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Scene-aware and Social-aware Motion Prediction for Autonomous Driving

Alfred Nguyen

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Advisor:	Dr. Di Liu
Supervisor:	Prof. Dr.-Ing. Matthias Althoff
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Alfred Nguyen
Technische Universität München
Email: alfred.nguyen@tum.de

***Abstract*—The abstract goes here.**

I. Problem Statement

In our current approach, we rely on a method known as ballistic integration for discrete integration. However, a significant challenge arises due to the inherent discretization error associated with working with discrete data. Specifically, when we rearrange the integration formula to assess its fit with our data, we observe errors between the predicted acceleration and the ground truth. These errors will furthermore be explored in the results section.

The differences in the accelerations affect the performance of the neural network, as the integration results are used as inputs to the network.

II. Concept Overview

Our method revolves around the use of a linear model to estimate the acceleration of vehicles. By equating and rearranging the formula, we specifically ensure that the predicted accelerations remain consistent. Whereas, using the old method of ballistic integration the discretization error heavily influences the accuracy.

The motivation behind choosing a linear model stems from the hope of better performance compared to alternative models tested during our experimentation. Through rigorous testing, we found that the selected linear model consistently outperformed others in terms of accuracy in predicting the car's movement. Additionally, the simplicity and interpretability of the linear model make it an attractive choice for motion prediction tasks, as we can comfortably use established methods to solve these systems.

To validate the effectiveness of our approach, we plan to compare the results obtained with our linear model against the old Ballistic Integration method, particularly focusing on the accuracy and consistency of the predicted accelerations. Additionally, we will evaluate the performance of our model using standard linear regression metrics such as R-value and MSE. Furthermore, we aim to extend our analysis by rearranging the model to predict velocity and distance, allowing us to assess its predictive capabilities. In the end, we will visualize our results using the existing drone-dataset-tool repo, which was provided.

III. Method

In this section, we detail the methodology employed for motion prediction in dynamic environments, along with the implementation steps undertaken to validate our approach.

A. Dataset Description

For our experimentation, we utilized the inD, exiD, and rounD datasets. The datasets offer vehicle trajectories recorded at German intersections, highway exits and entries, and roundabouts, respectively. Additionally, a repo (drone-dataset-tool) was provided that allowed us to visualize the dataset for better understanding.

B. Model Selection Process

Our model selection process involved a systematic trial and error approach with a total of 8 different models. Each model underwent an evaluation process to assess its ability to accurately predict vehicle acceleration across various scenarios. Ultimately, the following linear model emerged as the most suitable choice based on its superior performance metrics.

C. Training and Testing Procedure

To facilitate model training and evaluation, we employed the common data-splitting techniques provided by the sci-kit-learn Python library. The $train\_test\_split()$ function was utilized, with a test size of 0.3, to ensure a sufficient amount of data for robust evaluation.

D. Evaluation Metrics and Results

The performance of our linear model was assessed using common metrics for linear regression, including R-squared (r2) and Mean Squared Error (MSE). Detailed evaluation results, including mock data for the evaluation metrics, will be provided later in the report, offering insights into the model's predictive capabilities.

E. Rearrangement of formulas

After computing the resulting linear regression model and its coefficients, we can rearrange the formula for the acceleration models. After adjusting the coefficients we receive the following formulas for the distance and velocity.

F. Notable Findings and Observations

During the evaluation process, several notable findings were observed. Most notably, after rearranging the formula for distance and velocity, a constant error was detected. However, increasing the size of NumPy arrays appeared to mitigate this error, indicating a potential floating-point precision issue.

G. Future Directions

Based on our implementation experience, future research and improvement areas include enhancing the precision of NumPy arrays by increasing their size and expanding the dataset to encompass a more extensive range of scenarios for comprehensive model training and testing.

IV. Results

V. Conclusion and Future Work

References

[1] H. Kopka and P. W. Daly, *A Guide to LaTeX*, 3rd ed. Harlow, England: Addison-Wesley, 1999.

VI. Introduction

This demo file is intended to serve as a “starter file” for IEEE conference papers produced under LaTeX using IEEEtran.cls version 1.8 and later. I wish you the best of success.

mds

December 27, 2012

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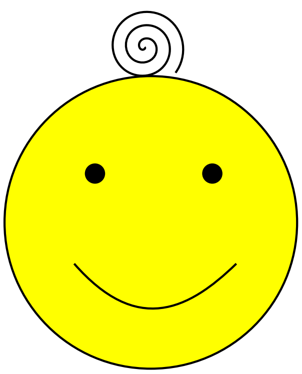

Fig. 1. A vector graphic loaded from a PDF file

VII. Conclusion

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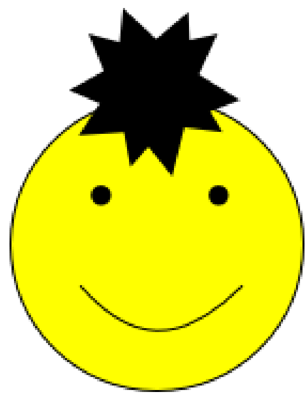

Fig. 2. A bitmap graphic loaded from a PNG file