

Vision-Based Navigation System for Autonomous Ground Robots in Dynamic Environments

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Abstract--- Autonomous Ground Robots (AGRs) in unstructured settings are an unresolved issue that necessitates an intelligent agent's capacity to identify and respond to possible impediments within its vicinity. Barriers include automobiles, people, or fixed items in an ordered setting, such as highway or urban navigation, and unexpected static and dynamic obstacles in informal settings like woodland roads. The second condition is often more challenging to manage, owing to its greater uncertainty. This work presents a vision-based dynamical methodology for route planning and guidance of a quadruped AGR operating in a disordered setting, especially on a forest road. The computational dynamics methodology employs a recurring neural network that utilizes a sensor for data acquisition, generating sequences of prior depth sensor measurements and forecasting upcoming measurements over a limited temporal interval. The research evaluates the methodology against other leading techniques in obstacle-driven path planning methods. It conducts ablation tests to assess the effects of architectural modifications on the model elements. This shows that the approach attains enhanced performance in effectively creating collision-free paths for the clever agents.

Keywords--- Vision-Based Navigation, Autonomous Ground Robots, Dynamic Environment, Navigation.

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I. Introduction

Autonomous Ground Robots (AGRs) (Liu et al., 2022) are likely the first category of contemporary autonomous mobility platforms to emerge in studies on robotics. The first instance of an autonomous intelligent movable wheeled robot is traced, where the study conceived and constructed the electro-mechanical tortoises, propelled by biologically inspired control systems. Since then, field research in robotics has achieved several achievements, including developing the first semi-autonomous planetary rovers and fully autonomous off-road automated cars (Xiao et al., 2022).

Despite the extensive history of AGR, several unresolved challenges persist in self-navigating inside unstructured situations. Unstructured settings have not been altered to facilitate robot task performance (Wijayathunga et al., 2023). This effort addresses operating situations without discernible routes or useful markers that enable the AGRs' self-navigating capabilities.

A substantial corpus of autonomous terrestrial navigation scholarship has concentrated on indoor, organized settings. In recent years, significant impetus on outdoor settings has arisen from studies on AGRs, which have already become well-established. In contrast to the indoor environment, where self-navigating navigation has achieved a high Technological Readiness Level (TRL) (Bukar & Asif, 2024), the objective of developing a dependable, fully AGR remains unfulfilled, even in urban settings where road markings or curbs facilitate the recognition of navigable routes. Other factors must be considered in this context, mostly from traffic regulations and, more significantly, various outside parties and AGRs inside the same operational context.

The research selected a deep learning design for its capacity to capture temporal relationships in the input information (Morid et al., 2023). This facilitates incorporating obstacle characteristics within each layer and permits using this supplementary information in the route planning component to provide a safer path for the AGRs.

The research used data gathered while the AGR traveled a woodland route, encountering dynamic impediments nearby. Active barriers were shown by human beings pursuing the AGR as it traversed the woodland road setting. The trials demonstrate superior performance compared to the baseline.

II. Background

In recent years, the proliferation of AGR navigational systems has gained traction among researchers, primarily because of advancements in artificial intelligence. Numerous publications have examined different facets of the self-navigating challenge, such as perception and control. In recent years, the proliferation of AGR navigation systems has gained prominence within the scientific community, mainly attributable to advancements in Machine Learning (ML) (Pugliese et al., 2021). Numerous publications have examined different facets of the navigational AGR challenge, such as perception and control.

A comparable methodology for an AGR that does not use artificial intelligence is introduced. This work presents an end-to-end route planning and guidance system that the machine uses to traverse its surroundings. A nonlinear optimization technique produces the course of the AGR.

The suggested approach employs Light Detection and Ranging (LiDAR) (Villa et al., 2021) data and a map-less self-navigating technique to facilitate AGR movement in an unstructured urban setting. This methodology integrates range sensing with Deep Learning (DL) (Jadhav et al., 2024) and traditional route planning to enable the robot to navigate changing obstacles in an urban setting.

These studies illustrate the efficacy of object identification and DL methodologies for obstacle avoidance in dynamic settings. They continue to encounter obstacles like resilience to occlusions, variations in light, and object distortion. The training approach for these detectors of things is label-intensive. Several approaches use costly sensors (e.g., LiDAR) to delineate the AGR surroundings and prevent object-related accidents.

III. Proposed Vision-Based Navigation System for UAGRs

The proposed system has three main elements: the graph-based scenario alteration, the dual-layer, and the actor-critic policy network. This part starts with the transition from crowd situations to heterogeneous charts, accompanied by an elaborate exposition of the policy system derived. The research integrates the two-wheeled divergent drive system into the DL-based architecture. The specifics of the training procedure are included after this section.

Conversion of Scenario into Graph

To address the fluctuating quantity of nearby individuals and barriers, agent-level setups of the crowd situation are converted into a graph $G(V, E)$, where V denotes the nodes and E signifies the edges. The vector of characteristics of nodes is constructed from the agent-level perception of things.

The borders in the graph arise from relationships among nodes. This study constructs a directional and heterogeneous diagram, distinguishing it from prior studies. An interaction from item i to j indicates that object j must aggressively avoid colliding with item i , represented as a directed edge from component i to j . It illustrates a transition from a sample situation to a directed and diverse network. Static barriers are not obligated to be used in collision prevention and hence cannot be used to communicate with other things. Conversely, the AGR must engage with all the objects around it to prevent crashes. This study presents a network including four distinct sorts of nodes.

Automaton: A node designated for the AGR. This study concentrates on the navigation of a solitary AGR. Hence, only one AGR is shown in the charts. To prevent collisions, it must engage with all other entities. In this context, the AGR is imperceptible to people, resulting in no contact between the AGR and humans. This study emphasizes an active avoidance of crashes strategy, necessitating that the AGR assumes all responsibility for preventing collisions. This represents the most challenging case in AGR crowd management—a node designated for human use. The node communicates with connections of other individuals and fixed impediments. People who are presumed oblivious to the AGR will not engage with it.

Circular challenges: Node representing a static circular impediment, such as an upright or refuse bin. It does not engage with other items.

Line barrier: A node representing a static line challenge, such as the walls of a space. It fails to interact with other items.

Vision-Based Model

It first computes a dynamic frame w for the AGR orders, predicated on physical limitations concerning velocity and acceleration. Each instruction $u+1$ and $t+1$ from the created dynamic frame is used to construct a candidate path. Forecasts generated by the scene kinematics encoder networks are employed with current sensor measurements to exclude potential paths that overlap with any obstacles (either anticipated or seen). Each possible path that was not dismissed in the preceding stage is further evaluated against multiple performance metrics, and the corresponding penalties are calculated:

- Target cost (e.g.) denotes the disparity between the Cartesian location of the terminal state on the prospective path and the geographic location of the target point situated on the global standard path.
- Orientation cost (e) denotes the discrepancy between the pointing angle of the proposed trajectory's final position and the original alignment angle.
- Speed cost (E) denotes the AGR and standard speed disparity.
- Smoothness cost (es) denotes the disparity between the preceding and the latest instruction; significant variations between consecutive orders result in a coarse movement of the AGR in motion.
- Path cost (et) denotes the aggregate of distances that separate the cartographic coordinates of the proposed path and the original path.

IV. Results

The simulated scenario is derived from CrowdNav and includes an AGR, people, static circular challenges, and static linear obstacles formed by a rectangular obstacle and two walls of the space. The radius of static circular barriers is measured within the range $[0.1, 0.4]$. To guarantee regular encounters between line barriers and the AGR body, as well as enough unobstructed space for the movement of both the AGR and people, the focal point of the rectangular obstacle is arbitrarily positioned inside a rectangular rectangle of 2.0m on each side, placed at the middle of the room. The dimensions of the rectangular obstruction are constrained to the range of $[1.0, 3.0]$. The beginning and goal locations of the humans are approximately equally situated relative to the beginning of the world coordinates system, with the gap between the initial and goal locations fixed at about 9.0 meters. Upon reaching the designated goal location, another target will be arbitrarily produced inside the room, and the previous goal location will serve as a turning location.

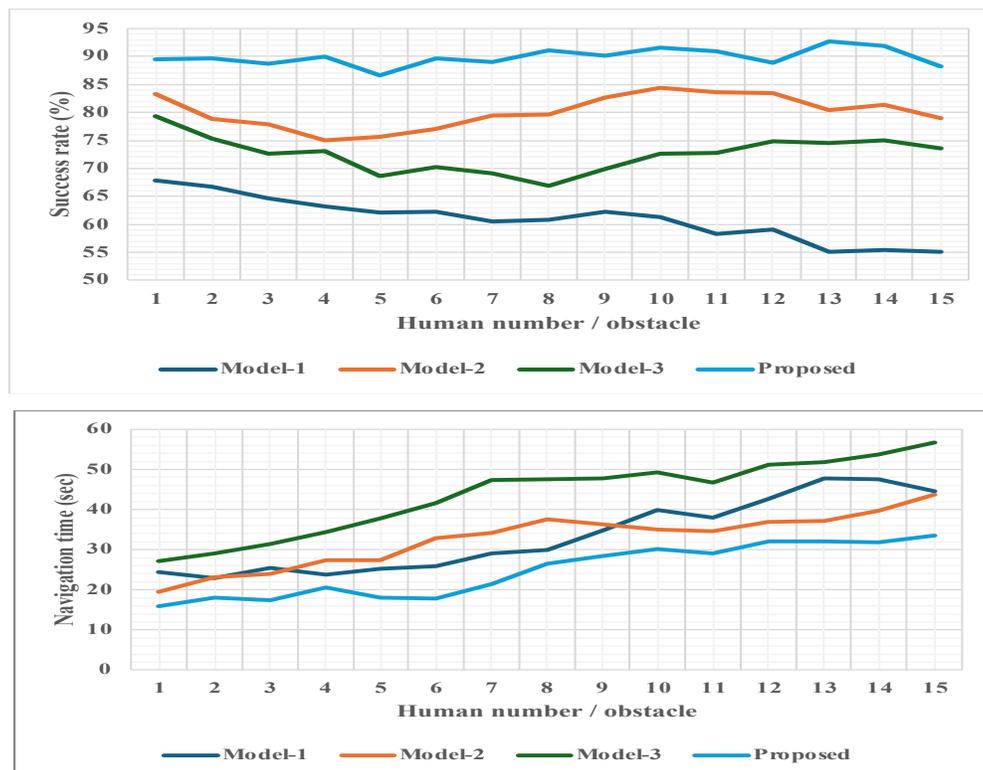


Figure 1: Success rate and Navigation Analysis

As seen in Figure. 1, in the sparse situation characterized by a limited number of persons and static impediments, the strategies exhibit comparable performance, with a success rate over 90%. If the quantity of individuals or fixed circular obstructions escalates, the achievement rate of the proposed system diminishes at a slower pace compared to the other two methodologies. The proposed system consistently attains a superior achievement rate and reduced navigation time compared to the other two approaches. Despite 10 individuals or stationary circular obstructions, the proposed system maintains an accuracy level of over 72% and an average navigational time of around 16.3 seconds.

V. Conclusion

This research presents a vision-based dynamical learning methodology for AGR in unstructured situations. The technique utilizes a DL that analyzes past information from depth sensors and generates forecasts for future time intervals over a predetermined prediction window. The research detailed the procedure for transforming the depth picture into a three-dimensional point cloud, then voxelizing the points into a two-dimensional grid of voxels suitable for input into the DL system.

The research has assessed the model using empirical data collected during the AGR traversal of a road. The capacity to directly store scene motion through a DL model has considerable ramifications for AGR, facilitating a better comprehension of the outside world and enhancing connections between the AGR and the outside world, thereby improving decision-making in tasks like navigation.

Future studies investigate implementing more sophisticated neural network designs and incorporating supplementary sensor components, such as pictures or LiDAR information, to enhance the model's precision and resilience.

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