Modeling the Braking Behavior of Micro-Mobility Vehicles

Tianyou Li, Jordanka Kovaceva, Marco Dozza

Department of Mechanics and Maritime Sciences
Chalmers University of Technology
Hörselgången 4, 417 56, Gothenburg, Sweden
email: tianyou.li@chalmers, jordanka.kovaceva@chalmers.se, marco.dozza@chalmers.se

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1 INTRODUCTION

According to the community database on accidents on the roads in Europe, 2035 cyclist fatalities happened in Europe in 2019 [5]. In Sweden, 10440 bicycle crashes were reported in the Swedish Traffic Accident Data Acquisition database during 2019, and 30% of the cyclist fatalities were in car-to-cyclist rear-end crashes [6]. Nowadays, new micromobility vehicles (MMVs), for example, e-scooters, and Segways, are becoming more popular. Unlike traditional bicycles, these new MMVs usually have novel designs in appearance, kinematics, operation method, and power source (e.g., electricity-driven/assisted), which bring new hazards to traditional road users [1, 4]. Thus, it is essential to understand and quantify the behavior of the new MMV users to improve road safety.

Advanced driving assistance systems (ADAS) are proven to reduce road fatalities and increase road safety efficiently. ADAS need to know the behavior of road users to predict their intention to avoid crashes. From 2023, the European New Car Assessment Programme (Euro NCAP) will include new car-to-cyclist scenarios to test the capability of the new ADAS, which may also include other MMVs in the future. In ADAS threat assessment studies, maneuver jerks can be used as unique parameters to describe the required corrections for the driver to reach the goal [7]. However, state-of-the-art commercial ADAS make limited use of constant jerk or deceleration from the modeling of drivers and other road users. This study presents new models that describe the longitudinal velocity, deceleration, and jerk of different MMVs in braking events, typical of a rear-end collision-avoidance scenario. The proposed models are computationally efficient and can support ADAS development and its safety assessment (e.g., counterfactual simulations [2]).

2 METHODS

This study analyzed the field data collected from 34 participants who rode a bike (with and without electrical assistance), an e-scooter, and a Segway and performed comfort and harsh braking maneuvers. Each vehicle was equipped with a data logger composed of a Raspberry Pi single-board computer, an inertial measurement unit, a potentiometer, and a GPS module. In addition, a LIDAR mounted near the braking location recorded the velocity and position of the rider. An arctangent function was used as a smooth function to fit the velocity data obtained combining the IMU signals with the information from the LIDAR. A smooth function has all derivatives continuous, which makes it particularly appropriate for dynamic control and approximation [10]. The first derivative of velocity (deceleration) and the second derivative (jerk) were calculated analytically from the data collected in the experiment.

For each participant, 12 fittings were performed over the velocity data: four vehicles (bike, e-bike, e-scooter, and Segway) and three braking maneuvers (comfortable, harsh, and unexpected harsh braking). Then, the velocity was fitted with the function in Equation 1.

$$V = a \cdot \arctan(b \cdot x + c) + d \tag{1}$$

In Equation 1, ***a***, ***b***, ***c***, and ***d*** are the four coefficients that are produced by the non-linear data-fitting method ***lsqnonlin*** in MATLAB. The deceleration of the vehicle can be obtained by differentiating Equation 1 and is presented in Equation 2.

$$Deceleration = \frac{a \cdot b}{(b \cdot x + c)^2 + 1} \tag{2}$$

By differentiating Equation 2, jerk was calculated (Eq. 3).

$$Jerk = -\frac{2 \cdot a \cdot b \cdot (b \cdot x + c)}{((b \cdot x + c)^2 + 1)^2} \tag{3}$$

3 RESULTS

Figure 1 shows the fitted velocity, deceleration, and jerk for one participant during comfort braking with the e-bike. Fitting the vehicle velocity with the arctangent function demonstrated a high goodness-of-fit (an average R-squared value of 97.41%). In our previous work [3] the velocity was fitted with linear regression. The derivation of the fitted velocity curve produces similar results for maximum deceleration compared with linear regression, and the latter has a better goodness-of-fit, around 98% on average.

During all three braking tasks, the participants were able to brake with larger decelerations when riding e-bike and bike compared to when riding e-scooter and Segway. The braking performances of the Segways were poorer even if the maximum speed is limited to 15 km/h (lower than bike, e-bike, and e-scooter). The average decelerations of all vehicles were significantly larger in the harsh braking tasks than the decelerations in the comfort braking tasks, and the decelerations were slightly larger in the unexpected harsh braking task than in the planned harsh braking task. As for the jerks, the non-assisted bike achieved a larger jerk than other three electric vehicles during comfort and unplanned harsh braking. The e-scooter and Segway had significant smaller jerks than the bikes, the minimum jerk of the Segway was about a half of the minimum jerk of e-scooter, in average. Similarly to the decelerations, the jerks in the harsh braking tasks were larger than the jerk in comfort braking. Further, during unplanned harsh braking the jerk was larger than that in the planned harsh braking.

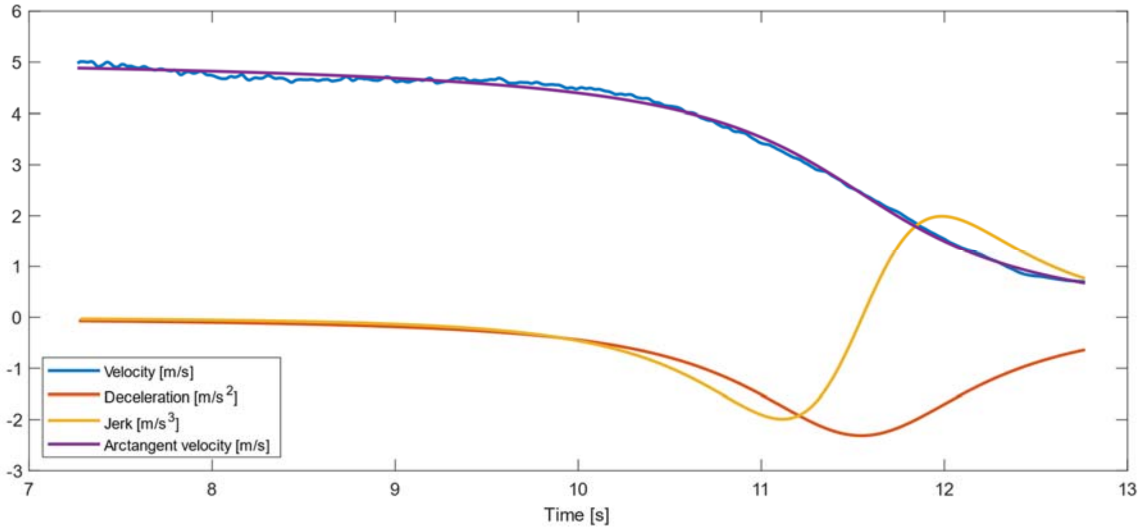

Figure 1. A plot of velocity, deceleration, and jerk in a comfort braking maneuver for one participant riding e-bike.

4 DISCUSSION

This study exemplifies a method that can rapidly compute the minimum deceleration and jerk for modelling MMVs braking maneuver. The velocity curve fitted with arctangent function describes the braking more naturally than a uniform deceleration model [7, 9]. There are several potential applications of the models presented here. First, in threat assessment of ADAS for low-speed scenarios, the arctangent speed function may be used as a new braking model to calculate required deceleration and jerk more accurately than to calculate with a constant jerk and linear deceleration model. Second, in Euro NCAP safety tests, the model can be used for planning of speed and trajectory for a robot MMV. The arctangent model is deterministic and may not be as ecologically valid as models obtained from large naturalistic databases by using other modelling approaches that can incorporate the road user variability (e.g., Bayesian [8], and deep learning [11]). However, due to its simplicity and low computational complexity, the arctangent model is suitable for both ADAS implementation and simulating MMVs' behavior in large road networks.

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