Constructing Model of Bicycle Behavior on Non-signalized Intersection Using Nonlinear Autoregressive Exogenous Model

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1 INTRODUCTION

This study focuses on bicycle travel flow to prevent traffic accidents at non-signalized intersections. A bicycle's behavior can be characterized by various parameters, such as travel speed, position, trajectory, acceleration, and deceleration. The prevention of vehicle collisions with bicycles traveling at 10–15 km/h was regulated in the Advanced Emergency Braking System (AEBS) for passenger cars in regulation No. 152 of the World Forum for Harmonization of Vehicle Regulations in the United Nations. Therefore, it is essential to analyze the characteristics of bicycles in a real traffic environment to prevent traffic accidents involving cyclists. Meijer et al. (2017) investigated bicycle behavior and characteristics using measurement devices installed on bicycles [1]. Ma et al. (2016) conducted a model of acceleration behavior on eleven cyclists using GPS data [2]. And it was pointed out that there was a need for modeling research for more cyclists. Hirose et al. (2021) examined bicycles' both travel speed and trajectory as bicycle travel flows based on data obtained from fixed-point observations at a non-signalized intersection in Tokyo, Japan [3]. This used fixed-point observations to obtain raw data of bicycle travel flows in a real traffic environment and reported various travel speed, trajectory, and acceleration/deceleration patterns for bicycles entering intersections. The purpose of this study was to construct a model of bicycle travel flows based on fixed-point observations. It could simulate actual bicycle behaviors based on data that was obtained from measuring bicycle travel flows for 2828 cases from fixed-point observations. Furthermore, the data was divided into five patterns of bicycles entering intersections, and the accuracy of the model was evaluated for each pattern.

2 METHOD

2.1 Data for bicycle model

In this study, the proposed model was constructed based on data that was obtained from measuring bicycle travel flows for 2828 cases at a non-signalized intersection in Tokyo, Japan. Bicycle accidents were reported at this intersection due to restricted visibility by buildings at the corners of this intersection. The intersection had a stop line before entering the intersection, and the range of modeling was 10 m to the stop line in this intersection. The bicycles' traveling positions, speeds, and acceleration/deceleration were analyzed based on these data. Our previous study reported that most bicycles entered the intersection traveling at speeds between 3.13 m/s and 3.76 m/s [4]. In addition, the acceleration/deceleration of bicycles was 0.08–0.34 m/s^2 [4].

2.2 Classification of bicycle behavior

In this study, we focused on multiple patterns of both the speeds and acceleration/deceleration of bicycles traveling through the intersection. Note that the model accuracy would be decrease if all the data were targeted for the model. Therefore, to tackle this issue, we constructed multiple models. In the construction of driver models using nonlinear autoregressive exogenous (NARX), it has been confirmed that the accuracy of the model decreases when the driving speed at the time of model construction differs from the driving speed targeted for modeling [5]. In addition, the data used in this study was classified into the following five bicycle behavior types. Type 1: entering the intersection at a constant speed immediately after deceleration. Type 2: entering the intersection after significant deceleration. Type 3: entering the intersection at a constant speed. Type 4: entering the intersection at a constant speed immediately after acceleration. Type 5: entering the intersection at a constant speed and after repeated acceleration/deceleration. The models were construct for each behavior type.

2.3 NARX model

In this study, we constructed bicycle behavior models using NARX. NARX uses machine learning to build a model of time-series data [5]. The inputs were the distance to the intersection's stop line and the bicycle speed for the NARX, and the output was the acceleration/deceleration of the bicycle. From the analysis described in Section 2.1, bicycles had various accelerations/decelerations before passing through the intersection. Herein, we intended to construct models for acceleration/deceleration based on the natural behavior of bicycles. The internal parameters of NARX were as follows: the number of delays in input and output was 2; number of neurons in the middle layer was 2; and number of epochs was 300. The model's accuracy was evaluated based on the output of the trained NARX model. Evaluation was performed using the evaluation data, which were not used as training data. Because training data affect the model's accuracy, it is possible to build a high-precision model efficiently even if it is constructed from a small amount of data. Therefore, this study used 2000 data as the maximum training data. For comparison of the model's accuracy, three different models were constructed using 500, 100, and 50 data, respectively. The model's accuracy was evaluated from the root mean squared error (RMSE) of the acceleration/deceleration. The RMSE was calculated from the measured data at the intersection and output of the NARX model. The smaller the RMSE value, the more accurate the model. Furthermore, MATLAB was used to construct the NARX model.

3 RESULTS

Figure 1 shows the relationship between acceleration/deceleration, calculated by the model, and distance to the stop line in the intersection. In Figure 1, the bicycle behavior types shown are types 1 and 3. Herein, the zero on the x-axis indicates the stop line of the intersection, and the acceleration/deceleration occurs 10 m before the stop line at the intersection. The blue line denotes the measured acceleration/deceleration of the cyclist at the intersection, whereas the red line denotes the output of the NARX model. Figures 1 (a) and (b) report an RMSE of 12.5×10^{-3}, 2.84×10^{-3}, respectively. Thus, it can be inferred the NARX model was able to simulate bicycle behavior in terms of acceleration and deceleration. Moreover, similar results were obtained for Figure 1 (a) where the RMSE was 12.5×10^{-3}, which had a lower accuracy than that of Figure 1 (b).

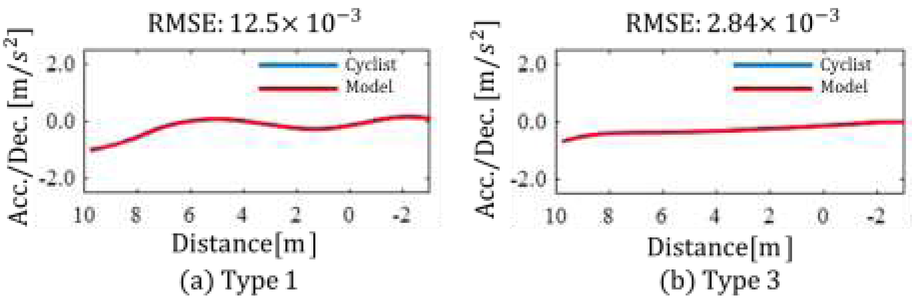

Figure 1: Result of NARX model for acceleration and deceleration of bicycle.

Further, we examined the mean and standard deviation of the RMSE values, listed in Table 1, to evaluate the model accuracy for all data. Table 1 shows the values of both average and standard deviation of the RMSE values of the five bicycle behavior types; the numbers of training data were 2000, 500, 100, and 50. The results showed that the lowest accuracy was obtained with 50 training datasets, and similar accuracy was obtained with the 2000, 500, and 100 training datasets. These results indicate that the model accuracy for bicycle behaviors at non-signalized intersections had less significant effects even if the NARX model was constructed using 100 training data. Reducing the number of training data to below 100 affected the model's accuracy. Regarding the characteristics of the bicycle behavior types, Type 3 had the highest accuracy; Types 2, 4, and 5 had similar accuracy; and type 1 had lowest accuracy among all the types.

Table 1: Result of model accuracy on bicycle behavior types and the number of training data.

	Number of training data							
	2000		500		100		50	
	Avg.	S.D.	Avg.	S.D.	Avg.	S.D.	Avg.	S.D.
Type 1	22.361	7.272	21.138	7.741	19.86	5.899	95.719	61.986
Type 2	17.419	7.087	15.95	5.583	17.282	6.362	92.382	57.976
Type 3	10.193	3.751	9.307	2.938	9.926	3.142	71.67	46.985
Type 4	18.935	7.875	16.032	4.764	17.824	5.933	74.717	53.342
Type 5	17.8	7.449	15.937	6.208	17.604	6.479	89.497	58.877

Here, "Types" refers to the classification of bicycle behavior; the values in the table are RMSE × 10^{-3})

4 CONCLUSIONS

This study focused on constructing a model of bicycle traffic flow that can simulate natural bicycle behavior. The data for constructing the model was obtained by measuring the bicycle travel flow for 2828 cases at a non-signalized intersection in Tokyo, Japan. Models were constructed using NARX; the inputs were the distance to the stop line of the intersection and the bicycle speed, and the output was the acceleration/deceleration of the bicycle. Consequently, it was observed that the NARX model could simulate bicycle behavior in terms of both acceleration and deceleration. Furthermore, reducing the number of training data to below 100 affected the model's accuracy. The Type 3 bicycle behavior had the highest accuracy; Types 2, 4, and 5 had similar accuracy; and type 1 had the lowest accuracy among all the types. However, the number and types of bicycle behavior and intersections are limited. This study divides the bicycle behavior types into five, but it is necessary to investigate the model accuracy when further dividing the types. We should apply this model to other non-signalized intersections in further study.

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