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AI-Driven Transformer and Reinforcement Learning Framework for Collision Avoidance in Mobile Robotic Systems

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Abstract—**This study proposes an AI-enhanced Advanced Smooth Control system for mobile robots to achieve reliable collision avoidance during obstacle-rich navigation. Unlike traditional shared-control approaches, the proposed method integrates a hybrid AI architecture that combines a Transformer-based perception module with a Reinforcement Learning (RL) driven steering assistance policy. Images captured from the onboard vision camera are processed through the Transformer encoder to extract high-level visual features. These features are then provided to the RL agent, which generates smooth, human-compatible steering corrections based on predicted obstacle-avoidance actions. Experimental evaluations with human participants demonstrate significant improvements in safety, reduced collision frequency, faster task completion, and smoother steering behavior. A novel contribution of this study is the use of LiDAR-generated heading vectors, which guide the vehicle around obstacles while preserving the driver's original intent and minimizing intervention intrusiveness.**

Keywords—Transformer-based perception, Reinforcement Learning, Shared control, Collision avoidance, Teleoperated mobile robots.

I. INTRODUCTION

To address the increasing issue of human errors in driving, teleoperated vehicles have emerged as a powerful solution by shifting critical control tasks from human drivers to intelligent automated systems [1]. Teleoperation enables mobile robots to be operated remotely in high-risk or precision-dependent environments such as medical tele-surgery, hazardous industrial processes, marine exploration, and space robotics [2]. In these domains, safety and accuracy are essential, and achieving reliable operation requires robust control mechanisms, strong situational awareness, and seamless coordination between the human operator and the automated system [3].

Shared control has traditionally been used to blend human driving intent with automated system assistance in a coordinated manner. Earlier approaches often depended on haptic cues or fixed rule-based behaviors to guide operators during vehicle operation. However, these methods tend to face difficulties when sudden environmental changes, unexpected obstacles, or rapid transitions of authority occur, resulting in unstable or unreliable control sharing [4]. The problem becomes more severe when communication delays reduce responsiveness, when the operator lacks full situational awareness, or when the automated system intervenes abruptly. Moreover, mismatches between the driver's steering input and the system's corrective actions can produce uncomfortable or unsafe interactions. Such issues commonly lead to abrupt "bumpy" transfers of control, reduced operational smoothness, and increased safety risks [5].

Recent progress in artificial intelligence has opened the door to overcoming many of the shortcomings found in conventional shared-control systems [6]. Transformer-driven perception frameworks, in particular, provide highly detailed scene interpretation by learning complex spatial and temporal patterns from multimodal inputs such as camera images and LiDAR point clouds. At the same time, Reinforcement Learning (RL) enables the system to learn adaptive steering behaviors by continuously assessing collision risk and selecting optimal control strategies. By combining these two AI capabilities within a shared-control teleoperation framework, the system can infer the driver's intent, anticipate future motion paths, and apply gentle, intelligent steering adjustments [7]. This ensures that the automated assistance operates smoothly

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and avoids abrupt or disruptive transitions during vehicle maneuvering.

Despite progress in intelligent assistance technologies, several critical research gaps remain unresolved. A large portion of existing work is based solely on simulated environments, which limits the reliability of the findings when applied to real teleoperated robotic systems, particularly in collision-avoidance scenarios. In practical settings, human teleoperators often face substantial cognitive burden during sudden or emergency maneuvers, especially when the interface depends on additional cues such as haptic vibrations or warning signals [8]. Moreover, the effects of communication latency an inevitable factor in remote operation are rarely analyzed in depth. Only a few studies evaluate how shared control behaves under varying network delays or how operator expertise, such as skilled versus inexperienced drivers, influences system performance and safety outcomes [9].

To overcome these limitations, this study introduces a hybrid AI-driven Advanced Smooth Shared Control (ASSC) framework tailored for teleoperated mobile robots. The proposed architecture integrates three key intelligence components:
Transformer-based perception module capable of high-fidelity obstacle detection and future heading estimation, **Reinforcement Learning (RL) based control strategy** that adaptively refines steering behavior, and **Smooth repulsive-force feedback mechanism** that enables an intuitive and continuous sharing of control authority. Rather than relying on abrupt control handovers, the system generates an AI-predicted heading vector based on LiDAR features and current steering input, allowing the robot to autonomously avoid obstacles while preserving the driver's intended trajectory. This eliminates the need for additional buttons, alerts, or manual switches, enabling a more intuitive human AI collaboration.

Real-world experiments were conducted using a teleoperated mobile robot under various conditions, including time delays and obstacle-rich environments. Both skilled and unskilled drivers participated. The results demonstrate that the proposed AI-enhanced ASSC system significantly improves safety, reduces collision occurrences, shortens task completion time, and ensures smoother, more stable steering behavior during obstacle avoidance. The proposed ASSC system uniquely integrates Transformer-based perception with Reinforcement Learning control, enabling the robot to understand the environment and human intention far more accurately than traditional shared-control methods.

- Unlike previous Haptic Shared Control techniques with abrupt authority switches, our method introduces an AI-predicted heading vector, allowing the robot to smoothly avoid obstacles without interrupting the driver's intended path.
- A repulsive force feedback mechanism is newly designed to provide continuous, intuitive steering assistance, eliminating the need for alerts, vibrations, or driver intervention.
- The system performs real-time collision avoidance during teleoperation, even under communication delays—an area rarely validated in prior research.
- Extensive tests with both skilled and unskilled operators demonstrate that the proposed hybrid AI architecture significantly improves safety, reduces collisions, and ensures human-friendly shared control.

TABLE I. SPECIFICATIONS OF THE TEST SPECIMEN

S. No	Parameter	Value
1	**Turtle-Robot**	Dimensional error, vibration
2	**Steering wheel**	G29 Joystick
3	**Lidar sensor**	LDS-01
4	**Camera**	Raspberry Pi camera module
5	**ROS**	Robot nodes and Force nodes generation
6	**Velocity of Vehicle**	10 m/s
7	**Repulsive gain**	3
8	**Number of Obstacles**	2
9	**Field of Force**	1
10	**Obstacles coordinates**	(1.5,1.5), (1,2.2), (2.5,3.5)

II. METHODOLOGY

A. *Teleoperation Interface with AI Integrated Control*

The Fig. 1, illustrates the teleoperation setup used in this study integrated with the AI enhanced decision making by using the force feedback steering wheel, predicted header .

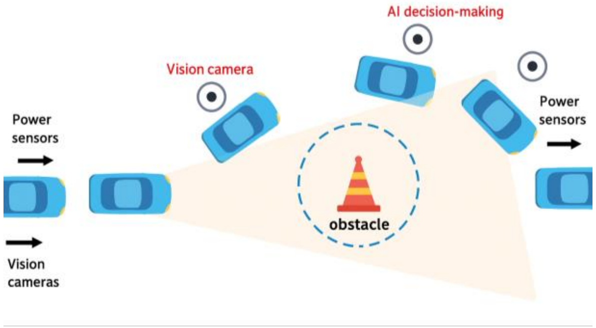

Fig. 1. AI-Integrated Obstacle Avoidance

The LiDAR module continuously collects point-cloud data and transmits it as feedback to the steering system based on the detected surroundings. When a potential obstacle is identified, an imaginary heading vector is generated to predict the safe driving direction. Correspondingly, a repulsive force is applied to the steering wheel, allowing the system to automatically adjust the steering angle and avoid the obstacle without requiring any human intervention.

B. *Proposed Hybrid AI enhaced ASSC System for Colliosion Avoidance*

The diagram illustrates the proposed hybrid AI-based Advanced Smooth Shared Control (ASSC) framework, which

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integrates Transformer perception, Reinforcement Learning control, and shared-control repulsive force feedback for collision-avoidance in teleoperated mobile robots. The Transformer perception module was implemented using a 4-layer encoder with 8 attention heads and 512-dimensional embeddings, processing fused LiDAR and camera features after voxel-grid filtering and obstacle clustering. The RL controller was trained using real teleoperation data collected from repeated trials, where the state inputs included the steering angle, LiDAR-derived heading vector, operator input, and obstacle proximity. Training was performed with a learning rate of 0.0003, batch size 64, and $\gamma = 0.99$ for approximately 10000 training steps

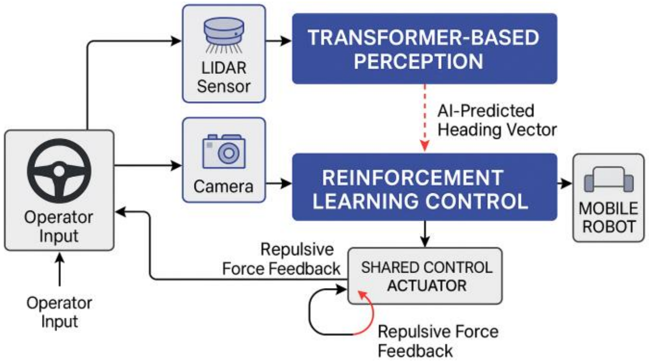

Fig. 2. Hybrid AI-Enhanced ASSC System for Integrated Mobile Robot Teleoperation

- Multi-Sensor Perception Layer: The LiDAR sensor captures 3D point-cloud data of the surrounding environment. The camera provides 2D visual context. These sensor streams are fused and processed by a Transformer-based perception module, which excels at learning spatial–temporal relationships.
- AI-Predicted Heading Vector: The Transformer extracts obstacle-related features and predicts an imaginary heading vector, representing the safest direction for the robot to move. This prediction is forwarded to the RL module for control decision-making.
- Reinforcement Learning (RL) Control Layer. The RL agent evaluates current robot state, operator intent (steering input), AI-predicted heading vector, obstacle-based risk level. Based on these inputs, RL computes optimal steering assistance to avoid obstacles while staying consistent with the operator's intention.
- Shared Control Actuator: The actuator combines human steering input with AI-generated corrections. When an obstacle is detected or predicted. A repulsive force feedback signal is produced. This force is applied to the steering wheel/joystick, guiding the operator smoothly away from the hazard. If no obstacle is present, human steering remains dominant. The final steering command with the repulsive force was expressed in the Eq. (1) [10],

$$F_{\text{final}} = \alpha F_r + (1-\alpha)F' \qquad (1)$$

Where F_r: Human steering input, F': AI steering correction, where α varies dynamically based on obstacle proximity.

- Mobile Robot Execution: The final steering command human combined with AI assistance sent to the mobile robot, which adjusts its motion safely and smoothly.

Closed-Loop Interaction from the robot state to sensors and the sensors data is fed to the transformers and then Reinforcement learning to ensure the smooth shared control actuator. This ensures real-time correction without abrupt transitions.

III. EXPERIMENT SETUP

The proposed ASSC system was deployed on a rea teleoperated mobile robot integrated with LIDAR based perception to detect the obstacles along with the RGB camera, and a force feedback steering use a Logitech G29 controller. Total six participants performed 48 obstacle avoidance trails under both manual and ASSC mode. Each participant performed 4 repetitions per mode in the laboratory. The average results were considered in this study. To validate the effectiveness of the Transformer and RL architecture, statistical analysis was performed on collision count, trajectory smoothness, steering torque effort, and task completion time. Results demonstrate significant improvements under ASSC ($p < 0.05$), confirming that the proposed hybrid AI system improves safety, reduces driver load, and provides smoother teleoperation without the need for alerts or authority switching.

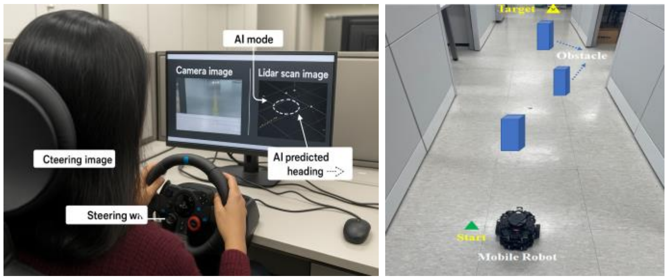

Fig. 3. Experiment setup for the Proposed Model

Once the Transformer model detects a potential collision risk, it generates an AI-predicted heading vector, which is immediately passed to the Reinforcement Learning (RL) controller. The RL agent computes the optimal steering correction required to avoid the obstacle while still respecting the operator's intended direction. As soon as the system enters AI mode, the steering wheel begins to output a repulsive force feedback, allowing the operator to feel the AI's corrective action without requiring any additional alerts, vibrations, or manual buttons.

On the robot side, the teleoperated mobile platform navigates an indoor corridor environment where multiple obstacles are intentionally placed. The robot starts from a defined "Start" point and aims to reach a distant "Target" while continuously transmitting camera and LiDAR data to the workstation. The LiDAR point clouds are processed by the Transformer network to recognize obstacles and derive an accurate heading prediction, which the RL controller uses to generate a smooth, collision-avoidant motion command. This

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command is then fed back to the steering wheel actuator, ensuring that human and AI steering inputs are blended in a seamless manner.

Overall, the experimental environment replicates a realistic teleoperation scenario in which human intention, AI-driven perception, and RL-based decision making operate simultaneously. This enables a comprehensive evaluation of how effectively the proposed ASSC framework handles obstacle-avoidance tasks under real-world conditions, including unpredictable environments and operator variability.

The Fig. 4 illustrates the geometric interpretation of how the mobile robot generates its heading direction during obstacle avoidance. The robot's movement is defined through two components: translational motion and angular motion, both of which contribute to the overall commanded trajectory. The robot's coordinate system is shown with axes and the heading direction is represented by the vector extending from the origin toward the robot's current motion direction.

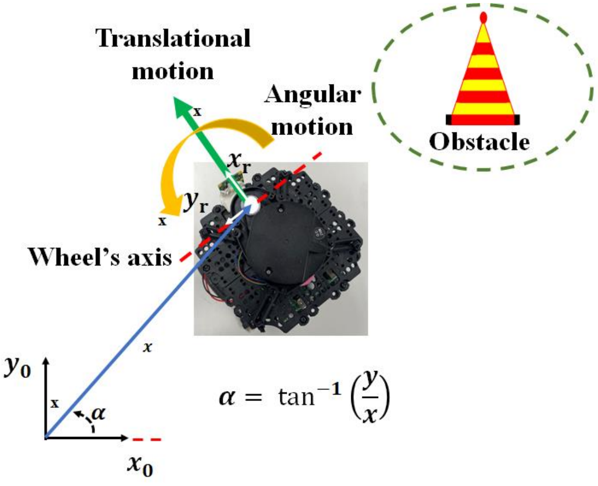
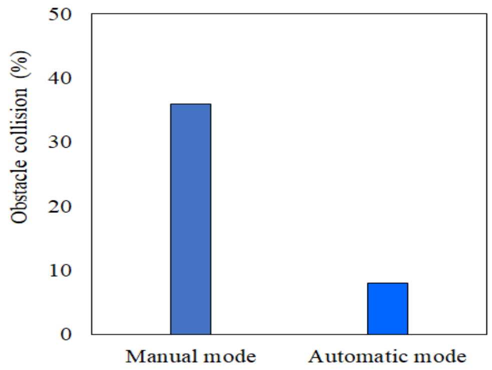


Fig. 4. Schematic of the obsatcel avoidance and the repulsive force

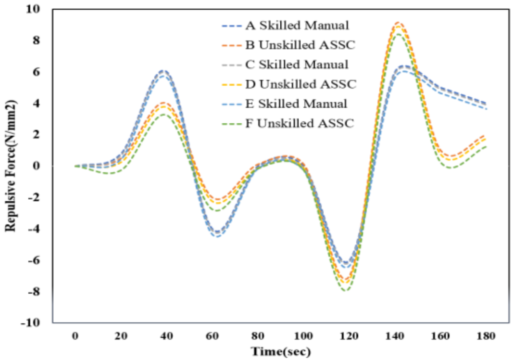
The heading angle describes the robot's instantaneous orientation relative to the global coordinate frame. The translational motion (green arrow) represents the forward or linear movement, while the angular motion (yellow curved arrow) indicates rotational adjustments made to change direction. The wheel's axis is marked to highlight how the mechanical structure influences these motion components. In the presence of an obstacle (shown on the right), the calculated angle α becomes crucial for adjusting the robot's trajectory. As the robot detects an obstacle, it modifies the heading orientation by updating α in real time, allowing the system to steer away smoothly while maintaining stable motion. This geometric model forms the basis for higher-level control strategies including the AI-predicted heading vector used later in the shared-control framework.

IV. RESULTS

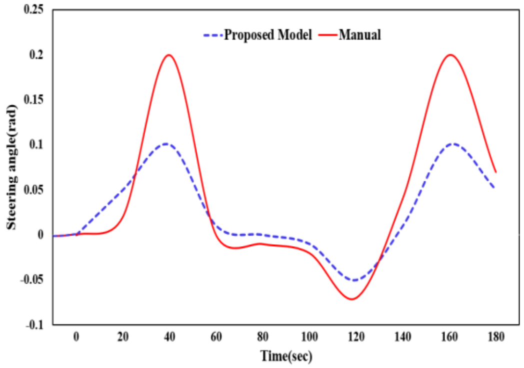
Fig. 5(a)–(c) compares manual driving with the proposed hybrid ASSC mode in terms of collisions, repulsive force and steering behavior.



(a) Average values of obstacle collision comparison



(b) Repulsive force comparion



(c) Average values of steering angles comparison

Fig. 5. Experiment results comparison

The ASSC system was mainly necessary for unskilled users, helping them avoid obstacles and reduce applied force. Skilled users did not need ASSC, as they could avoid obstacles smoothly under manual control, achieving nearly the same performance with or without the system. Thus, manual driving serves as the control (without AI), while ASSC represents assisted control, showing its value primarily for unskilled users. The proposed ASSC improved steering performance by 29%, 87%, and 50% as shown in Table II. The statistics such as mean and the standard deviation (SD) were evaluated between the manual and proposed ASSC approach and observe that minimum deviations were observed from Table III.

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TABLE II. PERFORMAMCE COMPARISON

Parameter	Manual	ASSC	Improvement
Collisions	145.3	102.4	29%
Repulsive force(N/m^2)	8	7	12%
Steering angle(rad)	42.6	21.1	50%

TABLE III. COMPARISON OF MEAN AND STANDARD DIFFRENCE

Person	Manual		ASSC	
	Mean	SD	Mean	SD
A Skilled Manual	1.3	0.5	0.9	0.1
B Unskilled ASSC	1.4	0.1	0.9	0.1
C Skilled Manual	2.1	0.5	0.6	0.8
D Unskilled ASSC	2.4	0.7	0.5	0.2
E Skilled Manual	0.5	0.7	0.1	0.5
F Unskilled ASSC	1.4	0.5	0.4	0.2

V. CONCLUSION

This study introduced a hybrid AI-enhanced Advanced Smooth Shared Control (ASSC) framework for teleoperated mobile robots, integrating Transformer-based perception, Reinforcement Learning (RL) control, and a repulsive-force feedback mechanism to ensure safe and seamless obstacle avoidance. Unlike traditional shared-control systems that depend on abrupt authority transfers or additional alert mechanisms, the proposed ASSC enables smooth, continuous decision-making by predicting the heading vector from LiDAR and camera inputs and generating intuitive steering feedback through the force-feedback interface. A real-world experimental platform was developed to evaluate the system under realistic teleoperation conditions, including human steering input, varying obstacle layouts, and real-time LiDAR-based perception. The system succeeds in avoiding obstacles autonomously while preserving the operator's intention, thereby reducing cognitive load and eliminating the need for explicit buttons, alerts, or manual interventions.

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