A Literature Review on Techniques for Describing and Modelling the Interaction Between Automated Vehicles and Pedestrians

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Abstract. The safety of vulnerable road users consists a major pilar in the transportation field when designing, planning and managing transportation systems and road infrastructure. As automated vehicles are already on the streets and we are heading towards highly and fully autonomous vehicles, the safe coexistence between these vehicles and vulnerable road users is urgent. Numerous studies have dealt with these issues and various methods have been developed and implemented for analyzing the interaction between vehicles and pedestrians, particularly, as well as evaluating these interactions. Scope of this paper is to present the findings of an extensive literature review summarizing existing techniques for describing and modelling the interaction between automated vehicles and pedestrians applying artificial intelligence and machine learning techiques.

Keywords: automated vehicles, pedestrians, artificial intelligence, machine learning.

1 Introduction

The advent of autonomous vehicles creates the need to observe and model the behaviour of the 'machine - driver', consisting of various sensors exchanging information and acting according to the road context. One of the main challenges of automation is the urgent need to handle and process a huge amount of available data transmitting form the vehicles. Artificial Intelligence (AI) and Machine Learning (ML) techniques and algorithms have been developed to fulfil this need towards more reliable and advanced behavioral models and understand deeper the dynamic characteristics governing the interaction of the equipped vehicles with the other road suers. Existing research is mainly focusing on the interaction between vehicles and their surrounding vehicular traffic while the investigation of the interaction of autonomous vehicles with other road users is still in its infancy.

The interaction between automated vehicles (AVs) and pedestrians constitutes one of the most critical challenges in the transition toward fully autonomous transportation systems. Unlike interactions between vehicles, pedestrian behaviour is inherently uncertain, highly variable, and strongly influenced by contextual, psychological, and environmental factors. Pedestrians may change direction or speed abruptly, hesitate before crossing, or engage in risky behaviours such as jaywalking, making their actions difficult to predict and model accurately.

This unpredictability poses significant challenges for automated driving systems, which rely on sensor data and decision-making algorithms to ensure safe navigation. While AVs are designed to operate based on predefined rules and learned patterns, pedestrians often do not strictly follow traffic regulations and may behave differently depending on situational conditions such as traffic density, visibility, infrastructure design, and social interactions. As a result, ensuring safe and efficient coexistence between AVs and pedestrians requires a deep understanding of these complex interaction dynamics.

Moreover, the increasing presence of AVs in urban environments introduces additional layers of complexity, including communication between vehicles and pedestrians, either implicitly through vehicle motion or explicitly through external human–machine interfaces. Misinterpretation of vehicle intentions by pedestrians, or vice versa, may lead to unsafe situations, particularly in unstructured environments such as mid-block crossings or shared spaces.

These challenges highlight the importance of developing advanced modelling approaches capable of capturing both the physical and behavioural aspects of vehicle–pedestrian interactions. In this context, AI and ML techniques have emerged as powerful tools for analysing large-scale data, identifying behavioural patterns, and improving prediction and decision-making processes. A comprehensive understanding of these methods and their applications is therefore essential for advancing the safety and reliability of automated transportation systems.

2 Methodology

This study is based on a structured literature review aiming to identify and analyse existing AI and ML techniques applied to modelling interactions between automated vehicles and pedestrians.

The literature search was conducted using major scientific databases, including Scopus, Web of Science, and Google Scholar. A combination of keywords was used to retrieve relevant studies, including “automated vehicles”, “autonomous vehicles”, “pedestrians”, “vehicle–pedestrian interaction”, “machine learning”, “artificial intelligence”, “reinforcement learning”, and “trajectory prediction”. The search focused primarily on studies published in the last decade, while earlier seminal works were also included where relevant.

The selection of studies was based on specific inclusion criteria. Papers were included if they: (i) focused on modelling interactions between pedestrians and automated or autonomous vehicles, (ii) applied AI or ML techniques, and (iii) provided sufficient methodological detail regarding the modelling approach. Studies focusing exclusively on vehicle-to-vehicle interactions or lacking relevance to pedestrian behaviour were excluded.

In total, a broad set of studies was reviewed, covering various modelling approaches such as reinforcement learning, deep learning, inverse reinforcement learning, and multi-agent systems. Both simulation-based and real-world data studies were considered to capture the diversity of existing methodologies.

The selected studies were analysed and categorized according to the type of modelling approach, the interaction context (e.g., intersections, shared spaces), and the type of data used (e.g., real-world observations, simulation environments). This structured approach enabled the identification of key trends, methodological differences, and research gaps in the field. It should be noted that, despite efforts to ensure comprehensive coverage, the review may be limited by the availability of published studies and the selection of databases and keywords.

3 Modelling Pedestrians' and Automated Vehicles' Behaviour while Interacting

Vulnerable road users will be highly affected by the advent of automated vehicles and their interactions can lead to unsafe situations as the behaviour of VRUs is highly unexpected or the behaviour of the AV could be misinterpreted by the VRU. Till now, most studies include field tests [1, 2] or virtual experiments [3, 4] for observing these interactions and extract parameters describing the kinematic characteristics of the two agents. Additionally, various experiments have been conducted for investigating which types of communication displays (text, sound, etc) are the most suitable and preferable by pedestrians when they interact with AVs and can ensure safe pedestrian crossing [5-9]. When it comes to modelling the behaviour of vehicles and pedestrians during their interaction, the complex systems of the equipped vehicles and the unpredictable behavioural patterns of pedestrians impose the need of advanced models and techniques. In various studies, traditional behavioural models have been implemented and existing models have been parametrized to resemble the behaviour of an automated vehicle [10]. AI and ML applications are bringing about significant changes in this field.

Data driven methods are gaining increasing attention as they are more flexible than the traditional behavioural models and can easily be adapted to any data source and environment as well as reveal patterns ad profiles that other methods and algorithms fail to. Deep survival analysis models and more specifically a deep – neural network CHP model was applied in [11] for estimating pedestrian waiting time before starting crossing the road when an autonomous vehicle is approaching at an unsignalized crosswalk under different vehicles' levels of automation and arrival rates, road types, lane widths, time of the day and weather conditions. the off the sidewalk predictions (OSP), a probabilistic model, used for pedestrian – vehicle interactions in shared spaces [12]. [13] tried to express the interaction between a vehicle and an approaching pedestrian aims to cross an unsignalized intersection through a Markov Decision Process model. The authors are focusing on simulating an autonomous vehicle' behaviour resembling human controlled vehicle dynamic that would react appropriately to pedestrian movements and behaviour changes so that the vehicle would avoid any collision. The reward function penalized vehicles for entering the crosswalk area simultaneously with pedestrians.

Deep reinforcement learning principles have been applied for activating autonomous braking in risky situations [14] or predicting pedestrian trajectories [15], or assisting autonomous vehicles in planning their trajectories at intersections where they coexist with other road users, i.e. vehicles, pedestrians and cyclists. In the last case, the developed model resulted in safer driving trajectories, increased driving comfort and energy savings while the trajectories planned for a 5s horizon outperformed human driven ones. A deep Q Learning RL model was developed by Fridman et al. [16] for controlling an autonomous vehicle taking into consideration its interactions with other vehicles and pedestrians. The principles of maximum entropy were also used for developing a model for predicting pedestrian behaviour using continuous trajectories recorded in a real – world experiment [17]. The proposed model outperformed the social forces method and was then integrated in a mobile robot, which interacted successfully with humans. An autonomous braking system based on deep reinforcement principles was proposed in Charlton et al. [18] for controlling and adjusting vehicle speed in critical situations and especially in urban environments where a vehicle faces a crossing pedestrian. The state space of the vehicle is described by its speed and its distance from the pedestrian, while the action space depends on the value of its deceleration. The system was tested through computer simulations which revealed the good and consistent braking behaviour of the vehicle under different scenarios.

LSTM was combined also with a Deep Q-Network for modelling decisions of an autonomous vehicle in urban environments in the presence of pedestrians ay unsignalized crosswalks and jaywalking. The model was trained in CARLA simulator and the comparison with a rule – based model revealed its effectiveness and higher performance. One year later, the same research team developed a multi-objective deep reinforcement learning for assisting autonomous navigation in urban environments [19]. The results from their simulator revealed the better performance of the new approach compared to the single objective RL proposed in their previous work [20]. Vasquez et al. [21] used reinforcement learning principles for developing a safe speed function to assist an autonomous driving system when interacting with a distracted pedestrian aiming to ensure that the machine will successfully perform emergency braking maneuvers. The novelty of this approach is the fact that the capabilities of the autonomous diving are combined with a separate safe speed neural network, meaning that the cognitive abilities of the vehicle are extended and further improved for the case of an unpredicted and risky pedestrian reaction. The model integrated in a real test vehicle and interacted with emulated pedestrians performed successfully in the scenarios conducted on a real test track.

Inverse reinforcement learning (IRL) is also a very valuable tool in modelling vehicle and pedestrian behaviours when interacting with each other. A continuous Gaussian IRL was implemented for describing pedestrian behaviour using trajectories from a signalized intersection in China [22]. After estimating the pedestrian reward function, the Advantage Actor-Critic DRL method (A2C) was applied for revealing pedestrian policies and then for extracting pedestrian trajectories. The simulate trajectories revealed the high accuracy and good performance of the proposed model when compared with the real ones.

Pedestrian group behaviour and navigation strategies have also been investigated through reinforcement learning techniques. Focusing on pedestrians, inverse reinforcement algorithm and maximum causal entropy principles have been applied for learning their behaviour from real trajectories when navigating in a virtual 3D environment and predict trustworthy trajectories [23]. The results revealed the model effectiveness and its ability to adequately depict the pedestrian dynamics and its motion features and principles. Focusing also only on pedestrian behaviour, Merat et al. [24] developed a multi – agent reinforcement learning based framework for simulating pedestrian behaviour and navigation strategy in a virtual environment. In the three scenarios tested, i.e. election of the shortest path vs. quickest path, crossing between two groups of pedestrians walking in opposite directions inside a narrow corridor and two agents that move in opposite directions inside a maze, the proposed simulation approach succeeded in learning behaviours and policies that resemble pedestrians in all levels (strategical, tactical and functional) effectively and similarly to the traditional Helbing's social force model.

Apart from single agent algorithms maximizing the reward and optimize the behaviour of one of the interacting agents (vehicle or pedestrian), multi agent techniques are considered to be more realistic and accurate as they take into consideration the interacting behaviours of the users aiming to optimize both policies and maximize both reward functions. Wang et al. [25] proposed a deep multi agent reinforcement learning algorithm (DMARL) for modelling the behaviour of a pedestrian aiming to cross the road and an approaching autonomous vehicle at an unmarked crosswalk in a simulated driving scenario. A similar study was conducted by Rothenbücher et al. [26] applying Adversarial Inverse Reinforcement Learning for recovering the reward functions of the vehicle and the pedestrian while their policies where further optimized using multiagent Actor-Critic deep-reinforcement-learning.

The study of Kalatian et al. [27] focused on autonomous and manual vehicles and their interaction with pedestrians on unsignalized intersections using multi-agent deep deterministic policy gradient (MADDPG) algorithm. The results showed that the proposed algorithm outperformed single agent DDPG and DRL considering the reward score of all agents and its fluctuation. The addition of LSTM in the MADDPG algorithm resulted in a multi agent recurrent deep deterministic policy gradient algorithm applied for traffic light control at multiple urban intersections where vehicle and crossing pedestrians are interacting with each other. Apart from vehicles and pedestrians, the authors also include buses giving them higher priority to pass than the regular vehicles. The proposed algorithm succeeded in optimizing each traffic light control policy to achieve the highest reward and optimal decisions in the whole analyzed network as well as performing well in complicated road conditions and in an unstable external environment.

4 Discussion

While the reviewed studies highlight the strong potential of AI and ML techniques for modelling vehicle–pedestrian interactions, several important limitations remain. A key issue is the extensive reliance on simulated and synthetic data, which, although useful for controlled experimentation, often fails to capture the complexity, variability, and unpredictability of real-world conditions. This limits the generalizability of models when applied to real traffic environments characterized by behavioural uncertainty, environmental noise, and unstructured scenarios.

Different AI and ML approaches also present distinct strengths and challenges. Reinforcement learning methods are effective for modelling adaptive decision-making but require large datasets and careful reward design, while deep learning techniques can capture complex patterns but often lack interpretability, raising concerns for safety-critical applications. Multi-agent models provide more realistic interaction representations but introduce increased computational complexity and scalability challenges. Additionally, accurately modelling pedestrian behaviour remains difficult due to its dependence on cognitive, social, and contextual factors.

Another critical challenge is the transition from simulation to real-world deployment. Addressing this gap requires the integration of high-quality real-world data, such as trajectory datasets and naturalistic observations. However, data collection remains complex due to cost, privacy, and technical constraints, often relying on methods such as video analysis, LiDAR, and sensor-based systems.

Finally, the influence of road infrastructure and environmental conditions is often underexplored. Factors such as urban versus rural settings, traffic density, weather, and lighting conditions significantly affect both pedestrian behaviour and model performance, further challenging model robustness. Future research should therefore focus on developing context-aware and interpretable models, leveraging hybrid approaches that combine real-world and simulated data, and creating diverse datasets that better reflect real-world variability.

5 Conclusions

The era of autonomous vehicles imposes the need of their safe coexistence with their surrounding traffic and mostly with pedestrians and other vulnerable road users. Modelling the behaviour of automated vehicles and pedestrians when interacting in various types of intersections is not an emerging field; it is continuously enriched with more advanced methods and techniques as the amount of data is also rapidly increasing. This work attempted to enlighten this issue by analyzing existing literature and various methods developed and applied for modelling the interaction between these two agents based on machine learning and artificial intelligent techniques.

The shortcomings and advantages of each method can be served as a valuable tool for researchers aiming to further analyze this type of interaction and contribute to increase the safety levels for pedestrians when an automated vehicle is approaching. The review revealed the lack of availability of real automated and autonomous vehicle trajectory data as most of the studies use simulated generated data or data from driving simulators and virtual reality experiments. Finally, there is limited research on studying and investigating vehicle behaviour during their interaction with pedestrians at random locations where human decide unpredictably to cross deteriorating the safety levels.

6 References

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