Pedestrian Motion Classification for Autonomous Vehicles (6.867 Final Project)

Michael Everett & Björn Lütjens

(a) Ground robot in Stata   (b) Golf carts (MIT MoD fleet)

Fig. 1: Many types of autonomous vehicles operate among pedestrians and must account for pedestrian motion in the vehicle motion planning algorithms.

***Abstract*— TODO**

I. Introduction

Autonomous vehicles use onboard sensors to perceive their surroundings, and use the data to make decisions about where it is safe to drive. Today's research vehicles typically rely on Lidar and cameras as the main sensors, as these provide information about where/what obstacles are, and can help the vehicle maintain safe position in its lane and with respect to obstacles. In addition to static obstacles, vehicles interact with pedestrians in a variety of environments: people in crosswalks, jaywalkers, kids running across neighborhood streets. A campus shuttle could even drive on sidewalks among pedestrians, so the vehicle would be interacting with pedestrians almost all the time. These regular interactions mean the vehicle must be able to predict pedestrians' next moves in order to maintain safety.

Pedestrian motion prediction is difficult because people often behave very unexpectedly. Humans use many strategies to predict pedestrian intent while driving, such as body language, eye contact, and other non-verbal cues between human driver and human pedestrian, but autonomous vehicles can't easily communicate or read these signals. The information from sensors is typically fused: Lidar is used to measure the pedestrian position, and the camera is used to label the particular obstacle as a pedestrian. Therefore the only measurements collected are position over time (from which velocity can also be computed).

This project uses a dataset collected on MIT's campus over several months by three golf cart shuttles providing Mobility on Demand service to students, while simultaneously collecting pedestrian trajectory data to optimize vehicle routing strategy. The dataset contains about 65,000 pedestrian trajectories as well as the vehicles' trajectories, all in a global frame across the MIT campus.

M. E. **related works**

The objective of this project is to develop a classifier that can determine whether a person will step in front of a vehicle, based on a few seconds of their trajectory. We use a portion of our data set to train different classifiers, optimize hyperparameters with a separate portion, and evaluate performance with yet another portion. This classifier could be a useful component of an autonomous vehicle, or part of an active safety feature on a human-driven vehicle that could take over in case the driver does not see a pedestrian in time.

The main contributions of this work are (i) a pedestrian trajectory dataset with 65,000 trajectories over three months, (ii) an SVM classifier for predicting when pedestrians will step in front of a vehicle, (iii) a classifier using Deep RNNs for that same objective, and (iv) a pedestrian motion predictor using Deep RNNs.

II. Dataset

An important realization we made during this project is the challenge of working with a real dataset. Our data comes from golf carts equipped with Lidar and cameras [1], [2]. Fortunately, it is relatively straightforward to visualize trajectory data, as opposed to some high-dimensional datasets that exist for other applications.

The raw dataset's fields are shown in Table I, where (easting,northing) are the latitude/longitude global coordinates, and (x,y) are the coordinates in our global campus map. Veh id indicates which of the three vehicles corresponds to that data point, or in the pedestrian case, which vehicle sensed that pedestrian. Ped id is a unique id given to each pedestrian seen.

Type	Fields						
Vechicle	time	easting	northing	x	y	veh id	
Pedestrian	time	easting	northing	x	y	veh id	ped id

TABLE I: Raw data fields

There are some noise-related issues with the raw data, as it was collected on a research vehicle under development. One issue is that the vehicle's (x,y) position sometimes jumps, because the vehicle's localization system does not use GPS and is imperfect. Other minor issues include pedestrian trajectories that incorrectly split/merge or are too short to be useful for this project.

In addition to addressing noise, we also pre-process the data by converting pedestrian trajectories into the vehicle's local frame. Specifically for the purpose of our classifier, the pedestrian trajectories must be converted into the vehicle's local frame in order to determine if they cross in front of

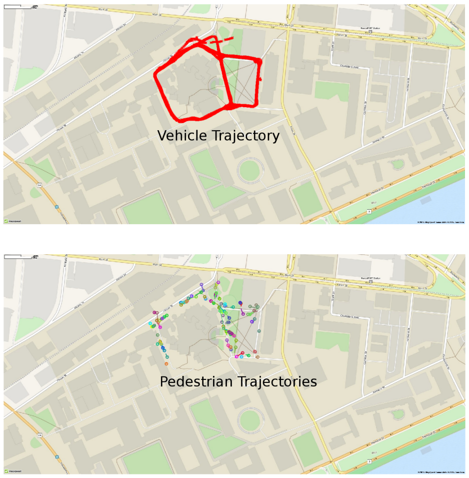

Fig. 2: The raw trajectories from one day of data collection visualized on a campus map. All trajectories are recorded in the global map coordinate frame.

the vehicle. That is, our dataset is initially unlabeled, and we must generate the ground truth label that we wish to learn to classify later.

The global-to-local transformation relies on knowledge of vehicle orientation (heading angle) and smooth vehicle trajectories, neither of which we have by default. Line 1 describes the procedure for filtering, transforming, and labeling the raw dataset.

Algorithm 1: Algorithm for extracting local trajectories

Input: V_g, P_g: global vehicle, pedestrain trajectories (Table I)

Output: P_l: pedestrian trajectories in local vehicle frame

1: **for** each vehicle **do**

2: $I_{posjump}$ = $\{i \in [1, len(V_g) - 1] \mid euclid\_dist(V_g(i) - V_g(i+1)) > 1.0\}$

3: $I_{timejump}$ = $\{i \in [1, len(V_g) - 1] \mid time(V_g(i) - V_g(i+1)) > 0.5\}$

4: J = $I_{posjump} \cup I_{timejump}$

5: T_{valid} = $\{[J(i), J(i+1)] \mid time(J(i+1) - J(i)) > 5.0\}$

6: **return** pedestrian trajectories

References

[1] J. Miller, A. Hasfura, S.-Y. Liu, and J. P. How, "Dynamic arrival rate estimation for campus mobility on demand network graphs," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2016.

[2] J. Miller and J. P. How, "Predictive positioning and quality of service ridesharing for campus mobility on demand systems," in *IEEE International Conference on Robotics and Automation (ICRA)*, 2017.