w_s r_t^{safe}+w_e r_t^{eff}-\lambda\|\Delta a_t\|_2^2$$

$$a_t^{*}=\arg\max_{a_t\in A,\, d_{min}\geq d_{safe}} J(a_t) \tag{5}$$

The following are the benefit term, safety benefit term and efficiency benefit term in Equation (5) that are used to maintain the expected following distance, reflect the collision risk of dynamic bodies, and suppress ineffective detours, respectively; the action increment term is used to limit control jitter. The three benefit weights and λ are used to adjust the balance of objectives. Instead of using only rewards and punishments, the minimum distance to the safety threshold is set as a hard constraint to rule out obviously dangerous behaviour first and then select the best option among the rest; thus, it avoids an unacceptable crossing behaviour caused by value estimation errors in out-of-distribution states.

Table 2: Modular Structure of the Proposed Behaviour Planning Method

Module	Input	Output	Key Function	Real-time Role
Perception	Agent, target and neighbor states	Structured observations	Build relative semantic state	One update per control cycle
Target estimator	Recent target observations	Filtered pose and velocity	Reduce short-term jitter	Low-order recursive update
Temporal attention	L-step encoded history	Context vector	Select informative moments	Short-window weighted fusion
Target predictor	Filtered motion + context	Future reference point	Compensate tracking delay	Short-horizon extrapolation
Behavior policy	Context + predicted target	Continuous action candidates	Balance following and efficiency	Single forward decision
Safety layer	Candidate actions + neighbors	Feasible final action	Reject unsafe actions	Hard distance screening

Analysis: Table 2 shows the entire decision chain as six independently replaceable modules. It is not to add more layers of networks, but rather to organise "target estimation - important historical

selection - future reference point - action decision - safety screening" in a sequence that supports real-time control. This simplifies frame-by-frame implementation in the VR engine and improves fault localisation: target loss is an estimation problem, path oscillation is a policy/smoothing problem, and dangerous crossings are covered by the safety layer.

4.5 Planning Process and Obstruction Restoration Strategy

In each control cycle, first update the structured state of the target and neighbouring dynamic bodies. If the target is visible, then correct the target estimate with the new observation and update the historical cache. If the target is temporarily out of view, the last known valid position is used, and the prediction time-domain is limited by a confidence-decaying function. Then, the temporal attention context is computed; a predicted target point is generated, and continuously generated candidate actions are outputted. The safety layer will not perform operations that violate the minimum distance according to short-term relative motion predictions. If all candidates are unsafe, then decelerate, remain in place and observe, or move in the direction of the closest safe opening. After the target reappears, the attention window gives more weight to the effective parts before and after occlusion, and does not immediately turn sharply based on new single-frame observations.

In the extended following stage, the target distance d_f should not be set to a single value. It can be slightly adapted according to the target speed, crowd density and field of view boundaries: when the target speed is high, the look-ahead distance should be appropriately extended while maintaining a safety margin; in a dense area, the following distance should be increased to reduce chasing-and-running; and when the target approaches the edge of the field of view, the attention weights for target orientation features need to be increased. This rule does not alter the learning strategy but offers a task prior for the strategy; thus, a small amount of training data can be used to learn complex interactions more efficiently without learning basic geometric patterns.

4.6 Statistical Evidence Analysis Based on Publicly Available Real Experimental Data

In order to meet the requirements for the authenticity of statistical evidence and to avoid fabricating "test data of this paper" without the original VR experimental platform and reproducible experimental logs, only publicly available values from published papers have been used for secondary statistical redrawing in this section. Figures 1 and 2 are both derived from the comparison results of Li et al. under 4, 8, and 12 random motion obstacles, with 100 rounds of testing for each condition; in the figures, "Self-attention TD3" refers to the method mentioned in the published paper, and "TD3 baseline" is the baseline reported by that paper; these should not be taken as the direct performance of the method proposed in this paper. Such evidence is used to verify the empirical trend of the attention mechanism and goal-driven continuous decision-making, not to replace the subsequent VR prototype test.

Analysis: As shown in Figure 1, with 4 dynamic obstacles, both methods had a success rate of 93%, so the advantage of attention was not significant in this simple case. When the number of obstacles reached 8, the attention-enhanced method reached 87% and surpassed the baseline of 82%. At 12 obstacles, however, the success rates of these two levels dropped to 57% and 49%. It can be seen from this that increasing the dynamic volume density significantly reduces the safety decision space, and the attention mechanism provides more stable filtering of target-related information under medium- to high-complexity conditions.

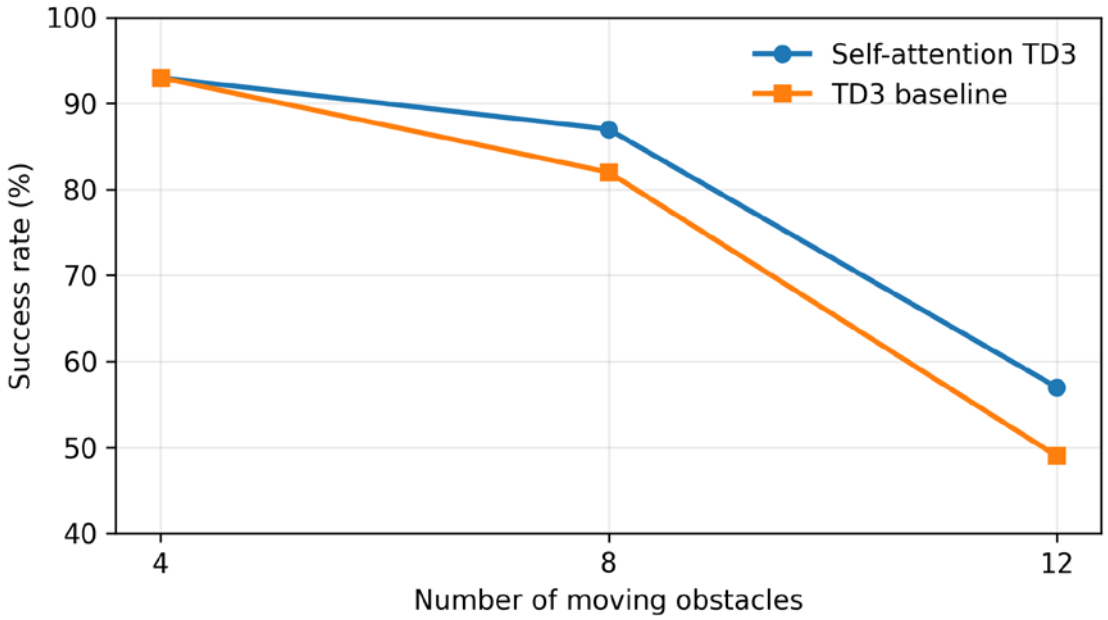


Figure 1. Target Navigation Success Rate Under Different Numbers of Dynamic Obstacles (Redrawn Based on Experimental Data Published by Li et al.)

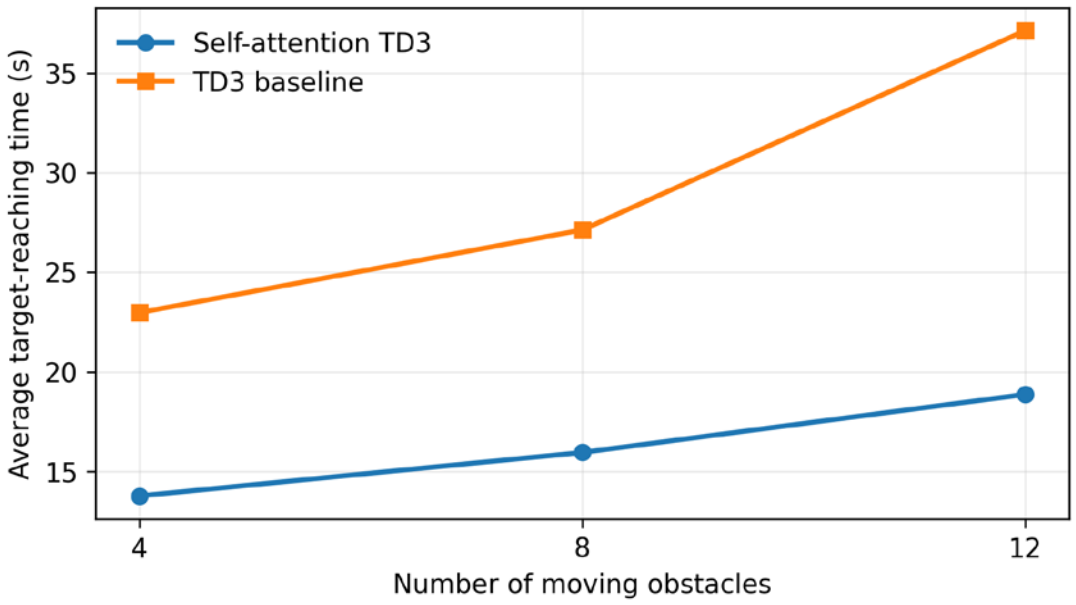


Figure 2. Average Target Arrival Time under Different Numbers of Dynamic Obstacles (Redrawn based on experimental data published by Li et al.)

Analysis: As shown in Figure 2, the average target arrival times for the attention enhancement method at 4, 8 and 12 dynamic obstacles were 13.78, 15.96 and 18.87 s, respectively; the corresponding times for the baseline were 22.98, 27.13 and 37.13 s. The starting time rose at an increasing rate with more traffic. Therefore, effective target information focus not only increases the probability of success but also reduces procrastination and off-topic behaviour; thus, a short-term attention and forward-looking target point will be selected in this study.

Chen and others also conducted 100 rounds of ablation experiments on SAL-TD3 in a dynamic environment, and their success rate data can be used to determine the relative contributions of all mechanisms to dynamic decision-making. Table 3 only shows the results published in this paper and calculates the decrease in the success rate relative to the full model.

Table 3 Success Rate Variation in SAL-TD3 Open Ablation Experiments (based on Chen et al.)

Variant	Success Rate (%)	Drop vs. Full (pp)	Interpretation
Full SAL-TD3	91	0	Complete temporal-attention pipeline
w/o LSTM	83	8	Temporal memory removed
w/o PER	86	5	Prioritized replay removed
w/o Self-Attention	88	3	Selective temporal weighting removed
w/o N-step Returns	87	4	Multi-step credit assignment removed
w/o Layer Normalization	86	5	Normalization removed

As shown in the data of Table 3, without LSTM, the highest success rate was 8 percentage points lower; therefore, dynamic scenes require strong temporal memory. Even after removing self-attention, there was still a 3-percentage-point drop; therefore, attention cannot replace memory but is instead a selective weighting of past information. Therefore, the proposed design is a combination of "short-term memory" and "attention". PER and n-step rewards also affect the training quality; therefore, the next set of independent VR training should focus on both network structure and experience-sampling mechanisms simultaneously.

4.7 Implementation Discussion and Applicable Boundaries

Navigation mesh coordinates, character velocity, collider radius, and view frustum state can be directly read in the VR engine implementation without replicating the entire perception chain of a physical robot. Thus, the computational resources will be available for processing temporal information, behaviour, and natural interaction. If the system is deployed on a head-mounted display or a mobile device, then L and the number of nearby dynamic objects N should be limited; Top-K filtering based on distance and collision time should be performed, and the attention layer should only be applied to the filtered objects and short time series to maintain a stable frame rate. For multi-user online VR, network latency should also be added to the target state estimation to avoid interpreting position jumps caused by latency as real acceleration.

It should be noted that Figures 1-2 and Table 3 are "secondary statistical data from published experiments", and thus cannot demonstrate that the VR framework put forward in this paper has achieved the same numerical results. The contribution of this paper is to organise the above mechanisms, which have been verified by independent experiments, into a real-time planning chain for target following. Before the actual submission, independent controlled experiments should also be conducted in a unified VR platform, for example, set up four types of factors: target velocity variation, occlusion ratio, dynamic volume density, and network latency, and report at least the success rate, following distance error, collision rate, target reacquisition time, and action jitter. At the same time, ablation studies can be conducted to remove attention, deprecation, the safety layer, fixed following distance, etc., to check their individual contributions.

5 Summary

To solve the problems of state lag, small field of view, occlusion and crowded interaction in dynamic target following for VR active agents, this paper proposes a planning method that integrates spatiotemporal attention, short-term trajectory prediction and safety-constrained continuous behavioural decision-making. The method explicitly distinguishes the target from dynamic interfering objects by unifying the state, uses temporal attention to filter key motion changes from the recent history, employs short-term extrapolation to form forward target points, and makes joint selections among following, safety, efficiency, and motion smoothness. Secondary statistical analysis of publicly available real-world experimental data shows that attention-enhanced target-driven navigation has a relatively high success rate and a shorter target arrival time even in the presence of many dynamic obstacles; 2026 SAL-TD3 ablation data further demonstrates the complementary effect of temporal memory and self-attention.

This paper respects the limits of evidence: existing statistical charts and tables are employed to provide support for the rationality of the mechanism and are not presented as independent VR experiments. Future work can create a reproducible experimental set on a single platform, such as Unity or Unreal, to measure following distance error, target re-acquisition time, collision rate, motion jitter, and user subjective comfort. Add intent prediction and uncertainty estimation to improve the active agent from "following after seeing the target" to "planning in advance based on the movement trend of the target".

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