Decision Making via Game Theory for Autonomous Vehicles in the Presence of a Moving Obstacle

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***Abstract*—We consider an emergency maneuver scenario involving two autonomous vehicles interacting with a road obstacle characterized by a random behavior. We employ game theory to solve the resulting problems, first framing a static game of compete information, and further adding incomplete information about the obstacle so as to transform it into a Bayesian game. Depending on the considered scenario, the autonomous vehicles can have multiple available actions, such as to stay at the same lane and swerve and move to another one. These actions can lead to different outcomes, such as keep driving on an empty lane, hit the obstacle, or hit another car. We analyse the Nash equilibria of the game and test the hypothesis that the knowledge of one vehicle about an obstacle can be advantageous to other road participants, which is key in the context of connected vehicles.**

***Index Terms*—Game theory; smart cities; autonomous driving; safety-critical application; risk reduction; self driving cars.**

I. Introduction

Autonomous vehicles (AVs), also called self-driving cars, are expected to become one of the most important innovations in the field of transportation for smart cities. AVs can bring several technological benefits. First of all, from an environmental perspective, a large-scale integration of self-driving vehicles reduces traffic congestions and sequentially fuel consumption, thereby significantly decreasing the CO_2 emissions [1], [2]. Moreover, AV can also bring logistics advantages such as decreasing the time spent commuting, reduce the cost of travel time, parking space saving and improving the ease of access to transportation for the elderly and disabled people [3], [4].

Another extremely relevant advantage on which we focus in the present paper is the application of AVs to increase road and vehicle safety, i.e., reduction of crashes and accidents that lead to fatalities and injuries. The United States National Highway Transport Safety Agency claims that 94% of road crashes are caused by human errors [5]. AVs give hope that these figures can be significantly reduced since self-driving cars have better perception and focus on the task than human drivers. Still, we argue that while AVs are already very efficient under ideal conditions (empty roads and/or static scenarios without other vehicles around) they lack the subtlety of interacting with one another in a safe way, which is possibly the strongest challenge of driving in the traffic.

This problem arises because, while technology for controlling locomotion is further improving [6] and computer vision capabilities have been dramatically increasing, so that they surpass the environmental awareness of human agents [7], [8], the decision making process of smart vehicles is, so far, only based on data processing and analytics via (sometimes even very refined) machine learning techniques, without much interconnection and feedback from the changing environment [9], [10].

Our proposal is to adopt *game theory* as a way to tackle the resulting multi-agent scenario that offers much more challenges in a holistic perspective as opposed that of a single autonomic vehicle. Game theory is the study of multi-players decision problems that capture strategic interactions among independent and rational players, who seek to maximize their outcome accounting for the presence of other agents [11]–[14]. In the game theoretical setup, the key ingredient is the contribution of all involved agents to the final outcome, which must be duly taken into account. Thus, even an individual agent driven by a purely selfish objective can turn to efficient interaction with the other players in order to avoid suffering losses in its own payoff [15], [16].

When game theory is applied to the problem of autonomous driving, AVs are identified as rational players, which makes sense in light of the advanced capabilities to bring computational intelligence inside the vehicles themselves. Actually, since traffic continuously flows and requires to make decisions in a timescale of the order of milliseconds, a computer can be much faster than a human driver in this respect. However, while it is safe to assume that AVs are capable of making fast and well-informed decisions, the analysis becomes tougher when it involves the dependance on (guessing) the behavior of other vehicles or objects [17].

We assume that the rational priority of each AV is to reduce the damage by avoiding accidents. However, there are several ways to implement this in the context of road safety, also depending on the ability of the individual vehicles of making autonomous intelligent decisions as well as to share them with other agents in a connected vehicle scenario.

In this paper, we model a situation of emergency maneuver through the game theory from a safety perspective. We consider two cars that have to make a simultaneous decision on how to respond to a sudden obstacle on a road. We complicated the scenario under consideration by introducing a part of traffic which is unknown to both players. For instance, it could be an animal crossing a road, which is case studied in this paper. Other possibilities could be the weather conditions or a pedestrian crossing a road [18], [19]. These objects or items

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can be incorporated into a game theoretic framework by a layer called *Nature* that randomly draws the behavior of an obstacle. This situation can be modelled as a Bayesian game, that models the outcome of player interactions with some degree of uncertainty, i.e., so-called games with *incomplete* information. This ultimately allows us to quantify the benefit of exchanging information among connected autonomous vehicles.

This paper is organized as follows. In Section II, we provide a background in AV problems solved by means of game theory. The problem model as a static game of complete information is given in Section III, where we consider two scenarios, that are with or without the AV being able to stop. The problem framed as a Bayesian game is instead provided in Section IV. Conclusions are drawn in Section V.

II. Background

Drivers have to make many decisions while on the road, such as whether to accelerate or decelerate [20], which lane to take [21], [22], which parking slot to choose [23], how to behave at an intersection [24], and how to interact with pedestrians [18]. The outcome of these decisions are affected by many external aspects, such as weather conditions, traffic, and human factors, for instance, tiredness and experience. In addition, driving styles might be quite different, either unpredictable, aggressive or, instead, calm. In the literature, a number of papers deal with the challenges caused by differences in a driving style [17], [25], [26].

The technology of autonomous driving aims at coping with these aspects, but in order to integrate it into daily operation in pervasive scenarios such a smart city or a congested traffic hub, a robust and efficient mechanism for making decisions is required. Many authors have attempted to employ game theory for this purpose [8], [19], [27], [28].

In this paper, we focus on lane changing games. An extensive overview on models for such a problem is provided in [29], and variations on this scenario are further explored in a number of contributions. For instance, in [30], the authors study a behavioral strategy in a conflict situations between the autonomous vehicles in a roundabout using game theory, representing the problem as a Prisoners' dilemma game with the objective for individual autonomous vehicles of reducing waiting time.

An algorithm based on the chicken game is proposed in [31], in which autonomous vehicles communicate their speed and location to the central agent at the intersection, and decide to either swerve or move straight. In [21], the authors study an urban traffic scenario framed as a game-theoretic decision problem, in which an *AV* needs to make a decision about changing a lane based on the level of cooperation of the vehicles in the adjacent lane. In [32], the lane-changing problem is represented as a multi-player non-zero-sum non-cooperative game where the real-time surrounding traffic data is a common knowledge.

The authors of [33] frame the lane-changing problem as two-player, non-cooperative, non-zero sum game where one player chooses either give or not a way, and the second player

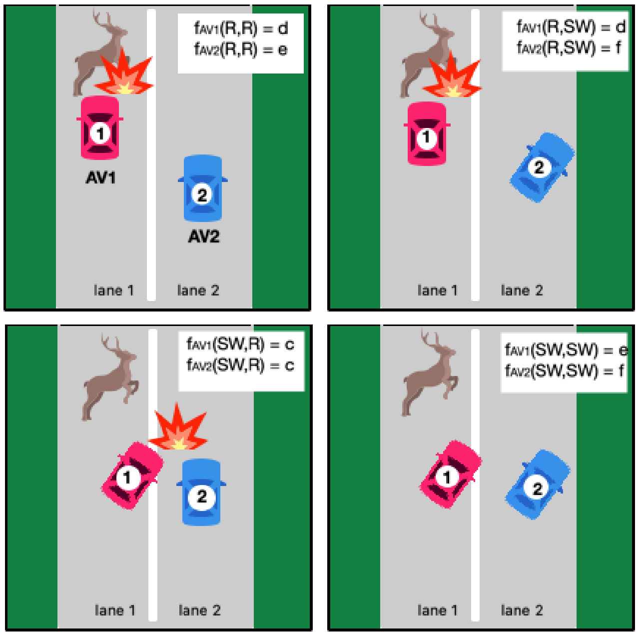

Fig. 1: Representation of the game

decides whether to take the gap in front of the mainline player. In [34], decision making game for merging maneuvers on a freeway is considered, which is based on the repeated game framework. Instead, in our setup, we consider a Bayesian game approach to cope with random externalities, framed in the virtual player "Nature."

III. Static Game of Complete Information

First, we consider the scenario described in Fig. 1, as a static game. This describes a situation of two AVs, which are the players labeled as "AV1" and "AV2'', driving side-by-side on a two-lane road in the same direction. AV1 occupies the left lane; AV2, instead, drives on the right lane. An obstacle appears in front of AV1; in the following, we will refer to this obstacle as a "deer," since this is a typical scenario also considered as a safety-critical application. This obstacle will be still during this initial game. AV1 has two choices, swerving right (*SW*) or remaining on the same lane (*R*). AV2 has the same space of actions. The outcome of a game depends on a chosen combinations of actions chosen by both AVs: The goal of each car is maximizing its payoff. Crashing into another car is assumed to cause more damage than crashing to an obstacle, so the corresponding payoff will be lower. If a car goes off the road, it will have a lower damage than hitting something, but higher than continuing on an empty road. Respectively, the payoffs are c if the two cars crash, d if a car hits the deer, f if a car swerves off the road and e if a car keeps driving on the road as intended. The payoffs are in this relation:

$$e > f > d > c \tag{1}$$

We can consider the cost of keep driving on road to be $e = 0$, which makes all the other outcomes as negatively-valued. We also remark that including a non-zero value for e would

TABLE I: Static base game with payoff values.

AV1 \ AV2	SW	R
SW	e, f	c, c
R	d, f	d, e

just result in more complex equations with basically the same insight.

The structure of the game is summarized in Table I. This game can be seen as an instance of Chicken Game [31]. Players strive for a minimal-cost outcome, but they seek for it through a selfish approach. This leads to identifying the predicted outcomes as the Nash equilibria (NEs), of which this game has three. Beyond two NEs in pure strategies, i.e., (SW, SW) and (R, R), the game also has one in mixed strategies, where, if α is the probability of AV1 playing "SW", and β the probability of AV2 playing "SW", we obtain

$$\alpha = \frac{c-d}{c} \quad \text{and} \quad \beta = \frac{f}{c} \tag{2}$$

IV. Imperfect Information with Deer Movement

We can add complexity to the game considering that the deer, upon seeing the approaching cars, can also move. The AVs cannot know in advance what the deer will do, but they know that the deer can move.

We consider three actions for the deer. First of all, the deer can stay in the left lane (as the situation model above); or, it can move to the right lane, i.e., the one where AV2 is located. Or finally, the deer can move out of the road entirely. These three events are described through probabilities p, q, and $1-p-q$, respectively. We assume that these values are common knowledge among the players.

A. Equal imperfect information

We start with a first scenario where the deer movement is unknown to both AVs, so that this is an externality known to the players only through its probability distribution. This can be split into three versions of the previous static games, depending on the deer movements. Thanks to the players being rational, the solution of this game consists in evaluating the best strategy that the AVs adopt in each of the three cases (leading to a NE) and averaging this over all the possibilities, with proper weights depending on the probabilities of each of them to happen.

The first case, happening with probability p is already represented in Table I and has the same solution as per the previous section.

Consider the case of the deer moving to the other lane, which happens with probability q. In Table II, we can see the different costs for the different actions taken by the cars. If AV1 swerves, it will hit the deer that has moved to the other lane, so its payoff will be d. In the case that AV2 remains on the road, the two cars will hit each other and hit the deer reaching a payoff of $d+c$ (the sum of the cost of the

TABLE II: Payoffs values for the case of the deer moving to the other lane.

AV1 \ AV2	SW	R
SW	d, f	$d+c$, $d+c$
R	e, f	e, d

accident and of hitting the deer). The same reasoning holds for action "R" of AV2, if AV2 remains on the same lane without swerving, it will hit the deer (and also AV1 if it swerves). If AV2 remains on its empty lane, it will get a payoff of e, while, if it swerves, the payoff will be f.

Now, consider the costs of the different strategies in the case of the deer moving out of the road, which happens with probability $1-p-q$. These costs are reported In Table III.

TABLE III: Payoffs values for the case that the deer moves out of the road.

AV1 \ AV2	SW	R
SW	e, f	c, c
R	e, f	e, e

We can notice that action "SW" of AV2 gives payoff f in any case, and action "R" of AV1 has a payoff of $e = 0$. Action "SW" of AV1 has a payoff of e if AV1 stops or swerves making the lane free for the other car. An incident happens if AV1 swerves and AV2 remains in the same lane. As the deer moves out of the road, no car will have the cost of d of hitting the deer.

The cost of the different actions if the player stays in the same lane can be found in Table I. Now we can compute the final cost of the actions. Since the AVs do not know what the deer will ultimately do, their strategies are the same for the previous game ("SW" and "R"), but the payoffs are now computed in expectation as a weighed average of the different payoffs over the probability of occurrence.

We can compute the mixed strategies at the NE as

$$\alpha = \frac{e-c-qd+p(d-e)}{e-qe-c} \tag{3}$$

$$\beta = \frac{f-e-qd+qe}{c-e+qe} \tag{4}$$

where α and β are the probabilities of AV2 and AV1, respectively, to play "SW". If we consider the payoff e as equal to 0, and the other payoffs as negative values as per (1), we obtain

$$\alpha^* = 1 - \frac{d}{c}(p-q) \tag{5}$$

$$\beta^* = \frac{f}{c} - \frac{d}{c}q \tag{6}$$

We can assign $K = d/c$, such that $0 < K < 1$, which allows for rewriting (5) as $\alpha = 1 + K(q-p)$. Recall that

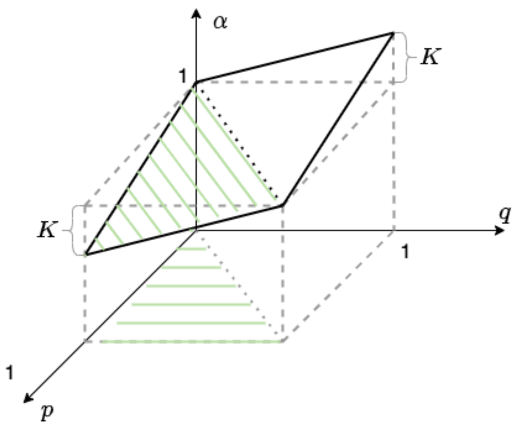

Fig. 2: α^* as a function of α and β

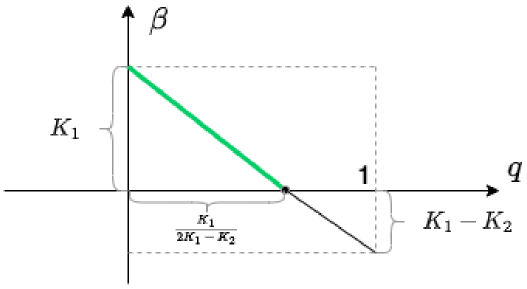

Fig. 3: β^* as a function of q.

$0 < \alpha < 1$, and it imposes the constraint $p \geq q$, i.e., the probability of moving deer to the right lane should be higher than that of staying in the same lane. If it is equally likely that the deer would stay either on left or right lane, then AV2 will adopt strategy SW ($\alpha = 1$). All other cases are covered in Fig. 2 that displays α^*, as a function of q and p in $[0, 1]$.

After setting $K_1 = f/c$ and $K_2 = d/c$, and following $K_1 < K_2$, one can see that the mixed strategy exists if the probability of the deer switching the lane does not exceed $q' = \frac{K_1}{2K_1 - K_2}$ (see Fig. 3). At q', strategy SW is never adopted. One can also notice that the maximum value for β is $K_1 < 1$, which means that SW is not a dominant strategy in any case.

If no particular behavioral pattern can be assumed on the deer behavior, one reasonable assumption for the priors of its movement is that all three events happen with the same probability, i.e., $p = q = 1/3$. In this case, $\alpha = 1$, meaning that SW is a dominant strategy and AV2 should always steer on the right, while the strategy of AV1 is defined by $\beta = K_1 - \frac{K_2}{3}$. Assigning $c = -3$, $d = -2$ and $f = -1$, $\beta = 1/9$, i.e., with higher probability AV1 should remain on its own lane.

B. Deer's Movement seen by AV1

We extend the previous results to a more advanced game, still involving two AVs and a moving obstacle (deer). The actions available to the vehicles are the same ("SW" and "R"), and once again the deer can move with three different actions as before, with respective probabilities p, q, and $1 - p - q$. However, we assume now that AV1 detects the movement of the deer and so can act on it. AV2 also has additional information since, unlike the previous version of the game where imperfect information is just an externality, now AV2 is aware of AV1 being able to predict the deer's behavior.

We stress that this further element emphasizes the need for a connected awareness among the vehicles. While the time for AV1 to undertake any action is too short to also communicate it to AV2 sufficiently in advance, the presence of such capability of AV1 can be reasonably common knowledge among other connected vehicles.

In the jargon of game theory, the situation that we are considering now is classified as a *Bayesian game*, since we categorize the deer's movement (known to AV1 but not AV2) as the *type* of AV1 [35], [36]. We remark that even the previous situation where the deer moves at random and its movement is only known through its prior probabilities p, q, and $1-p-q$ can be considered to be a Bayesian game (hereafter called "Bayesian game 1"), whose resulting normal form is displayed in Table IV. However, this game involves random choices by Nature ultimately determining the types of the players that are just resolved by taking expectations, as discussed in the previous section.

TABLE IV: Bayesian game 1, without detection: the deer is an externality choosing actions with known priors.

		AV2: SW	AV2: R
AV1	SW	$e + q(d - e)$, f	$c + qd$, $c + qd$
AV1	R	$e + p(d - e)$, f	$e + p(d - e)$, $e + q(d - e)$

Instead, we want to consider a more refined game, denoted as "Bayesian game 2," in which knowledge about the deer's movement determines a different type of player AV1 that is revealed to that player (but not to AV2) before taking action. The strategy for AV1 as a player consists now on choosing three binary choices, one for each of the possible types, which results in $2^3 = 8$ possible actions. AV2 does not have a type, so its strategy is a single action, which is however chosen knowing of this more detailed information available to AV1. Thus, while AV1's strategy is a response to each of the three scenarios (deer stays in its lane, deer moves to the right lane, and deer moves out of the road), AV2 can still apply rational decision making to knowing that AV1 knows the behavior of the deer. In Table V, we can see the payoffs for each strategy of AV1 and AV2, as functions of the values c, d, e, f and probabilities p and q.

We can notice that the action "R" of AV2 is dominated by the action "SW", however, it is not strictly dominated. Through sequential rationality, we can iteratively eliminate strictly dominated strategies, which are courses of action that

TABLE V: Bayesian game 2 with detection by AV1.

AV1 \ AV2	SW	R
(SW, SW, SW)	qd, f	$c + qd$, $c + qd$
(SW, SW, R)	qd, f	$(p+q)c + qd$, $(p+q)c + qd$
(SW, R, SW)	0, f	$(1-q)c$, $(1-q)c + qd$
(R, SW, SW)	$(p+q)d$, f	$(p+q)d + (1-p)c$, $qd + (1-p)c$
(SW, R, R)	0, f	pc, $pc + qd$
(R, SW, R)	$(p+q)d$, f	$(p+q) + qc$, $qd + qc$
(R, R, SW)	pd, f	$pd + (1-p-q)c$, $qd + (1-p-q)c$
(R, R, R)	pd, f	pd, qd

are not chosen by rational players. For AV1, (SW, SW, R), (R, SW, SW), and (SW, SW, SW) are strictly dominated by (SW, R, SW). Moreover, (R, SW, R), (R, R, SW) are strictly dominated by (SW, R, R) for any values of c, d, e, f that follow condition (1).

In Table VI, we provided a reduced game in a bi-matrix form, following from these eliminations, by assigning sample values $c = -3$, $d = -2$, $f = -1$ and $p = q = 1/3$. It is relevant to remark that these choices are just made for numerical convenience in discussing the example, but the results are actually more general given the ordinal meaning of the utilities, that are just required to satisfy (1).

This game has three Bayesian NEs in the pure strategies: ((SW, R, SW), SW), ((SW, R, R), SW) and ((R, R, R), R). No NEs were found in the mixed strategies. In general form, the mixed strategy for AV2 can be expressed as

$$\alpha = 1 - \frac{d}{c} \cdot \frac{p}{1-q} \qquad (7)$$

if α is a probability of AV2 to play strategy SW. However, there exists a special condition in which AV2 is indifferent between playing R an SW that is $p + q = 1$, i.e. the deer never goes away from the road. In this case

$$\alpha^* = 1 - \frac{d}{c}. \qquad (8)$$

Considering this scenario, one can notice that $\alpha^* = 1$ for Bayesian game 1, that is always higher than α^* for Bayesian game 2. Meaning that, in Bayesian game 1, for the worst possible scenario (i.e. the deer always stays on the road), AV2 must always choose the strategy SW providing the expected payoff equal to f. In Bayesian game 2, instead, the higher the difference between d and c, the higher the probability to choose strategy SW, but it is never a dominant strategy. In this case, the expected payoff will become $F = f(1 - \frac{d}{c}) + \frac{d}{c}\big(pc + (1-p)d\big)$. One can notice that $F < f$ for any c, d, f, p that satisfies constraints (1). This bring us to a not so intuitive conclusion that if AV1 is in possess of information about the deer movement, this does not provide an advantage for AV2, which is also supported by the fact that the game has multiple semi-separating NEs that complicates the prediction of the opponent's movement.

TABLE VI: Bayesian game 2 from Table V after removing the strictly dominated strategies.

AV1 \ AV2	SW	R
(SW, R, SW)	0, -1	-2, $-\frac{4}{3}$
(SW, R, R)	0, -1	-1, $-\frac{2}{3}$
(R, R, R)	$-\frac{2}{3}$, -1	$-\frac{2}{3}$, $-\frac{2}{3}$

V. Conclusions

Autonomous connected vehicles can solve many problems of road safety provided that they are enabled to achieve fast response to external events in a short time interval.

In this paper, we considered an interaction of autonomous vehicles with an occurring road obstacle and also with each other, where available actions consist of choosing the best available lane [22], [29]. The resulting scenario was modeled via game theory, and NEs were found. Furthermore, we consider an extension of the game to incomplete information available to the players and the resulting Bayesian equilibria, which offer further insight.

In particular, the most interesting conclusions of Bayesian game theory are drawn if we assume that only one of the vehicles is capable of anticipating the presence of the obstacle. The remaining AV, while not noticing the obstacle, is aware of the extra information available to the first vehicle. Bayesian NEs were found in this game, showing that this is often insufficient to obtain an effective reaction for the AV that is unaware of the obstacle.

We remark that this situation would be of particular interest for a scenario where AVs not only possess capabilities of intelligent decision making but, through their connectivity, are also aware of each other. However, without any more explicit interaction, the resulting NEs do not necessarily represent an improvement for the final outcome (as visible that certain NEs of the last game are even more accident-prone than the previous ones). Also, if there are multiple NEs, the best choice is not straightforward. As the problems become more challenging, the equations will bring more complex structures and finding multiple NEs will not solve the decision making process of the cars.

The take-away message is that beyond empowering self driving cars with safest equipments and powerful sensors, and especially the ability to make autonomous decisions, explicit interactions among the vehicles are also necessary to improve road safety [37]. If we assume AVs to be driven by selfish objectives, just improving their technologies without any communications will lead to worse interactions, as the vehicles will be prone to causing accidents to others for the others for their own safeguard.

Thus, emergency stop functions and explicit notifications among the vehicles should be foreseen [38]. In this spirit, game theory can be used together with communication exchanges [39] as an important tool in the decision making process that autonomous vehicles will have to face.

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