Mobility Scooter User Driving Behavior Classification based on Deep Neural Networks

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I. Introduction

A mobility scooter is an electrically powered scooter designed for people with restricted mobility [1]. The safety of mobility scooter driving is critical for drivers but often not assessed [2], [3]. The goal of the project is to assess the safety level of people with neurological conditions driving mobility scooters by classifying their behaviors using mobility sensor data. In this work, we propose a data-driven approach to build time-series deep neural network models for mobility scooter driving behaviors, and thus based on mobility sensor data enable the real-time classification of 5 behaviors, i.e., sudden acceleration, Sudden left turn, Sudden right turn, Sudden break, and non-sudden movement.

II. Method

Our system overview is depicted in 1.

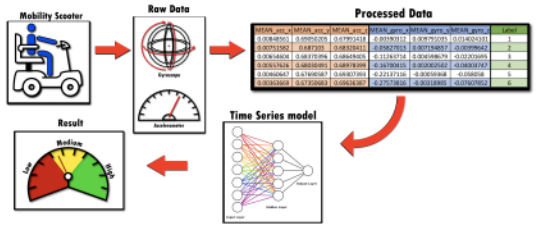

Fig. 1. Mobility Scooter Driving Behavior Classification Overview

In order to collect mobility data, a 4-wheel mobility scooter mounted with two Raspberry Pi-4 (one front and one back) and three action cameras was used. Each Raspberry Pi collects accelerometer and gyroscope data as time series to be used as features to train a long short term memory (LSTM) model. Raw sensor data is collected once every half second. The action cameras record the front of the driver, the side of the driver, and the steering wheel, providing the ground truth for data labeling.

III. Experiments and Pilot Result

The pilot training and testing collection was conducted on California State Polytechnic University, Pomona's campus as it provided variations of landscapes and slopes as depicted in Figure 2. In total, we collected 1113 samples which are balanced, and use 80% for training and 20% for testing. We build a LSTM model with 88 units, batch size 32 and softmax activation function in the output layer. We conducted three experiments on classification accuracy, each with a different time-window size. As shown in the figure 3, when increasing the time window size to 4 seconds, the LSTM accuracy level increases to 75.6%.

Fig. 2. Red lines illustrating several routes participants have done on Cal Poly Pomona's campus

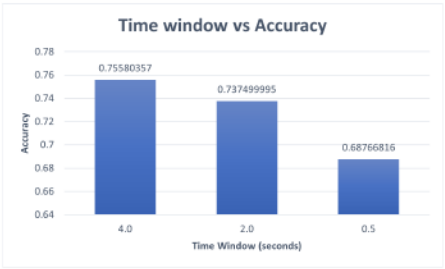

Fig. 3. Classification Accuracy of Different Time Window Sizes

In our next step, we plan to extend our work to collect data from different mobility scooter models, and different locations with more diverse groups of drivers.

IV. Acknowledgement

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