SIMULATION-BASED EVALUATION OF A GENERIC AUTONOMOUS EMERGENCY BRAKING SYSTEM USING A COGNITIVE PEDESTRIAN BEHAVIOR MODEL

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ABSTRACT

In 2020 pedestrians accounted for 21,4% of all deaths in the European Union. Considering all vulnerable road users (VRU: pedestrians, cyclists, motorcycles, and mopeds) they accounted for 51,4% of all deaths. To reduce the number of deaths and improve VRU safety, systems have been developed in the last decades. The autonomous emergency braking system (AEB) is one of these systems and aims to intervene in conflict situations by applying an emergency braking (in some cases only after the driver starts the brake itself). The performance evaluation of an AEB system via simulation reduces cost and time against real tests and allows better robustness evaluation because of the higher number of scenarios that can be simulated. In the virtual-world, safety-critical situations can also be tested without any problems. The modeling of pedestrian behavior plays an important role since the pedestrian is the vehicle's adversary in this context. Current studies use a simple pedestrian model, in which the pedestrian does not have any perception of the environment, moving on a pre-defined path with constant speed. Such trajectory-based models are available in the most common vehicle dynamic simulation tools. In reality, however, pedestrians usually react to the approaching vehicle in conflict situations by adjusting their trajectory, which can change the conflict situation and affect the performance assessment of AEB systems. This study compares the standard model with neuro-cognitive pedestrian model from cogniBIT and investigates if and how these models affect the performance assessment of AEB systems.

INTRODUCTION

Pedestrians are the road user group with the highest number of fatalities in Europe in 2021 with 51,4% of all fatalities [7]. Crashes involving pedestrians occur mainly, when pedestrians cross the road at not signposted cross-sections [16], [2]. In these situations, pedestrians change direction and speed generating paths with higher safety issues [14].

To protect pedestrians, the automotive industry has developed safety systems over the past decades. One of these is AEB-P, an active system, that activates braking maneuver in detected critical situations, with the aim of preventing or reducing the severity of a collision [12]. Figure 1 shows the reduction in the number of deaths on German roads since driver assistance systems (ADAS), like AEB, have been implemented in vehicles.

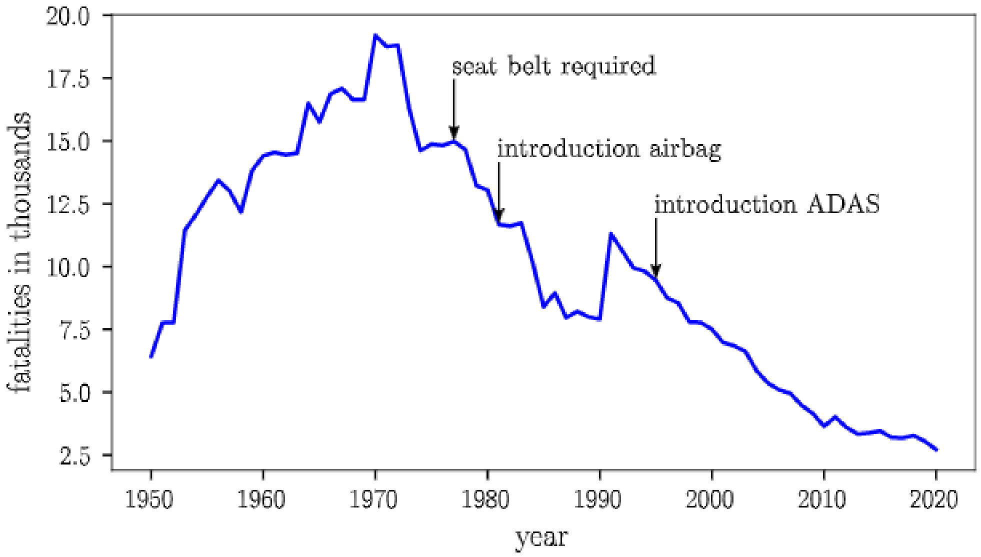


Figure 1. Fatalities on German roads since 1950 [12].

The evaluation of the AEB-P follows standards set by regulatory and consumer protection organizations such as Euro NCAP [10]. In the Euro NCAP test protocol for autonomous emergency braking for pedestrians (AEB-P) the pedestrian is represented by a dummy, which moves in a straight line with constant speed. However, real traffic situations are more complex and pedestrian crossing behavior is influenced by multiple factors such as road infrastructure (distance from the crosswalk, presence of traffic lights, number of lanes etc.), traffic situation (speed and flow), psychological and physiological characteristics, among other factors [16], [3], [14], [18] and [21].

To improve pedestrian safety, the next generation of active safety systems must be able to anticipate critical situations. For this, understanding pedestrian behavior and intentions in complex traffic situations is essential. Since simulation is used during the early stages of the development of new systems, it is necessary to use more realistic pedestrian behavior models for traffic situations which will allow the creation of more realistic scenarios.

This paper aims to evaluate a novel pedestrian behavior model for the evaluation of a generic autonomous pedestrian emergency braking system (AEB-P). First, we present a brief introduction to pedestrian behavior models and to the neuro-cognitive system architecture of the pedestrian model of CogniBiT (http://cognibit.ai). Next, the methods used to generate the scenarios and the metrics used to evaluate the performance of the AEB-P system are presented. Finally, the results are presented and discussed.

OVERVIEW PEDESTRIAN BEHAVIOR MODEL

The pedestrian model for use in simulations concerning ADAS falls into the category of microscopic models, since each pedestrian is modeled individually. [22], [6], [17], [23] present and discuss different microscopic pedestrian models. However, for the most part, the models do not consider intrinsic aspects of pedestrian behavior such as emotional state and intentions, and the influence of road infrastructure.

Commercial software also uses a simplified pedestrian model, in which the pedestrian follows a given trajectory, also called trajectory-based model. The pedestrian does not interact with the environment and does not consider other agents in its movement. In CARLA Driving Simulation the default pedestrian, used to populate the scene, walks randomly without considering other agents, which also cannot be considered a realistic model of pedestrian behavior. There are also commercial models that use other methods and can be integrated into third-party software. One promising approach uses Machine Learning, where the model is trained based on real data to reproduce pedestrian behavior in a specific scenario [11]. The approach looks promising but faces some limitations regarding scalability, once for each new scenario the model needs to be trained again.

A novel approach models the human cognitive process and will be referred to in this paper as the cognitive behavior model. The model is based on studies of pedestrian behavior and movement and reproduces the cognitive decision-making process of humans. Since it is not based on a specific scenario, the model can be applied in different traffic situations.

NEURO-COGNITIVE PEDESTRIAN BEHAVIOR MODEL

The neuro-cognitive pedestrian behavior model developed by cogniBIT is based on the so-called cogniBOT system architecture, (see Figure 2). Pedestrian behavior in complex traffic situations results from a sequence of processes that take place in the central nervous system. The model divides this process into three major parts. The first stage of information processing is visual perception, representing how humans acquire information from their surroundings. The Cognition creates an internal representation of the outside world. Finally, in the motoric action stage a decision is made and translated into a desired trajectory and the corresponding control signals. These signals are fed back to a pedestrian locomotion model, resulting in a closed-loop interaction with the simulation environment.

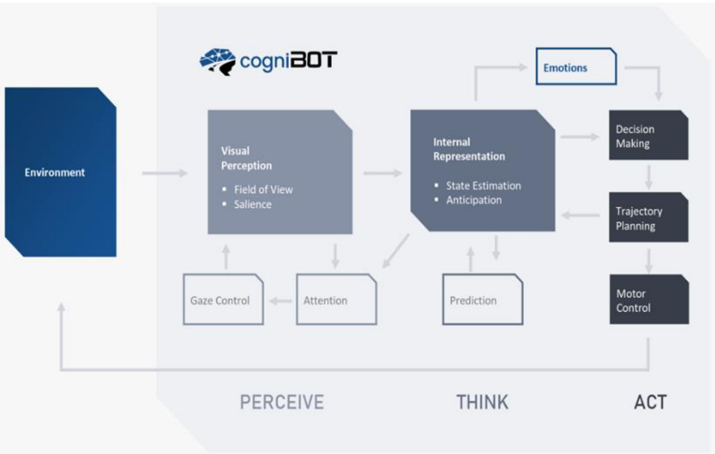


Figure 2. The cogniBOT neuro-cognitive system architecture.

The model considers different aspects of human sensorimotor information processing and their limitations focusing on the application in complex traffic situations.

Visual Perception

Sensory perception describes the intake of information from the environment, with the focus on visual perception in the simulation of traffic participants. The cogniBOT system architecture simulates relevant limitations of human road users, for example a restricted field of vision, which is compensated by eye movements. The simulated eye movements are controlled by a complex attention process that takes into account both top-down signals, such as the currently intended action, and bottom-up signals, for instance due to the recognition of other traffic participants in the peripheral field of vision.

Cognition

The information recorded in the perception modules is used to create an internal representation of the external world. Considering the objects that have been recognized, the cogniBOT AI architecture draws on previously identified information about the type, position and speed of other road users, as well as the internal map of the road course, to create a context-specific prediction from this information.

Motoric Action

The prediction of the situation forms the basis for decision making of the simulated traffic participant. For this purpose, the cogniBOT AI architecture implements a cost function that allows the simulated agent to make a trade-off for each traffic situation between speedy progress, distance to other road users, and the risk of an accident. Based on this decision, a desired trajectory is planned and translated into motor signals.

Emotions & Physiology

Human perception, cognition and action are under the influence of emotions and physiological states. Some emotions such as anger can lead to riskier behavior. These aspects are also considered within the model mainly through the behavior profile passed into the model.

Model usage
The user defines a starting position, a list of target destinations, initial and desired speed, and a behavior profile. It is possible to integrate a vehicle to be tested (VUT) or other external models of traffic participants into the simulation.

cogniBIT's models are stochastic as they simulate physiological processes such as perception and cognition which are probabilistic in nature. This allows automatic generation of variations of the same initial scene by different selection of the random seed. At the same time, cogniBIT's models are fully deterministic in the sense that exactly the same simulation results are reproduced when initial conditions and random seed are identical.

Behavior profile
Pedestrian behavior has many aspects that influences it, like age, emotional state and cultural background as internal aspects and traffic rules, surrounding traffic, road infrastructure and weather conditions as external ones. The behavior profile allows to define different types of behavior based on the intrinsic aspects, which in turn influence how the pedestrian interacts with his or her surroundings, the extrinsic aspects.

The behavior profile has five different parameters that can be defined by the user. The parameters are 'physical limitations', 'level of activity', 'rule adversity', 'cautiousness', and 'aggressivity'. Depending on the combination of these parameters, profiles ranging from very prudent and cautious to extremely risky and careless behavior can be generated.

Each parameter influences the pedestrian behavior differently. 'Physical limitations' simulates, for example, limitations caused by aging, handicap or intoxication and affects perceptive, cognitive, and motor skills. 'Level of activity' affects decision making and attention primarily. 'Rule adversity', along with 'cautiousness', are the parameters that most define pedestrian crossing behavior. Whereas the former defines the level of respecting traffic rules and signs, the latter rather refers to avoiding conflict situations with other traffic participants when jaywalking. The level of 'aggressivity' affects pedestrian-pedestrian interaction [15].

METHODS

The evaluation of ADAS and in vehicle safety system can be carried out in different ways. The method applied in this paper is based on [1], [20] and the ISO PDTR 21934 norm. The evaluation process consists of four main steps: (1) identification of the relevant traffic situations, (2) establishment of the baseline (3) establishment of the modified scenario, where the safety system is applied to the baseline and (4) the comparison of the results.

Relevant traffic situation
The relevant traffic situation represents the situation of interest where the application of the safety system could potentially be beneficial. According to ISO PDTR 21934, such situations can be derived from crash data analysis, naturalistic driving studies or from previous knowledge from technology development. As the focus of this paper is to evaluate the performance of the AEB-P system, scenarios involving the pedestrian were considered as relevant ones. The tests applied by Euro NCAP are already derived from crash data analysis, so the scenario chosen in this paper is also based on the Euro NCAP tests. Using the ISO PDTR 21934 nomenclature, the relevant scenario for this paper is **S**traight **C**rossing **P**ath, **p**edestrian from **r**ight (SCPpr), where the car is moving forward, and the pedestrian is crossing the path from right.

Figure 3 represents the baseline scenario. The road has two lanes and at one end, on the right side of the pedestrians' starting position, a signalized cross-section.

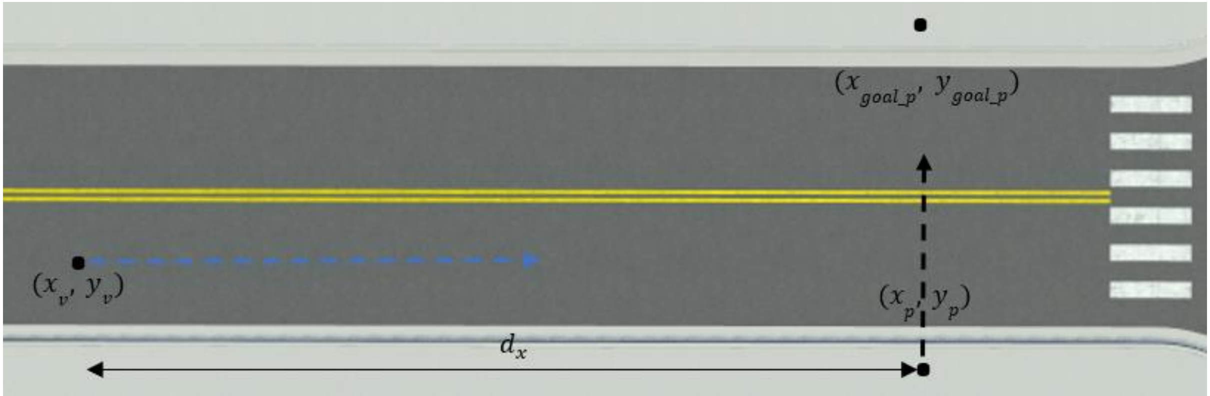


Figure 3. Relevant traffic situation.

(x_v, y_v) is the vehicle start position, (x_p, y_p) the pedestrian start position and (x_{goal_p}, y_{goal_p}) the pedestrian goal destination. The black dashed line indicates the direction of the pedestrian's movement. And the blue dashed line indicates the direction of movement of the vehicle. The distance between vehicle and pedestrian, d_x ,which was varied for the generation of the scenarios, is the distance in the x direction (see Equation 1).

$d_x = x_p - x_v$ Equation (1)

Baseline scenario
To generate the baseline scenarios, it is necessary to define the road infrastructure, as well as the number and type of road users, their starting speeds, and the vehicle trajectory. Following a similar approach as presented in [20] a parameter called 'initial vehicle waiting time' was implemented. By varying these three parameters in a virtual environment the baseline scenarios were generated. The parameters used and their distribution are listed in Table 1.

Table 1.
Baseline Scenario Input Parameters

Input name	**value**	**step**	**unit**
Vehicle speed	[10, 60]	5	km/h
Distance between vehicle and pedestrian	[10, 30]	5	m
Vehicle waiting time	[0.0, 1.0]	0.5	s

For a specific pedestrian behavior profile, 165 baseline scenarios were generated. In contrast to [20] the pedestrian trajectory was not predefined. Based on the pre-defined behavior profile and the specific situation, the neuro-cognitive pedestrian behavior model chooses a trajectory to reach the destination goal. The vehicle moves on a predefined trajectory.

Modified scenario
The modified situation is the baseline scenario, but with an AEB-P equipped vehicle. The AEB-P module contains two parts, an ideal sensor defined by a field of view and perception algorithm, and the braking module defined by time to collision (TTC), pedestrian detection status and braking profile. The used settings for the field of view are in Table 2, (see Figure 4). When the pedestrian enters the field of view, the TTC is calculated (see equation 2).

$TTC = \; |\vec{r}_{rel}|/|\vec{v}_{rel}|$ Equation (2)
$\vec{v}_{rel} \coloneqq \vec{v}_{car} - \vec{v}_{ped}$ Equation (3)
$\vec{r}_{rel} \coloneqq \vec{r}_{ped} - \vec{r}_{car}$ Equation (4)

Where the $\vec{v}_{rel}$ represents the relative speed between vehicle and pedestrian, and $\vec{r}_{rel}$ the relative position, [11]. When the TTC is less than or equal to 1 s, the vehicle starts braking following the defined braking profile, (see Figure 5 and Table 3).

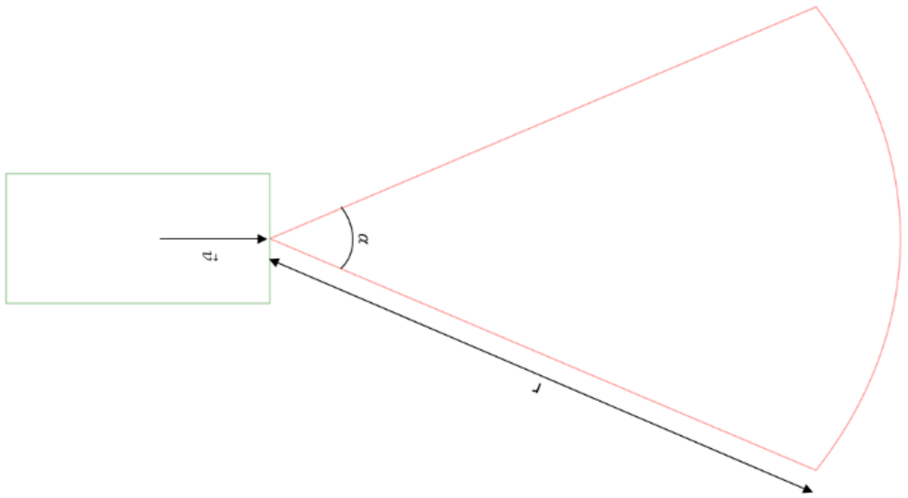


Figure 4. AEB Field of View [11].

Table 2.
Field of view parameters

Parameter	Value	Unit
Azimuth angle (α)	60	°
Range (r)	60	m

The braking profile used here is similar as in [20], (see Figure 4). It is divided into three parts: system delay, build up time, the time needed for full brake. During build up time the deceleration increases linearly over time.

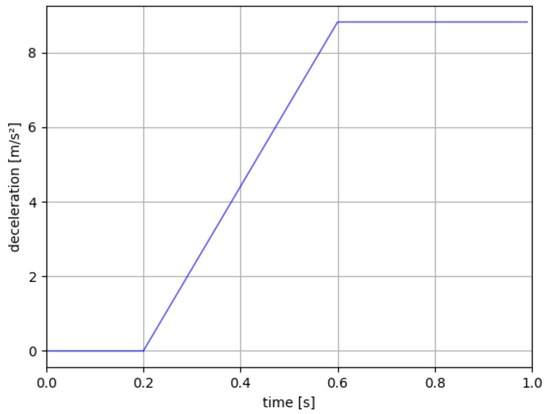


Figure 5. AEB Braking profile.

Table 3.
Braking profile settings

Parameter	Value	Unit
Delay	0.2	s
Build up time	0.4	s
Maximal deceleration	0.9	g

Safety Assessment
After simulating the baseline scenarios and the modified scenarios with the AEB-P system, the results were compared. The metric used in this paper is the reduction in frontal collision cases due to the AEB-P system. Figure 6 shows an overview of the process.

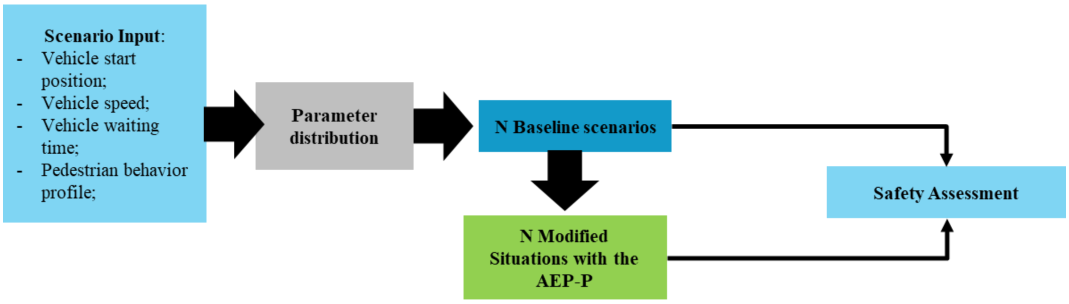


Figure 6. Safety Assessment approach.

Simulation Environment

The choice of the platform used in this paper was based mainly on the integration with the pedestrian behavior model, support to OpenDrive file format and the quality of the 3D model, relevant for future studies. Therefore, open-source programs were prioritized. This paper uses the CARLA (Car Learning to Act) Driving Simulator platform, an open-source software built on top of Unreal Engine 4 (UE4) for autonomous car research, [9]. In CARLA vehicle dynamics is modeled using the standard UE4 vehicle model, PhysXVehicles, which is focused on the gaming market and is limited when compared to specific vehicle modeling software. But for the purpose of this paper, the model was sufficient.

RESULTS

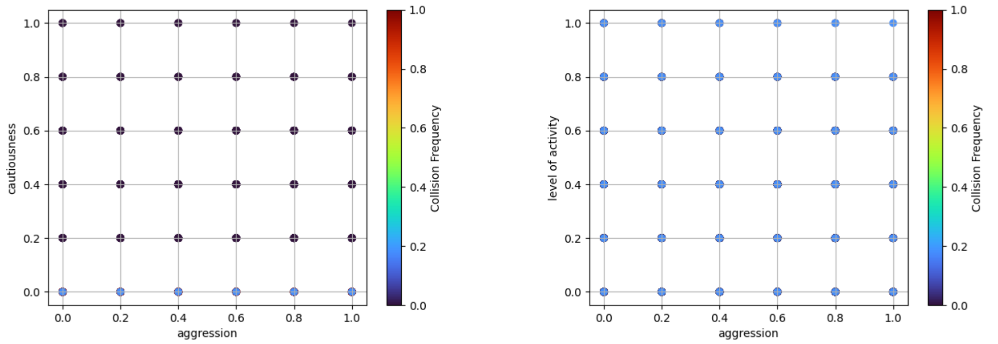
Pedestrian Behavior model parameter analysis

Different combinations of the parameters were evaluated in pairs in the scenario used to evaluate the AEB-P system in this paper. The parameters which were not being varied had the default value of 0. The evaluated parameters were varied with a step of 0.2, from 0 to 1. The initial conditions of the scenario are listed in Table 4.

Table 4.
Initial condition by the simulation for the behavior profile evaluation

Parameter	Value	Unit
Vehicle initial speed	4	m/s
Vehicle goal speed	10	m/s
Distance to pedestrian	12	m

Each combination of parameters was simulated with eleven different random seeds. The results were evaluated considering whether the pedestrian had a collision with the vehicle or not. For the second case there are two possible reasons, either the pedestrian waited at the curb for the vehicle to pass or the pedestrian managed to cross the road without being hit by the vehicle. The results were plotted on the diagrams present in figure 7. Each point has a color ranging from blue to red. The results for seed 1, which was used in the study of the AEB-P system, are available in appendices.



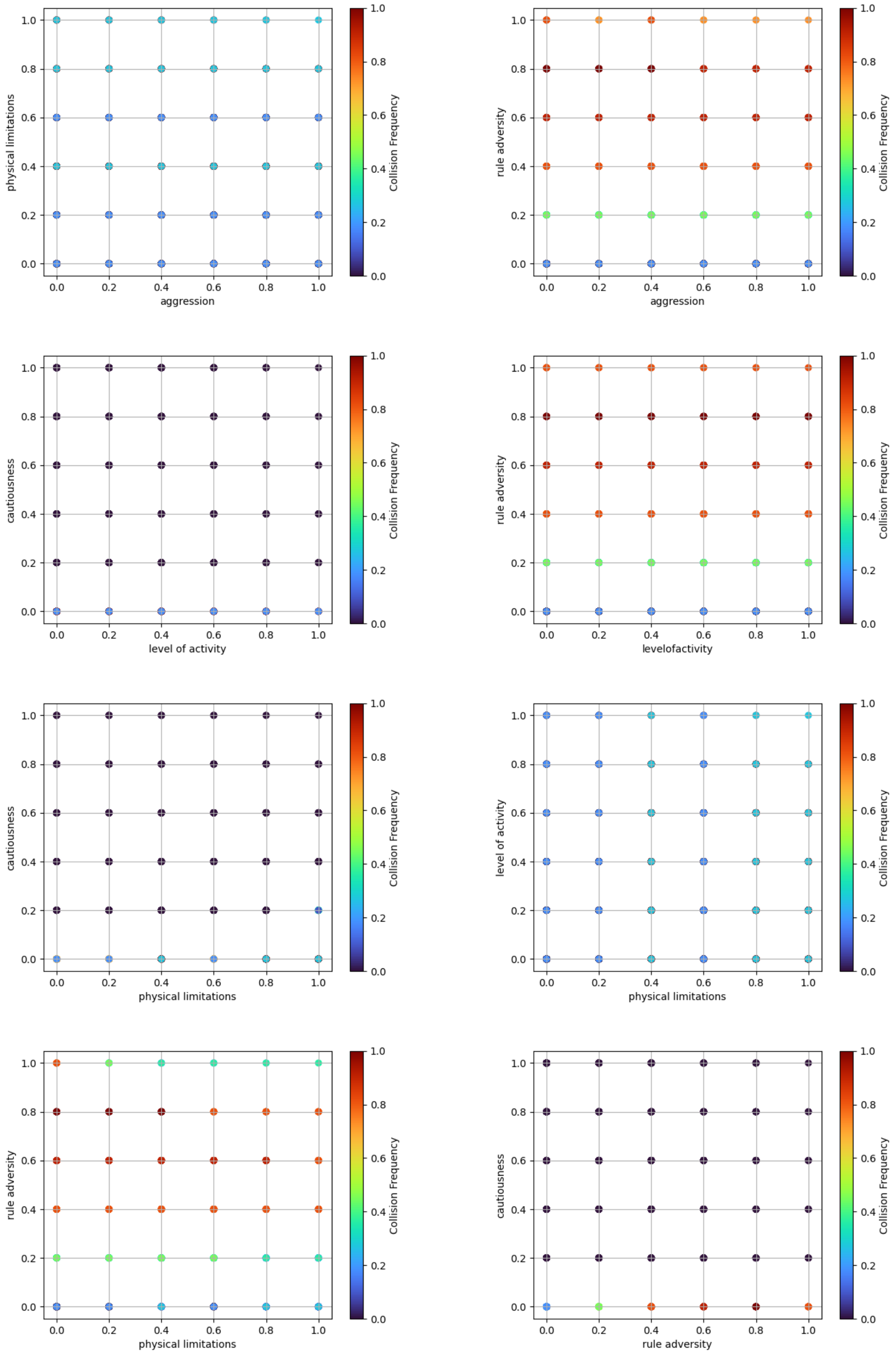


Figure 7. Pedestrian behavior profile parameter analyses. Dark blue means that in all cases the pedestrian was not hit by the vehicle, value of 0 on the scale, and dark red means that in all case there was a collision between the pedestrian and the vehicle, a value of 1 on the scale.

As was to be expected, the parameters "rule adversity" together with "cautiousness" were the parameters with the greatest influence on collision rate. With rule adversity greater than or equal to 0.4, in all cases (rule adversity vs physical limitation, rule adversity vs level of activity, rule adversity vs aggression) there were collisions between pedestrian and vehicle, once the pedestrian tried to cross the road without waiting at the curb. With “cautiousness” greater than 0.0 the pedestrian tends to wait at the curb, so in the cautiousness vs rule adversity graph, for cautiousness values above 0.2 there were no collisions. A cautious behavior profile also led the pedestrian to cross at designated cross-sections.

Another parameter with greater relevance is physical limitations. The presence of light blue dots was observed for values of physical limitations higher than 0.4, indicating that in some seeds there was a collision, see the diagrams physical limitations vs aggression, level of activity vs physical limitations and cautiousness vs physical limitations. In these cases, the pedestrian chose to cross the road before the vehicle passed, but slowly due to the higher "physical limitations". In other seeds the pedestrian opted to wait at the curb, avoiding the collision.

The combination cautiousness = 0.0, rule adversity = 1.0, physical limitations=1.0, aggression = 1.0 and level of activity = 1.0 is the combination that leads to the riskiest behavior in the analyzed scenario and was used in the simulations to evaluate the AEB-P.

Using this setting, the neuro-cognitive model presented either one of the following behavioral patterns:

1. walk to the curb, wait, and walk or run across the road in front of the vehicle.
2. walk to the curb, wait, and walk or run across the road after the vehicle has passed.
3. cross the road without waiting at the curb.

In none of the above cases did the pedestrian use the crosswalk when crossing the road.

Performance assessment of the AEB-P system

A total of 165 cases were simulated, varying the initial distance between vehicle and pedestrian, vehicle initial speed, and vehicle waiting time. In 16 cases frontal collisions between vehicle and pedestrian occurred, which represents 9,7% of all cases. Of these 16 cases, 3 were prevented by the AEB-P system, which represents a reduction of 18.8%.

The avoided collisions can be divided into two groups. In two cases the vehicle was able to stop completely and therefore avoided the collision. In 1 case, with the application of AEB-P, the vehicle reduced its speed, giving the pedestrian enough time to leave the conflict region before colliding with the vehicle.

DISCUSSION

In [20] the application of an AEB-P system reduced the collision rate by was 24.1%. In that study, however, the braking profile had a larger maximum deceleration of 7 m/s^2 and a longer delay of 0.25 s. Other studies found collision reduction values ranging from 20% to above 50% [20], when using different approaches and virtual environments. [11] used a machine learning based pedestrian behavior model and found values between 19.4% to 38.8%, depending on the braking profile. The performance of 18.8% is slightly lower compared to previous results. However, this finding is unlikely to represent a significant difference due to the low number of positive test cases. Assuming that by using the neuro-cognitive model more valid simulation results are produced, the observed difference might indicate a lower performance of the AEB-P system in real life situations in comparison to previous simulations results.

In contrast to previous studies, the neuro-cognitive pedestrian model varied the road crossing path as well as the walking speed, and often waited at the curb before crossing. The high value in behavioral variation has probably led to more false-negative assessments of the AEB-P system than in previous studies, where the pedestrian usually crossed the road in straight line without speed adjustment or waiting.

The model also produced situations of a false-positive activation of the AEB-P system. In these cases, the system was activated by mistake as the pedestrian was just standing at the curb waiting. Such a situation is not atypical in everyday life, and activation of the system in these situations can lead to a low acceptance of the system by consumers. It therefore becomes obvious that active safety needs to interpret and predict the pedestrian's intentions in such situations.

[18] analyzed pedestrian crossing behavior on different road infrastructure (number of lanes, designated and non-designated cross-sections), weather conditions, and gap between pedestrian and vehicle. The main pedestrian reactions to the approaching vehicle were “stop”, “clear path”, “slow down”, “speed up”, “hand gesture” and “nod”. “Stop” and “clear path” behaviors can be considered as cautious collision avoidance

strategies, and while "speed up" is representing greater rule compliance. Both behaviors were observed on the neuro-cognitive behavior model. “Hand gesture” and “nod” represents explicit communication between pedestrian and vehicle and are not yet implemented in the model. A “step-back” behavior was disabled due to limitations of the avatar in the simulation environment to handle it.

CONCLUSIONS AND FUTURE WORK

This paper aimed to evaluate the performance of a generic AEB-P system using the cogniBIT's neuro-cognitive pedestrian behavior model. The novel model is able to reproduce more complex behaviors with less effort than the conventional trajectory-based models, commonly used in commercial tools.

Of course, the study presented does not represent a complete evaluation of the neuro-cognitive pedestrian model. A more in-depth analysis evaluating for instance trajectories, gaze patterns, interactions should be considered in the future. The neuro-cognitive model in its current implementation is able to generate realistic pedestrian road crossing scenarios, but still limited in the types of pedestrian-vehicle interaction. By adding explicit and implicit communication mechanisms on both sides, pedestrians and driver [18] this limitation can be removed in the future.

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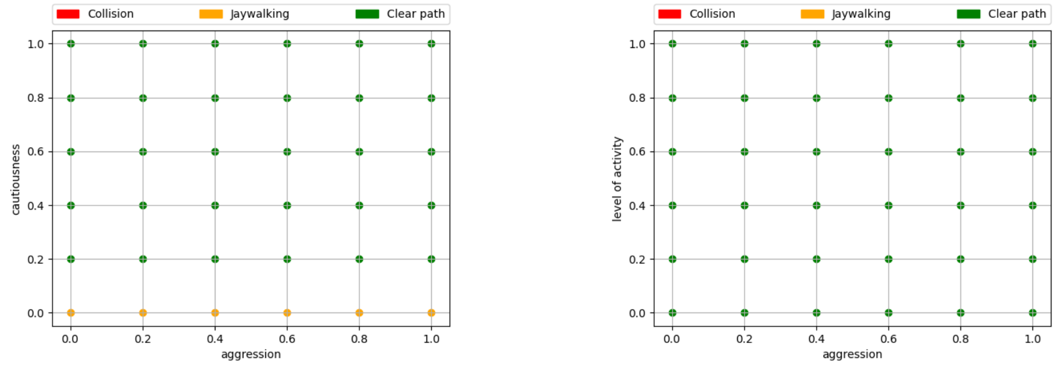
APPENDICES

Behavior profile parameter analysis results for seed with a value of 1. The parameters that were not being varied had the default value of 0.



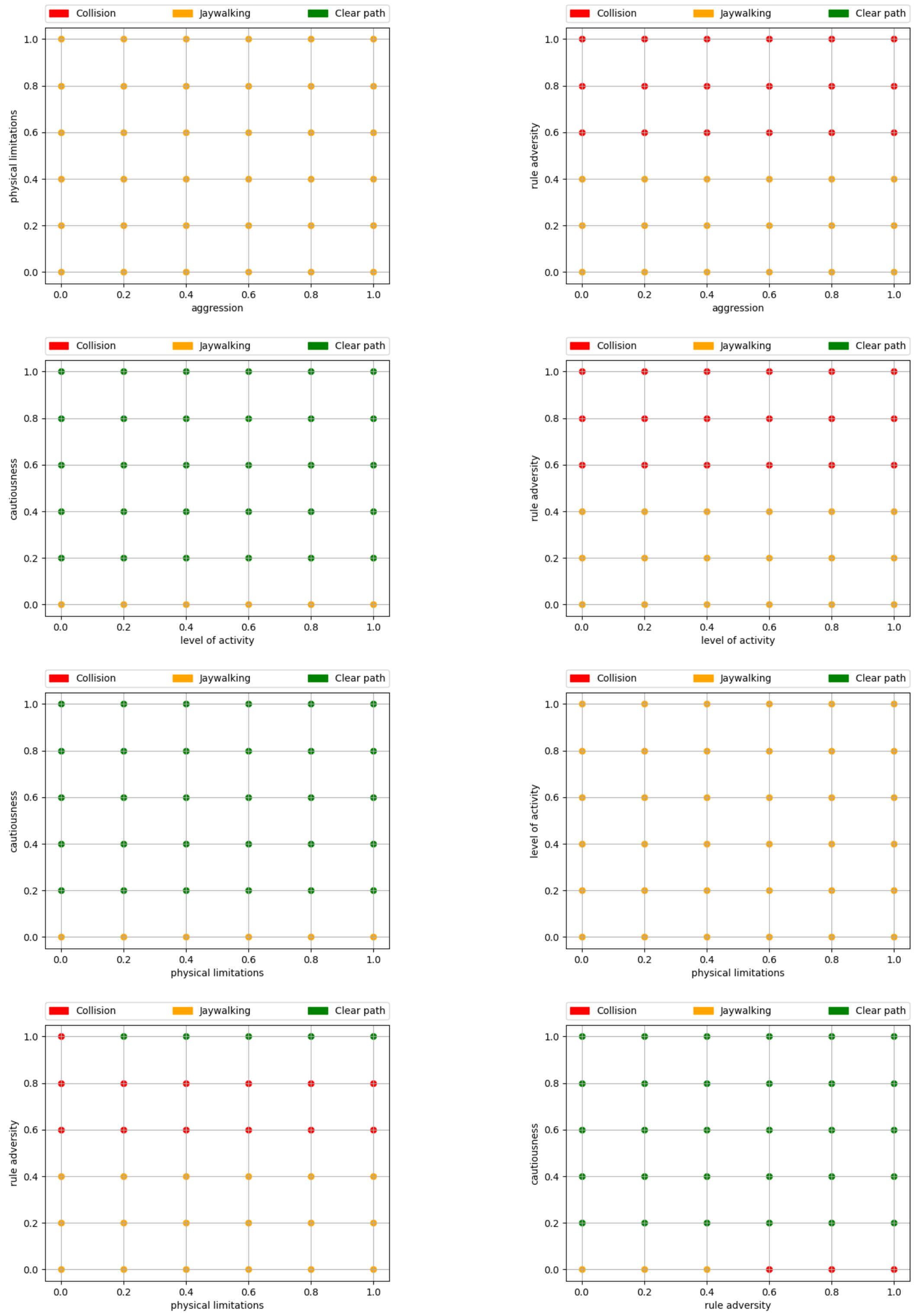


Figure 8. Pedestrian behavior profile parameter analyses. Green means that the pedestrian waited the vehicle to pass, orange means the pedestrian tries to cross the road and reaches the other side of road without being hit by the vehicle and red means that there was a collision between the pedestrian and the vehicle.