BICYCLIST BEHAVIOR ANALYSIS FOR PCS (PRE-COLLISION SYSTEM) BASED ON NATURALISTIC DRIVING

Ryo Fujishiro
Toyota Motor Corporation
Japan

Chao Liu
Lauren Christopher
Jiang Yu Zheng
Transportation Active Safety Institute, Indiana University-Purdue University Indianapolis
United States

Paper Number 15-0211

ABSTRACT

In recent years, automakers have introduced the PCS (Pre-Collision System) which is designed to warn a driver or to brake automatically to help avoid or mitigate accidents. One of the significant aspects of this system is to help protect vulnerable road users such as pedestrians and bicyclists. In this paper, the research is introduced which analyzes normal bicyclist behavior in order to design and evaluate PCS systems. The attributes of normal bicyclist behavior investigated are: TTC (Time-To-Collision), lateral position, vehicle speed and bicycle speed. This behavior was analyzed using TASI's (IUPUI's Transportation Active Safety Institute) naturalistic driving data from 110 cars.

INTRODUCTION

The PCS (Pre-Collision System) is designed to warn a driver or brake automatically to help avoid or mitigate potential accidents. This system is needed to detect and robustly classify surrounding objects. Therefore, a broad range of sensors are utilized for PCS systems such as: millimeter-wave radar [1], LIDAR [2], camera [3] and the combination of some sensors [4][5]. Each sensor choice has pros and cons. For instance, radar is good at detecting distances and relative speeds of an object, but not good at classifying the type of an object. On the other hand, a camera is good at classifying the type of an object, but not good at detecting distances and relative speeds of an object. Therefore, those sensors are selected by manufacturers to classify target objects such as vehicles, pedestrians and bicyclists. The number of targets is expanding with improved sensor technology. Consequently, one of the significant aspects of PCS systems is considered to help protect vulnerable road users such as pedestrians and bicyclists. In fact, a non-negligible number of fatalities in regard to pedestrians and bicyclists are reported by NHTSA (National Highway Traffic Safety Administration) [6][7]. According to [6] and [7], of all traffic fatalities in 2012, 14% were pedestrian deaths and 2% were pedalcyclist deaths.

This research is targeting normal bicyclist behavior in order to help design and evaluate PCS systems. By knowing what is considered normal, the PCS can concentrate on the abnormal behavior and react in the dangerous situations. Of course, bicyclist accident data analysis is also important for PCS design and testing. However, the accident data lacks some detailed parameters in general. Some bicyclist parameters which are needed to design or evaluate PCS systems should be analyzed in both accident analysis and normal bicyclist behavior analysis. For normal behavior analysis, an enormous data set, called TASI 110-Car Naturalistic Driving Data [8], is utilized for understanding bicyclist behavior relative to the driving vehicles. This data set includes 120 degree viewing angle videos observing traffic in front of the vehicles, together with Global Positioning System (GPS) location data and G-sensor information of the vehicles. From this data set, bicyclists were extracted using machine learning and pattern recognition techniques [9]. Pattern recognition enables the computer to find specified objects automatically. From these bicycle video clips, the bicyclist movement was tracked using visual tracking techniques [10]. Once an initial position is given, the tracking follows a bicyclist. From these tracking results and the GPS information, the TTC (Time-To-Collision), lateral position, vehicle speed and bicycle speed were calculated. Several important and intriguing findings were observed.

METHOD

Data Set and Tracking of Bicyclists

The TASI 110-Car Naturalistic Driving Data [8] was utilized and more than 10,000 videos containing bicyclists were extracted. The data has 120 degree viewing angle videos of observed traffic in front of the vehicles, GPS location, speed data and G sensor information. The data collection was conducted mainly in Indiana, United States from 2012 to 2013. The data consist of a total of 1.1 million miles (2T bites) in length. This data set was first used to analyze pedestrian behavior in a naturalistic driving condition. This paper presents the bicyclist research from this huge data set. Subject vehicles drove in the downtown area where many bicyclists were found.

Bicyclists were extracted from all the recorded videos using pattern recognition techniques in [9]. The results contained false positives (unsolicited detection), which were eliminated manually. Bicyclist position in an image was specified as a rectangle, but the detected position was not necessarily accurate. Therefore, the bicyclist position was corrected manually. This correction was conducted at one video-frame for one bicyclist video clip of 5 seconds. Once an accurate bicyclist position at one video-frame was obtained, that bicyclist was tracked using the referenced visual tracking techniques [10]. Bicyclist movement was represented as a sequence of a size-varying rectangle. The rectangle size information was used for calculation of TTC, lateral position, vehicle speed and bicycle speed.

TTC Calculation

TTC is one of the most significant variables for PCS systems since this signifies the level of danger in a convincing and direct manner. This section details TTC calculation method as the ratio of the depth over the first derivative of the depth. TTC is defined as Equation (1) provided that the distance from the camera is defined as Z.

$$TTC = -\frac{Z}{\dot{Z}} \qquad \text{Eq. (1).}$$

However, one problem of using this method is inaccuracy of Z. Generally, camera recognition is good at detecting object angle, but not good at detecting object distances. Since the TTC calculation is central to PCS systems, a different method was utilized to calculate TTC as described in [11]. In Figure 1, X, Y and Z denote world coordinates, S denotes the size of the bicyclist, s denotes the size of the bicyclist in the image, and F denotes the focal length.

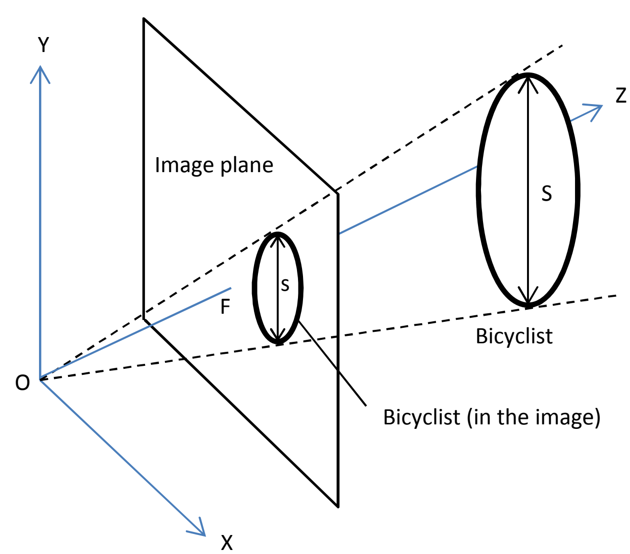


Figure 1. Geometrical relationship between a bicyclist and the projection to the image plane.

Equation (2) is derived from the geometrical relationship.

$$\frac{1}{s} = \frac{Z}{S \cdot F} \qquad \text{Eq. (2).}$$

Substituting Equation (1) for Equation (2), TTC is calculated as Equation (3).

$$TTC = \frac{s}{\dot{s}} \qquad \text{Eq. (3).}$$

In Equation (3), the only value necessary to calculate TTC is the size of the bicycle in the image. This size was detected using tracking techniques as stated above.

Lateral position calculation

Although TTC is central to PCS systems, TTC is not enough information to analyze bicyclist behavior since TTC signifies only longitudinal relative movement. This research also analyzed the lateral position of the bicyclist to the vehicle. In order to calculate the lateral position, the distance to the bicyclist was calculated first as described in [12], and then lateral position was calculated next.

In Figure 2, H denotes the height of the camera, Z_c denotes the distance between the camera and the bicyclist on the road, θ_h denotes the vertical angle of the horizon in the camera axis, and θ_{bv} denotes the vertical angle of the bicyclist's bottom in the camera axis. Provided that the horizon and bicyclist bottom are specified in the image, the angles of θ_h and θ_{bv} can be obtained. Horizon position was specified with human operators examining the videos, and bicyclist bottom was obtained from a rectangle which is the result of the tracking discussed above. Equation (4) details how to calculate the distance, Z_c.

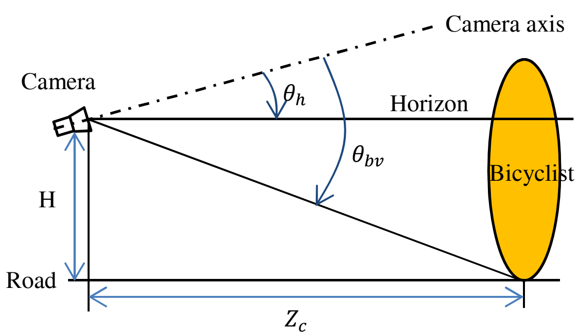


Figure 2. Geometry of a bicyclist (side view).

$$Z_c = \frac{H}{\tan(\theta_{bv} - \theta_h)} \qquad \text{Eq. (4).}$$

The camera height H should be a fixed value of each vehicle. However, there were some cases in which cameras dropped and were attached again in the naturalistic driving. That is why the camera height H was not able to be maintained strictly. One fixed value per vehicle was chosen that was considered to be the most likely.

In Figure 3, X_c and Z_c denote the bicyclist position in the camera coordinate system, X_v and Z_v denote the bicyclist position in the vehicle coordinate system, θ_c denotes the angle between the camera axis and the vehicle moving direction, and θ_{bh} denotes the horizontal angle of the bicyclist in the camera coordinate. The vehicle moving direction was specified with human operators examining the videos, and the angle θ_{bh} was obtained from a rectangle which is the result of the tracking stated above. Equation (5) and (6) detail a rotation of the coordinate system, which was used to calculate the lateral position X_v.

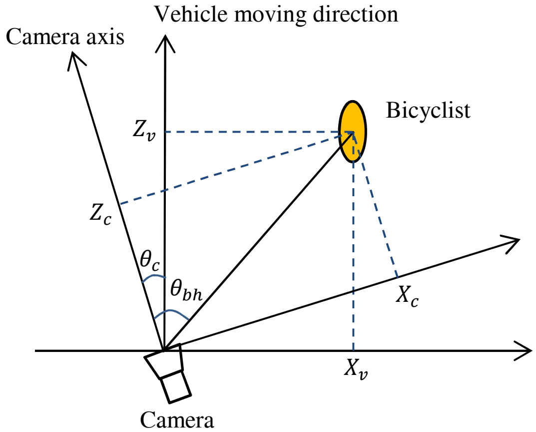


Figure 3. Geometry of a bicyclist (top view).

$$X_c = Z_c \tan \theta_{bh} \qquad \text{Eq. (5).}$$

$$\begin{bmatrix} X_v \\ Z_v \end{bmatrix} = \begin{bmatrix} \cos\theta_c & -\sin\theta_c \\ \sin\theta_c & \cos\theta_c \end{bmatrix} \begin{bmatrix} X_c \\ Z_c \end{bmatrix} \qquad \text{Eq. (6).}$$

Vehicle and bicycle speed calculation

Vehicle speed was obtained by the GPS devices. The speed information was extracted from the videos in which the subject vehicles encountered bicyclists.

Bicycle speed is also an important variable to design and evaluate PCS systems. Since bicyclist distance Z_v is calculated as in Equation (6), longitudinal bicyclist speed V_{br} relative to a vehicle is calculated by differentiating this value. Using the vehicle longitudinal speed V_v which is obtained by GPS, the longitudinal bicyclist speed V_b is calculated as in Equation (7).

$$V_b = V_{br} + V_v \qquad \text{Eq. (7).}$$

In light of the fact that vehicle turning motion is not recorded in this data set, lateral bicyclist speed is difficult to calculate because the lateral position X and its speed are strongly affected by the vehicle turning. Therefore, we chose not to calculate the horizontal bicyclist speed.

RESULT

The pattern recognition techniques stated above extracted bicyclists from all the videos corresponding 1.1 million miles, and the false positives were eliminated manually. The total of 4,259 cases has been processed so far. Then, the tracking was applied to them, and the results were narrowed down to 1,969 cases since some of them were excluded because of the stopped subject vehicles or false tracking. Cases in which subject vehicles were stopped are out of the scope of the PCS actions.

Figure 4 is a heatmap which shows TTC on a vertical axis and lateral position of the bicyclists on a horizontal axis. Each blue point shows the existence of a bicyclist in that position, and each red point shows it as well and means a bicyclist heading toward the vehicle. If the bicyclist direction was heading within +/- 1.5 m at TTC of 0 second, it was deemed heading toward the vehicle. Therefore, red points can be considered more dangerous than blue points. The darkness of the color signifies the frequency of appearances in that position. Therefore, the darker the color is, the higher the probability of existence of a bicyclist in that position. Moreover, the pink dashed line is depicted in Figure 4. This line shows the approximate boundaries between red point areas and the vehicle side.

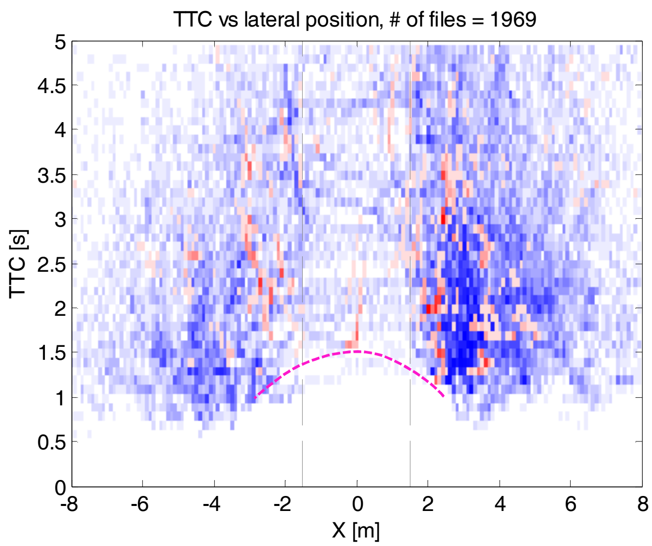


Figure 4. Heatmap of TTC and lateral position.

Several findings are observed from Figure 4. First, bicyclists were found more on the right side of the vehicles. This is due to US traffic rules which adopt right-hand traffic. This is why the bicyclists were captured by the cameras more on the right side. Second, the minimum TTC at each lateral position looks larger when lateral position is relatively small, e.g. within +/- 1.5 m. This might be understood as follows. Even if the TTC is small, a far lateral position from the vehicle does not cause dangerous situation. That is why a small TTC is quite normal outside the region where the lateral position is small. However, if a bicyclist is near the center of the vehicle, small TTC might lead to dangerous situation. Incidentally, there is no bicyclist whose TTC is less than 0.6 second in Figure 4. This comes from the limitation of the camera viewing angle. Third, red points imply that collision between a vehicle and a bicyclist might happen if either of them does not take an evasive action. In addition, there was no bicyclist heading toward a vehicle in the bell-shaped region specified by the pink line in this huge naturalistic driving data. This makes sense, as there were no traffic accidents in the entire data set. One conclusion we can find is that if a bicyclist is in this region and heading toward a vehicle, it can be considered abnormal and dangerous. The summit of this region is 1.6 seconds in TTC.

Those findings could be used to design PCS systems. For instance, if a bicyclist heading toward the vehicle is detected inside the region specified by the pink lines, the system may start warning since it can be considered dangerous. On the other hand, if a bicyclist is situated outside the region, PCS warning may be suppressed. Frequent warning should be avoided since it causes drivers to consider PCS systems annoying and switch them off.

Figure 5 shows a histogram of bicyclist lateral position. Only bicyclists moving in the direction parallel to the vehicle path were extracted. The cases were narrowed down to 478. The median of the right side was 3.9 m, and that of the left side was 4.4 m. Those data might be useful to establish PCS testing scenarios.

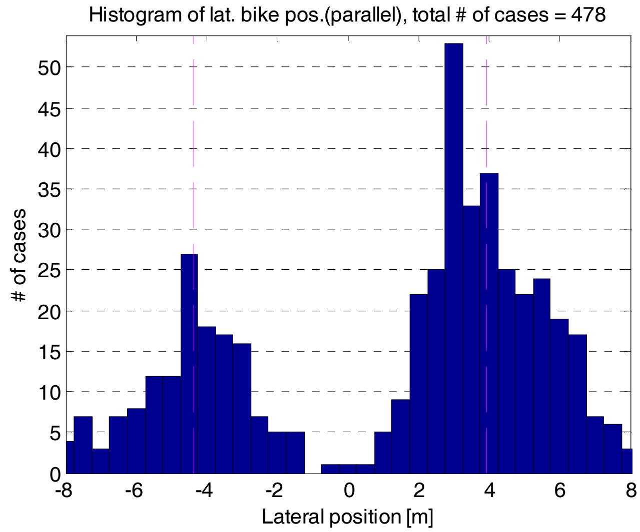
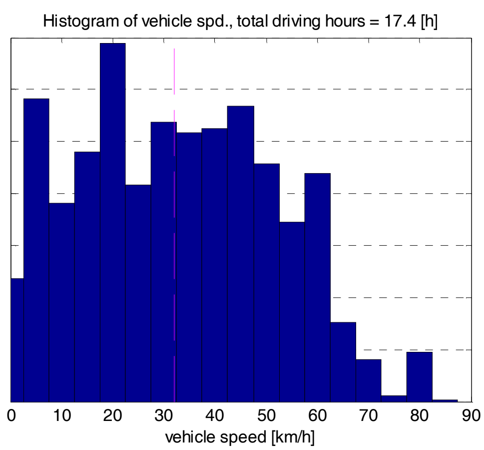


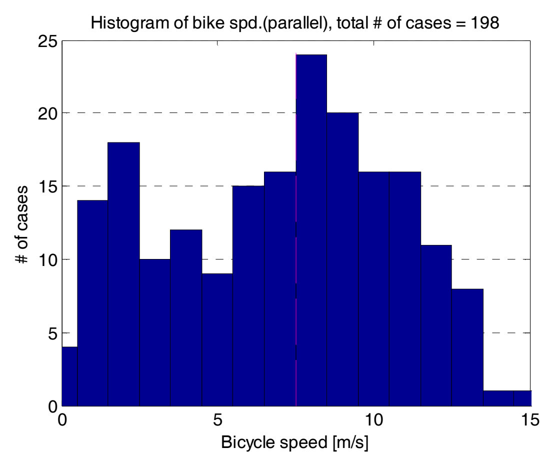
Figure 5. Histogram of bicyclist lateral position (parallel cases).

Figure 6 (a) shows a histogram of vehicle speed. Speed was detected by GPS device. The total of 17.4 hours in which the vehicles encountered bicyclists was used for this calculation. The median of the vehicle speed was 32 km/h. As described at the beginning of this section, cases in which vehicles were stopped were excluded since these are out of the scope of the PCS actions.

Figure 6 (b) shows a histogram of vehicle speed. Only bicyclists which satisfy following two conditions were extracted. First condition is that the bicycle is moving in the direction parallel to the vehicle path. Second condition is that the vehicle is moving at constant speed. The data set includes vehicle speed information using the GPS devices, but it contains time-varying delay. In order to evade the erroneous speed estimation, only the referenced-above cases were used. The cases were narrowed down to 198. The median of the bicycle speed was 7.5 m/s. This information might be useful to establish PCS testing scenarios. It has to be brought to attention that the direction of the bicyclists is parallel to the vehicle. In other words, the speed of bicyclists in cross traffic might be different.



(a) Histogram of vehicle speed



(b) Histogram of bicycle speed

Figure 6. Histogram of vehicle & bicycle speed (parallel cases).

CONCLUSIONS

This research analyzed normal bicyclist behavior to help design and evaluate PCS systems. TTC (Time-To-Collision), lateral position, vehicle speed and bicycle speed were calculated using TASI 110-Car Naturalistic Driving Data. Several important and intriguing findings were observed. First, there is bell-shaped region in front of the vehicle which can be considered abnormal and dangerous. This region might be used when PCS systems are designed. Second, lateral position of the bicyclists when they move in the direction parallel to the vehicle path was estimated. The median of the right side was 3.9 m, and that of the left side was 4.4 m. Those data could be useful to establish PCS testing scenarios. Third, vehicle and bicycle speed were estimated in limited conditions. The median of the vehicle speed was 32 km/h and that of bicycle speed was 7.5 m/s. This information might be useful to establish PCS testing scenarios. The results uncovered in this paper are based exclusively on US data. Those results might differ depending on the country or region.

REFERENCES

[1] Tokoro, S., Kuroda, K., Kawakubo, A., Fujita, K., & Fujinami H. (2003). Electronically Scanned Millimeter-wave Radar for Pre-Crash Safety and Adaptive Cruise Control System. *Intelligent Vehicles Symposium, 2003. Proceedings. IEEE*, 304-309

[2] Distner, M., Bengtsson, M., Broberg, T., Jakobsson, L. (2009). City Safety - A System Addressing Rear-end Collisions at Low Speeds. *Proceedings of the 21rd International Technical Conference on the Enhanced Safety of Vehicles (ESV), 09-0371.*

[3] Saneyoshi, K. (1996). Drive Assist System Using Stereo Image Recognition. *Intelligent Vehicles Symposium, 1996., Proceedings of the 1996 IEEE*, 230-235.

[4] Hayashi, H., Inomata, R., Fujishiro, R., Ouchi, Y., Suzuki, K., & Nanami, T., (2013). Development of Pre-crash Safety System with Pedestrian Collision Avoidance Assist. *Proceedings of the 23rd International Technical Conference on the Enhanced Safety of Vehicles (ESV), 13-0271.*

[5] Coelingh, E., Eidehall, A., & Bengtsson, M. (2010). Collision Warning with Full Auto Brake and Pedestrian Detection - a practical example of Automatic Emergency Braking. *Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on*, 155-160.

[6] National Highway Traffic Safety Administration. (2014). Pedestrians. *Traffic Safety Facts: 2012 Data, DOT HS 811 888.*

[7] National Highway Traffic Safety Administration. (2014). Bicyclists and Other Cyclists. *Traffic Safety Facts: 2012 Data, DOT HS 812 018.*

[8] Du, E.Y., Yang, K., Jiang, F., Jiang, P., Tian, R., Luzetski, M., Chen, Y., Sherony, R., & Takahashi, H. (2013). Pedestrian Behavior Analysis Using 110-Car Naturalistic Driving Data in USA. *Proceedings of the 23rd International Technical Conference on the Enhanced Safety of Vehicles (ESV), 13-0291.*

[9] Yang, K., Liu, C., Zheng, J.Y., Christopher, L., & Chen, Y. (2014). Bicyclist detection in large scale naturalistic driving video. *Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on*, 1638-1643.

[10] Jia, X., Lu, H., & Yang, M.H. (2012). Visual tracking via adaptive structural local sparse appearance model. *Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on*, 1822-1829.

[11] Nègre, A., Braillon, C., Crowley, J.L., & Laugier, C. (2008). Real-Time Time-to-Collision from Variation of Intrinsic Scale. In O. Khatib, V. Kumar, & D. Rus (Eds). *Experimental Robotics: The 10th International Symposium on Experimental Robotics* (pp. 75-84). Springer Berlin Heidelberg.

[12] Stein, G.P., Mano, O. & Shashua, A. (2003). Vision-based ACC with a single camera: bounds on range and range rate accuracy. *Intelligent Vehicles Symposium, 2003. Proceedings. IEEE*, 120-125.