UNCONSTRAINED CYCLIST TRAJECTORY SIMULATION FOR AGENT-BASED MODELS[1]

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Introduction

Bicycle microsimulation models can have many uses including bicycle facility assessment, bicycle energy and power modeling and bicycle behavior prediction models for safety applications. Agent-based modeling (ABM) is a promising approach for building accurate bicycle microsimulation models.An agent-based model represents individual agents interacting on the microscopic level by assuming sensory inputs give the agents information about the environmentwhich informs their decisions (Plekhanova, 2003). The environment of bicycle traffic on cycling paths includes bicycle facility geometry (bicycle path lane width, curves, grades,…), and other cyclists that can differ in their proximity (longitudinal or lateral). Previous research has shown that cyclists encounter different regimes of movement during their trips(Mohammed, Bigazzi, & Sayed, 2019). Cyclists can be in a constrained regime (their actions are correlated/dependent on the movement of other cyclists), or in an unconstrained regime (their actions are not affected by other cyclists).

Previous research in bicycle microsimulation includes attempts to model bicycle traffic in a cellular automata model (Jiang, Jia, & Wu, 2004; Xue, Jia, Jiang, Li, & Shan, 2017). Liang et al. (2012) developed a psychological-physical force model that assumes cyclists choose their trajectories (acceleration and direction) based on forces of collision avoidance and friction between interacting cyclists. Mohammed et al. (2019) developed a bicycle following model based on learning the reward function of cyclists using inverse reinforcement learning. No previous research exists for modeling unconstrained cyclist trajectories.

Although unconstrained cyclists may seem to move arbitrarily, it is hypothesized that their movements can be modeled given variables such as acceleration, change in direction and deviation from path centerline. Unconstrained cyclist trajectories can be thought of as correlated random walk movements, in which the state of the present time step is dependent on the previous time step. Hidden Markov Models (HMM) can be used to infer the hidden states that cyclist encounter at each time step given observations about their movement.

The purpose of this research is to formalize a generative model that can describe unconstrained cyclist movement and be used to generate cyclist trajectories that are similar to observed ones. This model can then be combined with other constrained bicycle models to generate realistic interactions for bicycle microsimulation.

Methodology

Cyclist trajectories were extracted from videos collected at a protected bicycle path on the Burrard Bridge in Vancouver, Canada. Video data with a frame frequency of 30 Hz were obtained over three days, April 12 through 14, 2016 from 7:00 to 19:00 (29 hours total). The weather during the three days was partly cloudy with an average temperature of 11 °C. The video image included bicycle traffic in a dedicated unidirectional path (without pedestrians) with a grade of 1% in the direction of travel. A total of 2675 unconstrained bicycle trajectories were extracted from the video data by means of computer vision

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techniques developed at the University of British Columbia(Saunier & Sayed, 2006; Ismail, Sayed, & Saunier, 2008).

Observed cyclist trajectory are used for Hidden Markov Model (HMM) estimation. HMM is a time-series model that assumes that observed data consisting of discrete time steps exhibit a Markov property wherein the agent's actions during the current time step are dependent on the state of the previous time step. The model assumes that there are certain unknown number of states that a cyclist encounters along the trajectory. These states cannot be directly observed, instead they can be inferred by the observed variables. The observed variables in our model include the cartesian position of the cyclist, which determines the distance and change in direction between each two consecutive time steps. At each time step, the cyclist transitions into a new state or stays at the same state according to a transition probability matrix. The transition probability matrix is learned directly using the observed trajectories. The transition probability is assumed to be covariant with the deviation from the center line of the path. Previous research has shown that cyclists prefer (gain higher utility with) small deviations from the centerline of apath(Mohammed, Sayed, & Bigazzi, 2019). The R package "move HMM" (Michelot, Langrock, & Patterson, 2016) was used for the HMM model estimation.

Results

Two models were estimated assuming two and three hidden states. The two-state hypothesis can be explained as cyclists encountering two states, the first characterized by mild actions (low distances and direction angles), the second having actions with higher values of the distances and angles. The three-state hypothesis is explained by having an intermediate state between the two extreme states. The mean values of distances and direction angles of the two models are shown in Table 1. The Akaike Information Criterion (AIC) value for the model with three hidden states was lower than for the two hidden states model (-48552.33 vs -37997.67), indicating a better fit to the observed trajectories. The three hidden states model was chosen as the better-fit model.

Table 1: Mean values of the state variables for the two estimated models

Two hidden states model		
	Distance (m)	Direction Angle
State 01	0.229	0.023
State 02	0.673	-0.510
Three hidden states model		
State 01	0.164	0.013
State 02	0.776	-0.340
State 03	0.342	-0.530

The transition probabilities (Figure 1) show that there are, generally, high transition probabilities to the same states. That means that cyclists tend not to change their states. In addition, usually, the transition probabilities from states with lower distances and angles to states with higher distances and angles is low compared to the opposite. By looking at the change of transition probabilities with path deviation, the transition probabilities at high values of path deviations are always higher when transitioning from states with higher distance and angle values to states with lower distances and angle values, and the opposite is true.

The estimated HMM model was used to estimate cyclist trajectories given starting times and locations. To visualize the model results, 20 simulated trajectories were plotted against 20 observed trajectories (Figure 2).

Figure 1: Three-state model transition probabilities

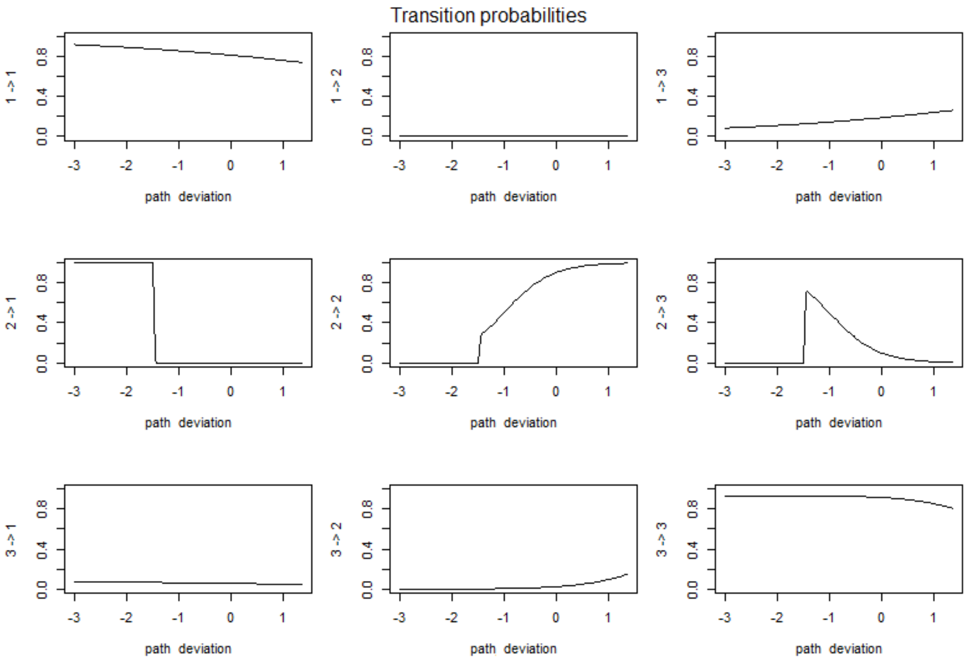
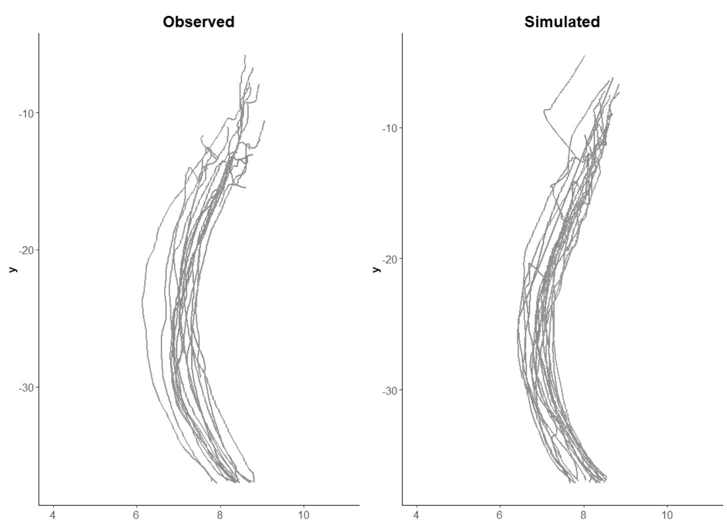


Figure 2: Observed vs simulated trajectories (samples of 20 trajectories)



Discussion and Conclusion

This research describes a method to estimate a model for generating unconstrained bicycle trajectories. The main aim of the model is to be used for generating trajectories for agent-based bicycle microsimulation. The model generated trajectories representing the change in environment dynamics from the perspective of the constrained cyclists. The generative model serves as a tool to make bicycle microsimulation more generalizable to test simulated scenarios that may not be observed in the original dataset.

The research has some limitations. First, the durations of trajectories are on average five seconds, which is small. Estimating the model with longer trajectories and different geometric features (curves, straight segments, obstacles, etc.) can provide more insights about unconstrained cycling behavior. Second, the model used for simulation should be compared to other models that may give better simulation results.Future research will include the described model in an agent-based microsimulation and combine it with constrained bicycle behavioral models to test the applicability of the model for recreating different interactions such as following and overtaking.

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