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A QUATERNION-DRIVEN DEEP LEARNING-BASED NOVEL APPROACH FOR MOBILE AND LOCOMOTIVE ROBOT PATH PLANNING AND MOTION PREDICTION

Jamie Pote*1

*1Department Of Computer Engineering, University Of Zimbabwe, Harare, Zimbabwe.

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ABSTRACT

In this study, I address the locomotive-robot dilemma in movement task sequences. Our method combines geometric motion planning and locomotion prediction using quaternions and deep learning architecture. This is comparable to human motion prediction. I begin by developing a collision-avoidance-based motion planning method. Then, using transformer deep learning, I anticipate robot locomotion. I used simulation to demonstrate my findings.

Keywords: Path Planning, Quaternion, Mobile Robot Step Prediction.

I. INTRODUCTION

In robotics, motion planning refers to the act of breaking down the desired movement job into discrete motions that satisfy movement limitations and may maximize some component of the movement. Consider a mobile robot moving within a building to a distant waypoint. It must complete this mission while avoiding walls and avoiding falling downstairs. A motion planning algorithm would take these tasks as input and generate the speed and turning commands that would be issued to the robot's wheels. Motion planning methods could be used for robots with more joints (e.g., industrial robots), more sophisticated jobs (e.g., object manipulation), various limitations (e.g., a car that can only go forward), and uncertainty. Understanding and forecasting robot motion are critical for assisting people and robots in interacting with their surroundings. Future robot locomotion prediction is an innate ability for locomotive robots to engage with other people, such as navigating crowds, defending against offensive opponents in a game, or shaking hands with others. Furthermore, intelligent machines must respond to robot behaviors, coordinate their positions, and project pathways during human encounters. In the field of robotics, motion planning and motion prediction are considered two separate problems. In this paper, I propose a unified approach that considers these two problems and simultaneously performs motion prediction and planning.

II. LITERATURE REVIEW

Due to the growth and acceptance of deep learning and inverse reinforcement learning, which perform better when dealing with non-linear and complex situations, research into motion planning is currently booming. As a result, many universities, businesses, and research organizations throughout the globe place a high priority on creating novel motion planning techniques by implementing DL algorithms or combining conventional motion planning algorithms with cutting-edge machine learning (ML) algorithms [1-16]. Autonomous vehicles are one example. Alphabet, one of the major tech firms, unveiled its self-driving vehicle called Waymo. Tesla promises to produce a completely autonomous vehicle. Baidu's self-driving cars have been tested successfully on highways close to Beijing, while Huawei's manually operated buses have already been replaced by automated buses in a few select Shenzhen neighborhoods. Other traditional automakers like Toyota and Audi also have their own autonomous vehicle testing fleets. Among research universities and institutions, MIT, Oxford University, and Carnegie Mellon's Navlab are the top three. Russia, France, Belgium, and the United Kingdom are among the Euro giants that plan to run autonomous car transportation systems by the year 2022. There is autonomous car legislation in place in many American states. Because of this, it is anticipated that autonomous vehicles will become more prevalent over time. Recently, Boston Dynamics created humanoid robots and locomotive robots like Spot.

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III. METHOD AND EXPERIMENT

Our method has two main steps. First, I perform motion prediction based on neural network-based motion planning. I compared three deep learning models LSTS, GRU, and Transformer. I trained the networks with simulated data where inputs are position (3x1 vector) and orientation (1x4 quaternions). The network predicts the next step's position and orientation based on the environment's geometric information. If this is done for manipulators, robot geometry needs to take into account. In Figure 1, I presented the motion prediction scheme. The location of the robot is obtained from GPS. The orientation data is obtained from the in-body IMU sensors. This data is then fed into the deep neural network to predict the position and orientation of the next step.

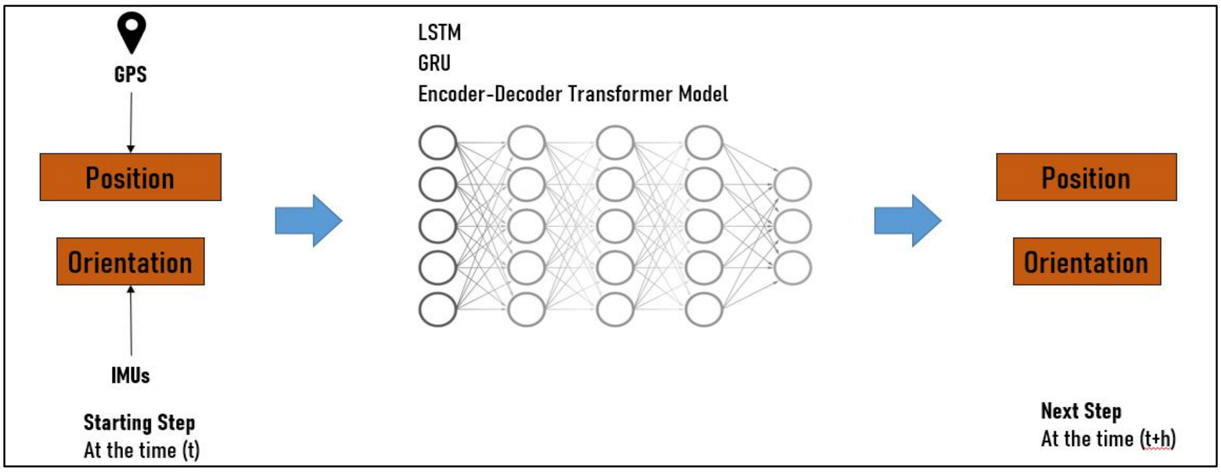

Figure 1: Next Step Prediction Based on Deep Learning Models.

Second, I perform path planning / local collision avoidance. Once I predict the position and orientation of the robot for the immediate step, I check if there is a collision present or not. I compare A-star, Dijkstra, and Trace path planning algorithms [30].

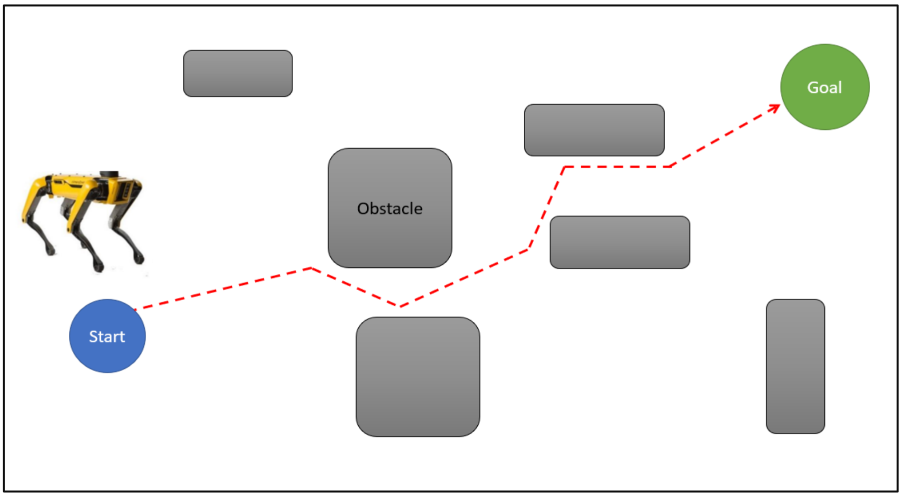

Figure 2: Path Planning of Locomotive/Mobile Robots

In Figure 2, I demonstrated the path-planning scheme. The blue circle indicates the starting location, and the green circle indicates the end location. The gray rectangle represents the obstacle. The red dotted line indicates the robot's path. In an obstacle falls into the robot's path, it uses path planning algorithms to find the collision-free path.

IV. RESULTS AND DISCUSSION

Next Step Prediction:

I compared the performance of 3 Networks LSTM, GRU, and Transformer. In table 1, I presented the hyperparameters.

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Table 1. Hyperparameters of Deep Learning Models

SN.	Hyperparameters	Value
1	Epochs	20
2	Learning Rate	0.01
3	Step Size	0.01
4	Total Nodes	3200

The results show that the Transformer model performs best, then LSTM and then GRU. In Figure 3, I presented the mean error vs. epoch graph for all three models. Which indicates the performance.

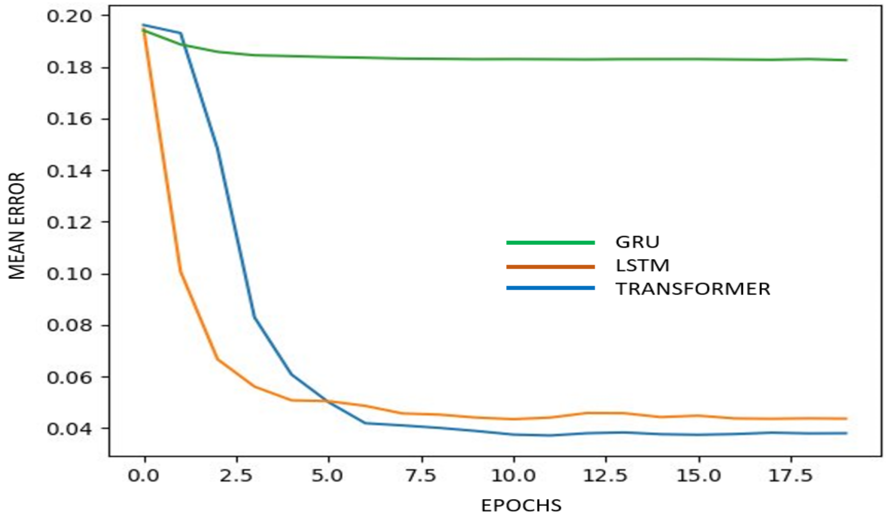

Figure 3: Performance of the Deep Learning Models

I then evaluated three path-planning algorithms. I used a java-script-based simulation platform as presented in reference [30]. I used the same obstacle for all three algorithms. My result shows that the trace algorithm performs better among all three. In Figure 4, the simulation result is presented.

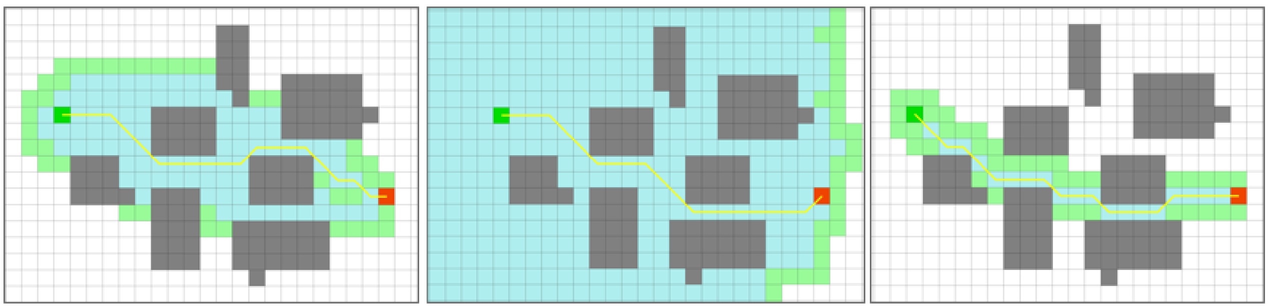

Figure 4: Performance of Path Planning Algorithms. a) A-Star Algorithm, b) Dijkstra Algorithm c) Trace Algorithm

In Figure 4, the yellow line is the path, and the green and red squares are the start and end locations. The grey squares are the obstacle. Noticeably all environment has the same obstacle. I used Euclidean distance to compute the final path. From the simulation result, the Dijkstra algorithm search around more space; hence it takes more time to compute the final path. Where Trace has lesser green and blue squares, which means it searches only a few nodes. Thus, it has the lowest computation time.

V. CONCLUSION

In this paper, I demonstrated how a mobile or locomotive robot can simultaneously use deep learning and path planning algorithms to predict its next step and avoid a collision. For training, the deep learning model, Intel

Core I 7, 550 SSD, and NVIDIA GeForce 2GB graphics card were used. I used algorithm simulation for path planning. In the future, I intend to use this algorithm in real robots.

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