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Identifying the Automated Vehicle's Driving Policy in the Vicinity of Pedestrians

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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. Existing research mainly focuses on interaction their interaction with the surrounding vehicular traffic. On the other hand, modelling the interaction of autonomous vehicles with vulnerable road users gradually gains increasing attraction due to its safety implications.

STATE AND ACTION DEFINITION

POSTER SESSION

12 states are defined based on k- means clustering of driving behaviour as a function of vehicle speed, speed difference of the vehicle with the pedestrian and their spatial gap (Table 1). For the action space (Table 1), we consider acceleration as the critical value to define the manner a driver / AV will react to an external states and Actions Identified

OBJECTIVES

This work aims to enrich existing research by modelling the behaviour of an automated vehicle when it interacts with a pedestrian with the intention to cross the road. For this purpose, vehicle and pedestrian trajectories from a virtual experiment are analyzed and the principles of inverse reinforcement learning are used for developing the model.

DATA COLLECTION

The data are collected through a virtual reality experiment, led by FZI Research Centre for Information Technology, which took place in Karlsruhe, Germany. In these experiments, a human expert immersed into the scene via a virtual reality (VR) headset as a pedestrian with the aim of crossing the road. At the same time, a simulated vehicle was approaching from the left, and it was either controlled by a human using a steering wheel and pedals or by a highly automated driving function.





States				Actions	
	Vehicle Speed	Speed Difference	Spatial Gap		Value
1	(0.005, 10.60)	(0.004, 10.50)	(4.20, 11.80)	Cruising	
2	[10.60, 25.20)	[10.50, 25.40)	[11.80, 19.50)	Smooth acceleration	(0, 1.57]
3			[19.50, 33.10)	Harsh acceleration	(1.57, 4.5]
4				Smooth deceleration	[-1.57, 0)
5				Harsh deceleration	[-9, -1.57)

RESULTS

States including vehicle speed of level 1 give higher reward indicating that the vehicle decelerates when the pedestrian appears and starts moving tending to cross the road. Concerning the spatial gap, the highest reward value is observed for level 3, corresponding to higher distance values between the two agents. Finally, as far as the speed difference is concerned, it seems that even though drivers decelerate in the vicinity of a pedestrian, they do not prefer to apply maximum deceleration but to keep a reasonable speed.



Figure 2: Driver's and pedestrian's views in the VR experiment

CONCLUSIONS

The present work is a preliminary attempt towards the study and modelling of the behaviour of an equipped vehicle that will ensure safe interaction with vulnerable road users and improve safety in every spot where a pedestrian could unexpectedly try to cross the road. The proposed model can be further improved with additional data, collected from the virtual experiment or data from real trajectories collected in real infrastructure pilots.

Figure 1: Driver's and pedestrian's views in the VR experiment

The data, collected every 100ms, include the position of the two agents, their speed and acceleration in the two axes, the time and spatial headway as well the lateral position of the vehicle from the central axis of the lane.

METHODOLOGY

Maximum Entropy Inverse Reinforcement Learning is used for modelling the vehicle behaviour when a pedestrian intends to cross the road, starting from the sidewalk. This algorithm assumes optimum behaviour and the optimum policy is considered to be extracted by the given n trajectories of an expert which are a sequence of states s and actions a. Each trajectory has a temporal horizon of h steps.

 $T = \left\{ (s_1^1, a_1^1), (s_2^1, a_2^1), \dots, (s_h^1, a_h^1), (s_1^2, a_1^2), (s_2^2, a_2^2), \dots, (s_h^2, a_h^2), \dots, (s_1^n, a_1^n), (s_2^n, a_2^n), \dots, (s_h^n, a_h^n) \right\}$

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