Influence of different pedestrian behavior models on the performance assessment of autonomous emergency braking (AEB) Systems via virtual simulation

Lucas Fonseca Alexandre de Oliveira [1], Martin Meywerk [2], Lars Schories [1], Maria Meier [3], Ramakrishna Nanjundaiah [3], Victor Paulthi [3], Francesco Foglino [3], Mark Carroll [3] and Arunaachalam Muralidharan [3]

[1] *ZF Friedrichshafen AG, Germany*

[2] *Helmut Schmidt University, Germany*

[3] *Phantasma Labs GmbH, Germany*

Abstract

Pedestrian safety is a central topic in the automotive industry because of the high number of deaths in car-to-pedestrian accidents. Different systems have been developed to protect pedestrians and other vulnerable road users. So-called Active Safety Systems are used to avoid possible collisions with the VRU or to mitigate injury severity by reducing the collision speed in case the collision can't longer be prevented. The autonomous emergency braking system (AEB) is one of these systems and aims to intervene in conflict situations by stopping the car, Haus et al. (2019). The performance assessment of the AEB System can be done via virtual simulation. One crucial aspect is the modeling of pedestrian behavior. Current studies use a simple pedestrian behavior model, sometimes called a trajectory-based model, in which the pedestrian moves with constant speed on a given path and without any interaction with the environment. This study investigates how the AEB Performance in virtual environments is influenced by using a more realistic pedestrian behavior model based on reinforcement learning approach, a particular Machine Learning branch perfectly suited for modeling decision-making processes. For that, a generic AEB-System, the trajectory-based pedestrian model, and the reinforcement learning model were implemented in CARLA Simulator. A scenario catalog was created by varying some parameters and used to evaluate the front collisions with and without the AEB system. The study indicates that due to some pedestrian reactions of the reinforcement learning model, like unexpected stopping in front of the car, the performance of the AEB-System is reduced.

Keywords: Pedestrian Crossing behavior, efficiency assessment, active safety, simulation

Introduction

Vulnerable Road Users (VRU) are non or poor-protected road users like pedestrians or users or passengers of non-motorized or powered two-wheelers e.g., cyclists or motorcyclists. They accounted for 51,4% of all total road fatalities in the European Union in 2021 (Decae, 2022). An Autonomous emergency braking (AEB) system, an active safety system used to avoid imminent collisions, can help to reduce this higher number of fatalities. Its performance assessment can be done via virtual simulation, but one current limitation is the pedestrian representation, which only walks a pre-defined path with constant velocity without interacting with the environment. This model is called in trajectory-based model in this study.

The aim of this paper was to investigate if a pedestrian behavior model with visual perception and interaction with the environment and other agents, changes the performance of the AEB-System in a virtual simulation. For that, a behavior model based on a reinforcement learning algorithm was developed by Phantasma Labs GmbH (https://www.phantasma.global/) and compared with the current trajectory-based model. In Methods, the simulation platform used in this study is presented together with the vehicle model and the two pedestrian models. In the same section, the generic model of the AEB system, the road network, and the parameterization of the simulation for the generation of different scenarios are presented. Finally, the results are presented and discussed for both pedestrian models.

Methods

Pedestrian Models

Modeling pedestrian behavior and movement are very complex, especially considering the decision-making process. Papadimitriou et al. (2009) highlight the relevance of two aspects of pedestrian behavior to be modeled. One of them is the route choice, which regards the decision process about the optimal path between the current location and destination. The other one is the crossing behavior regarding the decision of when and where to cross the road. They conclude that most pedestrian behavior models treat route choice and crossing behavior separately. Teknomo et al. (2016) reviewed different approaches to modeling pedestrian movement on a microscopic level, where the pedestrian is treated individually. In general, pedestrian movement between a start point and destination uses repulsive effects between the pedestrians and other obstacles and in most cases is not validated or calibrated on real pedestrian movement data. The pedestrian models available in most vehicle dynamic simulation tools, the trajectory-based models, don't model the route choice or the crossing behavior either. Both aspects are defined before the simulation and implemented manually by giving the pedestrian a pre-defined trajectory. The pedestrian in most cases is also devoid of visual perception and internal representation in such a way that the interactions with the infrastructure (avoiding obstacles) and with other road users, like vehicles and other pedestrians, is not present. Similar models are used in current studies by Lindman et al. (2010), Schanchner et al. (2020), and Hamdane et al. (2015).

Considering that car-to-pedestrian accidents occur in most cases in urban areas (Adminaité-Fodor et al., 2020) on the road or very close to it and involve mostly just one pedestrian, the microscopic approach is the most suitable for this study, Wakim et al. (2004). The pedestrian should also be able to choose different routes between start point and destination, exhibit an unsafe crossing behavior, have visual perception, and interact with road infrastructure and other agents. No model was found in the literature that achieves all the requirements above. For this paper, a new model was developed based on a reinforcement learning (RL) method, once this machine learning approach is perfectly suited for modeling decision-making process and therefore can directly be employed for the design of pedestrian behavior models. RL is a branch of machine learning that faces a real problem from the perspective of a learning agent interacting with its environment to achieve a goal. This requires that the agent is capable to perceive the state of the environment and to take actions to affect the state. By this category of learning algorithms, the agent always collects new data points by directly interacting with the provided environment and later uses them for training. In this study, the model will be called reinforcement learning behavior model (RL model) and it was developed for the specific traffic scenario analyzed in this paper. The learning agent is the pedestrian that interacts with the environment (road infrastructure and vehicles) to achieve the goal, a specific position on the other side of the road. During the development of the model, attention was paid to the maximum possible pedestrian-car interactions (this also covers the visual perception, internal interpretation, and decision making) and plausible, human-like, and diverse trajectories.

In this study, the trajectory-based model and the RL model were used. By the trajectory-based model approach, the pedestrian is spawned at the start position at the beginning of the simulation and crosses the road following a pre-defined path perpendicular to the vehicle's direction with a constant speed until it reaches the other side of the road. The pedestrian does not interact with the environment and other agents. This approach reflects the pedestrian dummy used in the Euro NCAP test protocol (Euro NCAP, 2019). The RL model, unlike the previous model, perceives its environment and interacts with other agents. The model moves towards in order to reach a defined destination. Unlike the previous model, the RL model developed for this study is not capable of being parameterized, so the speed cannot be set, and the starting point and destination cannot be changed.

Simulation Environment and Road Network

CARLA, Car Learning to Act, (Dosovistikiy et al., 2017) is an open-source simulator for urban driving. CARLA was built in a server-client architecture. The server runs the simulation, rendering the scene and the client, a python API, defines the scenario and establishes the interaction between the agent and the server. The simulation run in a synchronous mode with a constant time step of $\Delta t = 0.04$ s (25 Hz). The road network was designed based on the definition from the Euro NCAP test protocol. In addition to this definition, a parking area was added with two parking vehicles. In Figure 1 the road in CARLA can be seen.

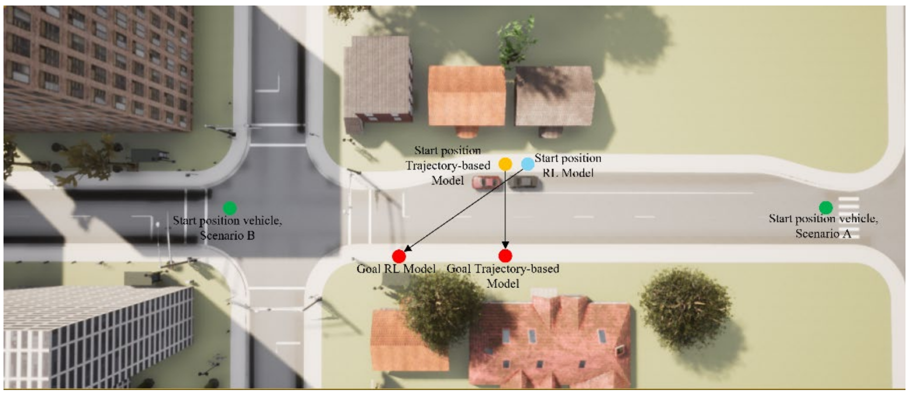


Figure 1 - A representation of the road. The blue mark indicates the initial position of the RL model and the orange mark of the trajectory-based model. The red is the destination of the pedestrian. The green mark is the start position of the vehicle. The road has 2 driving lanes and a parking lane with widths of 3.5 m. The arrows indicate the direction of movement of the pedestrian. The OpenDRIVE format was used to define the road network.

AEB System and vehicle model

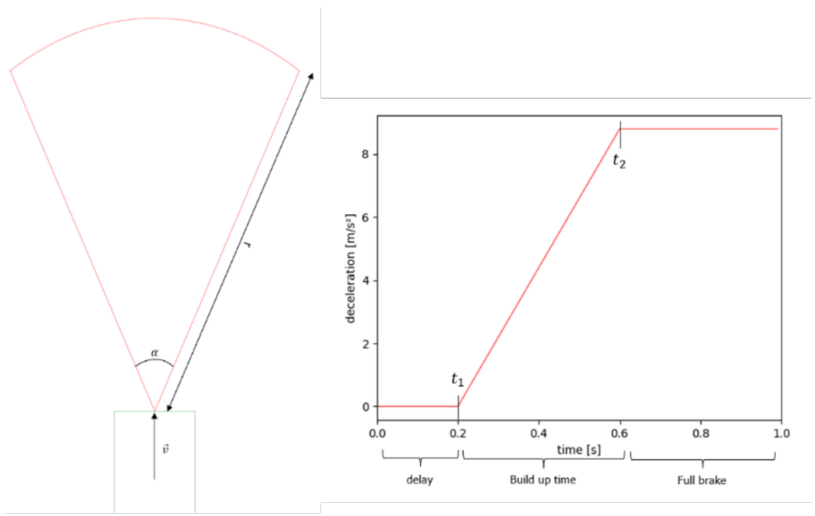
Against other simulation platforms, CARLA does not provide a pre-implemented AEB system. A generic AEB system was implemented based on the definition given by the harmonization group Prospective Effectiveness Assessment for Road Safety (P.E.A.R.S.), Page et al. (2015). The systems consist of an ideal sensor, a decision algorithm, and a control algorithm.

This study assumed an ideal sensor for pedestrian detection. An algorithm was implemented in the client that, based on the current position of the vehicle, calculates the field of view of the sensor as an arc of a circle using the maximum range and azimuth angle, see Figure 2 (a). At each timestep, the algorithm checks if the pedestrian is inside of the field of view using the current pedestrian position. In a positive case, the pedestrian is considered to have been detected by the sensor and a signal is sent to the decision algorithm.

The decision algorithm defines the intervention strategy of the AEB. It is based on the time-to-collision (TTC) and on the detection of the pedestrian. This calculation holds if the vector of relative velocity, $\vec{v}_{rel} \coloneqq \vec{v}_{car} - \vec{v}_{ped}$ is in the same direction as the relative position $\vec{r}_{rel} = \vec{r}_{ped} - \vec{r}_{car}$. Equation 1 hold:

$$\vec{v}_{rel}\, TTC = \vec{r}_{rel} \tag{1}$$

Once the pedestrian is inside of the field of view and the TTC gets equal to or smaller than 1.0 s, the vehicle starts the braking process. The control algorithm calculates the vehicle speed at each time step. By normal driving, the vehicle drives at a constant speed. Once the AEB is activated the new car velocity based on the current deceleration is calculated and applied to the vehicle. The deceleration profile is defined by an actuator delay, a build-up time, and a maximal deceleration. The deceleration increase over time is modeled to be linear until the maximum value. The deceleration profile can be seen in Figure 2 (b). Two settings for the AEB system were evaluated in this study (cf. Table1), one based on P.E.A.R.S. and the other based on the setting applied in Schachner et al. (2020).



(a) (b)

Figure 2 - (a) - Field of View of the ideal perception systems. It is parametrized through azimuth angle α and maximum range r. At each time step is checked based on the current position of the pedestrian and the vehicle if the pedestrian is in the sensor's Field-of-View. (b)The deceleration profile for settings 1. It is divided into three steps. It is divided into three steps: actuator delay, build up time (deceleration increases linearly with the time), and the full brake (maximum deceleration is achieved and stays constant until the vehicle stands still).

Table 1: AEB parameter settings

Parameters	*Maximum deceleration*	*Build-up time*	*Actuator delay*	*Braking gradient*	*Maximum range*	*Azimuth angle*
Settings 1	8,8 $\frac{m}{s^2}$	0,4 s	0,2 s	24,525 $\frac{m}{s^3}$	60 m	60 °
Settings 2	7,0 $\frac{m}{s^2}$	0,35 s	0,25 s	20 $\frac{m}{s^3}$	60 m	60 °

Scenario Generation

One approach to generate scenarios in order to assess the performance of the AEB system is to reproduce conflict scenarios based on accident data, Jeppsson et al. (2018), Gruber et al. (2019), Li et al. (2021). In this case, the pedestrian follows a given trajectory. Schachner et al. (2020) propose a different approach generating a scenario catalog of critical car-pedestrian conflict situations by varying the following parameters: vehicle speed, pedestrian speed, and pedestrian waiting time. The trajectory for vehicle and pedestrian was previously defined. A similar approach was implemented in this study with some adaptations considering some constraints of the RL behavior model. The base scenario was inspired by the Euro NCAP test cases Car-Pedestrian Nearside (CPNA) and Car-Pedestrian Farside (CPFA). Two conflict situations were simulated. In conflict situation A the vehicle drives forward on a straight road, and the pedestrian was crossing the road coming from the vehicle's nearside. This conflict scenario was simulated with both pedestrian models. In conflict situation B the vehicle drives forward on a straight road, and the pedestrian was crossing the road coming from the vehicle's farside. This conflict scenario was simulated only with the RL model. The parameters used to generate scenarios with the trajectory-based model and RL model can be found in Table 2. For the RL model, no pedestrian waiting time is possible since setting this as a tunable parameter is not possible, as well as the constant pedestrian speed. Instead, the waiting time was applied to the vehicle. The car waiting time was extended to 8 s, to generate more interaction between pedestrian and higher vehicle speeds.

Table 2: Parameters to generate different conflict scenarios for trajectory-based pedestrian model and RL model.

Parameter	*Value*	*Step size*
	Trajectory-based pedestrian model	
Vehicle speed [km/h]	10 – 60	2,5 km/h
Pedestrian speed [km/h]	1 - 12	1 km/h
Pedestrian waiting time [s]	0.1 – 3.6	0.5 s
	Reinforcement Learning behavior model	
Vehicle speed [km/h]	10 – 60	2,5 km/h
vehicle waiting time [s]	0 – 8	0.2 s

Results

The performance of the AEB was evaluated by comparing the number of frontal collisions between the baseline simulations (vehicle without an AEB system) and the simulations with the AEB system in conflict situations A and B. The results discussed here are referent to the AEB system with settings 1. Tables 3 and 4 show all results including the AEB system with settings 2.

Table 3: Results trajectory-based pedestrian model

	Baseline	*AEB System, setting 1*	*AEB System, setting 2*
Number of scenarios	2016	2016	2016
front collisions	201	123	162
Percentage of front collisions	10 %	6,1%	8,0%
Collision reduction due the AEB system	-	38,8%	19,4%

As expected, the results with a lower maximal deceleration and higher actuator delay led to lower performance. In 2016 baseline simulations with the trajectory-based model, 201 ended in front collisions. This number was reduced to 123 with the AEB system, a reduction from 38,8%. This result agrees with the literature, Lindman et al. (2010), Handame et al. (2015), Gruber et al. (2019), Schachner et al. (2020) that goes from 20% up to 50%. With the RL model, a total of 862 baseline scenarios were generated resulting in 182 frontal collisions, generating 10% more collisions concerning the total, than in the trajectory-based pedestrian model. This higher number of collisions is due to the unsafe behavior of the pedestrian. The pedestrian's trajectories make the pedestrian stay more time on the road in the same lane as the vehicle, see figure 3 (a). The average pedestrian speed over time is shown in Figure 3 (b).

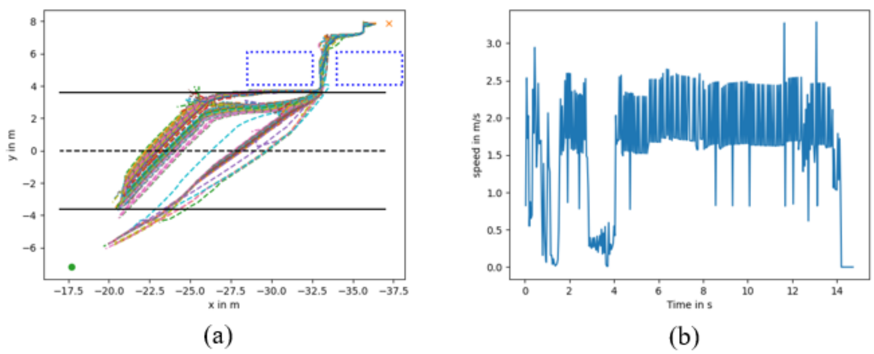


Figure 3 - (a) Pedestrian path over all simulations scenario A; (b) Pedestrian average speed

The AEB system reduced the number of front collisions to 108, a reduction from 40,6% similar to the results of the trajectory-based model. Unfortunately, in most cases of conflict situation A, the pedestrian crosses the road with his back to the approaching vehicle. Once the field of view of the pedestrian has an opening angle of 180°, he was not able to see the car and then did not react to it. To force this situation, the conflict situation B was simulated, where the vehicle was in the field of view of the pedestrian. In this situation, there were 191 front collisions in the baseline simulations and 138 with the AEB, a reduction from 27,7%.

Table 4: Results reinforcement learning behavior model

	Baseline, Scenario A	*Baseline, Scenario B*	*AEB System, Scenario A, setting 1*	*AEB System, Scenario B, setting 1*	*AEB System, Scenario A, setting 2*	*AEB System, Scenario B, setting 2*
Number of simulations	861	861	861	861	861	861
front collisions	182	191	108	138	140	149
Percentage of front collisions	21,1%	22,2%	12,5%	16%	16,2%	17,3%
Collision reduction due the AEB system	-	-	40,6%	27,7%	23,1%	21,9%

Discussion and Conclusions

All behavior shown were considered human-like, once he didn't walk into stationary objects, moves with an average speed not too fast or too slow, and didn't shake, walk laterally or backward. It was observed that the RL behavior model shows a higher variability in the trajectories when the car is in the field of view of the pedestrian. The pedestrian's most common reactions to the approaching vehicle were “waiting/looking around”,” slowing down”, “moving forward” and “standing still”. The “standing still” behavior together with the fact that the pedestrian walks in the opposite direction of the car in conflict situation B was one of main the causes of frontal collisions. The reinforcement learning behavior model showed to be useful to evaluate a generic AEB system by generating more collision and different corner cases due to the different trajectories and their interactions with the vehicle. These interactions have decreased the performance of the AEB system. It needs to be considered that the model was not trained for conflict situation B and the performance of the behavior could not be guaranteed in this situation. Further development of the model in this direction should be considered for future works. Another enhancement to the current study would be to include more pedestrians crossing the road, getting conflict scenarios closer to real-world situations. The vehicle model also needs to be improved with a better vehicle dynamic model.

Acknowledgments

The pedestrian behavior model developed using reinforcement learning approach were acquired from Phantasma Labs Gmbh in a proof-of-concept for ZF Friedrichshafen AG.

References

Adminaité-Fodor,D., & Jost, G., (2020). HOW SAFE IS WALKING AND CYCLING IN EUROPE?, PIN Flash Report 38, January 2020 – European Transport Safety Council. https://etsc.eu/wp-content/uploads/PIN-Flash-38_FINAL.pdf

Decae, R. (2022). Annual statistical report on road safety in the EU, 2021. European Road Safety Observatory. Brussels, European Commission, Directorate General for Transport. https://road-safety.transport.ec.europa.eu/statistics-and-analysis/data-and-analysis/annual-statistical-report_en

Dosovistikiy, A., Ros, G., Codevilla, F., Lopez, A., Koltun, V. (2017). CARLA: An Open Urban Driving Simulator. Proceedings of the 1st Annual Conference on Robot Learning. PMLR Vol. 78 of Proceedings of Machine Learning research, pp 1-16. https://doi.org/10.48550/arXiv.1711.03938

Euro NCAP, 2019, Test Protocol – AEB VRU Systems (Online). https://cdn.euroncap.com/media/62795/euro-ncap-aeb-vru-test-protocol-v304.pdf (Acessed 09 june 2022).

Gruber, M., Kolk, H., Tomasch, E., Feist, F., Klug, C., Schneider, A., Roth, F., Labenski, V., Shanmugam, K., Lindman, M., & Fredriksson, A. (2019). The effect of p-aeb system parameters on the effectiveness for real world pedestrian accidents. The 26th International Technical Conference and exhibition on the

Enhanced Safety of Vehicles (ESV), Pages 1-16. https://graz.pure.elsevier.com/en/publications/the-effect-of-p-aeb-system-parameters-on-the-effectiveness-for-re

Hamdane, H., Serre, T., Masson, C., & Anderson, R. (2015). Issues and challenges for pedestrian active safety systems based on real world accidents. Accident Analysis & Prevention, Volume 82, 53-60. https://doi.org/10.1016/j.aap.2015.05.014

Jeppsson, H., Östling, M., & Lubbe, N. (2018). Real life safety benefits of increasing brake deceleration in car-to-pedestrian accidents: Simulation of Vacuum Emergency Braking. Accident Analysis & Prevention, Volume 111, 311-320, https://doi.org/10.1016/j.aap.2017.12.001

Lindman, M., Oedblom, A., Bergvall, E., Eidehall, A., Svanberg, B., & Lukaszewicz, T. (2010). Benefit estimation model for pedestrian auto brake functionality. 4th International Conference on ESAR, (77). http://worldcat.org/issn/09439307

Page, Y., Fahrenkrog, F., Fiorentino, A., Gwehenberger, Helmer, T., Lindman, M., op den Camp, Lex van Rooij, O., Punch, S., Fränzle, M., Sander, U., & Wimmer, P. (2015). A comprehensive and harmonized method for assessing the effectiveness of advanced driver assistance systems by virtual simulation: the p.e.a.r.s. initiative. The 24th ESV Conference Proceedings, 1-12. https://graz.pure.elsevier.com/de/publications/a-comprehensive-and-harmonized-method-for-assessing-the-effective

Papadimitriou, E., Yannis, G., & Golias J. (2009). A critical assessment of pedestrian behaviour models. Transportation Research Part F 12, 242-255, https://doi.org/10.1016/j.trf.2008.12.004

Rasouli, A., Kotsureba, I., K. Tsotsos, J.K., 2018. Understanding pedestrian behavior in complex Traffic Scenes. IEEE Transactions on Intelligent Vehicles, volume 3, Issue:1, pages 61-70, http://dx.doi.org/10.1109/TIV.2017.2788193

Schachner, M., Sinz, W., Thomson,R., & Klug, C. (2020). Development and evaluation of potential accident scenarios involving pedestrian and AEB-equipped vehicles to demonstrate the efficiency of an enhanced open-source simulation framework. Accident Analysis and Prevention, 148. https://doi.org/10.1016/j.aap.2020.105831

Haus, S.H., Sherony, R., & Gabler, H.C. (2019) Estimated benefit of automated emergency braking systems for vehicle-pedestrian crashes in the United States. Traffic Injury Prevention. 2019, 20(sup1), 171-176. DOI: 10.1080/15389588.2019.1602729

Teknomo, K., Takeyama, Y., & Inamura, H. (2016). Review on Microscopic Pedestrian Model. Proceedings Japan Society of Civil Engineering Conference. https://doi.org/10.48550/arXiv.1609.01808

Wakim, C.F., Capperon, S., & Oksman, J. (2004). A Markovian model of pedestrian behavior. IEEE International Conference on Systems, Man and Cybernetics, 4, 4028-4033 vol. 4. https://doi.org/10.1109/ICSMC.2004.1400974