Obtain a Simulation Model of a Pedestrian Collision Imminent Braking System Based on the Vehicle Testing Data

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***Abstract* - Forward pedestrian collision imminent braking (CIB) systems has proven to be of great significance in improving road safety and protecting pedestrians. Since pedestrian CIB technology is not mature, the performance of different pedestrian CIB systems varies significantly. Therefore the simulation of a CIB system needs to be vehicle specific. The CIB simulation can be based on the component sensor parameters and decision making rules. Since these parameters and decision rules for on the market vehicles are not available outside of vehicle manufactures, it is difficult for the general research communities to develop a good CIB simulation model based on this approach. To solve this problem, this study presents a new method for developing a pedestrian CIB simulation model using pedestrian CIB testing data. The implementation was in PreScan. The simulation results demonstrate that a pedestrian CIB simulation model developed using this methodology could reflect the behavior of a real vehicle equipped with pedestrian CIB system.**

Keyword: Pedestrian Collision Imminent Breaking System, Pedestrian CIB simulation model.

I. INTRODUCTION

Pedestrian CIB is an active safety system component that aims to avoid or mitigate the collision with pedestrians [1]. Many automotive companies have been developing pedestrian CIB systems and have started to equip pedestrian CIB in some vehicles (e.g., Lexus 460L, Mercedes S550, and Volvo XC60). The performance of different pedestrian CIB systems varies significantly. Many research groups and government agencies are actively studying the methodologies for the evaluation of pedestrian CIB systems [2]. There are two ways to gather data to study the performance of pedestrian CIB system. The first is to conduct vehicle tests to gather the actual performance data. Due to the high cost of gathering the test data, and the complexity of test setup, only a limited number of tests with simple scenarios can be conducted practically. The second approach is to use a driving simulation for evaluating the effectiveness of a CIB system [3] in complex and severe crash scenarios. The requirement of the simulation approach is that the CIB simulation model must be sufficiently close to the actual CIB system being evaluated.

There are different approaches to generate a CIB model. The first one is to develop models of all components of a CIB system and link the component models together to make a CIB model. This approach is useful for the CIB system developer who has all the required component parameters. Without the parameters of the CIB components, it is difficult for a research institution to develop a CIB model that can mimic the actual performance of a real CIB system due to the complexity of the system. The second approach is to use physics principles to generate a demonstration model of the CIB systems. However, the model generated in this approach is not sufficient to determine the performance of a specific CIB system.

In this paper we propose a new approach to create a pedestrian CIB simulation model for a specific vehicle. The approach is to use the general knowledge of the CIB components which are published by the car manufacture, and use the collected pedestrian CIB performance test data of the CIB equipped vehicle in a set of test scenarios. This approach is implemented using the PreScan software [4]. PreScan is a strong physics-based simulation platform provided by TASS International. It is used in the automotive industry for the development of Advanced Driver Assistance Systems (ADAS). PreScan is also used for designing and evaluating vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication applications as well as autonomous driving applications.

Section 2 shows the information needed for developing a pedestrian CIB simulation model. Section 3 describes the method for designing and implementing the pedestrian CIB simulation model. Section 4 evaluates the performance of the CIB simulation model. Section 5 concludes the paper.

II. DATA COLLECTION FOR DEVELOPING CIB MODEL

The development of a CIB simulation model for a vehicle is based on two types of data, (1) the testing environment data and (2) the CIB performance data. Both of them can be obtained by researchers in a series of well-designed CIB tests. The environment data is recorded before or during each test. The pedestrian CIB performance of a vehicle may vary significantly in different test environments. According to the testing data, seven factors are considered significant to the CIB

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performance. Table 1 lists all the environment data and the CIB performance data that used for developing the CIB simulation model. The more data collected, the more accurate the simulation model will be.

TABLE 1: THE ENVIRONMENTAL AND PEDESTRIAN CIB PERFORMANCE DATA USED FOR DEVELOPING CIB SIMULATION MODEL

Environment Data	
Pedestrian Speed (m/s)	The actual moving speed of pedestrian.
Pedestrian Direction	Left to right, right to left, along traffic, against traffic
Pedestrian Size	Adult, child.
Pedestrian Cloth Color	The color of cloths of pedestrian.
Light Condition	Daylight, dark, dark lit.
Weather Condition	Sunny, cloudy, etc.
Vehicle Speed (m/s)	The actual moving speed of vehicle.
Performance Data	
Warning Starting Distance to Target (m)	The distance from vehicle to pedestrian when the CIB warning starts.
Warning Starting Time to Collision (s)	The Time to Collision (TTC) when the CIB warning starts.
Braking Starting Distance to Target (m)	The distance from vehicle to pedestrian when the CIB braking starts.
Braking Starting TTC (s)	The TTC when the CIB braking starts.
Total Braking Time (s)	The duration of the total CIB braking
Average Deceleration During Braking (m/s^2)	The average deceleration during braking process.
Stopped at Distance if Collision Avoided(m)	If the collision avoided successfully, this value represents the distance from vehicle to the pedestrian when the vehicle stopped.
Collision Speed if Collided (m/s)	If a collision with pedestrian occurred, this value represents the collision speed.
Estimated Minimum Safe TTC (EMST) (s)	When TTC to an object drops below this value, the object is considered to be dangerous. Then the pedestrian detection algorithm starts to verify whether this object is a pedestrian. This value is an estimated average value derived from the average of Warning Starting TTC.
Estimated Lateral Safe Distance (m)	When the lateral distance from vehicle to pedestrian drops below this value, pedestrian classification will start. This value is an estimated average value that derived from special test.

III. DEVELOP THE PEDESTRIAN CIB MODEL

A. *Structure of the CIB Model*

PreScan provides a demo of Pedestrian Protection System (PPS) which is similar to the pedestrian CIB system. The PPS provides early warnings when a potential collision with pedestrians is detected, and brakes automatically when a collision with pedestrian is inevitable. However, since the parameters used in PPS may not match the corresponding behavior in a specific CIB system, part of the PPS provided by PreScan is modified to match the result of the CIB tests. For simplification and compatibility, the input and output ports of our developed CIB model are made identical to PPS. The pedestrian CIB model also consists of three sub-models that are similar to PPS's Radar Detection Model, Pedestrian Identification Model, and Decision Making Model. Our pedestrian CIB model uses the same Radar Detection Model as provided in PPS, replaced the Camera Detection Model by a Pedestrian Identification Model since no video images are provided by the test data, and rewrote the Decision Making Model based on the pedestrian CIB testing data.

The purposes of sub-models of CIB are described as follows:

- Radar Detection Model - Based on the radar characteristics, this model can detect an object and calculate the time to collision (TTC). If the TTC drops below Estimated Min Safe TTC, this object will be considered to be dangerous.
- Pedestrian Identification Model - If a dangerous object is detected by the Radar Detection Model, this model continues to check whether it is a pedestrian, and provides a warning if a pedestrian classified.
- Decision Making Model - If an imminent crash to a pedestrian is identified by the Pedestrian Identification Model, this model decides the warning and braking behavior of the vehicle.

B. *Development of sub-models of the pedestrian CIB Model*

1) *Radar Detection Model*

Radar Detection Model simulates the radar behavior for detecting potential collisions to objects. Radar is an object-detection system that can determine the distance, motion direction and speed of objects. Based on the radar information, the absolute velocity vector of an obstacle can be calculated. Assuming that the vehicle and the obstacle are moving in straight lines, absolute velocity vectors may intersect at a point where the collision will take place. Then the TTC is calculated.

Our Radar Detection Model was developed based on the same model in PreScan's PPS model, but some output parameters of the original model unrelated to CIB model were eliminated. Only two output parameters, TTC and Radar Detection Flag are reserved. Radar Detection Flag is used to indicate whether a dangerous object is detected by radar sensor. And TTC is used to measure the severity of the dangerous object and relative decisions will be made based on it.

2) Pedestrian Identification Model

Usually, if an object is detected by radar sensor and considered to cause a potential crash, the pedestrian detection algorithm based on the camera sensor is engaged in order to determine whether the detected object is a pedestrian. However, it is hard for the researchers to know what technique and image processing algorithms are used in the CIB system. Hence it is not proper for the CIB simulation model to use any specific image processing algorithm for pedestrian classification. As a result, our study only focuses on the behavior of the pedestrian CIB system and does not care what image processing technique and algorithms that the CIB use. Specifically, our pedestrian CIB simulation model concentrates on determining the conditions that whether a pedestrian could be detected by the CIB system and how long the CIB would take to classify the pedestrian. It is a testing data based classification algorithm. Usually, the efficiency and accuracy of image processing based pedestrian detection algorithms vary significantly in different test environments. Our classification algorithm takes all these environmental factors into consideration to mimic the performance of real image processing algorithms. The input and output parameters of our algorithm are shown in Table 2.

TABLE 2: INPUT AND OUTPUT PARAMETERS OF WARNING DECISION MODEL

Input Parameters	
V_{car}[m/s]	The actual moving speed of vehicle.
Radar Detection Flag	A flag indicating whether a pedestrian has been detected by radar sensor.
V_{ped} [m/s]	The Moving speed of the pedestrian.
S_{ped}	The size of the pedestrian. (e.g. child, fit adult, overweight adult)
C_{ped}	The cloth color of the pedestrian. (e.g. white, black, green, red)
D_{ped}	The moving direction of the pedestrian.
Light Condition	The light condition. (e.g. day, night)
Weather Condition	The weather condition. (e.g. sunny, cloudy, snow, rain, fog)
Output Parameters	
Pedestrian Detection Flag	The flag to indicate whether a pedestrian is detected.

The single output parameter is a timed Pedestrian Detection Flag used to indicate if a pedestrian can be identified by the CIB and when it would be identified. According to the testing data, the performance of CIB system can vary significantly under different test conditions. Higher vehicle speed, higher pedestrian speed, smaller pedestrian size, or poor visibility due to lighting condition and weather may cause longer pedestrian recognition time or even fail to recognize a pedestrian. A longer recognition time may mean a shorter time period for CIB warning and braking, and may increase the probability of a crash. The testing data shows there are two circumstances that the vehicle collides with the pedestrian, (1) The vehicle fails to classify the pedestrian, and it hits the pedestrian directly without taking any action to avoid this collision (2) It takes too much time for the vehicle to classify this pedestrian successfully. Although automatic braking applied, the collision is still not avoided completely.

Within our pedestrian classification algorithm, the calculation of this Pedestrian Detection Flag is transformed to the calculation of Total Recognition Time. Since several parameters can affect the recognition time, the calculation process of the total recognition time is divided into several sub-problems. The recognition time relative to each parameter was calculated individually. Then these times are summed up to make a Total Recognition Time. However, we do not exactly know how much each of the parameters affects the image processing performance. Our approach to solve this problem is to manipulate the weights to match the testing data of a specific pedestrian CIB for each vehicle.

For example, the testing data of a CIB system shows that once the vehicle speed is higher than 45 mph, it always fails to warn and brake. During 0 to 45 mph, the vehicle speed is divided into several intervals. In this paper, the granularity of the intervals is assigned to be 5 mph. If a higher accuracy required, the granularity can be set smaller. The recognition time for each speed interval is denoted as $T_{VS}[x < v \leq y]$ (x is the start of the speed interval, and y is the end of the speed interval). Within each vehicle speed interval, the recognition time is considered to be the same as the higher value, so that $T_{VS}[x < v \leq y] = T_{VS}[v = y]$. In order to get the recognition time for each speed interval ($T_{VS}[y]$, $y = 5, 10, 15 \ldots 40, 45$), a set of vehicle tests and calculations are needed. For each speed interval, the tests are repeated five times and then the average value of the obtained Warning TTC (denotes as $TTC[x < v \leq y]$ is obtained. Therefore, the different Warning TTC for different vehicle speed intervals can be obtained (the difference of recognition time between different speed intervals can also be calculated). Then the recognition time can be calculated as follows:

$$\mathrm{T_{VS}}[\mathrm{x} < v \leq \mathrm{y}] = \mathrm{T_{VS}}[0 < v \leq 5] + (\mathrm{TTC}[0 < v \leq 5] - \mathrm{TTC}[\mathrm{x} < v \leq y]),$$

$$(\text{for } \mathrm{x} = 0, 5, 10, 15, \dots 35, 40, 45, \mathrm{y} = \mathrm{x} + 5) \quad (1)$$

$$\mathrm{T_{VS}}[\mathrm{x} < v \leq y] = \infty, \text{for } \mathrm{x} > 45\ mph$$

In equation1, $\mathrm{T_{VS}}[0 < \mathrm{v} \leq 5]$ is a base value, and $(\mathrm{TTC}[0 < \mathrm{v} \leq 5] - \mathrm{TTC}[\mathrm{x} < \mathrm{v} \leq \mathrm{y}])$ is a difference value between $\mathrm{T_{VS}}[\mathrm{x} < \mathrm{v} \leq \mathrm{y}]$ and the base value $\mathrm{T_{VS}}[0 < \mathrm{v} \leq 5]$. Since Warning TTC decreases with the increasing of vehicle speed, $\mathrm{TTC}[0 < \mathrm{v} \leq 5] - \mathrm{TTC}[\mathrm{x} < \mathrm{v} \leq \mathrm{y}] > 0, \text{when } \mathrm{x} > 0$. So the recognition time for each speed interval can be calculated based on the base value and the difference value between them. However, the value of base value $\mathrm{T_{VS}}[0 < \mathrm{v} \leq 5]$ is unknown. The only way to find the base value is to make a good guess and assign an initial value to it. After building the CIB simulation model, the correctness of the base value can be verified through simulations using the CIB test data. The base value can be adjusted to a more precise value by minimizing the difference of Warning TTC between the simulation data and CIB test data.

Table 3 is the recognition time with respect to the vehicle speed for a CIB being tested. $\mathrm{T_{VS}}$ is the recognition time delay caused by the vehicle speed factor. The recognition time for each speed interval was calculated based on the CIB test data. For example, $\mathrm{T_{VS}}[5 < \mathrm{v} \leq 10]$ was set as 0.1 s initially. Run the simulation with the CIB test scenario, TTC[0< v ≤5] is 2.31 s, and TTC[5< v ≤10] is 2.26 s. The difference value between them is 0.05 s. Then $\mathrm{T_{VS}}[5 < \mathrm{v} \leq 10]$ is reassigned as 0.1 + 0.05 = 0.15 s.

Table 4 – 7 present the recognition times caused by Pedestrian Speed, Pedestrian Type, Contrast and Pedestrian Direction. All of them are obtained in the same way as $\mathrm{T_{VS}}$.

TABLE 3: VEHICLE SPEED AND RELATIVE TIME COST

Vehicle Speed (mph)	**$\mathrm{T_{VS}}$(s)**
0-5	0.1
5-10	0.15
10-15	0.2
15-20	0.25
20-25	0.3
25-30	0.5
30-35	0.75
35-40	0.90
40-45	0.95
Others	∞

Table 4 depicts the recognition time relative to pedestrian speed. $\mathrm{T_{PS}}$ is the pedestrian recognition time caused by the pedestrian speed.

$$\mathrm{T_{PS}}[x < v \leq y] = \mathrm{T_{PS}}[v = 0] + (TTC[v = 0] - TTC[x < v \leq y]) \quad (2)$$

$$when(x, y = 0, 1.0, 1.5, 2.2, 2.5\ 3.0)$$

$$\mathrm{T_{PS}}[x < v \leq y] = \infty, when\ (x > 3.0)$$

TABLE 4: PEDESTRIAN SPEED AND RELATIVE TIME COST

Pedestrian Speed (m/s)	**$\mathrm{T_{PS}}$ (s)**
0.0	0.1
0.0-1.0	0.1
1.0-1.5	0.1
1.5-2.2	0.5
2.2-2.5	0.8
2.5-3.0	0.95
Others	∞

Table 5 depicts the recognition time relative to pedestrian size. $\mathrm{T_{PT}}$ is the time of recognition caused by pedestrian type.

TABLE 5: PEDESTRIAN TYPE (SIZE) AND RELATIVE TIME COST

Pedestrian Type	**$\mathrm{T_{PT}}$(s)**
Child	0.3
Fit Adult	0.1
Obese Adult	0.3

Table 6 represents the recognition time relative to the contrast of the pedestrian to the background. $\mathrm{T_C}$ is the recognition time caused by the contrast between the pedestrian and the back ground. The type of contrast is intuitively specified based on the Light Condition, Weather Condition, and the Cloth Color of Pedestrian. The principle is that, the easier to classify a pedestrian from the background, the higher the contrast is.

TABLE 6: CONTRAST AND RELATIVE TIME COST

Contrast	**$\mathrm{T_C}$(s)**
High Contrast	0.2
Medium Contrast	0.4
Low Contrast	0.7
Super Low Contrast	∞

Table 7 describes the recognition time relative to pedestrian direction. In this paper, the pedestrian is assumed to be moving straight forward. So five basic directions for pedestrian are defined and discussed. The calculation method of the recognition time is also based on base value and difference value.

TABLE 7: PEDESTRIAN DIRECTION AND RELATIVE TIME COST

Pedestrian Direction	**$\mathrm{T_{PD}}$ (s)**
Stand (Face to the vehicle)	0.1
L2R	0.2
R2L	0.2
Along Traffic	0.3
Against Traffic	0.3
Others	N/A

Based on the weights and time costs that described in Tables 3 to 7, the total recognition time was calculated.

$$T_R = T_{VS} + T_{PT} + T_{PS} + T_C + T_{PD} \quad (3)$$

Additionally, Warning Starting TTC (WST) can be calculated based on T_R. If T_R is *greater than EMST* (Estimated Minimum Safe TTC), it means that the Pedestrian Identification Model fails to classify the pedestrian, then the *Pedestrian Detection Flag* will not be triggered. Otherwise, if TTC drops below WST, *Pedestrian Detection Flag* will be triggered.

$$WST = 0, when\ T_R \geq EMST$$

$$WST \approx EMST - T_R, when\ T_R < EMST \quad (4)$$

3) Decision Making Model

In the CIB Simulation model, the Decision Making sub-model is the last step to determine the behavior of the vehicle. It is a modification of the Actuation Model provided by PreScan. In the original Actuation Model in PreScan, the Warning Flag is set if a pedestrian has been classified and TTC drops below 1.6 s, and the Braking Flag is set if the TTC drops below 0.6 s. Furthermore, the Braking Pressure is a preset value. Although the thresholds of Warning TTC, Braking TTC, and Braking Pressure can be modified in the original PreScan model, they are still not able to reflect the behavior of a pedestrian CIB system in a real vehicle. According to the CIB test data, the Warning TTC, Braking TTC, and Braking Pressure vary significantly in different test conditions. The threshold of Warning TTC has been described in the section describing the Camera Detection Model. In this section, the methods for calculating the thresholds of Braking TTC and Braking Pressure are discussed. Table 8 describes the input and output parameters of Decision Making Model. The output parameters are used by the action model and the display model provided by PreScan. If the Warning Flag is set, the action model will turn on the warning lights and beeps. If the Braking Flag is assigned, the action model will apply a specified braking pressure to the vehicle. All the actions and relative results will be displayed by the display model.

The Decision Making Model keeps examining the input parameters, Radar Detection Flag and Pedestrian Detection Flag. Once both Radar Detection Flag and Pedestrian Detection Flag are raised, the Decision Making Model triggers the Warning Flag immediately. Otherwise, the Warning Flag is not assigned.

TABLE 8: INPUT AND OUTPUT PARAMETERS OF DECISION MAKING MODEL

Input Parameters	
V_{car} [m/s]	The actual moving speed of vehicle.
TTC	The time to collision.
Radar Detection Flag	The output parameter of the Radar Detection Model.
Pedestrian Detection Flag	The output parameter of the Pedestrian Identification Model
Output Parameters	
Warning Flag	A flag to indicate whether a warning should be triggered.
Braking Flag	A flag to indicate whether the brake should start.
Braking Pressure [bar]	The pressure applied to brake. It can be used to calculate the vehicle deceleration.

According to the testing data, the threshold of Brake Starting TTC (BST) can be modeled as a linear function of vehicle speed. When a pedestrian is detected as a collision object and TTC drops below the threshold of BST, the Braking Flag is assigned. Then desired Braking Pressure (BP) will be applied until the vehicle stops.

Figure 1 shows the modeling result of BST based on the testing data of a 2013 model year sedan. The x axis is the speed of vehicle in mph. The y axis is the BST in seconds. 325 tests are shown in this figure. Using the polyfit function provided by MATLAB, a straight line representing BST is plotted. To make it more realistic, a random offset, is generated and added to the sum. The range of the offset is from –x to x. 2x is the range of the BST in the CIB test data under each vehicle speed. Then the BST can be calculated as follows.

$$BST = 0.0647 * V_{car} + 0.2225 + offset \quad (5)$$

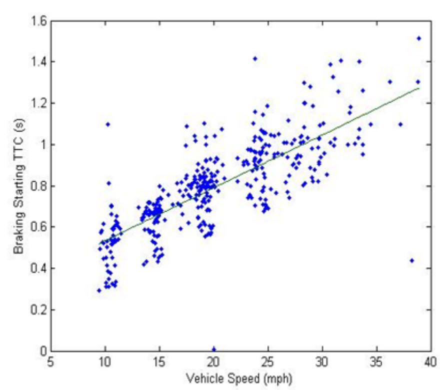

Figure 1. BST versus vehicle speeds.

In this study, the Braking Pressure was calculated based on the Average Deceleration in CIB braking. Figure 2 shows the desired deceleration under a specific vehicle speed of a 2013 model year sedan. The x axis is the speed of the vehicle in mph. The y axis is the Average Deceleration in CIB braking. To make it more similar to actual vehicle testing, a random offset is generated and added to the sum. The range of the offset is form –x to x. 2x is the maximum differences of the

Average Deceleration in the CIB test data under each vehicle speed. The following is the calculation method of desired Deceleration.

$$Deceleration = 0.0912 * V_{car} + 6.5953 + offset \quad (6)$$

Once the desired average deceleration is calculated, the brake pressure, BP, can be calculated based on this desired deceleration. In the original PreScan Actuation Model, the default Braking Pressure is Max Brake Pressure (MBP). Under MBP, the deceleration of the vehicle is exactly 1g (9.81 m/s2). If the desired deceleration is known, the portion of the desired deceleration versus 1G can be calculated. Furthermore, multiply the Max Brake Pressure by this portion, then the desired BP is obtained. Once the full braking is applied, the Braking Pressure will remain a constant until the vehicle halt. The following formula shows the method for calculating desired Braking Pressure.

$$BP = MBP * (Deceleration \,/\, 9.81) \quad (7)$$

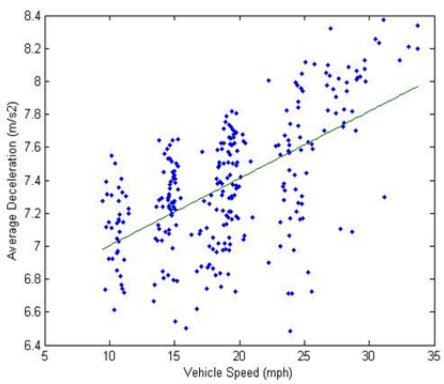

Figure 2. Average Deceleration versus vehicle speeds.

IV. Simulation and Results

Two different 2013 model year sedans with pedestrian CIB capability were tested. 400 test runs were for vehicle A, and 350 for vehicle B. 20% of the testing data were used to test our CIB simulation model (75 simulations were engaged for vehicle A and 63 for vehicle B). The average error of simulation results are shown in Table 9. Since the Stop at Distance is usually a small value (85% of them are less than 1 meter), so it is quite sensitive to the error of Warning Starting TTC, Braking Starting TTC and the Average Deceleration.

Table 9. Average error of simulation data for vehicle A and vehicle B

	Error for A	Error for B
Warning Starting TTC (s)	12.1%	16.7%
Braking Starting TTC (s)	6.3%	8.2%
Average Deceleration (m/s^2)	4.7%	5.6%
Collision Speed (m/s)	7.8%	8.6%
Stop at Distance (m)	31.1%	39.7%

V. Conclusions and Future Work

This paper described a systematic methodology to develop a simulation model based on the pedestrian CIB using vehicle test data. This vehicle model is developed in Simulink, so it has good maintainability and extendibility. Test results of the proposed vehicle model match closely to the actual vehicle test results. Currently, the vehicle model can only support straight road segment, so one future direction is to optimize it to support curved road and vehicle turning scenarios.

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