# Comparative Analysis & Modelling for Riders' Conflict Avoidance Behavior of E-bikes and Bicycles at Un-Signalized Intersections

Ling Huang, Jianping Wu, Ronghui Zhang*, Dezong Zhao, Yinhai Wang

***Abstract*—**With the increasing popularity of electric-assist bikes (E-bikes) in China, U.S. and Europe, the corresponding safety issues at intersections have attracted the attention of researchers. Understanding the microscopic behavior of E-bike riders during conflicts with other road users is fundamental for safety improvement and simulation modeling of E-bikes at intersections. This study compared the conflict avoidance behaviors of E-bike and conventional bicycle riders using field data extracted from video recordings of different intersections. The impact of conflicting road user type and gender on E-bikes and bicycles were analyzed. Compared with bicycles, E-bikes appeared to enable more flexibility in conflict avoidance behavior. For example, E-bikes would behave like bicycles when conflicting with motor vehicles/E-bikes, and behave more like motor vehicles when conflicting with bicycles/pedestrians. Based on this, we built an Extended Cyclist Conflict Avoidance Movement (ECCAM) model. (What is the advantage of this model?) Field data were applied to validate the proposed model, and the results are promising.

***Index Terms*—**Bicycles, Conflict, E-bikes, Fuzzy Logic, Intersection, Transportation.

## I. Introduction

In recent years, non-motorized vehicles have become important travel modes of commute in China, U.S and Europe [1-2]. Compared to conventional bicycles, electric-assist bikes (E-bikes) are faster and provide a more competitive alternative to the private car [3-4]. With the popularity of E-bikes, the corresponding safety issues have attracted the attention of researchers. Chinese accident statistics have shown that the number of crashes involving E-bikes has risen recently, and that the majority of such crashes occur at intersections [5-7].

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Understanding of E-bike riders' microscopic behavior during conflicts with other road users at un-signalized intersections is critical. First, it can provide a behavioral basis for improving facility design or traffic management to increase the safety of E-bikes at intersections. Second, characterizing E-bike conflict avoidance behavior can help to build the behavioral model for a microscopic traffic flow simulation models, which are widely used tools for intelligent transportation systems (ITS). Moreover, they could be applied to evaluate safety and performance improvements at intersections where E-bikes are likely to be present.

Bicycle crash data analysis methods have been widely used and supported facility design and management enhancement for bicycles/E-bikes at intersections [8-10]. However, these methods are found unsuitable to build the E-bike/bicycle microscopic conflict avoidance behavior model at intersections [11].

Researchers pointed out that field observation on road user behavior is a promising alternative for the purpose of investigating E-bike conflicts [12]. Due to technical limitations, using on-board instruments to monitor E-bike rider behavior in a naturalistic way is just reported recently [13-15]. In this naturalistic approach, it was found that pedestrians, light vehicles and other bicycles are the primary threats to rider safety. Furthermore, this research (Ronghui: which research?) suggests that E-bikes travel faster than conventional bicycles and interact differently with other road users [16]. By comparing two types speeds of E-bikes and conventional bicycles, it was found that on average the both types of E-bikes travel significantly faster than bicycles. Later, by reviewing the differences between E-bikes and bicycle concerning the probability to be involved in a traffic conflict, it has been found that the probability of E-bikes to be involved in traffic conflicts is twice as high as that of bicycles[17]. Recently, research shows that cyclists' riding and interacting behavior with other road users change when cyclists switch from conventional bicycles to E-bikes [18].

Though the naturalistic approach provides more information on E-bike conflicts, this method also has limitations. A possible problem is the reliance on voluntary participation, which might bias the subject sample to experienced and healthy riders. This is important because frequent and experienced cyclists tend to have higher crash severity [19]. Another issue with the naturalistic approach is that cameras installed on the E-bikes cannot completely cover the full traffic environment during conflicts. Most importantly, this approach makes it difficult to extract accurate trajectory the conflicting vehicles, and so cannot provide sufficient trajectory data for microscopic conflict avoidance behavior analysis & modelling [20].

Another suitable approach to collect cyclist conflict avoidance behavior data is to install an elevated high-definition camera with a top-down view of the facility (road section or intersection) to collect the video data of all road users. In this way, the full traffic environment during conflicts can be covered by the camera. By applying advanced computer vision technology for object detection & tracking, it is possible to extract the trajectories of bicycles and other vehicles/pedestrians [21- 22]. Other data, such as vehicle type, age, gender, volume and speed can then be collected manually [23]. This method is promising to overcome the insufficient camera coverage and trajectory data limitations of the above naturalistic approach.

Using this method, the bicycle moving behavior under conflicts with other road users (motor vehicles, other bicycles, and pedestrians) at un-signalized intersections is investigated. They (Ronghui, who are they?) observed the microscopic conflicting avoidance behaviors of the bicycles when conflicting with different road users. They(Ronghui, who are they?) also built a Cyclist Conflict Avoidance Movement (CCAM) model for simulation purposes. However, this study did not include E-bike riders as road users [21, 31-35].

The methods described in ref [21], are better choices for studying E-bike conflict avoidance behavior at intersections. E-bikes and bicycles are quite similar in vehicle structures and sizes. However, their riding characteristic may differ in terms of speed, acceleration, deceleration, turning, etc. It is likely that these differences will lead to differences in conflict avoidance behavior at intersections. Therefore, the objective of this work is to investigate and compare the microscopic conflict avoidance behavior of E-bikes and bicycles in mixed un-signalized intersections. By identifying the similarity and differences between conflict avoidance behavior of E-bikes and bicycles, we seek to discover the factors contributing to the risk and severity of accidents involving E-bikes. In addition, we extended the original CCAM model by adding E-bike riders to the model and building a conflict avoidance behavior model for E-bikes.

Here E-bikes refer to all two wheeled bicycles that are driven by electricity, including E-bikes, and scooters with vehicle weight less than 40 kg. It is assumed that the vehicle power is one of the important factors affecting the user's microscopic behavior (such as speed and acceleration). Therefore, the microscopic behaviors of E-bikes and man-powered bicycles may be different in both riding speed and conflict avoidance behaviors.

The paper is structured as follows: Section II introduces the research process; Section III describes the data collection and processing; section IV presents comparative analysis on conflict avoidance behaviors; section V proposes the extended cyclists' conflict avoidance model; and section VI presents the discussions on our findings. Conclusions and future works are summarized in Section VII.

## II. Methodology

Following are the assumptions and other basic issues of this work. (I do not think this sentence should be an independent paragraph. The same to the next paragraph)

Here the widely accepted definition of a traffic conflict is adopted as "an observable situation in which two or more road users approach each other in space and time for such an extent that there is a risk of collision if their movements remain unchanged."

According to the social force model, a road user is assumed to drive directly to (you should avoid ‘his’ or ‘he’, because you are not sure the road user is male) “destination” by current speed and direction if he does not involved in a conflict or affected by other road users [24, 39-41]. The “destination” here is the temporary destination (TD) rather than the final destination, but. The so-called TD refers to the place that an individual wants to reach in a relatively short period of time. For example, in this study TD often refers to somewhere in the bicycle lane across the intersection. That means, if a road user's speed suddenly changes, we consider the road user is under influence by other road users or involved in a conflict.

Thus, the criteria to determine whether an E-bike or bicycle is in conflict situations are whether there is an explicit change in the direction and speed, and if any of the future positions coincide both spatially and temporally with other road users, as the author of ref [25] proposed in their study on pedestrians’ evasive action conflict measures analysis.

We assume that even though the structure and size of the E-bikes is similar to that of conventional bicycle, there should be differences in collision avoidance behavior due to the different power sources for moving of E-bikes and bicycles. Under this assumption, we attempt to compare E-bikes and bicycles’ conflict avoidance behavior by investigating the changes in magnitude and direction of their instantaneous velocities in conflicts [26]. Therefore, we analyze the instantaneous velocity, speed change ratio in magnitude; turning angle and destination / direct angle (which represent the degree of detour) of the E-bikes and bicycles in conflicts (details see section IV *A.*).

Because the calculation time interval ΔT for instantaneous velocity is very small (in this study， \Delta T= 0.4 second), requirements for the reliability and accuracy of road users’ trajectory data are very high. In Section III, we introduce the data acquisition and processing, including Kalman filter for smoothing the trajectory data and a new error analysis method.

Thereafter, an Extended Cyclist’s Conflict Avoidance Movement (ECCAM) model is proposed for riders of E-bikes and bicycles based on the comparative analysis results on conflict avoidance behavior of E-bikes and bicycles. ECCAM is an extension of the original Cyclist’s Conflict Avoidance Movement (CCAM) model proposed by Zhang et al. (2017). It could be applied as a conflict avoidance behavior module in a mixed traffic flow simulation platform [27]. Considering that the E-bike riders’ complex situation of conflicts with other road users at intersections are similar to those of bicycle riders, ECCAM would follow the original CCAM, taking the fuzzy logic as main modelling method [21]. Detailed description is presented in Section V.

## III. Data Collection & Process

### *A. Data Collection*

A Large amount of reliable, high-quality trajectory data on each road users involved in conflicts is important for our research. We selected 6 different mixed traffic flow un-signalized intersections in three cities of China (two in Guangzhou, two in Nanning and two in Beijing) for field video data collection. At each intersection, at least two hours of videos were recorded, ranging from 6:00 am to 8:30 am. This period represented the buildup of mixed traffic flow volume of the six intersections during the morning peak hours. Fig. 1 shows one data collection site in Nanning. The average volumes of E-bike and bicycle during peak hours (7:30-8:30) at each of the six intersections are shown in Table I. For the sites in Nanning City, E-bikes had much larger volumes than bicycles, which is typical of the traffic characteristics of Nanning city.


Fig. 1. Data Collection Sites in Nanning.

*Actually, this intersection is an un-operating signalized intersection. The lights were not working when we recorded the video in 2013.

### *B. Data Process*

From [21], the software named VSpee was also used to track the moving objects and extract location information at a minimum interval of 0.04 seconds. To ensure the reliability and quality of dynamic E-bike and bicycle conflict avoidance behavior data, camera calibration and data validation were necessary procedures at each data acquisition site.

For camera calibration, we adopt the method proposed by the ref [27], using a few planers patterns shown at least two orientations. Here, the checkerboard planers were derived from the pedestrian crossings at the sites. According to the method, three different 6*6 data matrix are sufficient to get a unique solution for the camera calibration problem. Therefore, at each data collection site, the width, length and spacing of the crossings were measured in the field. And 3-5 checkerboard matrixes on the road surface were taken manually for camera calibration, as illustrated in Fig. 2. The yellow frame is the detection area and the checkerboard black frames were the calibration matrixes.

By camera calibration, the Vspeed could track the manually selected road users and transform the screen position to the real world position data at each frame. The output position data would be validated by field data before use.

After camera calibration, the Vspeed is able to track manually selected objects and output object trajectories from the video data. The output position data were validated before use.

TABLE I

E-BIKE AND BICYCLE TRAFFIC VOLUMES OF DATA COLLECTION SITES

| Volumes | Site 1 | Site 2 | Site 3 | Site 4 | Site 5 | Site 6 |
|---|---|---|---|---|---|---|
| Bicycles (bike/h) | 3808 | 2060 | 236 | 310 | 2544 | 1884 |
| e-bikes (bike/h) | 324 | 248 | 1388 | 2220 | 880 | 236 |


Fig.2 Illustration of Camera Calibration at Nanning Intersection

As our research was mainly focused on the relative distance, speed, or direction between two Road users, we chose the fixed relative distance of different vehicles (such as the wheelbase) as validation measurements. For example, Santana from Volkswagen (with wheelbase of 2.5 m), regular bus (with wheelbase of 6 m), E-bike and e -scooter (with wheelbase of 1.1 m). The relative distance error $e_{rdi}$ for each position were calculated as follows:

$$e_{rdi} = \sqrt{(\hat{x}_{fi} - \hat{x}_{ri})^2 + (\hat{y}_{fi} - \hat{y}_{ri})^2} - \Delta l_j \quad (1)$$

where $(\hat{x}_{fi}, \hat{y}_{fi})$ and $(\hat{x}_{ri}, \hat{y}_{ri})$ stood for the *i*th estimated positions of front and rear wheel of the vehicle, respectively; and $\Delta l_j$ for the wheelbase of vehicle of type j, m.

Here, we used the mean relative distance error $E_{rd}$ as the validation index:

$$E_{rd} = \frac{1}{n}\sum_{i=1}^{n} e_{rdi} \quad (2)$$

For better analyzing the E-bikes and bicycles' conflict avoidance behavior, a time interval of ΔT = 0.4 s was taken as time step length as it is similar to the average person's reaction time.

A Kalman filter method proposed in ref [28] was applied to the raw estimated position data of each object at every frame. The filtered position data were extracted by a time interval length of ΔT and then used for validation. Table II shown the relative distance error analysis of data collection sites. The maximum relative distance error $e_{rd}$ calculated by (1) was 0.48 m, and the mean relative distance error $E_{rd}$ calculated by (2) was 0.21 m, which seemed to meet the data quality requirements for analyzing dynamic E-bikes and bicycle conflict avoidance behaviors. After camera calibration and validations, the following analysis and definitions on E-bike and bicycle riders' conflict avoidance behaviors were all based on these trajectory data. And by the conflict judgment introduced in Section II, we got 4424 observations on the tracks and speeds of E-bike and bicycle and related conflicting road user in 316 conflict cases, and 1482 observations in 112 non-conflict cases. The conflict cases were judged manually by the criteria described in Section II. In conflicts, the E-bikes/bicycles with less right-of-way were taken as conflict subjects, as they usually had obvious evasive actions; and their counterparts in conflicts were with more or equal right-of-way. The travel directions of the two road users in a conflict were all vertically intersected. We randomly selected 3104 observations (about 70% of all observations) for the comparative analysis sample and parameter calibration, and the remaining 1320 observations for the model validation for ECCAM.

## IV. COMPARATIVE ANALYSIS ON CONFLICT AVOIDANCE BEHAVIOR

### A. *Conflict Avoidance Behavior Variables*

Zhang et al. (2017) (Please unify the reference format!) defined 4 motion variables to analyze bicycle conflicts. However, each of the motion variables applied were averaged over entire trajectories , which makes them unable to represent the microscopic changes in behavior of cyclists in conflict [21]. To address this limitation, the following four instantaneous conflict behavior variables are proposed:

1) Instantaneous velocity $\vec{v}_{\alpha}(t)$

The E-bikes or bicycle rider α's instantaneous velocity

TABLE II

RELATIVE DISTANCE ERROR ANALYSIS OF DATA COLLECTION SITES

| Sites | Relative Distance Error (m) | | | Num. of Validation Record |
|---|---|---|---|---|
| | Mean | S.D. | Max. | |
| Site 1 | 0.21 | 1.01 | 0.45 | 156 |
| Site 2 | 0.19 | 0.89 | 0.28 | 163 |
| Site 3 | 0.17 | 0.91 | 0.32 | 142 |
| Site 4 | 0.23 | 1.31 | 0.39 | 138 |
| Site 5 | 0.22 | 1.25 | 0.41 | 159 |
| Site 6 | 0.25 | 1.42 | 0.48 | 178 |
| Total | 0.21 | 1.19 | 0.48 | 936 |

$\vec{v}_\alpha(t)$ was derived from the positions at time $t$ and the last time step $(t-\Delta T)$, i.e.:

$$\vec{v}_\alpha(t) = \frac{\vec{P}_\alpha(t) - \vec{P}_\alpha(t-\Delta T)}{\Delta T}$$

$$\text{with } (T_\alpha^O + \Delta T) \le t \le T_\alpha^D \tag{3}$$

where $\vec{P}_\alpha(t)$ and $\vec{P}_\alpha(t-\Delta T)$ stand for the postion vectors α of at time t and (t-ΔT), respectively; $T^O_\alpha$ and $T^D_\alpha$ stand for the time when α is located at the Origin and Destination point of the conflict event; while ΔT stands for the time step length (selected to be 0.4 s).

The mean speed $\bar{V}$ is defined as the arithmetic mean of overall instantaneous velocity $\vec{v}_\alpha(t)$ samples:

$$\bar{V} = \frac{\sum_\alpha \sum_t |\vec{v}_\alpha(t)|}{n} \tag{4}$$

where $n$ stands for the sample size of instantaneous velocities.

2) Instantaneous speed change ratio $\lambda_\alpha(t)$

Instantaneous speed change ratio $\lambda_\alpha(t)$ is defined as the instantaneous speed ratio compared to the instantaneous speed at last time step:

$$\lambda_\alpha(t) = \frac{|\vec{v}_\alpha(t)|}{|\vec{v}_\alpha(t-\Delta T)|}$$

$$\text{with } (T_\alpha^O + 2\Delta T) \le t \le T_\alpha^D \tag{5}$$

The mean speed change ratio $\bar{\lambda}$ is defined as the arithmetic mean of all instantaneous speed change ratio overall:

$$\bar{\lambda} = \frac{\sum_\alpha \sum_t \lambda_\alpha(t)}{m} \tag{6}$$

where m stand for the sample size of instantaneous speed change ratios.

3) Instantaneous turning angle $\Delta\theta(t)$

Instantaneous turning angle $\Delta\theta_v(t)$ is defined as the absolute direction difference between current time $t$ and last time step t-ΔT, i.e.:

$$\Delta\theta_v(t) = \left\| \theta_v(t) - \theta_v(t-\Delta T) \right\| \tag{7}$$

where $\theta_v(t)$ stands for α's instantaneous direction at time t, which could be derived from the instantaneous velocity by:

$$\theta_v(t) = \arccos\left(\frac{v_\alpha^x(t)}{|v_\alpha(t)|}\right) \tag{8}$$

where $v_\alpha^x(t)$ stands for the X-axis component of $\vec{v}_\alpha(t)$.

The mean turning angle $\Delta\bar{\theta}$ is defined as the arithmetic mean of turning angles of all observed data:

$$\Delta\bar{\theta}_v = \frac{\sum_t [\Delta\theta_v(t)]}{m} \tag{9}$$

where m stands for the sample size of the instantaneous turning angles.

4) Instantaneous dest/dir angle $\theta_{d\text{-}v}(t)$

The instantaneous dest/dir angle $\theta_{d\text{-}v}(t)$ is defined by the absolute direction difference between the destination angle $\theta_d(t)$ and the moving direction $\theta_v(t)$, i.e.:

$$\theta_{d-v}(t) = \left\| \theta_d(t) - \theta_v(t) \right\| \tag{10}$$

The mean turning dest/dir angle $\bar{\theta}_{d-v}$ is defined as the arithmetic mean of the dest/dir angles of all observed data:

$$\bar{\theta}_{d-v} = \frac{\sum_t [\theta_{d-v}(t)]}{m} \tag{11}$$

where m stands for the sample size of the instantaneous dest/dir angles. Readers can refer to ref [21] for illustrations of the turning angle and destination / direct angle.

### B. *Comparative Analysis on Conflict Behavior*

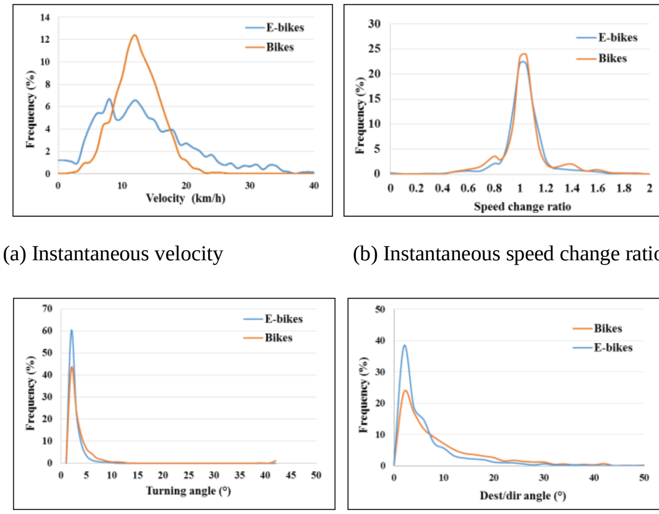
To verify our hypothesis on road users' behaviors in conflicts in section II, we compared the above conflict behavioral variables of E-bikes and bicycles between non-conflict and conflict situations. To investigate the significance of the difference between conflict and non-conflict behaviors, we applied the student t-test for H0: equal means and two samples with different deviations. The significance level is 5% (which means all p-value equal to 0.05) and, as the sample sizes are all over 30, the threshold is 1.96. Statistics results are shown in Table III. The 85% value stands for the 85% percentile value, which is a useful value for parameter for behavioral models.

Table III shows that there were significant statistical differences between the conflict and non-conflict riding behavior of riders of both E-bikes and bicycles. Specifically, for both E-bike and bicycle, their speeds are lower while the turning angle and dest/dir angels are larger when involved in conflicts. The instantaneous speed change ratios are nearly 1, turning angle and dest/dir angle are almost zero, which indicate that our hypothesis on road users' behaviors in non-conflicts is reasonable.

Fig.3 shows the distribution of behavior variables in conflicts.

## C. *Influence of Conflicting Road User Type*

To analyze the influence of conflicting user types on E-bike and bicycle riding behaviors, we compared the statistics of riding behavior variables for different conflicting user types in Table IV. Here, we use a capital to stand for each road user type: "**V**" sands for motor vehicles; "**E**" for E-bikes; "B" for bicycles and "**P**" for pedestrians. For example, "**EV**" stands for the conflict situation that an E-bike being in confliction with a motor vehicle. There are totally eight kinds of conflicts: EV, BV, EE, BE, EB, BB, EP and BP. The t-test method was also applied to test the difference significance between equal means in Table IV.




(a) Instantaneous velocity (b) Instantaneous speed change ratios

(c) Instantaneous turning angles (d) Instantaneous dest/dir angles

Fig. 3 Distribution of Behavior Variables in Conflicts.

For both E-bikes and bicycles, the mean speeds seemed to be the ***highest*** when conflicting with pedestrians, and the ***lowest*** when conflicting with **E-bikes**, which indicate that the conflicting E-bikes seem to have the most impact on riding speeds of E-bikes and bicycles. In general, the turning angle of E-bikes was smaller than that of bicycles, except the cases conflicts with other E-bikes (see Table IV).

Fig.4 showed the differences of mean riding speed and turning angles of E-bikes and bicycles when conflicting with different road users. It seems that when conflicting with the motor vehicle and E-bikes, there were ***minor differences*** between behaviors of E-bikes and bicycles. While conflicting with the bicycles and pedestrians, there were ***obvious differences***. This seemed to imply that the riding behaviors of E-bikes in conflicts were more ***flexible*** than bicycles. They

TABLE III

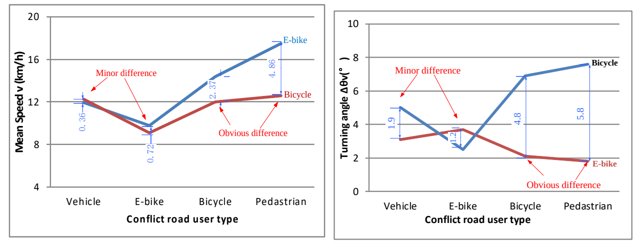
COMPARISONS OF THE BEHAVIORS STATISTICS IN NON-CONFLICT AND CONFLICT SITUATIONS

| E-bikes or Bicycles | Situation | Instantaneous velocity v (km/h) | | | Instantaneous speed change ratio λ | | | Instantaneous turning angle $\Delta\theta_v$(°) | | | Instantaneous dest/dir angle $\theta_{d\text{-}v}$(°) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **85% value** | **Mean** | **S. D.** | **85% value** | **Mean** | **S. D.** | **85% value** | **Mean** | **S. D.** | **85% value** | **Mean** | **S. D.** |
| | Non-Conf. | 27.31 | 22.69 | 4.85 | 1.06 | 1.01 | 0.13 | 4.7 | 2.4 | 2.6 | 6.4 | 3.3 | 2.46 |
| | Conflict | 20.40 | 14.49 | 7.91 | 1.11 | 1.02 | 0.22 | 7.2 | 4.8 | 3.2 | 10.2 | 5.5 | 8.29 |
| **E-bikes** | Difference# | 6.91 | 8.2 | -3.06 | -0.05 | -0.01 | -0.09 | -2.5 | -2.4 | -0.6 | -3.8 | -2.2 | -5.83 |
| | t. value | -- | **6.06** | -- | -- | **1.99** | -- | -- | **-3.25** | -- | -- | **-2.97** | -- |
| | p-value | | **0.000** | | | **0.020** | | | **0.001** | | | **0.001** | |
| | Non-Conf. | 26.87 | 16.81 | 3.21 | 1.08 | 1.01 | 0.15 | 5.2 | 3.7 | 11.8 | 7.3 | 3.8 | 6.73 |

tend to behave like bicycle when conflicting with motor vehicles and turn to behave like motor vehicles when conflicting with more vulnerable road users such as bicycle and pedestrians

### D. *Influence of Gender*

To analyze the influence of gender on riders' conflict avoidance behaviors, we compared the mean difference significance of the above behavior variables between male and female riders of E-bike and bicycle in conflicts. Again, the t-test method was applied to test the equal means at a significant level of 0.05 with a threshold t-value of 1.96. Statistics results shown that for both E-bikes and bicycles, the gender of riders had a significant influence on the mean conflict speeds in all conflict situations. The male riders tended to be 5~25% faster than their female counterparts in all situations. While the difference in mean speed change ratio, mean turning angels and dest/dir angles between male and female riders is negligible or insignificant.




(a) Mean instantaneous velocity (b) Mean instantaneous turning angle

Fig. 4 Differences of the impact of conflicting road user type on e-bikes and

## V. Extended Cyclists' Conflict Avoidance Model (ECCAM)

The above comparative analysis show that there exit significant differences between E-bike and bicycle riders' conflict avoidance behavior. These differences should be fully considered in developing the ECCAM model including factors such as E-bikes and different conflict situations. Thus, the model framework of ECCAM needs modification from that of the CCAM.

From the modeling perspective, these differences between E-bike and bicycle riders' conflict behaviors can be represented in the different behavior choice sets for riders of E-bike and bicycle. For example, under conflict with a motor vehicle, E-bike riders tend to change their speeds rather than

TABLE IV

Statistics of Riders' Conflict Avoidance Behavior Variables of Different Groups

| **Conflict situations** | **Number of cases** | **Instantaneous velocity v (km/h)** | | | **Instantaneous speed change ratio λ** | | | **Instantaneous turning angle $\Delta\theta_v$(°)** | | | **Instantaneous dest/dir angle $\theta_{d\text{-}v}$(°)** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 85% value | Mean | S.D. | 85% value | Mean | S.D. | 85% value | Mean | S.D. | 85% value | Mean | S.D. |
| **EV** | 42 | 17.96 | 11.92 | 10.37 | 1.14 | 1.02 | 0.25 | 4.7 | 3.1 | 5.82 | 11.0 | 6.0 | 8.76 |
| **BV** | 60 | 15.73 | 12.28 | 3.20 | 1.11 | 1.01 | 0.17 | 8.9 | 5.0 | 6.91 | 20.7 | 10.6 | 10.82 |
| **Difference** | | 2.23 | -0.36 | 7.17 | 0.03 | 0.01 | 0.08 | -4.2 | -1.9 | -1.09 | -9.7 | -4.6 | -2.06 |
| **t. value** | | | -0.68 | | | 0.42 | | | **-6.00** | | | **-7.84** | |
| **p-value** | | | 0.249 | | | 0.338 | | | **0.000** | | | **0.000** | |
| **EE** | 32 | 15.95 | 9.79 | 6.55 | 1.16 | 1.04 | 0.31 | 5.3 | 3.7 | 7.76 | 10.3 | 5.6 | 10.22 |
| **BE** | 25 | 11.70 | 9.07 | 3.02 | 1.05 | 1.01 | 0.04 | 4.1 | 2.5 | 2.18 | 12.5 | 6.6 | 6.27 |
| **Difference** | | 4.25 | 0.72 | 3.53 | 0.11 | 0.03 | 0.27 | 1.2 | 1.2 | 5.58 | -2.2 | -0.8 | 3.95 |
| **t. value** | | | **2.08** | | | **1.98** | | | **3.23** | | | **-1.94** | |
| **p-value** | | | **0.019** | | | **0.023** | | | **0.001** | | | **0.026** | |
| **EB** | 25 | 19.12 | 14.36 | 6.01 | 1.06 | 1.01 | 0.05 | 3.5 | 2.1 | 3.82 | 8.9 | 4.7 | 6.65 |
| **BB** | 56 | 15.77 | 11.99 | 3.78 | 1.11 | 1.02 | 0.25 | 6.7 | 6.9 | 16.89 | 80.7 | 50.3 | 58.50 |

directions to avoid the conflict. This suggests a choice set with smaller turning angles would be suitable for this conflict situation. While conflicting with other E-bikes, E-bikes tended to change both their speeds and directions to avoid the conflict, suggesting that a choice set with moderate turning angles would be suitable. Other aspects of the ECCAM such as the membership function of the fuzzy evaluation indexes associated with the E-bike behavioral features would also be considered.

Following were descriptions of the model framework, choice sets and the member functions of fuzzy evaluation index for E-bikes in ECCAM. (What do you mean??)

### A. Model Framework

Fig. 5 shows the model flow chart of ECCAM, where the modified module is marked with *. In the first step, the model is initialized with the start parameters for target object (E-bike or bicycle) α and the potentially conflicting object β, including road user type, initial positions, current/expected moving speed and direction, origin and destinations points, system start time, and so on. The influence of the rider's gender is reflected in different expected speeds, according to the above analysis results. The next step is the Conflict Judgement module. Because the vehicle size of E-bikes and bicycles are similar, ECCAM follow the original *Conflict Judgement* module in CCAM. If there is no conflict, the model proceeds directly to the *Decision* module. If a conflict is present, conflict situation is judged according to the user type of α and β. In the next step, the fuzzy index and choice set are built according to the conflict situation, and fuzzy evaluation rules are applied to evaluate each discrete movement choice j. The *Decision* module then determines the final output of the next movement of α. The dynamic state of both α and β is then updated to reflect the movement choices. The model operates at a time step of ΔT. This process is repeated until α is near his/her Destination $D_\alpha$, i.e. until:

$$\left\|\vec{p}_\alpha(t) - D_\alpha\right\| \leq \varepsilon_d \tag{12}$$

where $\vec{p}_\alpha(t)$ stands for the position of α at time *t*, and $e_d$ for the distance error, here $e_d = 0.3m$.

### B. Conflict Situation

Results show that the conflict situation has a significant influence on the riders' most conflict avoidance behaviors. The influence factors mainly include the types of the rider (E-bike or bicycle) and conflicting road user (motor vehicle, E-bike, bicycle or pedestrian). Thus, there are 8 different conflict situations "α- β" according to the rider type "α" and the conflicting road user type "β": "E-V", "E-E", "E-B", "E-P", "B-V", "B-E", "B-B" and "B-P" conflict situation. The extended discrete choice sets would be different for different conflict situations.

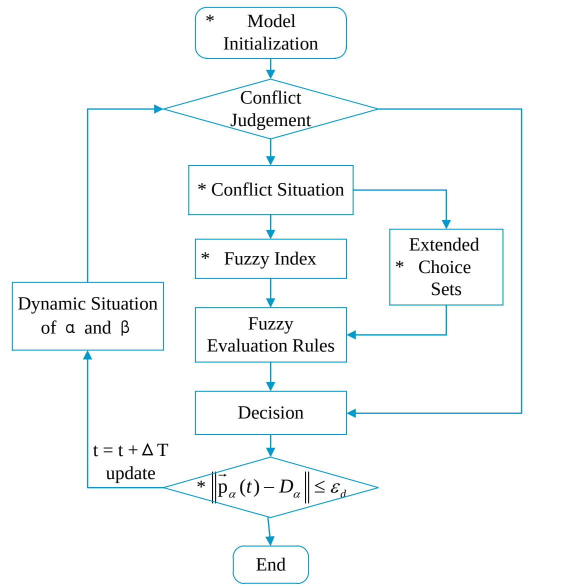



Fig. 5 Flow Chart of Extended Cyclists' Conflict Avoidance Model

### C. Extended Discrete Choice Sets

The extended discrete choice set $C_\alpha(\beta, t)$ is a dynamic variation that is influenced by the state of α and conflicting object β. It consists of a combination of direction change $\Delta\theta_\alpha(\beta, t)$ and speed change $\Delta v_\alpha(\beta, t)$.

Following the original CCAM model, the speed change $\Delta v_\alpha(\beta, t)$ has 3 choice items:0, $-\gamma_{\alpha\beta} v_\alpha(t)$ and $+\gamma_{\alpha\beta} v_\alpha(t)$, where $v_\alpha(t)$ is the speed of α at time t and $\gamma_{\alpha\beta}$ an acceleration/deceleration factor.

The direction change $\Delta\theta_\alpha(\beta, t)$ has 7 choice items, $-\theta_{\alpha\beta L}$, $-\theta_{\alpha\beta M}$, $-\theta_{\alpha\beta S}$, 0, $+\theta_{\alpha\beta S}$, $+\theta_{\alpha\beta M}$ and $+\theta_{\alpha\beta L}$, the $\theta_{\alpha S}$, $\theta_{\alpha\beta M}$ and $\theta_{\alpha\beta L}$ stand for the small, moderately and large turning angel of α when conflicting with β. Thus, a choice set $C_\alpha(\beta, t)$ at most includes 21 choices as shown in Fig. 6. Each choice *j* stands for the future state of the riders speed and direction at next time step.

The major difference of the extended choice sets is that these parameters for direction change $\Delta\theta_\alpha(\beta, t)$ and speed change $\Delta v_\alpha(\beta, t)$ is different according to the conflict situation "**α-β**". The parameters of speed and direction changes in different conflict situations are estimated from the field behavior statistics in Table V.

In CCAM, the $\gamma_{\alpha\beta}$ was taken as 0.2. In ECCAM, the $\gamma_{\alpha\beta}$ is taken according to the median of the difference between 85% and 15% values of the of speed change ratio λ, i.e.:

$$g_{ab} » \frac{1}{2}\left(l_{ab85\%} - l_{ab15\%}\right) \tag{13}$$

Because $\theta_{\alpha\beta S}$ of bicycles in CCAM is taken as 5°, and the stability of E-bikes is better than that of bicycles, here the $\theta_{\alpha\beta S}$ of E-bikes is taken as 3°. The $\theta_{\alpha\beta MAX}$ of E-bikes and bicycles are estimated from the maximum values of the turning angle in the corresponding conflict situations. While $\theta_{\alpha\beta M}$, $\theta_{\alpha\beta L}$ are estimated to be 1/5 and 1/2 of the corresponding maximum turning angle $\theta_{\alpha\beta MAX}$, as the 15% and 50% values of turning angles were too small. The estimated parameters for extended discrete choice sets are shown in Table VI.

### *D. Fuzzy Evaluation Index for E-bikes*

Similar to the original CCAM, the fuzzy evaluation of ECCAM includes 4 indices: {Safety, Directness, Quickness, and Comfort}.

In the origin CCAM model, the evaluation index of Safety was actually the cyclist's expected time-to-collision (TTC), and the membership function was built based on study results on the cyclists' lag acceptance behaviors when crossing conflicting motor traffic streams [29]. So far, we have not found any published papers on E-bikes' lag acceptance behaviors when crossing conflicting traffic flows. Therefore, we observed 283 E-bikes lag acceptance samples crossing the conflicting motorcar traffic flow in the video data, the 15%, 50% and 85% value of the accepted lag are 1.29 s, 2.25 s and 3.38 s. The membership function is built on this basis (see Fig. 7(a)).

The Directness index of E-bikes was built based on the distribution of the dest/dir angles in Fig.3 and Table III.

Here, the Quickness index is a fuzzy evaluation of α's current speed $v_\alpha$ (t) and the speed change ratio λ of choice j at time t+ΔT. We follow the fuzzy rules for the Quickness index, and adjusted the current speed membership function for E-bikes by the distribution of speed in Fig. 3 and Table III. The membership function of the Comfort index is built according to the distribution of turning angles of E-bikes in Fig.3 and Table III. Fig.7 shows the membership function of the fuzzy index for E-bikes and bicycles for comparison except the Safety index.

### *E. Model Validation*

In model validation, we developed a mixed traffic flow Extended Cyclist's Conflict avoidance model demo based on the flowchart of Fig.5. Field trajectory data with 1320 observations of E-bikes, bicycles and the conflicting road users at each step are used as the validation data set.

The inputs of the demo include speeds and positions of target E-bike or bicycle α and the conflicting vehicle β, the actual trajectory of β and destination position of α. The outputs to be validated include the *k* highest possible choices evaluated by fuzzy evaluation rules and the final choice *m* from the Decision module for the next time step (t+ΔT). The Fuzzy Evaluation Rules module follows the CCAM.

In model validation, we converted the position of the field trajectory data to the choice *j* of the according choice set $C_\alpha$ (β,t) and compared it with the model output. For the fuzzy logic outputs of k plausible choices, 92.2% of them included the actual movement choices of E-bikes and 90.7% of them included those of bicycles. This illustrates the validity of fuzzy logic in E-bike and bicycle conflict avoidance behavior modelling.

The estimated trajectories from the ECCAM were also compared with the actual trajectories of E-bikes and bicycles in different conflict scenarios, and the Root Mean Squared Error (RMSE) is taken as a model error evaluation measure:

$$RMSE(x) = \sqrt{\frac{\sum_{i=1}^{n} (\hat{x}_i - x_i)^2}{n}} \tag{14}$$

where $\hat{x}_i$ stands for the predicted value of sample $x_i$ . Table VII shown the RMSE of speed $v_x$ and $v_y$ (the speed in x and y axle, respectively) and trajectory $p_x$ , $p_y$ (the position in x and y axle, respectively) of E-bike and bicycle in different conflict situations. Fig. 8 compared the total speed and trajectory RMSE of E-bikes and bicycles in $v_x$ , $v_y$ , $p_x$ and $p_y$ in all conflict situations.

To some extent, the validation results shown that the ECCAM model could represent the conflict avoidance behaviors of the E-bikes and bicycle in mixed traffic flow situations.

## VI. DISCUSSIONS

In this paper, we compared the dynamic behavioral variables of E-bike and bicycle riders by field data taken at six different un-signalized intersections. We first compared the 4 behavioral variables of E-bikes and bicycles in conflict and non-conflict situations. For both E-bikes and bicycles, the behavioral variables were significantly different in conflict and non-conflict situations. And in both situations, E-bikes tend to have higher speeds and smaller turning angles compared to bicycles, which verified our assumption that different power sources for moving E-bikes and bicycles leading to the differences in collision avoidance behaviors. The speeds of bicycles and E-bike are consistent with previous studies.

We further compared the impacts of conflicting road user types on E-bike and bicycle riders' conflict avoidance behavior.

Interestingly, the E-bikes have different conflict avoidance ***modes*** in different types of conflicting road users----They tend to behave like bicycle when conflicting with motor vehicles (we called it ***bicycle mode***) and turn to behave like motor vehicles when conflicting with non-motorized road users such as bicycle and pedestrians (we called it ***motor mode***).

The so-called ***bicycle mode*** refers that the bicycles prefer turning to slowing down in the conflict avoidance behavior. And the so-called ***motor mode*** refers that motor vehicles tend to decelerate more than turning in the conflict avoidance behaviors. This indicates that E-bike riders are **more flexible** in collision avoidance behaviors than bicycles.

Therefore, we think the road user's conflict avoidance behaviors can be categorized into three main styles: ***motor mode***--- mainly speed change (with little direction change); ***bicycle mode*** ---mainly direction change (with little speed change), and ***E-bike mode***---change speed and direction flexibly.

In this sense, we may explain why people (both E-bikes and bicycles) tend to be more cautious (with lower speeds and smaller turning angles) when conflicting with E-bikes. This may be due to the greater flexibility of E-bikes in conflict avoidance behaviors, making the corresponding conflicting road users hard to estimate their speeds and directions, and hence increasing uncertainty and risk of the conflict avoidance process. This might help to explain why E-bikes have a much higher risk of being involved in a conflict with motor cars than bicycles.

We considered the difference in power source and vehicle weights were the leading reasons for the differences in their conflict avoidance behaviors. E-bikes are powered by batteries, thus, acceleration and deceleration is much easier than bicycles. Thus, it is reasonable for E-bikes to accelerate and decelerate in conflicts with the bicycle and pedestrian, who is usually slow in speeds and flexible in direction.

## VII. CONCLUSIONS & FUTURE WORKS

Here, we compared and analyzed the conflict avoidance behaviors of E-bikes and bicycles at six un-signalized intersections. The differences of E-bike and bicycles mainly included speed change and turning behavior when conflicting with bicycles and pedestrians. In conflicts with bicycles and pedestrians, E-bike riders tend to decelerate, while bicycles tend to change their direction. The phenomena indicates that E-bikes have more flexible conflict avoidance behavior than bicycles.E-bikes can behave like bicycles when conflicting with E-bikes and motor vehicles, and behave like motor vehicles when conflicting with bicycles and pedestrians. We think this is the unique behavior characteristic of E-bikes and motorcycles('We think' is not rigorous!). Understanding of this unique behavior characteristic of E-bikes is important for traffic safety, facilities design and traffic management for E-bikes [36-38].

The analysis results show that the conflicting road user type did have（why do you use 'did have' here?） a significant impact on both E-bike and bicycle riders' conflict avoidance behaviors. While the gender was not proven to have significant impacts on the speed change ratio and turning angles of E-bike and bicycle riders, though the mean conflicting speeds were different significantly.

Based on the analysis results, we proposed an extended CCAM (ECCAM) by improving the model framework, adding choice sets for different conflict situations and fuzzy index membership function for E-bikes. Compared to the original CCAM, ECCAM can reasonably reproduce the conflict avoidance behavior of E-bikes at un-signalized intersections. The validation results show that the ECCAM performs satisfactorily by capturing the true movement choice in 91.3% of all validation samples.

Traffic management departments could hence base on E-bike conflict motion characteristics or/and apply ECCAM simulation model to improve the un-signalized intersection facilities with a lot E-bikes volumes, such as reasonable channelization and, if necessary, signal control. In addition, setting a sigh of E-bike at appropriate locations might help in improving driver's attention and reducing E-bike crash.

Future work will be focused on comparisons of the riders' gap acceptance behavior of E-bike and bicycles. Petzoldt et al.(2015) has investigated drivers' gap acceptance in front of E-bikes and bicycles, and found that drivers appeared to select shorter gap times when conflicting with E-bikes [30, 42-44]. Considering this phenomenon, it is possible (Are you not assure?) that the E-bike riders' gap acceptance behavior would be different from cyclists.

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TABLE V

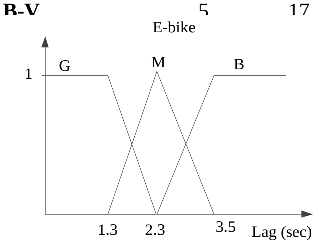
STATISTICS OF BEHAVIOR VARIABLES IN DIFFERENT CONFLICT SITUATIONS.

| **Conflict Situations** | **Turning angle $\Delta\theta_v$(°)** | | | | **Speed change ratio $\lambda$** | | | |
|---|---|---|---|---|---|---|---|---|
| | 15% value | 50% value | 85% value | Max. | 15% value | 50% value | 85% value | Max. |
| **E-V** | 0.4 | 2 | 5 | 49 | 0.88 | 1.01 | 1.14 | 2.23 |
| **E-E** | 0.5 | 2 | 5 | 58 | 0.88 | 1.01 | 1.16 | 1.87 |
| **E-B** | 0.2 | 1 | 3 | 52 | 0.95 | 1.02 | 1.06 | 1.19 |
| **E-P** | 0.2 | 1 | 3 | 15 | 0.92 | 1.00 | 1.06 | 1.15 |
| **B-V** | 0.7 | 3 | 9 | 87 | 0.91 | 1.01 | 1.11 | 2.36 |

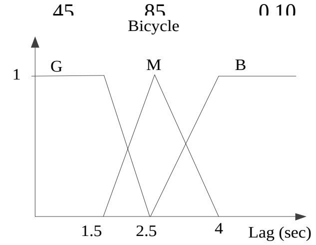
TABLE VI

ESTIMATED PARAMETERS OF SPEED AND DIRECTION CHANGES FOR EXTENDED DISCRETE CHOICE SETS.

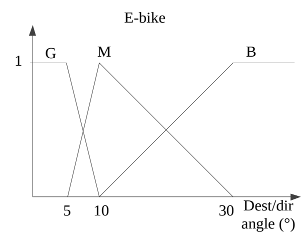
| **Conflict situations** | **$\theta_{\alpha\beta S}$ (°)** | **$\theta_{\alpha\beta M}$ (°)** | **$\theta_{\alpha\beta L}$ (°)** | **$\theta_{\alpha\beta MAX}$ (°)** | **$\gamma_{\alpha\beta}$** |
|---|---|---|---|---|---|
| **E-V** | 3 | 10 | 25 | 50 | 0.15 |
| **E-E** | 3 | 12 | 30 | 60 | 0.15 |
| **E-B** | 3 | 10 | 25 | 50 | 0.05 |
| **E-P** | 3 | 7 | 30 | 40 | 0.10 |
| **B-V** | 5 | 17 | 45 | 85 | 0.10 |



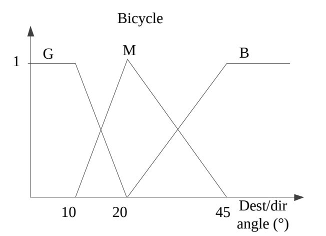

(a) Safety for E-bikes



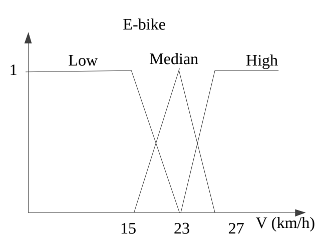

(b) Safety for bicycles



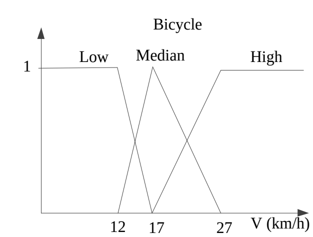

(c) Directness for E-bikes



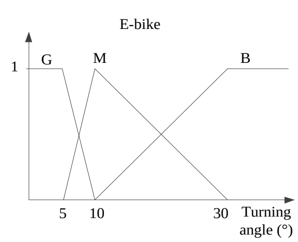

(d) Directness for bicycles




(e) Current speed for E-bikes




(f) Current speed for bicycles



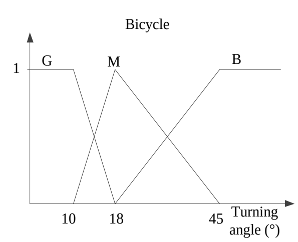
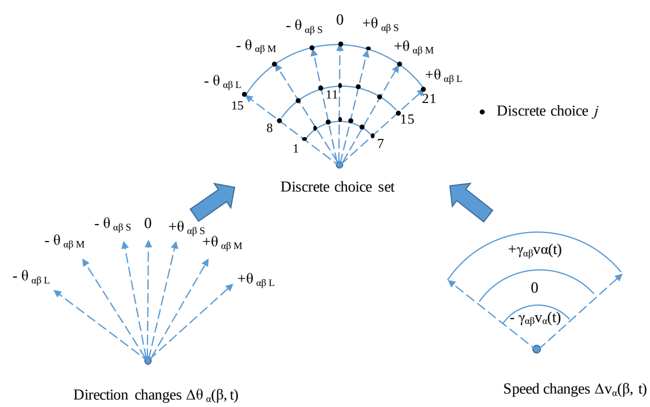




TABLE VII

SPEED AND TRAJECTORY RMSE OF E-BIKE AND BICYCLE IN DIFFERENT CONFLICT SITUATIONS.

| **Conflict Situations** | **$v_x$ (m/s)** | **$v_y$ (m/s)** | **$p_x$ (m)** | **$p_y$ (m)** | **Num. of Observations** |
|---|---|---|---|---|---|
| **E-V** | 0.56 | 0.49 | 0.77 | 0.98 | 120 |
| **E-E** | 0.45 | 0.61 | 0.69 | 0.85 | 178 |
| **E-B** | 0.53 | 0.62 | 0.82 | 0.65 | 85 |
| **E-P** | 0.39 | 0.59 | 0.67 | 0.70 | 176 |
| **E-bike Sub-total** | **0.47** | **0.58** | **0.72** | **0.80** | **559** |
| **B-V** | 0.49 | 0.44 | 0.89 | 0.63 | 308 |



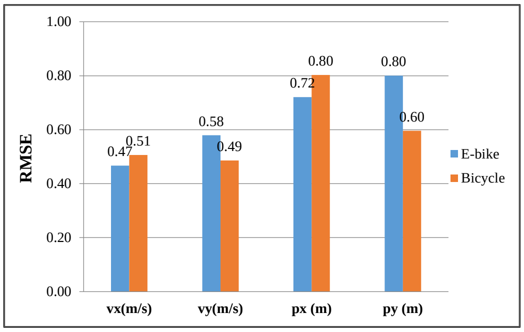



Fig.8 Comparisons of Total RMSE of Speed and Trajectory for E-bike and Bicycle.

## REFERENCES


[1] Lu Bai, Pan Liu, Ching-Yao Chan and Zhibin Li., Estimating level of service of mid-block bicycle lanes considering mixed traffic flow, Transportation Research Part A: Policy and Practice, July 2017, Volume 101, Pages 203-217. https://doi.org/10.1016/j.tra.2017.04.031.

[2] K. Schleinitz, T. Petzoldt, L. Franke-Bartholdt, J. Krems and T. Gehlert, The German Naturalistic Cycling Study – Comparing cycling speed of riders of different e-bikes and conventional bicycles. Safety Science, February 2017, Volume 92, Pages 290-297. http://dx.doi.org/10.1016/j.ssci.2015.07.027

[3] Fishman E, Cherry C . E-bikes in the Mainstream: Reviewing a Decade of Research. Transport Reviews, 2015, 36(1):72-91.

[4] S. Cairns, F.Behrendt, D.Raffo, C.Beaumont and C.Kiefer, Electrically-assisted bikes: Potential impacts on travel behavior, Transportation Research Part A: Policy and Practice, September 2017, Volume 103, Pages 327-342. https://doi.org/10.1016/j.tra.2017.03.007.

[5] Andrew A. Campbell, Christopher R. Cherry, Megan S. Ryerson, Xinmiao Yang, Factors influencing the choice of shared bicycles and shared electric bikes in Beijing, Transportation Research Part C: Emerging Technologies, June 2016, Volume 67, 399-414

[6] Wang, Chen, Xu Chengcheng, Xia Jinxin and Qian Zhendong, Modeling faults among e-bike-related fatal crashes in China, Traffic Injury Prevention, 2017, Volume 18(2), Pages. 175-181

[7] Xujun Zhang, Yaming Yang, Jie Yang, Jie Hu, Yang Li, Ming Wu, Lorann Stallones and Henry Xiang, Road traffic injuries among riders of electric bike/electric moped in southern China, Traffic Injury Prevention, 2018, Volume 19(4), Pages. 417-422.

[8] Schepers J P, Kroeze P A, Sweers W, et al. Road factors and bicycle–motor vehicle crashes at unsignalized priority intersections. Accident Analysis & Prevention, 2011, 43(3): 853-861.

[9] Hamann C, Peek-Asa C. On-road bicycle facilities and bicycle crashes in Iowa, 2007–2010. Accident Analysis & Prevention, 2013, 56: 103-109.

[10] Wang C, Lu L, Lu J. Statistical analysis of bicyclists' injury severity at unsignalized intersections. Traffic injury prevention, 2015, 16(5): 507-512.

[11] J.P. Schepers, E. Fishman, P. den Hertog, K. Klein Wolt, and A. L.Schwab, The safety of electrically assisted bicycles compared to classic bicycles. Accident Analysis & Prevention, December 2014,

Volume 73, Pages 174-180.

http://dx.doi.org/10.1016/j.aap.2014.09.010.

[12] Marco Dozza and Andre Fernandez, Understanding Bicycle Dynamics and Cyclist Behavior from Naturalistic Field Data, IEEE Trans. on Intelligent Transportation Systems, February 2014, Volume 15(1), Pages 376-384. doi: 10.1109/TITS.2013.227968

[13] Marco Dozza and Julia Werneke, Introducing naturalistic cycling data: What factors influence bicyclists' safety in the real world?, Transportation Research Part F: Traffic Psychology and Behaviour,

May 2014, Volume 24, Pages 83-91.

http://dx.doi.org/10.1016/j.trf.2014.04.001.

[14] Louise Gustafsson and Jeffery Archer, A naturalistic study of commuter cyclists in the greater Stockholm area. Accident Analysis & Prevention, September 2013, Volume 58, Pages 286-298

[15] Johnson, Marilyn; Charlton, Judith; Oxley, Jennifer and Newstead, Stuart, Naturalistic cycling study: Identifying risk factors for on-road commuter cyclists. Annals of advances in automotive medicine. Association for the Advancement of Automotive Medicine. Annual Scientific Conference, 2010, Volume 54, Pages 275–283

[16] Marco Dozza, Giulio Francesco Bianchi Piccinini, and Julia Werneke, Using naturalistic data to assess e-cyclist behavior. Transportation Research Part F: Traffic Psychology and Behaviour, August 2016, Volume 41, Part B, Pages 217-226

[17] Tibor Petzoldt, Katja Schleinitz, Sarah Heilmann and Tina Gehlert, Traffic conflicts and their contextual factors when riding conventional vs. electric bicycles, Transportation Research Part F: Traffic Psychology and Behaviour, April 2017, Volume 46, Part B, Pages 477-490

[18] P. Huertas-Leyva, M. Dozza and N. Baldanzini, Investigating cycling kinematics and braking maneuvers in the real world: e-bikes make cyclists move faster, brake harder, and experience new conflicts, Transportation Research Part F: Traffic Psychology and Behaviour, April 2018, Volume 54, Pages 211-222

[19] Peter A Cripton, Hui Shen, Jeff R Brubacher, Mary Chipman, Steven M Friedman, M Anne Harris, Meghan Winters, Conor C O Reynolds, Michael D Cusimano, Shelina Babul and Kay Teschke, Severity of urban cycling injuries and the relationship with personal, trip, route and crash characteristics: Analyses using four severity metrics. BMJ Open, 2015, Volume 5(1), Pages. 1–10.

[20] Kristiann C. Heescha, Jan Garrard, and Shannon Sahlqvist, Incidence, severity and correlates of bicycling injuries in a sample of cyclists in Queensland, Australia. Accident Analysis and Prevention, November 2011, Volume 43, Issue 6, Pages 2085-2092

[21] Zhang R., Wu J., Huang L. and You F., Study of Bicycle Movements in Conflicts at Mixed Traffic Unsignalized Intersections, IEEE Access, 2017, vol. 5, pp. 10108-10117.

[22] Huang Ling, Wu J., You F., Lv Z. and Song H., Cyclist Social Force Model at Unsignalized Intersections With Heterogeneous Traffic, IEEE Transactions on Industrial Informatics, 2017, vol. 13, no. 2, pp. 782-792.

[23] Sheng Jin, Xiaobo Qu, Dan Zhou, Cheng Xu, Dongfang Ma and Dianhai Wang, Estimating cycleway capacity and bicycle equivalent unit for electric bicycles, Transportation Research Part A: Policy and Practice, July 2015, Volume 77, Pages 225-248

[24] D. Helbing, P. Molnár: Social force model for pedestrian dynamics. Phys Rev E; 1995.vol.51, pp. 4282-4286.

[25] Ahmed Tageldin, Tarek Sayed and Khaled Shaaban, Comparison of Time-Proximity and Evasive Action Conflict Measures--Case Studies from Five Cities, Transportation Research Record: Journal of the Transportation Research Board, 2017, Volume 2661(1), Pages 19 - 29. http://dx.doi.org/10.3141/2661-03.

[26] Dong, Peng; Wang, Xifu; Yun, Lifen and Fan Hongqiang,. Research on the characteristics of mixed traffic flow based on an improved bicycle model, simulation-transactions of the society for modeling and simulation international, 2018, Volume 94(5).

DOI: 10.1177/0037549717736947

[27] Zhengyou Zhang, A flexible new technique for camera calibration, IEEE Transactions on Pattern Analysis and Machine Intelligence, November 2000, Volume 22(11), Pages 1330-1334. DOI: 10.1109/34.888718

[28] Cho H., Rybski P. E. and Zhang W., Vision-based bicycle detection and tracking using a deformable part model and an EKF algorithm,

13th International IEEE Conference on Intelligent Transportation Systems, Funchal, 2010, pp. 1875-1880. doi: 10.1109/ITSC.2010.5624993

[29] Huang Ling, and Wu J., A Study on Cyclist Behavior at Signalized Intersections. *IEEE transactions on intelligent transportation systems*. 2004, Vol. 5, No. 4; pp. 293-299.

[30] Petzoldt T., Schleinitz K., Krems J.F., Gehlert T., Drivers' gap acceptance in front of approaching bicycles – Effects of bicycle speed and bicycle type, Safety Science, 2017, Volume 92, pp. 283-289, https://doi.org/10.1016/j.ssci.2015.07.021.

[31] Jin, Sheng, Qu, Xiaobo, Xu, Cheng, Ma, Dongfang and Wang, Dianhai, An improved multi-value cellular automata model for heterogeneous bicycle traffic flow, Physics Letters A, 2015, Volume 379 (39), Pages 2409-2416

[32] Xu, Cheng, Yang, Ying, Jin, Sheng, Qu, Zhaowei and Hou, Lei, Potential risk and its influencing factors for separated bicycle paths, Accident Analysis & Prevention, 2016, Volume 87, Pages 59-67

[33] Kuang, Yan, Qu; Xiaobo and Wang, Shuaian, A tree-structured crash surrogate measure for freeways, Accident Analysis & Prevention, 2015, Volume 77, Pages 137-148

[34] Qu, Xiaobo, Zhang, Jin and Wang, Shuaian,. On the Stochastic Fundamental Diagram for Freeway Traffic: Model Development, Analytical Properties, Validation, and Extensive Applications, Transportation Research Part B: Methodological, 2016, Volume 104, Pages 256-271

[35] Qu, Xiaobo, Wang, Shuaian, and Zhang, Jin, On the fundamental diagram for freeway traffic: A novel calibration approach for single-regime models. Transportation Research Part B: Methodological, 2015, Volume 73, Pages 91-102

[36] Gooch, Jeffrey P., Gayah, Vikash V. and Donnell, Eric T., Quantifying the safety effects of horizontal curves on two-way, two-lane rural roads. Accident Analysis & Prevention, July 2016, Volume 92, Pages 71-81

[37] Abdel-Aty, Mohamed and Gayah, Vikash, Real-time crash risk reduction on freeways using coordinated and uncoordinated ramp metering approaches. Journal of Transportation Engineering, May 2010, Volume 136(5), Pages 410-423.

[38] Abdel-Aty, Mohamed; Pande, Anurag; Lee, Chris; Gayah, Vikash and Dos Santos, Cristina; Crash risk assessment using intelligent transportation systems data and real-time intervention strategies to improve safety on freeways, Journal of Intelligent Transportation Systems, 2007, Volume 11(3), Pages 107-120

[39] Lewin K. Field theory in social science: selected theoretical papers (Edited by Dorwin Cartwright). 1st ed. New York: Harper & Row;1951

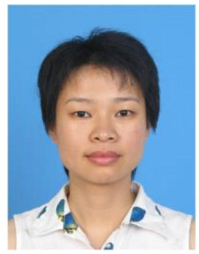
[40] Helbing, D., Farkas, I., Vicsek, T., 2000. Simulating dynamical features of escape panic. Nature 407, 407–487.

[41] Anvari B, Bell M G H, Sivakumar A, et al. Modelling shared space users via rule-based social force model. Transportation Research Part C Emerging Technologies, 2015, 51:83–103.

[42] Stieffenhofer, Krae E.; Barton, Michael and Gayah, Vikash V.; Assessing park-and-ride efficiency and user reactions to parking management strategies. Journal of Public Transportation, 2016, Volume 19(4), Pages 75-92

[43] Tarek Sayed & Sany Zein. Traffic conflict standards for intersections, Transportation Planning and Technology, 1999, vol.22, no.4, Pages 309-323.

[44] Tageldin A , Zaki M H , Sayed T . Examining pedestrian evasive actions as a potential indicator for traffic conflicts. IET Intelligent Transport Systems, 2017, 11(5):282-289.



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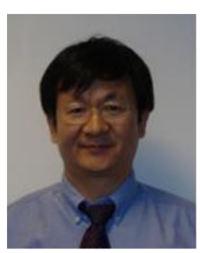
Dr. Huang is the author of two books, more than 40 articles, and more than 20 inventions. Her research interests include cyclist behavior, traffic simulation, behavior analysis, driving behavior, pedestrian, computer vision, and traffic simulation applications. She is a peer reviewer of journals as *IEEE Trans. ITS*, and holds 16 patents.



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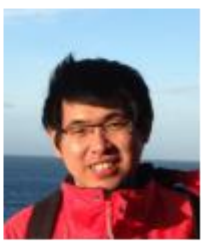

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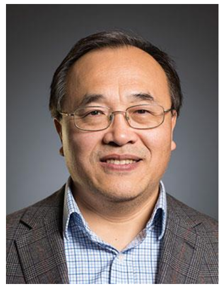

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