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A collision avoidance scheme for autonomous vehicles inspired by human social norms☆

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ABSTRACT

This paper introduces the novel idea of using human social norms and human emotions to improve the collision avoidance of Autonomous Vehicles (AVs). Until now, the literature has been concerned with theoretical debates regarding ethical issues connected to AVs, while no practical steps have yet been undertaken. This paper introduces the concept of an artificial society of AVs with different personalities and with social norms coded into their autopilot so that they act like well-behaved drivers. For proof of concept, the standard agent modelling tool Netlogo is utilized to simulate the artificial society of AVs. Furthermore, comparisons are made with random walk-based non-social-based collision avoidance techniques. Extensive testing has been carried out using the behaviour space tool to determine the performance of the proposed approach regarding the number of collisions. A comparative study undertaken with a random walk method indicates that the proposed approach provides a better option for tailoring the autopilots of future AVs, while also promising to be more socially acceptable and trustworthy regarding safe road travel.

1. Introduction

Autonomous Road Vehicles (ARVs) are considered better than human-driven vehicles about road safety and traffic management. According to the study by Riaz and Niazi [1,2], Autonomous Vehicles (AVs) are considered helpful in decreasing the number of road accidents as compared to human-driven vehicles. According to Mersky and Samaras [3], the issue of traffic jams can be resolved by replacing human drivers with fully connected autonomous cars. Also, Mersky and Samaras [3] illustrate that AVs are very helpful in decreasing road pollution and in protecting the environment. By these benefits, it is conceivable that legal authorities will delegate the task of driving to AVs by issuing driving licenses to them. However, to perform the complex task of driving, there is a need for a mechanism which supports autonomous vehicles – a robot which would obey both the road rules and the social rules that are practised by well-behaved drivers.

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The role of ethics and social norms is considered to be important in making robots social, well-behaved and more compatible with humans. According to Malle [4], robots can serve as competent social agents by integrating moral norms. Rakotonirainy et al. [5] prove that social norms can be utilized in designing human-compatible social AVs robots. According to Kummer et al. [6], social norms can be used in tailoring crash-free AVs robots to operate on roads wisely. From the above discussion, it is implied that social norms combined with a norm-compliance mechanism can be used to tailor the next generation of more trustworthy social AVs.

Furthermore, emotions can be used as a norm-compliance mechanism, as it has already been proven that emotions help in sustaining the social norms of human society. According to Elster [7], self-attribution emotions like shame help humans to avoid violations due to the fear of losing their social status. According to Criado [8], prospect-based emotions like fear influence humans to follow the social norms to avoid punishment from law enforcement agencies. Researchers have used emotions as a norm-compliance mechanism for artificial agents as it has been proven by Staller et al. [9] that emotions play an important role in the sustainability of social norms in human society [9]. Hence, it is implied that we can use emotions as a norm-compliance mechanism to design social norm-enabled AVs. While Gerdes and Thornton [10] propose the mathematical model of social norms for designing the control algorithms of AVs, their work still lacks the simulation or proof of concept of the proposed mathematical models.

Problem statement. The existing research is not focused on procedures that would allow AVs to configure their autopilots to make collision avoidance decisions about norm compliance using emotional motivation in the same way that human drivers can. For example, Tavani [11] suggest the use of social norms in AVs in theoretical respect for discussing a mathematical model and its implementation. Rakotonirainy et al. [5] propose a novel concept of measuring the emotional state of a driver using the HUD-UP technology and transmitting the social norms from driver to driver to modify the behaviour behind the steering of an AV. However, the concept of social norms is not integrated into the autopilot of the AV in a way that would help them to make collision avoidance decisions automatically. The major challenge for AVs is the question of how they will take decisions at the time of a crash; this issue is addressed by Kumfer and Burgess [6]. In this regard, the authors use social norms as a decision mechanism for choosing a less harmful crash among possible collision options. However, this paper does not provide a collision avoidance strategy using a social norm compliance mechanism to avoid collision situations.

Contribution. The existing research is associated with a set of contributions to building a norm-compliant collision-free artificial society of AV inspired by human social norms and related emotions. We aim to provide humans with reliable AVs that can delegate driving tasks regulated by legal and social norms. The main contributions of the paper are the following:

- Modeling of a social norms-inspired artificial society of AVs.
- Simulation of the social norms-compliant artificial society of AVs using NetLogo.
- The rigorous analysis regarding the number of collisions of the proposed approach in comparison with a random walk travelling strategy.

This paper is organized as follows: Section 2 illustrates the related work, while Section 3 describes the methodology. In Section 4, a description of the proposed model is provided, while Section 5 illustrates the experiments. Section 6 elaborates the results and includes a discussion, and Section 7 provides a conclusion and points to future directions in research.

2. Related work

The literature review is divided into three main categories. The first category addresses the literature supporting the role of ethics in robots and the related theoretical debate. The second category contains the literature that supports the role of using theoretical concepts of ethics or norms in the design of AVs. The third category deals with state-of-the-art literature concerning the social norms in autonomous vehicles based on a simulation approach.

According to Voort et al. [12] computers are becoming more autonomous every day and capable of making decisions on their own. Intelligent computer systems can get information from a human, analyze it, take decisions and store that information or provide it to third parties. However, there is a need to monitor the moral values of computer decisions. Researchers [12] have suggested that there is a need to add ethics to technology, as it lags behind in this respect. Malle [4] points out that from 1995 to 2015 few efforts have been made concerning the implementation of ethics in robots. Past studies have considered whether a robot could be a moral agent or not. Also, researchers [4] have found that a robot could be treated as a living thing that can take actions based on its own decisions, and it can decide what is right and what is wrong together with humans.

According to Etzioni and Etzioni [13], the latest smart machines like AVs are becoming smarter due to the incorporation of Artificial Intelligence (AI) algorithms. Furthermore, these AVs are becoming more and more autonomous in the sense that they are now taking decisions using these AI algorithms. Etzioni and Etzioni [13] suggest that since these AVs' basic purpose is to serve humans, there is a need to equip them with ethical and social rules so that the autonomous devices can take decisions on their own that will not harm passengers and other road commuters [7]. According to Gerdes and Thornton [10], it is the responsibility of researchers and programmers to devise ethics-enabled control algorithms for AVs that can make them more acceptable for human society. The authors argue that the incorporation of ethics in the society in which AVs operate will help courts to determine the level of responsibility of an AV in the case of an accident [10]. In this regard, they have proposed a mathematical model of ethical frameworks to incorporate into the control algorithms of autonomous vehicles [10]. The proposed model can read the error rate of the actual and the desired path of the car based on different constraints. However, the authors [10] do not mention any case study that implements any of the proposed mathematical models using simulation or real field tests.

Social and autonomous robots motivate to build social cars so that road accidents can be eliminated. Vehicle-to-vehicle (V2V) is a sub-part of Intelligent Transportation System (ITS) equipped with sensing technologies and wireless communication systems, which are helpful in road accident prevention [14]. Rakotonirainy et al. [5] propose a novel concept that uses HUDs, Human-Computer-Interaction (HCI) and communicating social information between cars to provide social awareness, which they call the 'social car'. The social car can sense the driving behaviour of a driver by capturing the driver's facial expression, gestures and eye contact. Further, the authors argue that self-efficacy and social norms can change the driver's behaviour. Social norms can be transmitted in V2V using social networks as well as in the form of non-verbal communication. Hence, the combination of driver and car (machine) become a cyborg, and the driver of one car treats the other driver as a machine. They also add that the "social pressure is particularly suitable to influence human driving behaviours for the better and that this aspect is still relevant in the age of looming autonomous cars".

A complete autonomous vehicle (AV) is introduced in response to Defense Advanced Research Projects Agency Grand Challenges. The major challenge for AVs is the question how it will take decisions at the time of a crash. This is the key point where ethics and social norms are required for the development of AVs. To address this requirement, Kumfer and Burgess [6] evaluate three ethical theories, i.e. utilitarianism, respect for persons, and virtue ethics, which support AVs in making the least harmful collision decision when the collision becomes unavoidable. They perform the experiments using MATLAB, and their results reveal that the utilitarian system produces the lowest number of deaths, while on the other hand, the virtue ethics system results in the highest number of losses. However, virtue ethics, if fully integrated with good AI techniques, can be the best ethical solution [15]. It is suggested that these ethical theories can be implemented in AVs in different scenarios and complex environments. A deep reinforcement learning-based socially autonomous robot is proposed by Chen et al. [16]. The purpose of the research work is to evaluate human social norms to avoid collisions between autonomous robots and pedestrians. However, the drawback of this research is that the proposed technique is not proposed in the context of AVs. In a recent research, Bench-Capon and Modgil [17] justify the need to introduce social norms in the use of AVs along with the justification of violating them when it is necessary to violate them. The drawback of the research work [17] is that it is only a theoretical debate, and its practical implementation or proof of the concept has not been provided.

3. Methodology

This section presents the methodology that is used to propose the social norm- and emotion-inspired artificial society of AVs. Fig. 1 represents the proposed methodology. To introduce emotions, a suitable appraisal model is required. According to [19], the OCC model is the best emotion appraisal, model. In a previous paper by Riaz and Niazi [1], we present a complete mechanism for generating and computing the emotion of fear using the OCC model. In this research work, instead of computing the fear emotion from scratch, we utilize the intensity values of fear computed by Riaz and Niazi [1]. Then social norms and emotion-based rules are designed which define the code of conduct for the artificial society of AVs. Also, artificial social actors along with their different characteristics are also defined. To test the behaviour of the non-social norms and social norm-based artificial society, the standard agent-based modelling tool NetLogo is used. Using the Sim-connector approach, the numeric values of the fear emotion are provided in the simulation of artificial society.

Furthermore, the method of using prospect-based emotion for generating emotions in agents is compared with the existing work in the literature.

4. Description of the proposed solution

To include the social norms and emotions in the AVs, their fundamental design is modified as this can lead to more human-like behaviour on roads in the future. It is important to note that emotional action is a social action that helps to regulate and adapt other actors' emotions and emotional expressions according to valid norms and rules [18]. The emulation of emotions and social norms in the design of AVs can help in building potentially more comfortable, trustworthy and collision-free AVs. However, the exact mode of implementation is still debatable. The supposition guiding this method would be that the rules and norms guiding human-human interaction/communication might also be pertinent in AV design. Thus, the design principle is to introduce anthropomorphism capabilities in AVs. To analyze the above discussion further, let us examine a conjectural interaction situation of two autonomous vehicles. Suppose a heavy *autonomous truck* is followed by a smaller-sized *autonomous car* that has a considerably lower weight. Here, one way of representing the *autonomous truck* is to consider it a strongly influential person with strong social status, whereas the *autonomous car* is a less influential person with a weak social character. For safe driving, both actors have to follow social norms and rules. The a*utonomous car* should maintain a safe distance from the *autonomous truck*, or the *autonomous truck* should practice sympathetic emotion for the *autonomous car* to avoid a collision. Let us consider that the autonomous truck decreases its speed without taking care of the in-between distance to the *autonomous car*, which might lead to a collision. Suddenly another actor, an *autonomous bus* (with strong social status), appears on the road. The autonomous truck starts feeling the fear that if it collides with the *autonomous car*, then the *autonomous bus* will have evidence of its cruelty. The social norm, "*You will be punished for*

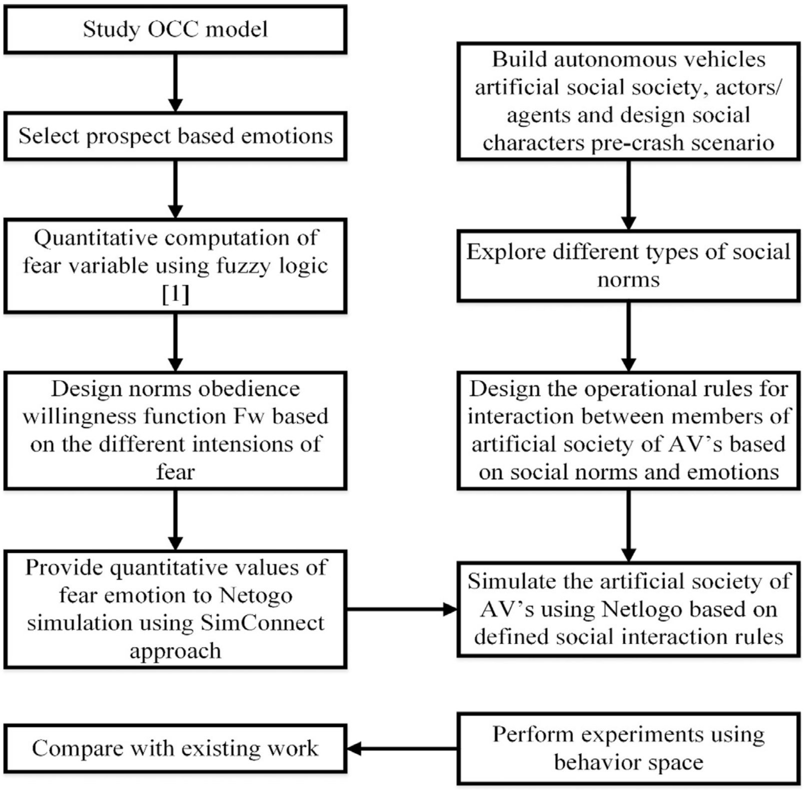

Fig 1. Proposed methodology.

Table 1
Different actors of the artificial society of AVs.

Actor	Symbol of actor	Personality type	Weight
AV_Truck	T	Very dominating	>5000
AV_Bus	B	Very dominating	4500 < ∧ < 50,000
AV_Toyota_Small truck	TY	Dominating	3000 ∧ < 4000
AV_Carry	C	Weak dominating	2000 ∧ < 2800
AV_Car 3000cc	CB	Weak dominating	2000 ∧ < 2500
AV_Car 2000cc	CS	Weak dominating	1500 ∧ < 1700
AV_Rickshaw	R	Weak dominating	1200 ∧ < 1400
AV_Ambulance	A	Weak dominating	1200^ < 1400
AV_Motorbike	M	Very weak dominating	800 ∧ < 1100
AV_Cycle	CL	Very weak dominating	400

your crime" generates an emotion of fear of losing one's status in society and getting punished by the law enforcement authorities. Consequently, the *autonomous truck* maintains a safe distance from *B* and avoids a collision.

What happened here? The primary event of worrying about the weaker autonomous vehicle can be defined by an appraisal theory. This is the social norm that "any actor of any status will be punished for performing an evil deed". Therefore, the autonomous actor *truck* avoids or feels hesitation in the execution of collision scenarios in the presence of witnesses. This social norm generates the fear of being punished. It means that fear forces the actor to adhere to the norm.

5. Artificial social society of AVs

To further elaborate on the idea presented in the previous section, we present a concept of an artificial society of AVs consisting of different actors, with each one having a different characteristic which depicts their different social personalities. These different actors with different personality characteristics along with their short abbreviated nicknames are presented in Table 1. These characteristics are assigned to the AVs based on the real-life behaviour of human drivers driving these types of non-autonomous vehicles. It is observed that drivers of heavy vehicles act dominantly and do not let the lighter vehicles overtake them or treat them harshly in real road traffic. In Table 1, T represents the AV truck and is a highly dominating road commuter due to its height, width and weight characteristics. In the same way, we classified the autonomous bus (B)

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Table 2
Social norms and emotions based road interaction rules.

Road scenarios	Social norm	Emotion	Action
T is leading the CB and CB is tailgating the T	Maintain distance from stronger one	Fear	CB decelerate
CB is leading the T and T is tailgating the CB	Maintain distance from stronger one	Fear	CB accelerate
CB–CB following scenario or T-T following scenario	Give the right or Tit for Tat	Fear	Following CB decelerate and leading CB accelerate

Table 3
Different intensity levels of fear computing using fuzzy logic [1].

VLF	LF	MF	HF	VHF
0–0.24	0.1–0.5	0.25–0.73	0.51–0.9	0.76–1

as belonging to the dominating category. The small truck is in the second class due to its lower weight than that of the autonomous truck and bus. The autonomous cars in the range of 4000 cc to 200 cc are categorized as the third dominating social actors. We placed autonomous bikes and cycles in the category of very weak dominating social actors because of their small size and lower weight.

5.1. Operational rules for the artificial society of AVs

Humans follow social rules that help them to live peacefully and to avoid possible conflicts if followed properly. In analogy to these social rules, we propose some rules for the proposed artificial society of AVs. The purpose of the rules is to encode the ethical guidelines in the autopilot of different AVs, which will ultimately help the AVs to avoid collisions by following social norms. These rules are designed in light of different possible road scenarios, although all of them cannot be mentioned here. The social norms are also presented along with the best-suited emotions. To make sure that following social norms according to the given condition does not lead to a violation of the road traffic rules, we have applied a check to assure that the social norm is only followed when the social norm and the road norm are both in compliance with each other. The last column of Table 2 presents the action that the actor has to take to avoid the road collision.

4.3.2. Utilization of fear emotion using the OCC model

Ortony et al. [19] have developed a model of emotions known as the OCC model [19]. The reason for choosing the OCC model is that it presents 22 basic emotions along with the concept of computing the emotions. In the OCC model, the authors answer the question that indicates the strength of the emotions. They employ some variables in endeavouring to address this problem. In one of our previous research papers, Riaz and Niazi [1], we have devised a complete mechanism for generating the fear emotion using fuzzy logic. In this research paper, we utilized the different intensities of fear from [1] to test the social norms in the autopilot of different types of AVs. Table 3 presents the different intensity levels of fear.

In Table 3, VLF, LF, MF, HF and VHF are the lexemes representing very low fear, low fear, medium fear, high fear and very high fear, respectively. Their corresponding values are represented between 0 and 1. For example, the VLF range is between 0–0.24 and the VHF is between 0.76–1. The interested reader is referred to the paper by Riaz and Niazi [1] for details; the paper presents the complete mechanism used in generating Table 3.

5.2. Functionality of the proposed approach

The functionality of the proposed approach is presented in Fig. 2, and its description is given as follows:

1. In EventPart1, CB is following T, and it requests the T to give safe passage for performing an overtaking manoeuvre. Belief will depict the situation awareness of CB and T. The current values of belief are passed to the prospect-based emotion-generation-module.
2. Prospect-based emotion generation module computes the emotion fear based on Eqs. (1) and (2) that are provided by the OCC model [20]. However, in this research work, we did not compute them from scratch, as we already computed different intensity levels of fear in one of our previous research papers, Riaz and Niazi [1].

$$Fear-Potential(Av_i,\ e_i,t_i)=f_{f[|Desire\ (Av_i,e_i,t_i)|,\quad Liklihood(Av_i,e_i,t_i),\ I_g(Av_i,e_i,t_i)]} \tag{1}$$

$$Fear-Intensity(Av_i,\ e_i,t_i)=Fear-Potential(Av_i,\ e_i,t_i)-Fearthreshold(Av_i,\ e_i,t_i) \tag{2}$$

3. The computed intensity of fear, Table 3, will update belief of the agent.
4. Based on the intensity of fear, F_w is computed. The F_w function is computed using Eq. (3) that shows the willing function of T that allows the overtaking, depending on the intensity of fear.

$$F_{w(obey-norm)=}\ Fear-Intensity(Av_i,\ e_i,t_i). \tag{3}$$

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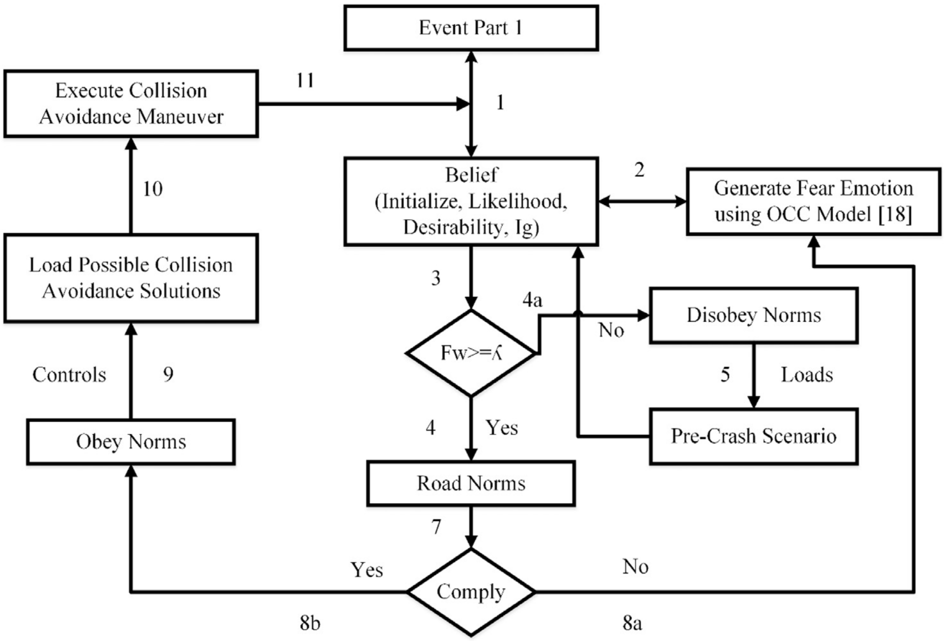

Fig 2. The functionality of proposed approach.

In the first iteration, the value of the emotion will be zero. In the willing function part, it will be checked whether the value of a willing function of T is higher than λ or if it is less than λ. Here two scenarios exist: (i) if the F_w of T is less than λ, (ii) second if the F_w is greater than λ.

5. If the value of F_w is smaller than the egoist value of the agent, then it disobeys the norm.
6. In the case of disobeying the norm, T will be entered in the pre-crash scenario. For the pre-crash scenario, we have considered the variables defined by Najm et al. [21].
7. The event of pre-crash scenario will contribute in the shape of the high likelihood of an accident, and it will increase the intensity of fear. Again, the belief of agent will be updated, and F_w will be computed. If the F_w is still smaller than λ, then the emotion generation centre will be consulted again to depict a highly dangerous situation. If the value of F_w is greater than λ then the egoist agent will change its mind and turn into the emotional agent and the emotions act as a norm-compliance mechanism. In the next step, the agent will check the road norm.
8. If the request is not against the road norm, then it will load possible solutions using step 9 and execute the maneuver by following step 10, which will ultimately help in CB in performing an overtaking maneuver by avoiding a rear end collision.

6. Experiments

The purpose of the experiments is to simulate the concept of an artificial society of AVs that consists of different actors which have different characteristics. Another reason for the simulation is to study the behaviour of these actors according to the defined social rules during autonomous driving. For this purpose, NetLogo 5.3 is utilized, as it is a standard agent-based simulation environment. The NetLogo environment consists of patches, links, and turtles [22]. This scenario can also be borrowed in a social Internet of Things (IoT) environment [24]. The idea in [23] regarding the white space optimization scheme using a memory-enabled genetic algorithm in cognitive vehicular communication can also be merged with this idea to make a good contribution to better vehicle design. The algorithms used in these experiments have already been given in Section 3.1.3. Fig. 3 presents the experimental environment along with the input and output parameters. The detailed description of the different parts of the simulation are given as follows:

(1) The simulation setup and running options.
(2) The simulation is controlling parameters as mentioned in Table 4. Their details are given in Section 5.2.1.
(3) The simulation helps to evaluate the performance of the proposed scheme. It can be seen that different autonomous trucks and autonomous vehicles are shown clearly. Further, it can be seen that there are different scenarios, such as T is following CB and CB is following T, as presented in Table 2.
(4) The fear computation variables.
(5) The different intensity levels of fear perceived by simulation actors while following T-CB or CB-T or T-T and CB-CB scenarios. These different levels of fear help in decision making as presented in Fig. 4 (they obey the social norms).

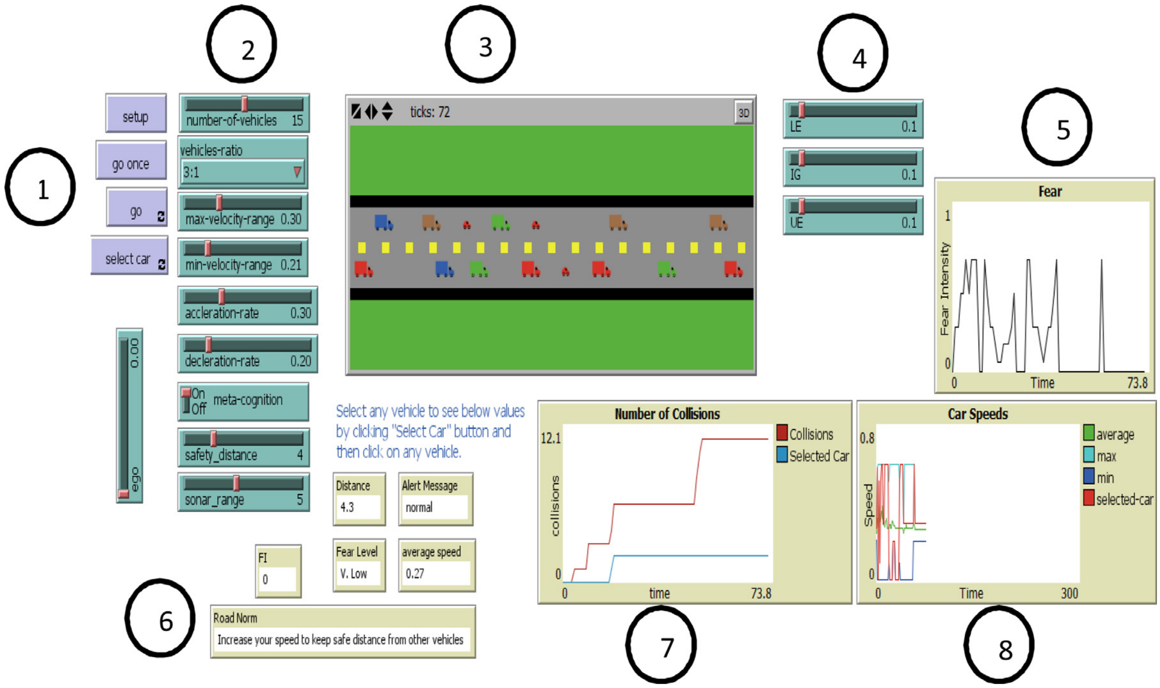

Fig. 3. Main simulation screen of social norms and emotions inspired artificial society of AVs.

Table 4
Simulation parameters and their description.

Simulation general parameters	Range	Description
Number of autonomous vehicles agents	[1–30]	This slider helps in defining the maximum number of members of the artificial society of AVs.
Vehicles ratio	[2:1, 3:1, 4:1]	It defines the ratio of AV trucks and cars within a total number of vehicles set by the Number of Autonomous Vehicles Agents slider.
Maximum velocity	[0 –1; with increment of 0.01]	This slider helps in defining the maximum velocity that can be achieved by all actors of the artificial society.
Minimum velocity	[0 –1; with increment of 0.01]	This slider helps in defining the lower boundary of velocity achieved by all actors of the artificial society.
Acceleration-rate	[0 –1; with increment of 0.05]	This slider helps in defining the maximum acceleration rate that can be used by all actors of the artificial society.
Declaration-rate	[0 –1; with increment of 0.05]	This slider helps in defining the minimum declaration- a rate that can be used by all actors of the artificial society.
Safety distance	[2 –10-; with increment of 1]	This slider helps in defining the safety distance between each actor.
Sonar range	[1 –10-; with increment of 1]	This slider helps in defining the sonar range of each AV to find out the position and distance between neighbouring AVs.
Metacognition	On/Off	This switch helps in defining that the simulation is in Randomwalk or social norms mode.
Prospect based emotion, i.e. Fear generation parameters	**Range**	**Description**
Likelihood	[0 –1; with increment of 0.1]	This slider helps in defining the likelihood of an accident perceived by AV.
Desirability	[0 –1; with increment of 0.1]	This slider helps in defining the current desirability value of AV.
Ig	[0 –1; with increment of 0.1]	This slider helps in defining the current Ig value of AV.

(6) The current road norm being practised by the actors.
(7) The number of collisions.
(8) The variation in the speed of the actors.

6.1. Simulation parameters

The simulated world consists of different types of input and output parameters. To provide the inputs, different sliders are used, whereas to get the outputs, monitors and plots are used. The description of each input and output object along

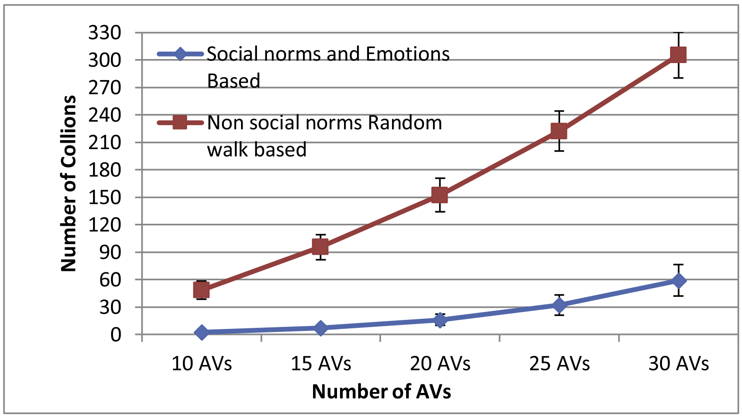

Fig. 4. Graphical representation of the results of Experiment_Type A set 1 Vs Experiment_Type B set 1.

Table 5
Experiment_Type A set 1: parameters and their values.

Experiment no	Number of AVs	Min velocity range	Max velocity range	Acceleration rate	Deceleration rate	Safety distance	Sonar range
1	10	0.14	0.8	0.1	0.1	3	2, 5
2	15	0.14	0.8	0.1	0.1	3	2, 5
3	20	0.14	0.8	0.1	0.1	3	2, 5
4	25	0.14	0.8	0.1	0.1	3	2, 5
5	30	0.14	0.8	0.1	0.1	3	2, 5

with a defined range is presented in Table 4. The first parameter is the number of autonomous vehicle agents, which helps in setting the number of actors, and its range is 1–30. The vehicle ratio parameter helps in setting the ratio of autonomous trucks and autonomous vehicles. Using this parameter, different types of road traffic patterns can be identified. One example of such a pattern would be a higher number of autonomous trucks and a lower number of autonomous vehicles and vice versa. The parameters maximum velocity and minimum velocity help in testing the performance of the proposed technique with the variations of velocity ranges. The acceleration-rate and declaration-rate parameters help in setting the acceleration and declaration values of the social actors. The safety distance parameter helps in defining the safety distance between each actor. Finally, the fear generation parameters are presented, and their values are taken from the work of Riaz and Niazi [1]. It is important to mention here that these three variables help in computing the different intensity levels of fear presented in Table 3.

6.2. Experimental design

In this section, a further experimental design is proposed to perform further experiments in proper manners.

6.2.1. Experiments_Type A

In this category of experiments, a total of five sets of experiments is designed to test the non-social norms random walk-based artificial society of AVs. In the first set of experiments, the maximum velocity range parameter is set to 0.8, which represents a high velocity of AVs. The acceleration/ deceleration rate parameters are set to 0.1 along with the safety distance which is equal to 3. In the second set of experiments, the maximum velocity range parameter is set to 0.5, which represents a medium velocity of AVs. The acceleration rate parameter is set to 0.2 along with the safety distance which is equal to 2. In the third set of the experiment, the maximum velocity range is set to 0.3, which represents the low velocity of AVs. The acceleration rate and declaration rate parameters are both set to 0.1. In the fourth set of experiments, the acceleration and deceleration rates are set to 0.3, and the values of safety distance and sonar range are set to 3. The purpose of these experiments is to measure the performance of a non-social norms random walk-based artificial society of autonomous vehicles which have an equal safety distance and sonar range. In the fifth set of experiments, safety distance and sonar range parameters are set to 1. The purpose of these experiments is to test the behaviour of AVs having an equally low safety distance and sonar range. All of these sets of experiments are executed using the behaviour space tool within the Netlogo5.3 environment. Furthermore, each set of experiments has been repeated seven times, and the total number of collisions along with their mean and standard deviation has been computed. The details of these 5 sets of experiments are presented in Tables 5–9.

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Table 6
Experiment_Type A set 2: parameters and their values.

Experiment no	Number of AVs	Min velocity range	Max velocity range	Acceleration rate	Deceleration rate	Safety distance	Sonar range
1	10	0.14	0.5	0.2	0.2	2	2, 5
2	15	0.14	0.5	0.2	0.2	2	2, 5
3	20	0.14	0.5	0.2	0.2	2	2, 5
4	25	0.14	0.5	0.2	0.2	2	2, 5
5	30	0.14	0.5	0.2	0.2	2	2, 5

Table 7
Experiment Type A set 3: parameters and their values.

Experiment No	Number of AVs	Min velocity range	Max velocity range	Acceleration rate	Deceleration rate	Safety distance	Sonar range
1	10	0.14	0.3	0.1	0.1	2	2
2	15	0.14	0.3	0.1	0.1	2	2
3	20	0.14	0.3	0.1	0.1	2	2
4	25	0.14	0.3	0.1	0.1	2	2
5	30	0.14	0.3	0.1	0.1	2	2

Table 8
Experiment_Type A set 4: parameters and their values.

Experiment no	Number of AVs	Min velocity range	Max velocity range	Acceleration rate	Deceleration rate	Safety distance	Sonar range
1	10	0.14	0.3	0.3	0.3	3	3
2	15	0.14	0.3	0.3	0.3	3	3
3	20	0.14	0.3	0.3	0.3	3	3
4	25	0.14	0.3	0.3	0.3	3	3
5	30	0.14	0.3	0.3	0.3	3	3

Table 9
Experiment_Type A set 5: parameters and their values.

Experiment no	Number of AVs	Min velocity range	Max velocity range	Acceleration rate	Deceleration rate	Safety distance	Sonar range
1	10	0.14	0.3	0.1	0.1	1	1
2	15	0.14	0.3	0.1	0.1	1	1
3	20	0.14	0.3	0.1	0.1	1	1
4	25	0.14	0.3	0.1	0.1	1	1
5	30	0.14	0.3	0.1	0.1	1	1

Table 10
Experiment_Type B set 1: parameters and their values.

Experiment no	Number of AVs	Min velocity range	Max velocity range	Acceleration rate	Deceleration rate	Safety distance	Sonar range	LI, UD, Ig
1	10	0.14	0.8	0.1	0.1	3	2, 5	0.1–0.1–1
2	15	0.14	0.8	0.1	0.1	3	2, 5	0.1–0.1–1
3	20	0.14	0.8	0.1	0.1	3	2, 5	0.1–0.1–1
4	25	0.14	0.8	0.1	0.1	3	2, 5	0.1–0.1–1
5	30	0.14	0.8	0.1	0.1	3	2, 5	0.1–0.1–1

6.2.2. Experiments_Type B

In this category of experiments, a total of five sets of experiments are executed in parallel. The Experiments_Type B is designed to test and compare the social norms and emotions-inspired artificial society of AVs with the non-social norms random walk-based artificial society of AVs. These five sets of experiments are designed in parallel to the Experiments_Type A. These sets of experiments use the same values of parameters as Experiments_Type A. However, the additional parameter added in these experiments are the variables of fear (Likelihood, Undesirability and Ig) that help in computing the intensity of fear. Tables 10–14 present these 5 sets of experiments.

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Table 11
Experiment_Type B set 2: parameters and their values.

Experiment no	Number of AVs	Min velocity range	Max velocity range	Acceleration rate	Deceleration rate	Safety distance	Sonar range	LI, UD, Ig
1	10	0.14	0.5	0.2	0.2	2	2, 5	0.1–0.1–1
2	15	0.14	0.5	0.2	0.2	2	2, 5	0.1–0.1–1
3	20	0.14	0.5	0.2	0.2	2	2, 5	0.1–0.1–1
4	25	0.14	0.5	0.2	0.2	2	2, 5	0.1–0.1–1
5	30	0.14	0.5	0.2	0.2	2	2, 5	0.1–0.1–1

Table 12
Experiment_Type B set 3: Parameters and their values.

Experiment no	Number of AVs	Min velocity range	Max velocity range	Acceleration rate	Deceleration rate	Safety dis-tance	Sonar range	LI, UD, Ig
1	10	0.14	0.3	0.1	0.1	2	2	0.1–0.1–1
2	15	0.14	0.3	0.1	0.1	2	2	0.1–0.1–1
3	20	0.14	0.3	0.1	0.1	2	2	0.1–0.1–1
4	25	0.14	0.3	0.1	0.1	2	2	0.1–0.1–1
5	30	0.14	0.3	0.1	0.1	2	2	0.1–0.1–1

Table 13
Experiment_Type B set 4: parameters and their values.

Experiment no	Number of AVs	Min velocity range	Max velocity range	Acceleration rate	Deceleration rate	Safety distance	Sonar range	LI, UD, Ig
1	10	0.14	0.3	0.3	0.3	3	3	0.1–0.1–1
2	15	0.14	0.3	0.3	0.3	3	3	0.1–0.1–1
3	20	0.14	0.3	0.3	0.3	3	3	0.1–0.1–1
4	25	0.14	0.3	0.3	0.3	3	3	0.1–0.1–1
5	30	0.14	0.3	0.3	0.3	3	3	0.1–0.1–1

Table 14
Experiment_Type B set 5: parameters and their values.

Experiment no	Number of AVs	Min velocity range	Max velocity range	Acceleration rate	Deceleration rate	Safety distance	Sonar range	LI, UD, Ig
1	10	0.14	0.3	0.1	0.1	1	1	0.1–0.1–1
2	15	0.14	0.3	0.1	0.1	1	1	0.1–0.1–1
3	20	0.14	0.3	0.1	0.1	1	1	0.1–0.1–1
4	25	0.14	0.3	0.1	0.1	1	1	0.1–0.1–1
5	30	0.14	0.3	0.1	0.1	1	1	0.1–0.1–1

Table 15
Set 1 Type A and B experiments results.

No. of AVs	Social norms and emotions-based		Nonsocial norms random walk-based	
	Mean	Stdev	Mean	Stdev
10 AVs	2.573837	1.597861	48.63886	10.05186
15 AVs	7.317401	3.12966	95.57575	13.87058
20 AVs	16.17935	6.106475	152.584	18.13361
25 AVs	32.20731	11.09385	222.3648	21.98538
30 AVs	59.35412	17.14856	305.439	25.01929

7. Results and discussion

This section provides a detailed discussion of the results achieved for the experiments. The results of both Experiment_Type A set 1, and Experiment_Type B set 1 are presented in the form of an average number of accidents along with standard deviation as shown in Table 15. From these results, it is concluded that there is a high average number of accidents in the case of non-social norms random walk-based artificial society of AVs as compared to the social norms and emotions-based artificial society of AVs. For example, the average number of accidents performed by non-social norms random walk-based technique are 48.63 for 10 AVs. Comparatively, 2.57 is the average number of accidents performed by the social norms and emotions-based technique. In the same way, for 30 AVs, the total average number of accidents by the non-social norms random walk technique are 305.43, and 59.35 by the social norms and emotions-based technique. From

Table 16
Set 2 Type A and B experiments results.

No. of AVs	Social norms and emotions-based		Nonsocial norms random walk-based	
	Mean	Stdev	Mean	Stdev
10 AVs	0.83308	0.75219454	44.35492	10.41238
15 AVs	2.688164	1.50878434	92.14185	12.76792
20 AVs	6.358672	2.40534634	147.0383	15.39402
25 AVs	13.37643	3.34040996	207.6984	17.56855
30 AVs	24.06544	4.45493639	276.0833	19.05506

Table 17
Set 3 Type A and B experiments results.

No. of AVs	Social norms and emotions-based		Nonsocial norms random walk -based	
	Mean	Stdev	Mean	Stdev
10 AVs	0.785513	0.916095	22.66486	10.09421
15 AVs	2.268417	1.664854	55.82655	13.73423
20 AVs	4.767293	2.38503	101.9607	17.59697
25 AVs	8.728624	3.078323	158.7121	20.06934
30 AVs	14.69935	3.936857	222.0574	22.18164

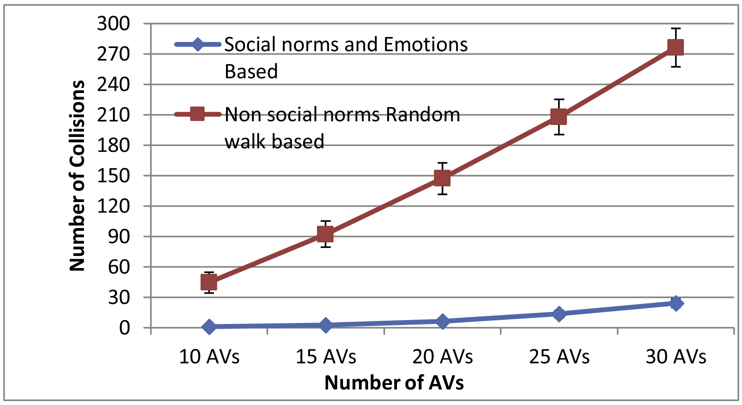

Fig. 5. Graphical representation of the results of Experiment_TypeA set 2 Vs Experiment_TypeB set 2.

the results, another interesting phenomenon is observed, namely that the average number of accidents in both techniques gradually increases as the number of AVs increases. Fig. 4 represents the graphical representation of the results of Table 15.

Table 16 is presented in comparison to Table 15. Table 16 presents the results of both Experiment_Type A set 2 and Experiment_Type B set 2 in the form of the average number of accidents along with standard deviation. Before discussing the results of Table 16, it would be interesting to compare Tables 15 and 16. Experiment_Type A set 1, and Experiment_Type B set 1 have a high maximum velocity range, i.e. 0.8 with acceleration and deceleration rate 0.1. On the other hand, Experiment_Type A set 2, and Experiment_Type B set 2 have a medium, maximum velocity range, i.e. 0.5 with acceleration and deceleration rates 0.2. From Table 16, it can be seen that the average number of accidents decreased due to medium, maximum velocity range as compared to the average number of accidents presented in Table 17 with a high maximum velocity range. For example, for the social norms and emotions-based technique in Tables 15 and 16, the average number of accidents performed by 10 AVs are 2.57 and 44.35, respectively. In the same way, in the case of 30 AVs, the average number of accidents performed by the social norms and emotions-based technique is 59.35 and 24.065, respectively.

From Table 16 it can be seen that the social norms and emotions-based technique have a lower number of collisions as compared to the non-social norms random walk-based technique. For example, the average number of accidents performed by the social norms and emotions-based artificial society is 6.35 for 20 AVs. However, for the same number of AVs, the average number of accidents performed by the non-social norms-based artificial society (Table 15) are 147.03. Fig. 5 represents the graphical representation of the results of Table 16.

In the same way, for each class of 10, 20, 25, and 30 AVs, the average number of collisions in the social norms and emotions-based artificial society of AVs is less than those of the non-social norms and random walk-based artificial society of AVs. Figs. 6 and 7 are the graphical representations of Tables 17 and 18, respectively.

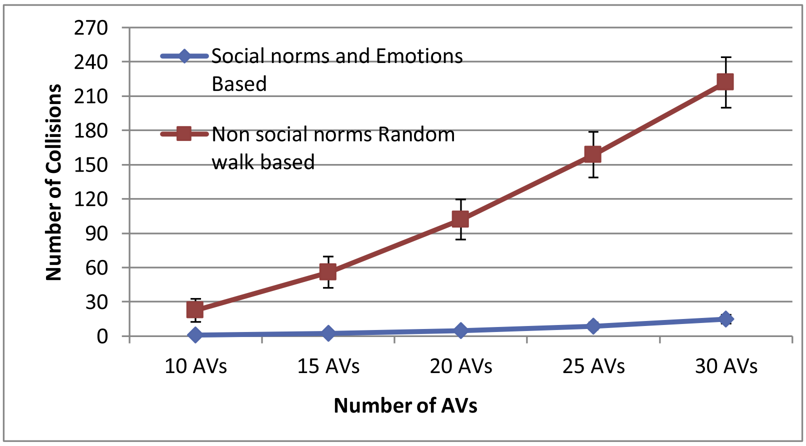

Fig. 6. Graphical representation of the results of TypeA set 3 Vs Experiment_TypeB set 3.

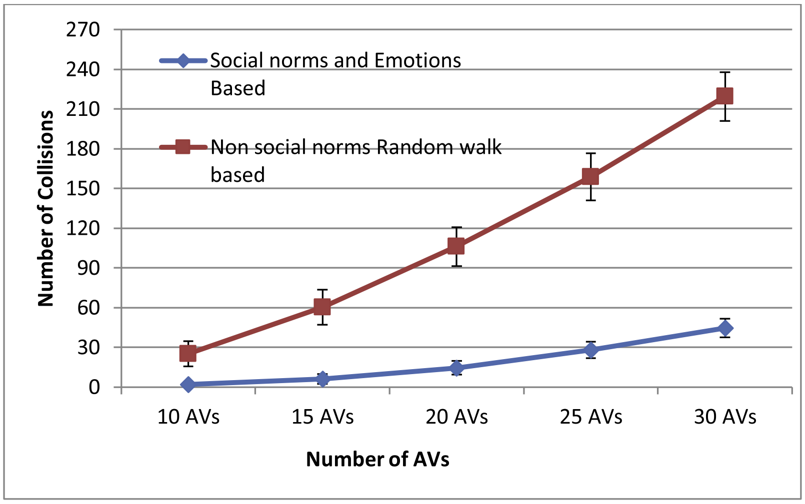

Fig. 7. Graphical representation of the results of Experiment_TypeA set 4 Vs Experiment_TypeB set 4.

Table 18
Set 4 Type A and B experiments results.

No. of AVs	Social norms and emotions-based		Nonsocial norms random walk-based	
	Mean	Stdev	Mean	Stdev
10 AVs	1.889218	2.067026	25.12701	9.707391
15 AVs	6.042479	3.723965	60.30161	13.30325
20 AVs	14.54727	5.010924	106.1374	14.68821
25 AVs	28.01678	6.281523	158.8475	17.78358
30 AVs	44.53196	7.017011	219.4805	18.46683

Furthermore, it would be interesting to present a comparative analysis of the results of set 1 and set 2 of Experiment_Type B with the set 3 results of Experiment_Type B. From the comparative study, it is concluded that the set 3 results of Experiment_Type B are better than the set 1 and set 2 results of Experiment_Type B. For example, for 30 AVs, the average number of collisions performed in set 1 and set 2 are 59.35 and 24.06. In contrast, there are only 14.69 collisions on average in Experiment_Type B set 3. We have not presented the experiment results of both Experiment_Type A set 4 and 5, and Experiment_Type B set 4 and 5. However, from the above-discussed results, it can be concluded that the social norms and emotions-based artificial society of AVs can have a lower number of collisions by adopting a low maximum velocity range, i.e. 0.3, and with both safety and sonar distances equal to 2.

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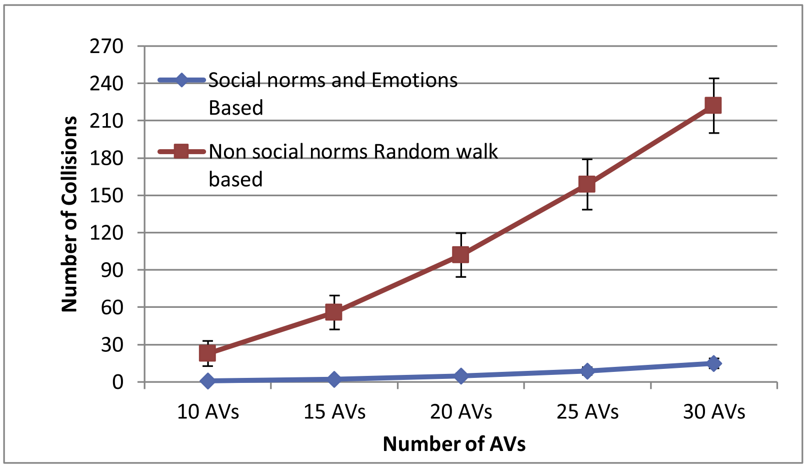

Fig. 8. Graphical representation of the results of Experiment_Type A set 3 Vs Experiment_Type B set 3.

8. Conclusion

This paper has proposed a novel collision avoidance solution for AVs operating as the main actors in road traffic. In the near future, it is likely that AVs will be very common and that people will delegate their driving powers to them. This raises the question of how AVs will be able to meet the expectations of humans regarding safer road operations with a lower number of collisions and a great number of harmless interactions with each other, especially when human drivers no longer play a role in their operations. An answer has been provided through the protocol of human social interactions, which lies at the core of humans' ability to interact with each other, avoid conflicts, and keep society in equilibrium. The key is following social norms under the influence of primary emotions. The simulation results presented here provide optimal parameters, such as the optimal sonar range and various optimal speeds suitable for avoiding road collisions in different road traffic situations. This research might be suitable for AV vendors when reinventing autopilot design to include social norms, emotions and optimal operating parameters. We hope that this research will make the designers of AVs better able to cope with the current challenge of making AVs more trustworthy regarding safe travelling.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.compeleceng.2018.02.011.

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