Negotiation Between Vehicles and Pedestrians for the Right of Way at Intersections

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***Abstract*— The higher social attention and negotiation among road users while crossing the road is as much a challenge for self-driving cars as it is for pedestrians. Self-driving cars in their current state are not able to understand cues from other road users and are rather reactive to pedestrian behavior, which may result overall in a slower traffic flow. In this paper, a vehicle–pedestrian negotiation model is proposed describing the processing and exchange of negotiation cues from both parties in order to speed up the traffic flow. The motion strategy for the vehicle approaching the pedestrian is formulated in order to negotiate its best chance to pass first, a process that closely mimics the common scenarios of everyday negotiation on roads. Simulation results show an improvement in the overall travel time of the vehicles as compared with the current best practice behavior (always stop) of autonomous vehicles. The cost-benefit analysis of negotiation among both parties is also discussed in this paper.**

***Index Terms*— Negotiation, autonomous vehicles, pedestrians, intentions, traffic flow, interaction design.**

I. Introduction

THE industry's attention in the development of self-driving cars is focused on technology towards safer mobility. One of the challenges is how these vehicles will communicate with pedestrians, cyclists, and other human drivers. The industrial effort in this direction is evident from the proposed interaction design concepts by the leading autonomous vehicle manufacturers. For example, *Nissan* has proposed the use of intention indicators in the form of a high belt line of light around the vehicle to alert the pedestrians. Similarly, *Google* proposed text message display for the pedestrians at the vehicle's windshield, while *BMW* and *Mercedes* reveal as a potential solution the projection of a crosswalk in front of the car when it stops, signaling the pedestrian to cross.

These current interaction design approaches focus on the communication channel. However, autonomous vehicles will be also required to exhibit a socially acceptable behavior such as recognizing a user's intention in the form of gestures or other communication cues. Similarly, pedestrians would also like to be informed about the vehicles' intentions in order to avoid any potential conflicts. A conflict may arise due to competing interests of both parties to pass the crossing point first. Negotiation is a solution to balance these competing interests, establish an agreement, and reward both parties in some way. Therefore, the concept of negotiation between self-driving vehicles and pedestrians needs to be understood and generalized.

A. Challenges for a Self-Driving Vehicle

Negotiation in traffic poses the following challenges for a self-driving vehicle.

1) Intent Perception: Pedestrians in their intention to cross the road engage with car drivers in some interaction. This interaction is through the exchange of cues such as gaining attention through eye gaze or using gestures to indicate one's desire. They do so at unmarked locations but often even at marked pedestrian crossings or signaled intersections to negotiate for the right of way. Human drivers are able to judge the pedestrians intention through such cues and react to the situation. Similarly, pedestrians perceive the intentions of human car drivers from some driving behavior cues, or hand waving. But for self-driving vehicles it is still challenging to behave in a similar manner.

2) Social Behavior: Human road users cooperate at shared zones using social rules. While the signalized junctions are controlled by traffic laws, informal social rules play an important role at unmarked intersections. The road users understand the intentions of other users, simulate the consequences of a particular planned action, and then react accordingly. Self-driving vehicles do not exhibit such social behavior yet, and also lack the ability to take human-like decisions in unregulated areas where there might be a conflict among road users for the right of way.

3) Agreement in Negotiation: An important aspect of social behavior in traffic is reaching an agreement with the other road users to get the right of way. Humans do it by intuitive assessment of risks given the perceived cues and estimated intentions. This becomes challenging for the self-driving vehicles due to the uncertainty in recognizing the intentions of the pedestrians.

B. Research Summary

This paper proposes a negotiation framework between pedestrians and self-driving vehicles. The *research hypothesis* is that the negotiation between self-driving vehicles and

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pedestrians will result in a better coordination among both parties, reduce the travel time of vehicles, and thus improve the overall traffic flow at these crossing points.

To prove the above hypothesis, this paper *first* conceptualizes the vehicle-pedestrian negotiation process. *Secondly*, the conceptual model is realized through agent based simulation using *SUMO* and *MATLAB*. The simulation focuses on the interaction of a pedestrian with the leader vehicle (in a random vehicle flow) approaching the intersection. Particularly, it compares the proposed negotiation model to the conservative assumption that a self-driving vehicle always stops for a pedestrian with an intention to cross. The considered parameters are the traffic disturbance and pedestrian delay. The traffic disturbance is measured in terms of the average travel time of vehicles, the time headway between vehicles, and the overall intersection throughput. *Lastly*, a qualitative cost benefit analysis for both parties is discussed in terms of the social, environmental, and economic impacts of negotiation.

C. Contributions in This Paper

This paper proposes a model for self-driving vehicles to negotiate for the right of way. The model shows how negotiation provides a better coordination among both parties, which reduces conflicts of interests at unregulated intersections or pedestrian crossings. The simulation results show that the travel time of negotiating vehicles is significantly reduced, thus improving the overall traffic flow, which will have positive environmental and economic impacts. The benefits to the parties and related costs involved are discussed in this paper.

The following section reviews the literature discussing the social behavior of autonomous or human-driven vehicles and pedestrians. Section III describes the proposed conceptual model of negotiation. Section IV describes the simulation experiment design and the associated behavior modeling. Section V presents the results obtained from the analysis of different measurement data followed by a detailed discussion of the results in Section VI. Section VII concludes the paper with a brief summary of results, limitations of the current model and the future work required.

II. Literature Review

Pedestrians always have the right of way is an unsettled statement. For example, the traffic laws in US give the right of way to pedestrians at an intersection while the vehicle is turning, at zebra crossings and childrens crossings, and at marked foot crossings at signalized junctions (when pedestrian lights are on). In other situations, the law gives right of way to no one but states who must yield in order to maintain safety on roads [1]. The traffic safety guidelines for most of the countries suggest to look out for pedestrians at pedestrian crossings, intersections, around parked cars, near schools and shopping centers. Similarly, pedestrians are required to prefer crossings instead of running through the middle of the driveways. In these situations, common sense and courtesy are required from both ends along with social negotiation. This section, first, provides a review on human drivers and pedestrian behavioral research in traffic psychology followed by a discussion on the social behavior of current self-driving vehicles.

A. Behavioral Research in Traffic Psychology

1) Age-Related Road Crossing Behavior Among Individuals: The decision to cross a road requires higher social attention and the associated cognitive abilities differ among individuals. For example, children often ignore the safe gap while crossing when compared to adults [2]. Young individuals are willing to take more risks even when they perceive the safety gap because they have the ability to cross quickly [3]. Older people exhibit a different road-crossing behavior when compared to younger people as they take a longer time to sense their surroundings due to their reduced cognitive abilities [4].

2) Impact of Environment on Pedestrians Road Crossing Behavior: Crossing a road in any traffic situation is a decision-making process which involves the integration of multiple sources of sensory information. Humans respond to the social information perceived through their environment. The environment factors include the vehicular traffic, infrastructure such as street lights or road markings, and other people on road.

a) Information perceived from vehicular traffic: The oncoming vehicle (driver) transmits the information to the pedestrian through some non-social signals such as the speed of the vehicle. Pedestrians are more likely to stop or wait at the crossing if the vehicle is approaching at a higher speed. Their behavior is also affected by the number of vehicles approaching. It is found that pedestrians often restrict their crossing movement when a large number of vehicles is approaching them [5]. Other factors affecting their judgment are the vehicles direction and distance which helps in judging the safe gap to cross the road [6]. This safe gap is a perception of different individuals rather than a general measure.

b) Information perceived from infrastructure: Pedestrian street lights and marked road crossings are the source of information for pedestrians through regulated infrastructure. Early studies in traffic psychology provide literature on the safe design of infrastructure to reduce accident risks [7] and these have been improved over time by studying pedestrian dynamics through traffic simulations [8], [9]. These studies have helped in designing regulated traffic infrastructure, but even in such situations, humans are likely to show non-compliance behavior [10]–[12]. Such behavior may include scanning the vehicular traffic and taking a decision to cross quickly or in other ways directly forcing the vehicle to stop by giving a hand signal.

c) Information perceived from other pedestrians: The other reason for rule violations by pedestrians may be the influence of following the crowd ahead. Rastogi *et al.* [13] reported that pedestrians who fall behind in a group of people crossing the road tend to increase their speed to catch up with the group flow and quickly cross the road. The other scenarios of such group formation can be observed in sidewalks closely related to lane formation in public places [14]. The pedestrian dynamics is simulated based on certain models assuming that pedestrians are influenced by their desires to reach the destination, as well as from the geometry of the environment. But these self-organizing models in traffic fail to address the issues of individual perceptions.

3) Factors Influencing Human Drivers Behavior in Traffic: Most of the interactions in urban traffic are between pedestrians and vehicle drivers for the right of way. Drivers also process information by looking at the behavior of pedestrians. An individual can gain attention from social cues, such as eye gaze and facial expressions of human drivers on the road [15]. Pedestrians often negotiate for the right of way with human drivers using such social cues. Apart from this, hand signaling is also common among pedestrians and drivers to indicate their intentions. The signaling gestures may also show differences across individuals and cultures [16]. Not only there are differences in driving styles, but also differences in the pedestrian behavior across cultures [17].

B. Human-Machine Interaction Through Gestures

The above discussion provides insight into the elements perceived by the pedestrians while crossing the road and what the human drivers look around for to ensure safety. The pedestrian interaction with a vehicle on the road involves cues such as eye contact and hand signals. Establishing multi-modal human-machine interaction is challenging. With advancements in robotics, machines can be trained to perform gestures [18] and generate facial expressions [19] which are an attempt towards developing effective interaction between humans and machine. The concept of robotic eyes and using the gaze cues to draw attention towards human-robot collaborative task is also investigated in [20] but is limited by its application context.

The existing machines are designed for specific applications and cannot independently be involved in a non-verbal communication with humans. The open question is whether machines can decode and react to dynamic cues from their environment. How will the future self-driving car react to the nod or wave by the pedestrian in complex traffic conditions? And even more important is how will it communicate its intentions to the other road users as the human drivers do?

C. Social Behavior of Self-Driving Cars

While the auto industry targets to introduce the level five (full automation) autonomous vehicle by 2025, some experts still argue that it may take few decades to develop a socially acceptable self-driving car [21]. The acceptability of fully autonomous vehicles in future transportation systems will depend on how intelligent it appears to the other road users. A socially acceptable behavior would be adapting the social rules of the road and understand the intentions of different road users to take critical traffic decisions. As such, they can be described as *'intelligent actors in a complex socio-technical system'* [22]. Technologies such as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications provide cooperation between vehicles and road infrastructure. If the vehicles in future are social actors moving on the road then it is required that they exhibit a behavior which is understood by the human road users including pedestrians.

The recent crashes of level three (limited automation) self-driving car models developed by Google and Tesla reveal the limitations of current automated systems. One of them is the reduced attention of the passenger on board. The time-critical interface designed to warn passengers on board and making them learn to react in a short time for unexpected situations is still challenging for the partially automated driving system [23].

Another issue is the social dilemma, which raises the question of moral ethics [24]. There may be situations where the vehicle needs to tackle more complex decisions, such as whether it is justified to sacrifice a passenger on board for a group of pedestrians at risk. Developing such moral algorithms for self-driving cars adds to the complexity of the system. Standards need to be set up by the lawmakers before introducing any machine trained for ethical decisions.

The other concern is the accuracy of vehicle's understanding of its outside environment including human road users, and how it will exhibit a behavior that can be understood by humans. This demands an understanding of how various road users perceive the traffic in different situations. Video analytics is becoming a popular tool among social scientists to derive the road-using behavior of pedestrians. Interviewing road user participants is helping in understanding their trust towards the autonomous vehicles. Sucha *et al.* [25] performed an analysis of the behavior of both pedestrians and drivers, and studied the factors involved in risk perception and communication between them. Similar studies are conducted by other groups to understand the action and reaction of pedestrians towards self-driving cars [26], [27]. Such type of research is also gaining attention by the industry to design a socially acceptable autonomous vehicle. For example, a team of researchers at Nissan is focusing on integrating the understanding of social interaction contexts in their autonomous vehicle design [28]. Google's efforts in this direction are indicated in one of their patents, involving signage and audible warnings to notify the intent of the vehicle [29].

When it comes to self-driving cars interpretation of road user's gestures, there is much less research. For example, there are only few research papers concerned with recognizing traffic controllers' hand signals [30]. Google talks about the capability of its driverless cars detecting cyclists' hand signals in one of its patents [31]. According to the patent, the Google car can recognize and assess the cyclist's hand signal based on the conventions followed in North America.A recent patent published by Delp and Caveney [32] claims an automated driving system that can recognize traffic controllers' hand signals and respond to the command. These hand signal rules encoded by traffic authorities of the individual states vary broadly among countries, but also show a base in affordance which raises the expectation that an affordance-based vehicle control may be the key for interaction with future self-driving cars [16].

D. Road Users Intention Recognition by Driverless Vehicles

Vehicle-to-vehicle (V2V) communication technology allows the vehicle to broadcast its data to other vehicles within a range of few meters. The interaction between self-driving cars in unregulated environment can deal with the intention uncertainties through V2V cooperative control operations [33]–[35]. But sharing roads with human road users requires perception of each others motion intentions to avoid any potential conflicts.

There are frameworks in decision theory to model the social behavior in autonomous vehicles. An example is POMDP (Partially Observable Markov Decision Processes) based approach which integrates uncertainty in human intention as a hidden state in the decision process [36]. Experimental results have shown that POMDP model can map beliefs (probability distribution) about human intentions to actions as compared to simpler Hidden Markov Models [37]. These approaches have been used to develop the human drivers behavior prediction model. Song *et al.* [38] proposed autonomous driving decision-making method in uncontrolled intersections considering the uncertain intentions of other human-driven vehicles. Another cost function based method is the Bayesian probabilistic driving intention estimator which was implemented to test the cooperative behavior of vehicles while merging at freeways [39]. However, its application is limited to in-lane driving. Coordinating vehicles at merging zones through connected vehicle systems can improve the traffic flow on roads by reducing stop and go driving [40], [41].

The observable entities to estimate intention to yield in the above methods are the position and acceleration of the vehicle. These observables are good enough for interaction between two vehicles as the vehicles motion for the next few seconds can be precisely mapped with these parameters. But in the case of pedestrians, this method may involve large uncertainty in intention estimation as their intention may change significantly at any moment.

Thus, there are gaps in the current design of self-driving cars behavior. The safe design of these vehicles includes the detection of pedestrians, cyclists and other obstacles on the way and stop whenever such obstacles are encountered. This conservative behavior will affect the traffic flow on roads and thus negotiation might be a necessity for future vehicles. Negotiation itself is challenging as it depends on the perception of the environment. This paper attempts to conceptualize negotiation model for vehicles and describe the overall impact of this process on the surrounding environment.

III. Negotiation Framework

This section discusses the process of negotiation, and then describes a conceptual model for the vehicle-pedestrian negotiation.

A. What Is Negotiation?

In business literature, negotiation is defined as the *'process of combining conflicting positions into a common position, under a decision rule of unanimity'* [42]. This means, negotiation parties have to agree upon a solution for a conflict. The agreement is advanced by their common interest, mutual perception and dependence [43]. The theory of principled negotiation (seeking win-win solutions) defines seven prescriptive components for negotiation comprising interests, people, options, legitimacy, alternatives, commitments, and communication. As a starting point for defining a negotiation process in traffic, these elements of negotiation theory are explored below:

a. *Identifying parties and their interests*: The parties involved in the negotiation have underlying interests which can be identified from the parties' hidden or stated objectives.
b. *Identifying the options*: The possible solutions to the problem shared by both parties should be explored during negotiation.
c. *Criteria*: Fair criteria for a joint decision-making should be established to reach an agreement among parties.
d. *Commitments*: Once an agreement is reached the parties should make commitments to honor it.
e. *Alternatives*: The alternative solutions must be available to meet one's goals if there is no cooperation from the other side.
f. *Communication*: An effective communication is important to describe one's intention to the other party and also to learn about the other party's intentions during the negotiation process.

The above elements of the negotiation theory are used for defining the process of negotiation in traffic, which is discussed in the next section.

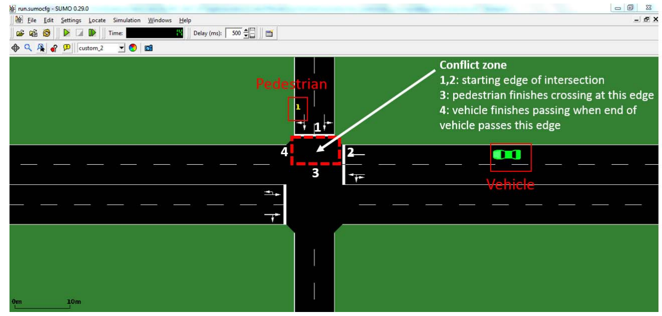


Fig. 1. Vehicle-pedestrian interaction scenario: The interaction environment is restricted to unregulated junctions where the pedestrian appears at the curbside and is attempting to cross the road (screenshot in SUMO).

B. Conceptual Model

The situation to be studied is depicted in Fig 1. The vehicle and the pedestrian are approaching an unmarked intersection and their goal is to pass the intersection with minimum waiting time. Each party estimates its time to reach the conflict point (T_{veh}, T_{ped}). In a conflicting situation, both parties will try to negotiate for the right of way and at least one of them has to change their intention to allow the other party to pass first.

The conceptual model of a negotiation framework is presented in Fig. 2. At any time *t*, the two agents (vehicle and pedestrian) have a particular *speed* and *direction of movement*. It is assumed that both agents are able to communicate their intentions through a communication channel. For example, the vehicle can blow the horn, use light indicators, or send text messages to alert the pedestrian, and the pedestrian can use

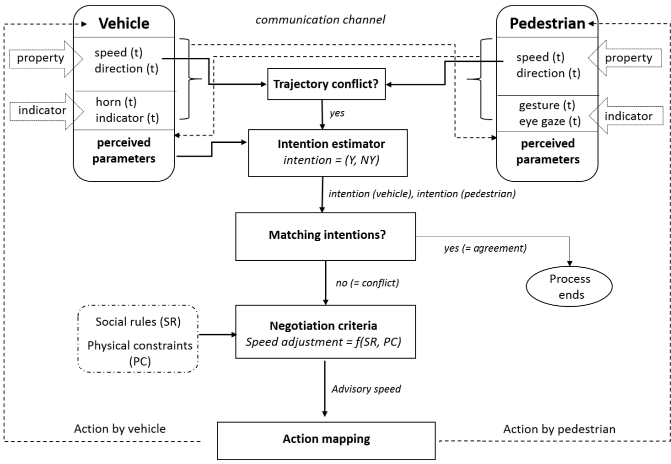


Fig. 2. The proposed vehicle-pedestrian negotiation framework.

eye gaze and gestures to indicate their intentions. It is assumed that the vehicle is able to detect the gaze and gestures of pedestrian through appropriate sensors with a known accuracy of detection. This assumption is reasonable as technologies such as face and gesture recognition already exist in other domains. So it can be expected that the future self-driving cars will also be able to detect and decode cues from human road users (gaze, hand signals, and body movement).

The vehicle continuously looks for any pedestrian around, and whenever a pedestrian is detected near the curbside, it checks for any conflict with the estimated trajectory of the pedestrian. It perceives the speed, direction, and other cues of the pedestrian to estimate their intention to yield or not to yield. Similarly, the pedestrian also perceives speed, direction, and other cues of the vehicle. Each party estimates the intention of the other party as a function of these parameters.

If there is a conflict in the intentions of two parties, then negotiation starts at that instance. The vehicle estimates its chance to pass first and communicates its intentions in the form of a communication act (*for example*, speeding up or slowing down, or using indicators to warn the pedestrian). The pedestrian also has an interest to pass first. Both parties form a negotiation strategy based on social rules and physical constraints. However, this paper only focuses on physical constraints to formulate the negotiation strategy as social rules play a more significant role in more complex environments (in presence of multiple vehicles and pedestrians), which is out of the scope of this paper.

Both parties are looking for an agreement during the negotiation process. The pedestrian is expected to react to the vehicles action. This reaction may be a change in their intentions. The pedestrian may honor the vehicle's intention to pass first and stop at the curbside (or wave allowing the vehicle to pass first). In this case an agreement between two parties is established.

In another case, the pedestrian may show an aggressive behavior and continue to cross (speeding up action). The vehicle will either decide to stop (slow down) in the next step or continue to negotiate its chance to pass first based on its assessment of the physical constraints and risks involved. In this negotiation process, non-verbal cues are exchanged continuously till an agreement is reached (in which case the negotiation ends).

The negotiation model benefits the vehicle if it encounters a cooperative pedestrian, but this model also ensures that the vehicle exhibits conservative behavior towards an aggressive pedestrian to maintain safety on the road. In case of large uncertainty in the pedestrians intention to yield, the vehicle always slows down for a pedestrian to cross. Thus, safety is the overarching principle, but in contrast to a standard conservative behavior the one-to-one negotiation is also providing gains in throughput.

C. Vehicle-Pedestrian Interaction Scenarios

The different scenarios of everyday negotiation between vehicles and pedestrians are discussed below. Note that in these examples the communication is through non-verbal cues and the parties can perceive each other's intentions through their actions (such as indicating one's intention of not to yield by speeding up or gesturing to stop).

In the first three scenarios, the vehicle indicates its desire to pass first as its estimated time to cross is less than that of the pedestrian ($T_{veh} < T_{ped}$, Fig. 1). This message is communicated to the pedestrian through some communication channel.

Scenario 1: The pedestrian shows an aggressive behavior and decides to cross first (reacts by starting to cross). The vehicle perceives this intention of the pedestrian and prepares to slow down.

Scenario 2: The pedestrian honors the social rules and agrees to yield to the vehicle. The pedestrian slows down (acknowledgement in negotiation) which is perceived by the vehicle as an agreement, and in the next step the vehicle speeds up to pass the intersection.

Scenario 3: Another case is when the vehicle can't stop before the crossing point due to acceleration constraints, and thus generates an alert to the pedestrian. In this scenario, the vehicle indicates to pass first but the pedestrian shows an aggressive behavior by starting to cross anyway. In the next step, the vehicle generates an alert and the pedestrian reacts by stopping for the vehicle.

Scenario 4: The pedestrian initiated the negotiation by indicating to pass first (through gestures). The vehicle perceives this intention and prepares to slow down for the vehicle. The slowing down action of the vehicle is assumed as an agreement by the pedestrian. The pedestrian crosses first.

D. Negotiation Strategy

The negotiation strategy is based on pedestrian's behavior, which may be either aggressive or cooperative. In this paper the focus is to formulate negotiation strategies for the vehicle to deal with these two types of pedestrian behavior which have some indirect benefits to pedestrian as well. This section describes the formulation of *advisory speed* for vehicle.

The negotiation starts when a vehicle detects a pedestrian approaching the curbside. First, the vehicle estimates the intention of the pedestrian in terms of chances of them yielding (Y) or not yielding (NY) to the vehicle.

TABLE I
TERMINOLOGY

Term	Description
d_{veh}	distance of vehicle from the starting edge of intersection
d_{ped}	distance of pedestrian from the starting edge of intersection
v_{veh}	current speed of vehicle
v_{ped}	current speed of pedestrian
TTR_{ped}	time taken by pedestrian to reach starting edge of intersection
TTR_{veh}	time taken by vehicle to reach starting edge of intersection
w	width of the lane
l	length of the vehicle
MAXIMUM	maximum allowed speed for vehicles
accelToStop	required deceleration to stop before intersection
accelLimit	acceleration or deceleration limit of the vehicle
ALERT	status variable to alert pedestrian
$gaze$	accuracy of pedestrian's gaze detection by the vehicle
$gesture$	accuracy of pedestrian's gesture detection by the vehicle

Secondly, the vehicle forecasts the speed limits within which it can move in the current situation:

a. Minimum speed (*minSpeed*): The required speed of the vehicle such that the pedestrian crosses the end of the intersection before the vehicle reaches the starting edge of intersection.
b. Maximum speed (*maxSpeed*): This is the required maximum speed to pass the intersection before the pedestrian steps on the starting edge of the intersection.

To initiate the negotiation, next the vehicle offers to pass first, *if* (i) it can pass before the pedestrian based on its knowledge of current motion parameters of both parties, (ii) *or* it cannot stop before the pedestrian finishes crossing (alert generated).

If the pedestrian expresses an intention to pass first then the vehicle estimates its chances of negotiation based on the conditions described above.

1) Advisory Speed for Vehicle: The advisory speed for the vehicle is based on the vehicle understanding of pedestrian's intentions at any instance. If the chance of the pedestrian yielding is high then the vehicle speeds up (within limits) to pass first and reduce the waiting time for the pedestrian as a reward, rather than moving with the same speed towards the crossing point. On the other hand, if the chance of yielding is low, then the vehicle should slow down and negotiate again its chance to pass first. Human drivers do this intuitively and adjust their speed considering the confusion in estimating what a pedestrian is going to do next. The uncertainty involved in estimating pedestrian's intention should be considered to calculate advisory speed of vehicle. Thus, the advisory speed can be computed by taking the weighted average of predicted minimum and maximum speed (*minSpeed* and *maxSpeed*).

$$advisory\ speed = Y \times maxSpeed + NY \times minSpeed$$

Here, weights are taken as the perceived pedestrian's chances of yielding or not yielding (Y and NY).

The stepwise algorithm for negotiation process by the vehicle is presented in *Algorithm 1*. The advisory speed for vehicle is computed at the end of each negotiation cycle. The associated terminology is listed in Table I.

Algorithm 1 Pseudo-Algorithm for Negotiation by Vehicle

Input: Motion and indicator parameters of agents
Output: Advisory speed for vehicle

check if pedestrian has reached $2m$ before the curbside
for each negotiation cycle **do**
  if no trajectory conflict with the pedestrian **then**
    no negotiation required; CONTINUE
  else
    estimate intentions of the pedestrian
    $Y = IntentionEstimator\ (gaze, gesture, v_{ped})$
    $NY = 1 - Y$;
    if acknowledgement to yield by the pedestrian with some action ($Y >> NY$) **then**
      (agreement is reached in favor of vehicle);
    else if ALERT is true **then**
      vehicle generates an alert to the pedestrian
    else
      (conflict in intentions)
      if $T_{veh} < T_{ped}$ **then**
        vehicle indicates to pass first
      else
        (vehicle waits for pedestrian's action)
      end if
    end if
    compute minimum required speed (minSpeed)
    $TTR_{ped} := (d_{ped} + w)/v_{ped}$
    $minSpeed := d_{veh}/TTR_{ped}$
    compute maximum required speed (maxSpeed)
    $maxSpeed := (d_{veh} + w + l)/TTR_{ped}$
    $maxSpeed := min(maxSpeed, MAXIMUM)$
    compute the advisory speed
    $advisoryspeed := Y * maxSpeed + NY * minSpeed$
    check whether advisory speed satisfies acceleration limits
    update advisory speed keeping the acceleration limits
    compute required deceleration to stop before start of intersection (*accelToStop*)
    compute ALERT status:
    if $accelToStop > accelLimit$ OR $d_{veh} < 0$ **then**
      ALERT := true
      advisory speed = maxSpeed
    else
      ALERT := false
    end if
  end if
  return $advisory\ speed$
end for

IV. EXPERIMENT DESIGN

A. Simulation Environment

The simulation of vehicle-pedestrian interaction scenario is done using *MATLAB* and *SUMO* (Simulation of Urban Mobility). The *TraCI* (Traffic Control Interface) protocol is used to interact with SUMO in a client-server scenario. A random vehicle flow of 800 vehicles/hour is generated in SUMO, and the simulation is run for about 7 hours (24000 steps of $1s$). The flow of vehicles generated by SUMO is by default binomially distributed which approximates a Poisson distribution. This simulation is run for two different frequencies of pedestrian flow - every $35s$ (total 685 pedestrians) in first experiment, and every $14s$ (total 1714 pedestrians) in another experiment. The pedestrian behavior modeling is described in section IV-C.

B. Negotiation Model

In the proposed negotiation model, interaction with pedestrian starts when they reach a distance of $2m$ or less from the curbside. From this instance, the negotiation model algorithm is applied. At the time of their appearance, their distance from the lead vehicle is different each time. In the free flow of vehicle, each vehicle starts (enters the simulation) with zero speed and accelerates (upto maximum allowable speed). Most of the vehicles accelerate to the maximum at a distance of around $40m$ from the conflict point. Thus, the speed of leader vehicle at the time of pedestrian encounter depends on its distance from the conflict point. For each step in the simulation, parameters recorded are speed and position of vehicle and pedestrian, and their respective distance from the crossing point (both at lane center and at curbside).

The assumptions in this modeling are:

i) The environment considered is an unregulated road intersection and the vehicles are moving along a straight line on the road; there is no lane changing or passing around the pedestrian.
ii) Vehicles enter and exit the simulation in the same order; there is no overtaking.
iii) Different road scenarios may be complex due to the presence of multiple interacting agents. Before considering those complexities, as a first step in defining negotiation concepts on roads, this paper only focuses on the simple case of negotiation between a single self-driving car and a single pedestrian.
iv) The approaching pedestrian interacts only with the next approaching vehicle.
v) The current model considers only a vehicle's interaction with a pedestrian approaching from a conflicting direction whose goal is to cross the intersection; other road users as well as other pedestrian behaviors are not considered.

Assumptions (i-iv) allow a proof of concept for the negotiation model. Assumption (v) suggests that the negotiation model has to be embedded in a multi-agent framework in future.

C. Pedestrian Behavior Modeling

Pedestrians are modeled with a dynamic behavior in the simulations. In the first experiment, a pedestrian is introduced into the environment every $35s$ from a fixed origin (at some distance from the crossing point). In a second experiment the pedestrian frequency is changed to $14s$. By default, the pedestrian is moving with an average walking speed (assuming $1.2m/s$). The pedestrian stops if *(i)* the oncoming vehicle is at less than a distance of $30m$ from the intersection, or *(ii)* an alert is generated by the vehicle because it cannot stop before the pedestrian crosses due to its deceleration constraints.

Apart from the motion dynamics, there is an intention value associated with pedestrian behavior at any simulation step. Here, the intention value means: the pedestrian's chances of yielding (Y) or not yielding ($NY = 1 - Y$) as perceived by the vehicle. Since gaze and gestures of pedestrians cannot be modeled in SUMO, and neither can the perception of these by vehicles, the initial intention values are assigned randomly to show cooperative ($Y > NY$) or aggressive behavior ($NY > Y$). This value changes depending on the distance of the vehicle. The waiting time is minimum for the vehicles if pedestrian always shows a cooperative behavior towards them. The waiting time is maximum for the vehicles if they always encounter an aggressive pedestrian in which case the negotiation and conservative model would produce same results. The assumption here of 50% likelihood of encountering an aggressive or cooperative pedestrian demonstrates the average between the two extremes. The model can be adjusted for local culture.

Initially, the pedestrian is approaching the intersection to pass first with an average walking speed so the intention value is assigned as $Y = 0.2$. But during negotiation, if the pedestrian slows down or stops for the vehicle to pass first then the intention value changes (value of Y changes proportionally to the change in speed of pedestrian). The possible interaction scenarios in the simulation have been discussed in Section III-C.

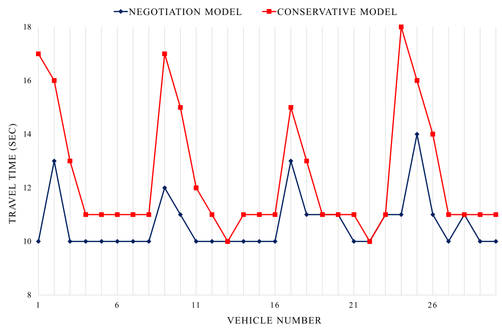
D. Conservative Vehicle Model

A second simulation with a conservative vehicle behavior provides the benchmark for comparing the performance of the proposed negotiation model. A vehicle shows conservative behavior if it always stops when it detects a pedestrian at the curbside, i.e., with the intention to cross. In this case the vehicle waits until the pedestrian finishes crossing. This mimics the current state of self-driving vehicles. The pedestrian behavior, in this case, is modeled to show an aggressive behavior and always gets the right of way (passes first). The simulation environment is the same as the negotiation model.

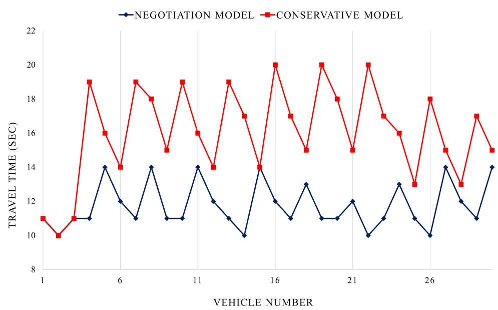
E. Observables

For each model, the following parameters are observed at the time of simulation to measure the traffic disturbance:

a. *Travel time of vehicles:* This is the time vehicle takes to pass the intersection from the starting point. The timestamps at which a vehicle enters the simulation environment (entry) and passes the other end of the intersection (exit) are recorded for each vehicle in the simulation. The entry and exit timestamps provide the travel time for each vehicle.
b. *Time headway:* This is the difference in passing time of successive vehicles in the traffic flow. The time headway for each vehicle pair is calculated by taking the exit timestamps difference of the current and last vehicle which passed the intersection.

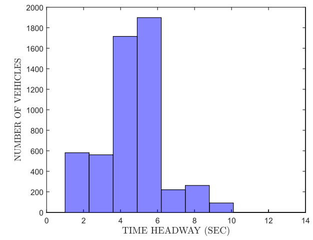


(a)

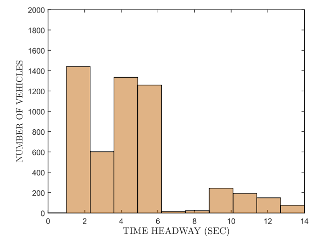


(b)

Fig. 3. Travel time series: Travel time of first 30 vehicles in the simulation for negotiation model (blue) and conservative model (red). (a) Pedestrian frequency $= 35s$. (b) Pedestrian frequency $= 14s$.

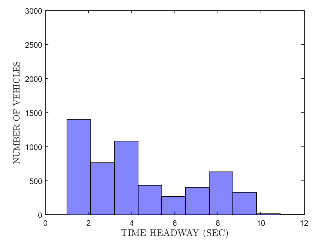


(a)

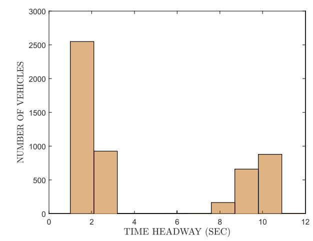


(b)

Fig. 4. Time headway analysis with the pedestrian frequency of $35s$. (a) Negotiation model. (b) Conservative model.



(a)



(b)

Fig. 5. Time headway analysis with the pedestrian frequency of $14s$. (a) Negotiation model. (b) Conservative model.

c. *Pedestrian delay:* This is measured in terms of the time taken by the pedestrians to cross the road (from curbside to curbside). This includes the waiting time for a pedestrian at the curbside.
d. *Overall intersection throughput:* Throughput is the number of vehicles passing the crossing point per hour. The overall crossing point throughput is calculated as the total number of vehicles which passed the crossing point divided by the simulation run time.

V. Results and Discussion

A. Travel Time Analysis

The travel time series for the first 30 vehicles is shown in Fig. 3. It is clear from the graph that the travel time of vehicles is less for negotiating vehicles (in blue color) as compared to the conservative vehicles (in red color). The peak indicates the increase in travel time of vehicles due to waiting for pedestrian to cross. This waiting time is higher for leader vehicles interacting with the pedestrian.

1) Pedestrian Frequency 35s: The first three data points in the conservative model (Fig. 3a, red) show that the leader vehicle interacting with a pedestrian is delayed with maximum waiting time. This delay is propagated to the vehicles queuing up behind. After a few of delayed vehicles have passed, the vehicle flow stabilizes again (represented in red data points 4-8) until another pedestrian is encountered. On the other hand, this situation is improved in the negotiation model (blue color) as negotiating vehicles can anticipate the situation and slow down or speed up in agreement with the pedestrian. The results show that the first vehicle is able to negotiate and pass first with minimum total travel time. The second vehicle slows down for the pedestrian and experiences some delay but the following vehicles are not affected. The negotiating vehicle travel pattern shows that vehicles in queue are less affected as compared to the conservative model.

2) Pedestrian Frequency 14s: If the pedestrian frequency is increased to $14s$, then the travel time for vehicles further increases (Fig. 3b). The first three vehicles in both models pass without conflicting with a pedestrian. The fourth conservative vehicle (red) stops for the pedestrian and experiences some delay, which is propagated to the following vehicles. Due to frequent encounters with pedestrians more vehicles are experiencing delays, which indicates that traffic density increases over time, thus causing disturbance in traffic flow and congestion on roads. This is evident from the simulation results as the average travel time for the first 100 vehicles is $16.2s$, which increases to $43.5s$ for around 5000 vehicles at the end of simulation. This high increase in average travel time of conservative vehicles reveals the accumulation of delays over time affecting the flow of vehicles near the points of crossing. In case of the negotiation model (blue), the travel time of vehicles is higher than in the previous experiment due to the higher pedestrian frequency. But the lower peaks in the negotiation model still show less traffic disturbance as compared to the conservative model. This is also evident from the average travel time for negotiating vehicles, which remains almost constant at the end of the simulation (average travel time $11.8s$).

B. Time Headway Analysis

The traffic disturbance can also be understood in terms of the time headway distribution for vehicles in both models, which is represented in Fig. 4 and Fig. 5. In road traffic,

TABLE II

TIME HEADWAY (TH) DISTRIBUTION FOR NEGOTIATION (NM) AND CONSERVATIVE (CM) MODEL (PEDESTRIAN FREQUENCY 35s)

TH	2s	4s	6s	8s	10s	12s	14s
NM (%)	10.9	42.7	35.6	9.0	1.7	0	0
CM (%)	27.0	36.3	23.6	0.7	4.6	6.4	1.4

TABLE III

TIME HEADWAY (TH) DISTRIBUTION FOR NEGOTIATION (NM) AND CONSERVATIVE (CM) MODEL (PEDESTRIAN FREQUENCY 14s)

TH	2s	4s	6s	8s	10s	12s	14s
NM (%)	26.3	34.6	13.2	19.4	6.5	0	0
CM (%)	49.1	17.8	0.0	3.2	29.6	0.1	0.0

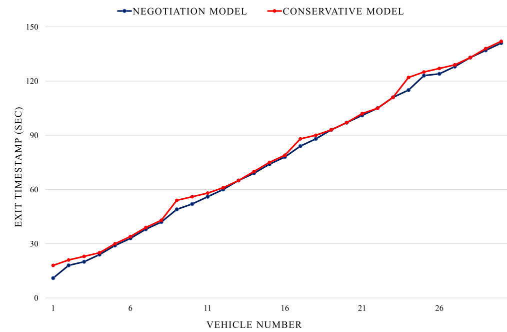
a minimum time headway of two seconds to the vehicle in front is to be maintained to avoid any rear-end collisions and the same is implemented in SUMO by default. In simulations, the average headway of vehicles in the initial vehicular flow is 5s. The quantitative distribution of time headway of vehicles (numbers represent the % of total vehicles) for both models is listed in Table II and Table III, respectively. This will be further discussed in the following sections.

1) Pedestrian Frequency 35s: Interestingly, the average time headway for both models is the same (about 4.5s) but the variance in the distribution of the conservative model is higher. An analysis of variance using *F-Test* showed that this difference is significant ($F_{1,5330} = 2.97$, $p < 0.05$). This indicates that traffic disturbance is higher in conservative model. The graphical representation of the time headway distribution for the conservative model is presented in Fig. 4b.

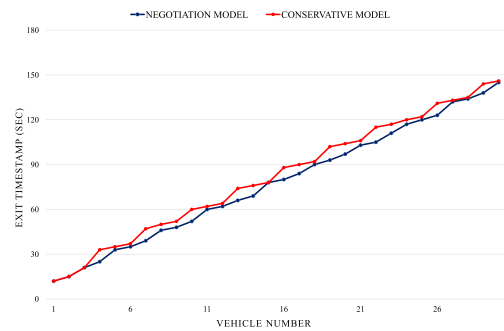
In Fig. 4b, the higher time headway values (10s, 12s, and 14s) reflect the higher waiting time for leader vehicles. These leader vehicles interact with the pedestrians and count for *12.3%* of the total vehicles in the flow. Table II shows that the stopping of leader vehicles has delayed another *27%* of the total vehicles as they have the minimum time headway (2s). This implies that the flow of conservative vehicles is not uniform and vehicles are stacking up (waiting behind leader) during pedestrian encounters, causing disturbance or congestion. However, in the negotiation model (Fig. 4a) the maximum headway is 10s, and 80% of the total vehicles have a time headway between 4s to 6s representing a smoother flow of vehicles (Table II). Negotiation improves the flow of 20% of those vehicles that were affected by delay in the conservative model, thus reducing the disturbance in traffic.

2) Pedestrian Frequency 14s: It is expected that increasing the pedestrian frequency will increase the waiting time for vehicles. The results show that negotiation performs better in this case as well. The graphical representation shows that the time headway distribution is uniform for negotiations (Fig. 5a) as compared to the conservative model, which still shows a large variance in the distribution (Fig. 5b). In this case also, the analysis of variance using *F-Test* showed that this difference is significant ($F_{1,5127,5330} = 2.05$, $p < 0.05$).

In the conservative model, the number of leader vehicles stopping for pedestrians increases by 30% when the pedestrian frequency is increased to 14s (Table III). Also, the number



(a)



(b)

Fig. 6. Exit time analysis: The exit timestamp of vehicles in SUMO is plotted against the simulation runtime. The above plot is shown for first 30 vehicles to visualize the pattern in traffic flow. (a) Pedestrian frequency 35s. (b) Pedestrian frequency 14s.

of following vehicles delayed due to frequent pedestrian encounters is about 50% (headway of 2s) in this case. But with negotiation, about 50% of the total vehicles passed with time headway between 4s to 6s, while only 26% of the total vehicles are affected by slowing down of the lead vehicles. The results show that negotiation has improved the traffic flow as compared to the conservative vehicles in line of the arguments stated in previous sections. Both travel time and time headway analysis results support the hypothesis of this research.

C. Throughput Analysis

1) Pedestrian Frequency 35s: The results of experiments with pedestrian frequency of 35s reveal an interesting fact: Although travel time of vehicles show significant differences in the two models, overall throughput at crossing points does not change. This observation can be explained by the analysis of crossing point exit timestamps of vehicles in the two models (Fig. 6a). The peaks in the time series show the interruption in free flow of traffic by the pedestrians. These peaks are higher for conservative vehicles (red color). The dots in the curve around these peaks represent the waiting vehicles.

The above results show that negotiation brings down these peaks by reducing the waiting time of vehicles (blue color). The difference in exit timestamps for the same vehicles in both models is higher for the first few waiting vehicles. Then the delay in waiting of the conservative vehicles reduces, and after some time conservative model converges to the negotiation model (Fig. 6a). The delayed vehicles are queued up behind

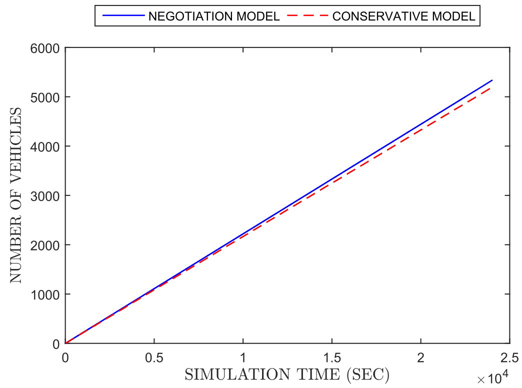


Fig. 7. Throughput analysis: The above graph shows the exit timestamp of each vehicle at intersection until the end of simulation (24000*s*). The two time series represent the negotiation (blue) and conservative (red) model.

a leader vehicle while they are waiting for a pedestrian to cross. As the pedestrian passes, the stacked vehicles accelerate to pass one after the other without any interruption. The time headway in this case is minimum (2*s*), which is reflected in the headway distribution (Table II). After the delayed vehicles are cleared up from the road near the crossing point, the traffic density stabilizes again until the next pedestrian is encountered. Thus, overall throughput does not change at the end of simulation. However, if throughput is computed at a time when a queue of vehicles is waiting at the crossing point, then the throughput difference in the two models will be significant. This leads to another hypothesis that if pedestrian frequency is increased then there should be significant difference in intersection throughput, i.e., negotiation model should perform better than conservative model. This is discussed next by changing the pedestrian frequency to every 14*s*.

2) Pedestrian Frequency 14s: By increasing the pedestrian frequency the distance between exit timestamps of both models increases as well (Fig. 6b). The above hypothesis is supported by the throughput analysis results in Fig. 7. The graph shows the total number of vehicles that passed the intersection in the simulation. The results show that by negotiation around 200 more vehicles passed in total as compared to the conservative model. This observation also supports the observations in Sections V-A and V-B that traffic flow is improved by negotiation as more vehicles are passing the intersection.

D. Cost Benefit Analysis

This section discusses the benefits of negotiation for both parties (vehicles and pedestrians) and their surroundings, and the costs associated with taking particular actions. The cost-benefit analysis is done considering the social, economic and environmental impact of negotiations.

1) Social Impact: Negotiation allows a vehicle to get best chances to pass first thus reducing the waiting time for vehicles at points of encounter. This behavior might increase the pedestrian waiting time. The simulation results show that there is no delay for pedestrians in the conservative model as vehicle always stop for the pedestrians. The crossing time in this case is 4*s*. But with negotiations, the average pedestrian waiting time is 2*s* (or the average crossing time is increased to 6*s*). This pedestrian delay is much less than the waiting time for conservative leader vehicles and a large number of following vehicles. This means, negotiation will benefit multiple vehicles by reducing their waiting times, also allow them to maintain a smooth speed profile and reduce congestion on roads. The benefit to the pedestrian at the cost of an acceptable waiting time is better coordination with the vehicle and the reduced risk involved in taking a decision to cross.

2) Economic Impact: Economic factors are involved in running vehicles on the road. Negotiation will allow the vehicle to drive smoothly and thus reduce the fuel consumption as compared to the conservative vehicles (stopping and then again accelerating requires a larger amount of fuel) [44]. Also, sudden breaks may cause wear and tear of tires and road surfaces. This will be reduced if vehicle operate smoothly on road [45].

3) Environmental Impact: The negotiation process has also an indirect impact on the environment. Reduced fuel consumption by negotiating vehicles will result in lesser CO_2 emissions in environment [44]. Lesser emissions and reduced road congestion will impact on the surroundings of the crossing point - a reduction in health hazards to the people around including pedestrians and maintaining a liveable community.

VI. Conclusions

This paper proposes a conceptual model for negotiation between self-driving vehicles and pedestrians which is realized through agent based simulation in SUMO and MATLAB. The proposed model is compared to the conservative behavior of self-driving vehicles of always stopping for the pedestrians stepping into the road to cross. The simulation results show that the average travel time for negotiating vehicles is improved and the traffic disturbance is reduced as compared to the conservative vehicles. These results support the hypothesis of this research.

Another interesting observation from this model is that although the travel time of vehicles is improved, there is no difference in the overall intersection throughput in the two models when pedestrian frequency is low. However, this difference in throughput increases when the pedestrian frequency is increased in a different experiment - negotiation model performs better and allows more vehicles to pass the intersection. This indicates that current conservative behavior of self-driving cars will cause congestion on roads and negotiation is a solution to this problem.

The negotiation process has some costs and benefits to both parties. The waiting time for vehicles at intersections is reduced but pedestrians may experience some delay in crossing. However, a qualitative analysis of the benefits to the pedestrian shows that at the cost of some delay (which is less than waiting time for vehicles) pedestrians have better coordination with the driverless vehicles. The other indirect benefits to them are reduced emission hazards and congestion-free surroundings providing them a liveable community.

The proposed model only considers the simple cases of negotiation between one vehicle and one pedestrian. Also, the negotiation strategies are based on physical constraints.

But in a more realistic scenario negotiation strategies of both parties are affected by the presence of multiple vehicles and pedestrians around the interaction site. While the presented single vehicle and single pedestrian negotiation model is based on one-to-one interactions, the negotiation among multiple vehicles and multiple pedestrians relies to a larger degree on informal social rules including groups. Thus, the presented conceptual negotiation model will be encapsulated in a future expanded model that will deal with multiple vehicles and multiple pedestrians by incorporating social rules of groups in the negotiation criteria. Formulating such informal social rules will be challenging as they also depend on the behavior of pedestrians. The focus of the next experiments will be to identify and formulate negotiation strategies in complex scenarios which should mimic the everyday negotiation on roads.

REFERENCES

[1] D. Shinkle, "Pedestrian crossing: 50 state summary," in *Proc. Nat. Conf. State Legislature*, 2016. [Online]. Available: http://www.ncsl.org/research/transportation/pedestrian-crossing-50-state-summary.aspx

[2] J. D. Demetre, D. N. Lee, T. K. Pitcairn, R. Grieve, J. A. Thomson, and K. Ampofo-Boateng, "Errors in young children's decisions about traffic gaps: Experiments with roadside simulations," *Brit. J. Psychol.*, vol. 83, no. 2, pp. 189–202, 1992.

[3] S. Schmidt and B. Färber, "Pedestrians at the kerb—Recognising the action intentions of humans," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 12, no. 4, pp. 300–310, 2009.

[4] J. Oxley, B. Fildes, E. Ihsen, J. Charlton, and R. Day, "Differences in traffic judgements between young and old adult pedestrians," *Accident Anal. Prevention*, vol. 29, no. 6, pp. 839–847, 1997.

[5] V. Himanen and R. Kulmala, "An application of logit models in analysing the behaviour of pedestrians and car drivers on pedestrian crossings," *Accident Anal. Prevention*, vol. 20, no. 3, pp. 187–197, 1988.

[6] R. Lobjois and V. Cavallo, "Age-related differences in street-crossing decisions: The effects of vehicle speed and time constraints on gap selection in an estimation task," *Accident Anal. Prevention*, vol. 39, no. 5, pp. 934–943, 2007.

[7] A. Ceder, "An algorithm to assign pedestrian groups dispersing at public gatherings based on pedestrian-traffic modelling," *Appl. Math. Model.*, vol. 3, no. 2, pp. 116–124, 1979.

[8] C. Burstedde, K. Klauck, A. Schadschneider, and J. Zittartz, "Simulation of pedestrian dynamics using a two-dimensional cellular automaton," *Phys. A, Stat. Mech. Appl.*, vol. 295, no. 3, pp. 507–525, 2001.

[9] K. Teknomo, "Application of microscopic pedestrian simulation model," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 9, no. 1, pp. 15–27, 2006.

[10] O. Keegan and M. O'Mahony, "Modifying pedestrian behaviour," *Transp. Res. A, Policy Pract.*, vol. 37, no. 10, pp. 889–901, 2003.

[11] X. Wang, Z. Z. Tian, O. D. Eng, and P. J. Koonce, "Pedestrian delay models at signalized intersections considering signal phasing and pedestrian treatment alternatives," in *Proc. Transp. Res. Board 88th Annu. Meeting (DVD)*, 2009, p. 22, paper 09-2537.

[12] B. Mullen, C. Copper, and J. E. Driskell, "Jaywalking as a function of model behavior," *Personality Soc. Psychol. Bull.*, vol. 16, no. 2, pp. 320–330, 1990.

[13] R. Rastogi, I. Thaniarasu, and S. Chandra, "Design implications of walking speed for pedestrian facilities," *J. Transp. Eng.*, vol. 137, no. 10, pp. 687–696, 2010.

[14] D. Helbing and A. Johansson, *Pedestrian, Crowd and Evacuation Dynamics*. New York, NY, USA: Springer, 2011.

[15] S. R. H. Langton, R. J. Watt, and I. Bruce, "Do the eyes have it? Cues to the direction of social attention," *Trends Cognit. Sci.*, vol. 4, no. 2, pp. 50–59, Feb. 2000.

[16] S. Gupta, M. Vasardani, and S. Winter, "Conventionalized gestures for the interaction of people in traffic with autonomous vehicles," in *Proc. 9th ACM SIGSPATIAL Int. Workshop Comput. Transp. Sci.*, 2016, pp. 55–60.

[17] M. L. Patterson, Y. Iizuka, M. E. Tubbs, J. Ansel, M. Tsutsumi, and J. Anson, "Passing encounters east and west: Comparing Japanese and American pedestrian interactions," *J. Nonverbal Behav.*, vol. 31, no. 3, pp. 155–166, 2007.

[18] P. Bremner and U. Leonards, "Iconic gestures for robot avatars, recognition and integration with speech," *Frontiers Psychol.*, vol. 7, p. 183, Feb. 2016.

[19] M. J. Han, C. H. Lin, and K. T. Song, "Robotic emotional expression generation based on mood transition and personality model," *IEEE Trans. Cybern.*, vol. 43, no. 4, pp. 1290–1303, Aug. 2013.

[20] T. Onuki, T. Ishinoda, Y. Kobayashi, and Y. Kuno, "Design of robot eyes suitable for gaze communication," in *Proc. 8th ACM/IEEE Int. Conf. Human-Robot Interact.*, Mar. 2013, pp. 203–204.

[21] S. E. Shladover, "The truth about 'self-driving' cars," *Sci. Amer.*, vol. 314, no. 6, pp. 52–57, 2016.

[22] L. Müller, M. Risto, and C. Emmenegger, "The social behavior of autonomous vehicles," in *Proc. ACM Int. Joint Conf. Pervasive. Ubiquitous Comput., Adjunct*, 2016, pp. 686–689.

[23] S. M. Casner, E. L. Hutchins, and D. Norman, "The challenges of partially automated driving," *Commun. ACM*, vol. 59, no. 5, pp. 70–77, 2016.

[24] J.-F. Bonnefon, A. Shariff, and I. Rahwan, "The social dilemma of autonomous vehicles," *Science*, vol. 352, no. 6293, pp. 1573–1576, 2016.

[25] M. Šucha, "Road users' strategies and communication: Driver-pedestrian interaction," in *Proc. 5th Conf. Transport Solutions Res. Deployment, Transport Res. Arena*, 2014, p. 9.

[26] F. Keferböck and A. Riener, "Strategies for negotiation between autonomous vehicles and pedestrians," in *Proc. Mensch Comput. Workshopband*, 2015, pp. 525–532.

[27] T. Lagström and V. M. Lundgren, "AVIP—Autonomous vehicles' interaction with pedestrians," Ph.D. dissertation, Dept. Product Prod. Develop., Division Des. Human Factors, Chalmers Univ. Technol., Gothenborg, Sweden, 2015.

[28] E. Vinkhuyzen and M. Cefkin, "Developing socially acceptable autonomous vehicles," in *Proc. Ethnograph. Praxis Ind. Conf.*, 2016, pp. 522–534.

[29] C. P. Urmson, I. J. Mahon, D. A. Dolgov, and J. Zhu, "Pedestrian notifications," U.S. Patent 8 954 252 B1, Feb. 10, 2015.

[30] F. Guo, J. Tang, and C. Zhu, "Gesture recognition for Chinese traffic police," in *Proc. Int. Conf. Virtual Reality Visualizat. (ICVRV)*, Oct. 2015, pp. 64–67.

[31] H. Kretzschmar and J. Zhu, "Cyclist hand signal detection by an autonomous vehicle," U.S. Patent 9 014 905 B1, Apr. 21, 2015.

[32] M. J. Delp and D. S. Caveney, "Autonomous vehicle detection of and response to traffic officer presence," U.S. Patent 0 144 867 A1, May 26, 2016.

[33] R. L. Bertini, H. Wang, T. M. Borkowitz, and D. H. Wong, "2015 automated vehicle literature review as part of preparing a possible Oregon road map for connected vehicle/cooperative systems deployment scenarios," Dept. Civil Environ. Eng., California Polytech. State Univ., San Luis Obispo, CA, USA, Tech. Rep. FHWA-OR-RD-16-12, 2016.

[34] J. Lee and B. Park, "Development and evaluation of a cooperative vehicle intersection control algorithm under the connected vehicles environment," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 3, pp. 81–90, Mar. 2012.

[35] J. Wu, F. Perronnet, and A. Abbas-Turki, "Cooperative vehicle-actuator system: A sequence-based framework of cooperative intersections management," *IET Intell. Transp. Syst.*, vol. 8, no. 4, pp. 352–360, Jun. 2014.

[36] L. P. Kaelbling, M. L. Littman, and A. R. Cassandra, "Planning and acting in partially observable stochastic domains," *Artif. Intell.*, vol. 101, nos. 1–2, pp. 99–134, 1998.

[37] F. Broz, "Planning for human-robot interaction: Representing time and human intention," Ph.D. dissertation, Robot. Inst., Carnegie Mellon Univ., Pittsburgh, PA, USA, 2008.

[38] W. Song, G. Xiong, and H. Chen, "Intention-aware autonomous driving decision-making in an uncontrolled intersection," *Math. Problems Eng.*, vol. 2016, no. 1, pp. 1–15, Mar. 2016, Art. no. 1025349.

[39] J. Wei, J. M. Dolan, and B. Litkouhi, "Autonomous vehicle social behavior for highway entrance ramp management," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2013, pp. 201–207.

[40] J. Rios-Torres and A. A. Malikopoulos, "Automated and cooperative vehicle merging at highway on-ramps," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 4, pp. 780–789, Apr. 2017.

[41] L. Li, D. Wen, and D. Y. Yao, "A survey of traffic control with vehicular communications," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 1, pp. 425–432, Feb. 2014.

[42] I. W. Zartman, "Common elements in the analysis of the negotiation process," *Negotiation J.*, vol. 4, no. 1, pp. 31–43, 1988.

[43] A. Tanya and C. Azeta, "Negotiation theory and practice: A review of the literature," *Fao Policy Learn. Programme, Easypol-Module*, vol. 179, pp. 6–16, Jan. 2008.
[44] A. Alessandrini, A. Cattivera, F. Filippi, and F. Ortenzi, "Driving style influence on car CO_2 emissions," in *Proc. 20th Int. Emission Inventory Conf.*, 2012, pp. 1–11.
[45] D. Stalnaker, J. Turner, D. Parekh, B. Whittle, and R. Norton, "Indoor simulation of tire wear: Some case studies," *Tire Sci. Technol.*, vol. 24, no. 2, pp. 94–118, 1996.

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