Game Theoretic Analysis of Road User Safety Scenarios Involving Autonomous Vehicles

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***Abstract*—Interactions between pedestrians, cyclists, and human-driven vehicles have become a major concern for traffic safety over the years. The upcoming age of autonomous vehicles will further raise major problems on whether self-driving cars can accurately avoid accidents; on the other hand, usability issues arise on whether human-driven cars and pedestrians can dominate the road at the expense of the autonomous vehicles that will be programmed to avoid accidents. This paper proposes some game theoretical models applied to traffic scenarios, where the strategic interaction between a pedestrian and an autonomous vehicle is analyzed. The games have been simulated to demonstrate the theoretical analysis and the predicted behaviors. These investigations can shed new lights on how urban traffic regulations and inter-vehicle communications could be required to allow for a general improved management of traffic in the presence of autonomous vehicles.**

I. Introduction

Smart connected machines are expected to be one of the most sensational innovations developed over the next ten years. Present-day technologies benefit from the computational improvement of processors and the data collection ability of smart sensors, as well as the empowerment of machine learning techniques such as deep neural networks.

In the European Union alone, more than 25 thousand deaths in road accidents happen every year [1]. Autonomous vehicles (AVs) are expected to significantly reduce road accidents, since they can be less error-prone than human drivers and are designed to avoid unnecessary risks. Still, the human factor will be present in the interaction with pedestrians. Thus, besides being risk averse per se, connected vehicles should implement additional mechanisms; for example, they might notify their presence to distracted pedestrians [2], [3].

An open challenge still involves the description of scenarios where human drivers and AVs, as well as pedestrians and cyclists, will coexist. Many studies have been proposed in the literature to investigate these aspects. An interesting survey of future transport systems can be found, e.g., in [4], whose predictions gained momentum thanks to divulgative versions such as [5]. Specifically, the idea of [4] is to build up a two-player game between a pedestrian crossing a street and a (possibly self-driven) vehicle reaching the pedestrian crossing. The actions of the players in face of a possible collision are either to keep moving in the intended direction or to yield. The analysis concludes that pedestrians will be unsure on whether to cross or yield if they assume that the incoming vehicle is human-driven, but they will more boldly cross the street in front of an AV, relying on it to stop. Thus, pedestrians might achieve supremacy over the AVs and it may be necessary to regulate the traffic response.

Inspired by this issue, we study road scenarios involving pedestrians and vehicles but expanding the point of view and implementing more sophisticated game theory techniques. We derive these conclusions that are also verified by simulation. First, we discuss the impact of the increase in the share of vehicles that are autonomously driven in a classic scenario involving a pedestrian/cyclist crossing a street and an incoming vehicle. Beyond concluding that pedestrian and cyclists will eventually get control of the road over the AVs, we provide a quantitative evaluation of this phenomenon, also related to the occurrence of accidents caused by the false sense of security induced by AVs becoming more and more common. Furthermore, we analyze the behavior of pedestrians in a more detailed situation where they can decide whether or not to cross, involving different parameters settings.

The remainder of this paper is organized as follows. Section II reviews the applications of game theory to road user problems already existing in the literature. Sections III and IV present two scenarios, a Bayesian model for a cyclist–AV interaction and a pedestrian crossing modeled as a Bayesian entry game, respectively, and discuss some results. Section V concludes the paper and outlines the main guidelines and possible expansions for future work.

II. Related Work

In the last few years, interest toward the implementation of game theoretical techniques in traffic scenarios increased significantly. Traffic interactions are an ideal field of application for game theory, as they involve: conflicts with different perspectives of the users (and, as a result, different utilities); a generally limited but clearly distinguishable set of options for the involved players; occurrence in many instances, thus allowing for large numbers and generality. Conversely, works not based on game theory mostly use statistical models, and, as argued by [6], fail to capture the causal relationship between road traffic events. Thus, game theory offers an accurate strategic analysis that can clarify whether certain road users have common or conflicting interests; it is also able

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to make specific predictions about road user behaviors, which are empirically testable.

For example, Bjørnskau [7] investigated a *Zebra Crossing Game*, i.e. a Stackelberg-type game of a cyclist versus a driver where the former moves first and can yield, cycle, or dismount from the bike and walk, while the latter can either drive or yield. By backward induction, the only perfect Nash equilibrium is "Cycle" for the cyclist and "Yield" for the driver, since the cyclist has the advantage of being the first mover [8]. Interesting reviews of road user behaviors can be found in both [9], which explores the dynamics of traffic accidents, and [10], where a set of road interactions among vehicles is proposed.

A more detailed study about the micro-dynamics between vehicles and pedestrians is [11], which studies the relative speed between the pedestrian and the approaching car at uncontrolled mid-block crosswalks. Game theory is also exploited for conflict resolution over a scenario concerning crossing cars, using Cellular Automata [12], and to review the decision model involved in avoiding collisions when approaching a blind corner, combined with theory of evidence to account for uncertainty [13].

Our study brings the contribution of using more advanced game theory techniques than those used in the existing literature. Usually, game theory is employed as a ready-to-use tool, which gives a marginal role to the game theoretic model itself. Instead, we consider a Bayesian approach with emphasis on the characterization of the types of the involved players, e.g., probability of a vehicle being human-driven or autonomous, as seen from the perspective of a pedestrian/cyclist. Moreover, we infer a behavioral characterization from numerical evidence, as it is reasonable to expect that, as the share of AVs increase, it will be more likely to encounter them and the human cyclist or pedestrian can adapt their prior to reflect that. This way, we can derive specific quantitative conclusions with useful numerical insights.

III. Cyclist versus Vehicle Game

Consider the zebra crossing of a cyclist where a vehicle is upcoming, either autonomous or human-driven (the cyclist tries to detect this as well). As in [7], the cyclist has three options: to yield (Y), to dismount from the bike and walk (W), or to cycle (C). The vehicle can either go, or stop and let the cyclist cross (actions denoted as G or S, respectively). Street regulations generally state that zebra crossing are for pedestrian only; cyclists cannot cross there, instead they should dismount from the bike and walk. At the same time, the driver is supposed by the same regulations to stop and let the cyclist cross only if they has dismounted.

This can be modeled through a simultaneous Bayesian game with two types as depicted in extensive form in Fig. 1 where the payoffs are set for a vehicle incoming at a medium speed. As customary in Bayesian game analysis [8] a virtual player called "nature" randomly

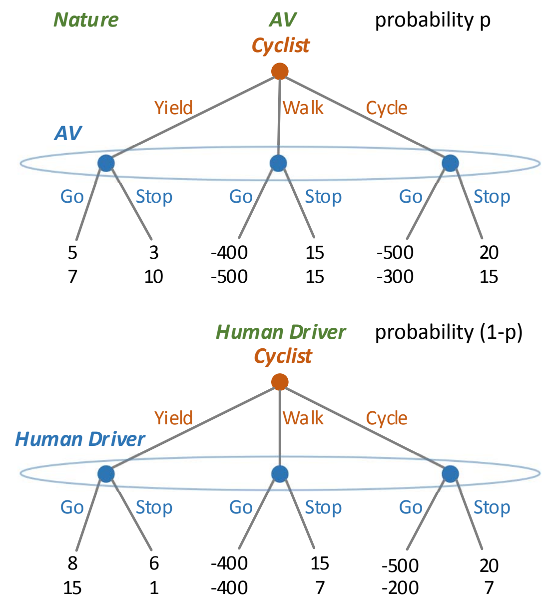

Figure 1. Extensive form of the game in Section III considering medium speed, payoffs of the cyclist are given first.

draws, according to a prior distribution, the character of the vehicle, i.e., whether it is autonomous or human-driven, with probabilities p and $1 - p$, respectively. The value of p is common knowledge. The game is modeled as simultaneous because we consider only one chance for both players to act. The novelty here is that we take into account the uncertainty on the type of the vehicle.

Although road users have to make key decisions in fractions of a second, we can assume that common knowledge and full rationality apply. We compare the cyclist's behavior when facing an autonomous or a human-driven vehicle and verify whether the accident rate is reduced by increasing the share of autonomous vehicles. In principle, AVs are programmed to be prompter to prevent accidents; on the other hand, human road users can be bold in the presence of AVs. The outcome predicted by game theory are the Nash Equilibria (NEs), in either *pure* or *mixed* strategies, the latter being seen as providing a probability distribution over the set of pure strategies. From this latter case, we can infer, e.g., accident rates.

It is assumed that both players prefer not to collide (as their primary goal) and secondly whether they can continue to move over having to stop and wait. Thus, payoffs reflect a heavy penalty in case of collisions (high absolute value for negative payoffs) and at the same time they do not overestimate the daily-action of crossing roads (low absolute value for positive payoffs). Beyond these assumptions, the evaluation of the payoffs are challenging, thus we resorted to arbitrary but descriptive quantifications. The worst outcome for the cyclist (arbitrarily set to -500, to reflect a strongly negative outcome) happens when the cyclist crosses the road and is hit by the vehicle, no matter whether autonomous or human-driven; this is even worse than to be hit when walking (which is set to -400) because in this case, the cyclist is at least right according to the traffic regulations. Then, the next worst outcome for the cyclist is when both the cyclist and the AV stop (slightly positive because the cyclist acted following the road rules, e.g., set to 3); since the cyclist can cross after a while,[1] this is considered worse than to yield to an AV which does not stop, whose payoff is set to 5 for the cyclist. Same reasoning applies in case of a human-driven vehicle, which leads to higher payoffs (6 and 8, respectively) because the cyclist knows that the AV is programmed to be *risk averse* as much as possible, while a human driver can be absent-minded. The best outcomes for the cyclist are to cycle over the zebra crossing with a yielding vehicle, which is set to 20, and to dismount from the bike and walk over the zebra crossing with a yielding vehicle, whose payoff is 15.

The worst outcome for the driver is an AV hitting a pedestrian (quantified as -500) because it is a machine-type evaluation error, considered to be worse and less socially accepted than a human-type error (quantified as -400). Same considerations apply in case of a crossing cyclist (with payoffs for AV and human-driver of -300 and -200, respectively): the only difference is that the cyclist is accountable for the accident, so the payoffs of the vehicle are higher than the previous case. The next considered outcome for the driver is when both players yield; for a human driver, we assign a payoff 1 to this case, lower than the same payoff for an autonomous driver, set to 10, because the AV is programmed to avoid accidents, and has a higher incentive to pursue this outcome. This last situation is slightly preferable to a yielding human-driver when a cyclist cycles over the zebra crossing (set to 7); this outcome is very similar to a yielding human-driver when the pedestrian walks, as well as an AV keeping driving when the cyclist yields, which is not as good as a yielding AV because it is *risk averse*. The best outcome for the vehicle, reflected by a payoff of 15, is achieved when an AV stops in front of a crossing cyclist because it is the right action for the AV and when an human-driven vehicle keeps going as the cyclist yields and stops.

In this game, there are two pure NEs: (CC, SS) and (CY, SG). They can be found simplifying the game via *iterated elimination of strictly dominated strategies* [8] and then seeking for the NEs. Indeed, a cyclist knows that S is a strictly dominant strategy for the AV, and the best response is to cycle; when the driver is human instead, the car can either stop or go, and the cyclist should cycle or yield accordingly. In both cases, no player has an incentive to deviate given the actions of the other.

A mixed NE is to always play (C,S) in case of an autonomous vehicle and to mix between yield and cycle

[1]Since we are considering a single vehicle–cyclist interaction, we consider this to be a terminal node of the game; however, a possible extension is to consider this as a multi-stage game, which does not end and goes instead to a further stage when both players yield.

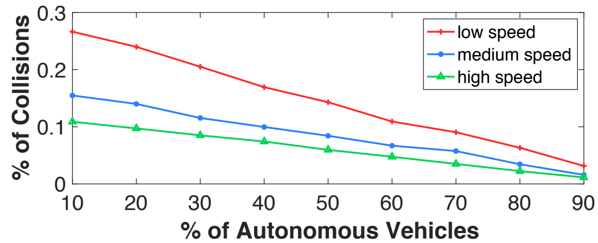

Figure 2. Percentage of collisions versus fraction of AVs.

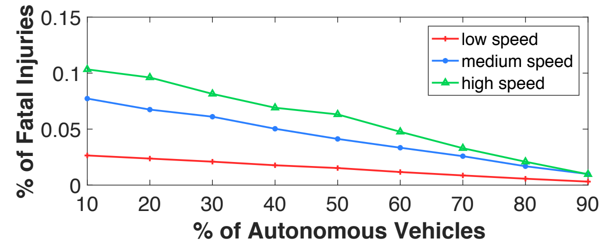

Figure 3. Percentage of fatal injuries versus fraction of AVs.

(with probabilities $207/221$ and $14/221$) and between go and stop (with probabilities $7/261$ and $254/261$) in case of a human driver. These results, whose numerical values depend on the considered payoffs, can be found by setting indifference between best responses and solving the resulting linear system. From a general perspective we can infer that, whatever the specific values chosen, most of the times the players will yield/stop because the collision risk is too high; however, sometimes they can decide to go.

To see whether the rising number of AVs decreases the collision rate, we simulated the mixed strategies Nash equilibrium varying the probability of encountering an AV. In addition, we evaluated the robustness of the model, by analyzing a different scenario with two other speed values of the oncoming vehicle. We assume that changing the speed of the vehicle modifies the payoffs in Fig. 1 to keep into account an either more serious or more lenient effect of an accident. The (negative) payoffs of a cyclist hit by a vehicle at a higher speed will be even lower because the accident will be more serious, and vice versa.

The results are shown in Fig. 2. Remarkably, the collision frequency exhibits a decreasing trend; the exact slope of the curve depends on the evaluation of the outcomes, still, it may be worth investigating further. Also, we can see that it is more likely to have accidents at lower speeds because pedestrians tend to cross the road more often due to the lower perceived risk. Finally, we consider another effect of a different speed by evaluating the *death rate* of the cyclist, which we also connect to the seriousness of the accident, and ultimately to the speed of the vehicle. It is well known that death rates of road accidents increase when higher speeds are involved. For instance, we can think of *low* speed corresponding to about $30\ \mathrm{km/h}$, *medium* speed to about $45\ \mathrm{km/h}$ and *high* speed to about $70\ \mathrm{km/h}$. According to the report by the World Health Organization (WHO) in [14] the rates of fatal injuries are approximately 10% at $30\ \mathrm{km/h}$, 50%

at 45 $\mathrm{km/h}$ and more than 99% at 70 $\mathrm{km/h}$. With these assumptions, the fatal injury rate is reported in Fig. 3. The results highlight that vehicles driving at high speed cause fewer accidents but these are more often fatal, in agreement with intuition.

The proposed model shows that the AVs will always stop to act safely, and in turn pedestrians and cyclists will be bolder: there will be no risk for them to cross in front of an AV, while a human driver may be absent-minded or fail to see the cyclist crossing. The model also assumes that the cyclist can recognize an AV from a human-driven vehicle, which is sensible since AVs will likely be aesthetically different from current vehicles. Thanks to this, the cyclist can determine whether to cycle or mix between cycle and yield. If the number of human drivers is limited, then the cyclist will keep cycling very often.

If AVs end up to be the majority of vehicles, it could be very likely that pedestrian and cyclists tend to dominate the scenario, i.e., they always win the contention for crossing the street. To mitigate this behavior, some expedients can be used, for example crosswalks can be re-designed by city-planners with physical barriers in order to reduce the direct interactions between pedestrians and AVs and, at the same time, street regulations could be changed so that pedestrians do not always have priority when crossing the road, as pointed out in [4]. For example, a fine could be introduced for cyclists crossing without waiting some time when an AV is approaching. This would be possibly reflected into payoffs variations, and a new game analysis.

IV. Pedestrian versus Vehicle: Entry Game

We consider a different game, capturing the specific interaction between a pedestrian, who have to decide whether to cross by jaywalking, and an upcoming vehicle. The differences from the previous model are:
– the absence of zebra crossing and the unknown types
– actions are sequential
– payoffs are not axiomatic, but computed as functions of environmental variables, such as the vehicle speed
– the game itself does not consider AVs and human drivers at the same time: a comparison is made afterwards based on the results obtained in different cases.
Thus, consider an *Entry Game*, where the first mover is the pedestrian, who decides whether to cross the road or to stay on the sidewalk, and after that, the car decides whether keep going or brake. A possible payoff is time, because a pedestrian will consider, in first approximation, the estimated car arrival time to decide whether to cross or not. Fig. 4 shows the extensive form of the game.

In the proposed model, the pedestrian spends a constant time to cross the road, computed using the parameters indicated in [15], for what concerns the preferred speed-walk of 1.4 $\mathrm{m/s}$, and in [16], for the worst-case lane width of 3.75 m, as typical of many European countries. The crossing time for the pedestrian is $t_a \approx 2.67$ s.

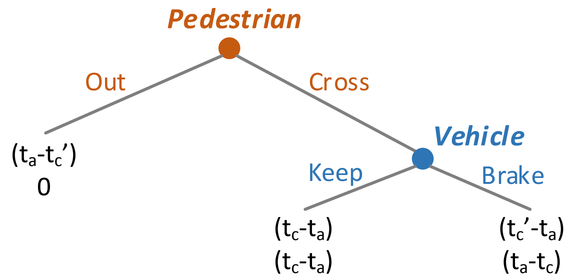

Figure 4. Extensive form of the Entry Game of Section IV.

	Case 1	Case 2	Case 3
Condition	$t_a < t_c$	$t_c < t_a < t'_c$	$t_a > t'_c$
NE	CK	CB	O

Table I
NE SHIFT BASED ON ENVIRONMENTAL VARIABLES. CK=CROSS/KEEP, CB=CROSS/BRAKE, O=OUT.

The time for the AV to reach the intersection point is

$$t'_c = \frac{\sqrt{v^2 + 2ad} - v}{a} \quad \text{in case of deceleration}$$

$$t_c = \frac{d}{v} \quad \text{otherwise}$$

where a is the acceleration (taken as constant and negative for a braking vehicle), d is the distance between vehicle and pedestrian, and v is the car speed.

The payoff for the pedestrian, in case of crossing, is computed as the difference between the time taken by the car to reach them (t'_c or t_c according to the cases) and their crossing time. It will be negative in case of collision and will increase as much as the pedestrian's perception of safety. On the other side, if the pedestrian decides to stay out gets a gain equal to the difference between their crossing time and the car approaching time (braking case, t'_c). This value becomes negative if t'_c is enough to allow them crossing. The payoff for the car, in case of a static pedestrian, is set a priori to 0, according to the absence of actions carried out by the vehicle. In the crossing scenario, instead, $t_c - t_a$ acts as a pivot: if it is greater than 0, the car has no incentive to brake because it reaches the intersection point only later; otherwise, the vehicle ought to brake, even if it is not sure to stop in time (this computation is demanded to the pedestrian before making a decision). As a sequential game, it can be solved via backward induction [8]; the equilibrium discovered is not only a NE but also subgame-perfect, since the strategies chosen by the players always lead to a NE in each subgame. Since backward induction focuses only on pure strategies, the equilibrium is not influenced by the cardinal values of the payoffs but only by their order. Solving the game leads to three cases, which become NEs depending on the specific d and v, as shown in Table I.

For the simulation, it is assumed that the AV, in case of braking, uses a constant deceleration $a = -2.5$ $\mathrm{m/s^2}$ from the initial distance, generated as a uniform random

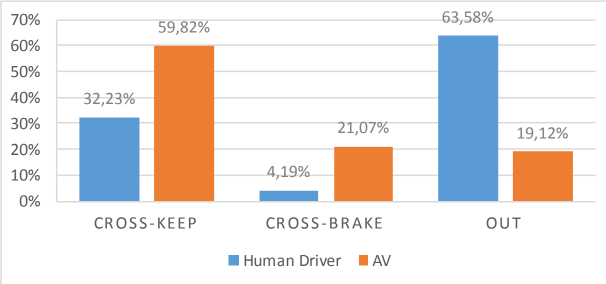

Figure 5. Histogram of occurrences for comparison between human-driven vehicle and autonomous vehicle.

variable $d \sim \mathcal{U}(10, 50)$ m; the speed value, instead, is assumed to be a truncated Gaussian variable distributed around 30 km/h, i.e., $v \sim \max(\mathcal{N}(30, 10), 0)$ km/h. The number of iterations is set to 1000000 and we show the distribution of the NE over the three different cases.

As a second experiment, we consider the same interaction but involving a human driver. Braking is revised due to the driver reaction time, set to the conservative value of $t_r = 1.5$ s [17], accounting for both brain processing time and car dynamics, even though other parameters may influence the result as well; thus, the approaching time for the car in case of deceleration becomes

$$t''_c = \frac{\sqrt{v^2 + 2a(d - d_r)} - v}{a} + t_r \quad \text{where } d_r = v \cdot t_r$$

Another modification needed in order to adapt the model to human behavior is the larger average speed, as human drivers tend not to always respect the speed limits. Thus, speed value is chosen according to $v \sim \mathcal{N}(50, 10)$ km/h.

The results, summarized in Fig. 5, show a decreasing number of overall *Cross* situations in case of human driver, while in case of AV there is an increasing number of such situations. In the case of AVs, the pedestrian will not only be safer but also cross more frequently due to general lower speed of AVs and faster reaction time of machine-type drivers with respect to human-drivers. Moreover, since the AVs tend to slow down in presence of pedestrians, there is a higher occurrence of Cross-Keep.

However, a human driver may not be alert, and the pedestrian be unaware of it; an inattentive driver with a mean reaction time of about one second may not be able to stop in time and the evaluation of the pedestrian may be wrong. This situation can be modeled considering an exponential reaction plus movement time starting from 0.8 s: $t'_r \sim 0.8 + \text{Exp}(0.2)$ s. With these considerations, about 3% of the times the pedestrian implicitly assumes a lower reaction time than the actual one and 0.036% of the times it ends in a road accident. We remark that all the values must be taken with a pinch of salt as they derive from arbitrary assumptions; of course a realistic analysis should be supported by real data acquisitions. Still, the baseline game theoretic framework would apply in its essence, with just different numbers.

V. Conclusions and Future Work

We applied a mixture of game theoretic techniques with sensible assumptions to infer conclusions on the impact of AVs on future road traffic scenarios. The increasing number of AVs will reduce the number of collisions but also change the approach to road safety, demanding for new regulations. Moreover, communication systems among AVs will be needed to better regulate the traffic and game theory procedures can be implemented in a distributed lightweight fashion inside the vehicles.

Possible developments include the exploitation of statistical tools, to validate fairness and calibration of the models. We also intend to improve accuracy, by means of in-depth investigations on the statistical road-user behaviors to faithfully set the payoffs, as well as perform adaptation on real data whenever available. Additionally, some assumptions, such as AVs always yielding, can be relaxed under specific conditions. Finally, we can include further elements of uncertainty, such as the correct recognition of an AV, into a Bayesian framework.

References

[1] European Commission, "Annual accident report 2016," *European Road Safety Observatory*, 2016.
[2] A. Hussein, F. García, J. M. Armingol, and C. Olaverri-Monreal, "P2V and V2P communication for pedestrian warning on the basis of autonomous vehicles," in *Proc. IEEE ITSC*, pp. 2034–39, 2016.
[3] A. Rasouli and J. K. Tsotsos, "Autonomous vehicles that interact with pedestrians: A survey of theory and practice." *Submitted to IEEE Trans. Intell. Transp. Syst.*, (to appear). Available at: https://arxiv.org/pdf/1805.11773.pdf.
[4] A. Millard-Ball, "Pedestrians, autonomous vehicles, and cities," *Journal of Planning Education and Research*, 2016.
[5] K. Hurley, "How pedestrians will defeat autonomous vehicles," *Scientific American*, March 21, 2017.
[6] E. Hauer, "Cause, effect and regression in road safety: a case study," *Accid. Anal. Prevent.*, vol. 42, no. 4, pp. 1128–35, 2010.
[7] T. Bjørnskau, "The zebra crossing game–using game theory to explain a discrepancy between road user behaviour and traffic rules," *Safety science*, vol. 92, pp. 298–301, 2017.
[8] M. J. Osborne and A. Rubinstein, *A course in game theory*. MIT press, 1994.
[9] T. Bjørnskau, *Game Theory, Road Traffic and Accidents: a Theory of User Interaction*. No. TOI-287-1994, 1994.
[10] R. Elvik, "A review of game-theoretic models of road user behaviour," *Accid. Anal. Prevent.*, vol. 62, pp. 388–396, 2014.
[11] P. Chen, C. Wu, and S. Zhu, "Interaction between vehicles and pedestrians at uncontrolled mid-block crosswalks," *Safety science*, vol. 82, pp. 68–76, 2016.
[12] A. Rane, S. Krishnan, and S. Waman, "Conflict resolution of autonomous cars using game theory and cellular automata," in *Proc. ICROIT*, pp. 326–330, 2014.
[13] T. Okamoto and Y. Yamada, "Decision model for determining the behavior of pedestrians approaching from both sides of a blind corner by considering tactics and information uncertainty," in *Proc. IEEE ROBIO*, pp. 1494–1501, 2012.
[14] M. Peden, R. Scurfield, D. Sleet, D. Mohan, A. A. Hyder, *et al.*, "World report on road traffic injury prevention," 2004.
[15] R. C. Browning, E. A. Baker, J. A. Herron, and R. Kram, "Effects of obesity and sex on the energetic cost and preferred speed of walking," *J. Appl. Physiology*, vol. 100, no. 2, pp. 390–398, 2006.
[16] L. Hall, R. Powers, D. Turner, W. Brilon, and J. Hall, "Overview of cross section design elements," in *International Symposium on Highway Geometric Design Practices*, 1995.
[17] M. Green, ""how long does it take to stop?" methodological analysis of driver perception-brake times," *Transportation human factors*, vol. 2, no. 3, pp. 195–216, 2000.