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Intelligent Decision Support System for Automobiles

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Abstract*: Intelligent decision support system is a system that mimics human like thinking. There are situation where every time a presence of human is contradictory so in order to reduce the human MANPOWER we present the intelligent decision support system that gives the impression of the human-like thinking replacing a human in the spheres that is required. Intelligent decision support system can be incorporated in automobiles also which is one of the sphere among the millions .In an automobile the Intelligent decision support system can instigate a change. Instead of having a human driven vehicle we have proposed a method to have an autonomous driven vehicle. This autonomous driven vehicle is otherwise iterated as an Intelligent driver model where an Intelligent decision made is credited to the Intelligent driver model .Intelligent decision support system in automobiles can confide in with the human the confidence of automobile should drive with crash-less independent driving style. This would increase the confidence with the decline in the careless human-driven vehicle. Intelligent driven vehicles based on intelligent decision support system can enable a car itself to find a slot, a vacant slot in a car-parking area and could predict the congestion in a traffic-led area and to have a crash-less driven vehicle. Intelligent decision support system in an automobile can take the aid of data mining, deep reinforcement learning and Genetic algorithm.

Keywords: Data mining, Deep reinforcement learning, Genetic Algorithm, Intelligent Decision Support System, Intelligent driver model.

I. INTRODUCTION

This paper proposes Intelligent Decision Support System in automobiles that trigger the intelligent driver model that helps to drive an automobile i.e. an automobile with a human-less-driver i.e. is an intelligent driver model. With an Intelligent driver model we can model an automobile that is human-less driver that can be confided with a cherished driving that is crash-less and safe and can overcome the careless carcasses by the human driver. There are times were we need to have an automobile system which is devoid of an human driver this is to harness the intelligence of an intelligent decision support system that is incorporated into an intelligent driver model. In this paper we have proposed the paper based on car automobile. A driverless car is a boon to the 22nd century because this could replace a human and would dwell an autonomous car driven model.

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This could replace a carelessly driven human- driven cars and could suffice a new era of a driving. Many changes are to be dealt to make this new era of driving with the driving of a car that is an autonomous driverless car. This is going to change the era of a driving style.

Autonomous car is a big buzzword in the 21st century. But still there are limitations of an autonomous car. Autonomous car, as proposed in this paper is a simulation model. Simulation model are a data-driven model. So there is a menace of accuracy. Accuracy cannot be determined. Accuracy cannot be determined the reason is that in our proposed system we have used an autonomous driven model which is depicted through a simulation model. So henceforth accuracy cannot be determined as a matter of fact of considering different parameters which account to a limited parameter taking into the consideration that the autonomous car following model. This autonomous car following model mimics a human like, human driven model. Because of this consideration of a autonomous car following model that mimics a human like, human driven model the parameters that we choose are limited. This parameter accounts to the parameter possessed by a human driver. Since a human-driven vehicles has been cloned for rejuvenating an autonomous car driven model which is Intelligent driver model, it's as a result trait that we take into consideration should be borrowed from the human drivers. Since the traits of an autonomous driven car should mimic a human driven driver car the parameters that ought to be considered are limited. All the parameter of a human driver is beyond the limit of possibility to consider. There can only be the consideration of a few important traits that could be depicted, so as a result entire behavior of a driver or an average of driver cannot be depicted. Hence all the scenario of an autonomous driven car that we have proposed as a data driven car, the entire human psychological trait cannot be harnessed. This may account for the disadvantage that the entire scenario cannot be witnessed. So some of the trait may be important but that cannot be cloned. As a result the style of a human driver cannot be injected or cannot be adopted by a data-driven car because it is a data-driven car so depicting a trait or a style of a human into the data is quite out of hand because harnessing every trait is near to impossible. Every human trait cannot be analyzed and instigated through an algorithm into a data-driven car. Because instigating a human trait or a style possessed by a driver into a data driven car would imply a series or an array of intense hard-work, intense concentration and a miracle of a string of knowledge to gather up or sum up the trait of the desire. This is a limitation.

This limitation can be overcome by continuous study in the field, continuous possession in the knowledge of the desired trait, endurance in the work, persistence to sum up and a hard work in the field to come up with the trait that mimic a human driver that can be incorporated into an data driven car. Continuous analysis and a realization can bore a result that could be a change and upcoming of a new era of an autonomous driven car.

The next limitation of a car driven model is that autonomous car driven model is its inability for a generalization capability. Autonomous car driven model cannot be generalized. There are a different styles of the human driven drivers each driver would have a different trait. So averaging out the entire trait is a task that is out of hand. So as a result generalization which implies that all the traits of a driver driving a car with the possession of different style is in out of hand to gather them up and sum up to give a trait that would represent all the traits or the style of a driver as a representation of the entire trait. So as a result this is a drawback. As already mentioned it is difficult to emulate a style of a human driver. As a result, the generalization is something near to impossible. This is because an autonomous driven car in our proposed system is actually a data driven car so as a result emulating all the trait of a car driver which is actually a human into a data driven model is near to impossible as it would require meditating on a extreme level to the knowledge to gain to have the style or the trait of a human driver into a data driven model is in the hands that is near to incapability. Because different drivers possess different traits, to form a generalized trait that could represent the entire driver's is out of order.

There is another limitation that accounts to the fact that the there is an inability to have an adaptive updating. Because it is an autonomous driving that is not possessing the intelligence of an human but mimics the human-like intelligence is possessed with the trait that adapting to an unexpected situation is out of hand and out of situation.

Traditional car following model is a model that follow a traditional fashion. Gaxis-Herman-Rothery model is an optimal velocity model is actually an Intelligent Driver model. There a following four types of car following model:

a. Stimulus-based
b. Safety distance
c. Psycho-physical
d. Desired-measures model.

Stimulus based model is a model that is based on a stimuli that maintains or select an acceleration and maintains and maintains a gap sufficient to stopping the vehicle safety.

Safety distance model is a model in which a driver maintains a safety distance between a stimulus car and the real driven car.

Psycho-physical model is a model in which the psychological trait of a driver is being detected, the trait that suggests taking the direction at the course of driving to avoid accident.

Desired measure model is a model that the driver has a preferred situation that can be represented by certain traits.

We have also proposed a situation where vehicles find their automatic way to a parking slot. Where each area is divided into a slot the vehicles use the intelligent decision support system to find a way to the parking lot. Here in this system the vehicles communicate with each other and adapt themselves in an intelligent manner to the parking lot to park themselves in a meticulous manner. Whenever a vehicle parks itself it communicates with other vehicle. The other vehicle judge the space based on the information provided by other vehicle in a space and provide information to the other vehicle specifying the gap sufficing for a vehicle to park or not. Sometimes the vehicle parking is based on a fee cost a parking lot charges a free fee cost in such a situation the car would be parked in that area but it could be at far away distance from the destination. Sometimes the distance is calculated by using Euclidian distance by a fastest algorithm and the distance is measured and the parking is done.

Sometimes update of a car has to be given that is main stream of communication that could ensure the car's behavior. These updates are made in order to judge other car behavior this can be done by using on the air update through a wireless fidelity medium. That could be best way of communication between a two car medium.

Association rule mining can also be used to judge a traffic congestion and method to deviate the car itself from the congestion that could work well in well congested situation.

Intelligent decision support system can also be used to analyze a car pedestrian behavior to judge a road that is accident free.

Accurate car positioning on the Earth's surface is required for many state-of-the –art automotive application.

II. LITERATURE REVIEW

This section proposes about the survey made on different literature that has analyzed and made intuitions thoroughly.

Meixin Zhu et al., has proposed a system of human-like autonomous car following model with deep reinforcement learning. In this they have come out of a solution to have an autonomous car following model instead of a human driven cars through reinforcement learning and Deep Neural Network. Autonomous car following model has been stipulated in order to have a car model with an intelligent driver. Intelligent driver model is a model that depicts the intelligent decision support system that possesses a car with a driverless model. This can be done using reinforcement learning algorithm and the deep neural network algorithm. Two thousand car following periods along extracted from Shanghai Naturalistic Driving study has been extracted to compare with a traditional driven model and the data driven model. Traditional car following models describe the action of a human driven vehicle. One of the famous Traditional car driven models is Gaxis-Herman-Rothery model. The famous traditional driven models are stimulus based safety distance, psycho-physical and desired-measures models. Stimulus based model is a model that is based on a stimuli that maintains or select an acceleration and maintains and maintains a gap sufficient to stopping the vehicle safety. Safety distance model is a model in which a driver maintains a safety distance between a stimulus car and the real driven car. Psycho-physical model is a model in which the psychological trait of a driver is being detected, the traits that suggest taking the direction at the course of driving to avoid accident .Desired measure model is a model that the driver has a preferred situation that can be represented by certain traits.Figure1shows the Experimental setup of Deep Reinforcement Learning.

In this model all the data Here in this model the data is acquired using data acquisition and fed into the database the data that is fed into the database is passed to the environment in this environment the simulation is made and trial and error method is used to detect the autonomous car driven model to determine if it behaves in a well suggested manner. In such a situation trial and error method can play a most important role. Here Reinforcement learning plays a most important role.

In reinforcement learning a time t is being assigned and at this time the reinforcement learning agent is adapted to a state S_t and an action A_t is performed for this a reward R_t is given aftermath the state is changed to S_{t+1} . This proceeds and moves on until the accumulated reward enlarges. Value based reinforcement learning predicts the expected long term reward, measuring the quality of each state, or a state action pair. Policy based reinforcement learning is a function approximation; policy-based methods calculate the gradient ascent and update the parameter policy. Deep reinforcement learning provides a weight to every neuron. Deep Q-Network is a

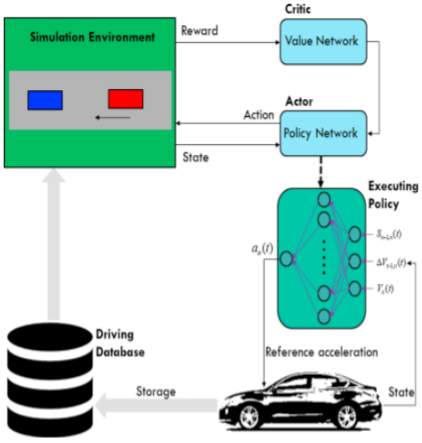

Figure 1 Experimental setup of deep reinforcement Learning (Meixin Zhu et al.,)

Types of deep reinforcement learning, it tends to predict the value function. Deep Q Network work well when there is only continuous action space. This is the greatest disadvantage. To curb this disadvantage Deep deterministic policy gradient algorithm is used that works on the continuous action space. In this paper Reinforcement Learning agent interacts with the environment through a sequence of states, actions and rewards. A neural network has been used to depict the actor network and a critic network. Figure 2 shows the neural network.

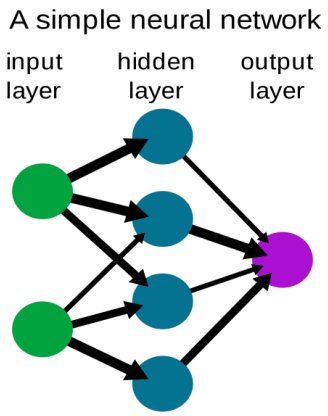

Fig. 2. Example of neural network.

This is a structure of a neural network, input layer, hidden layer and an output layer. Figure 3 shows the Experimental setup of Actor and a Critic model. Evaluation of metric and a reward function is done this is done using root mean square percentage error. The network architecture is as proposed. It consists of 3 layers: one input layer, 30 hidden layers and an output layer. So this study has been intended to propose a framework for human-like autonomous car following model based on deep reinforcement learning to learn the autonomous car following model.

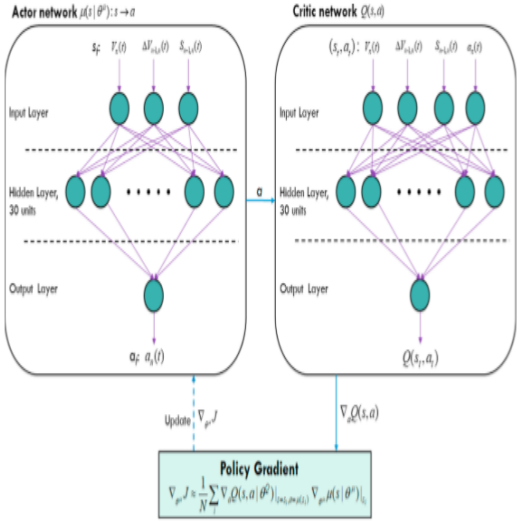

Fig. 3; Example of Actor and a Critic model. (Meixin Zhu et al.,)

Carlose E. Andrade et al., proposed a paper that specifies scheduling software updates for connected cars with limited availability. This paper proposes wireless communication. In this paper authors have taken into consideration of connected cars that send updates to each other the update is on the Air Update An over-the-air update is the wireless delivery of new software or data to mobile devices. Wireless carriers and original equipment manufacturers (OEMs) typically use over-the-air (OTA) updates to deploy firmware and configure phones for use on their networks. The initialization of a newly purchased phone, for example, requires an over-the-air update. With the rise of smart phones, tablets and internet of things (IoT) devices, carriers and manufacturers have also turned to over-the-air updates for deploying new operating systems (OSes) to these devices.

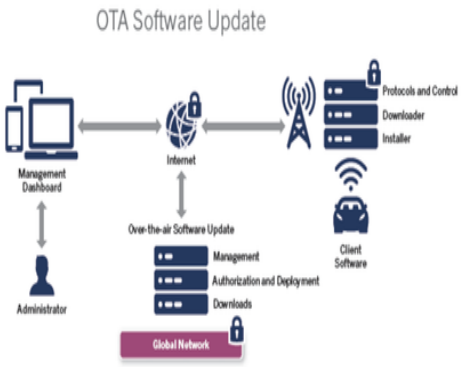

Fig. 4.Example of Software OTA Update.

Figure 4 shows OTA software update. There is a smart difference between smart phone connectivity and a vehicle-to-vehicle connectivity. Smart phone is connected to a network all the time whereas connected car very rarely appear on the network. This is because they may reach a zone that is out of a network or may reach a place such as garage was network coverage is limited. This is the reason that the vehicle connectivity to a network is different from that of smart phone connectivity. So a car may go out-of-range that is unpreventable. So to avoid this Firmware-over-the-update is being used. Firmware Over-The-Air (FOTA) is a Mobile Software Management (MSM) technology in which the operating firmware of a mobile device is wirelessly upgraded and updated by its manufacturer. FOTA-capable phones download upgrades directly from the service provider. FOTA updates be only carried out when the engine is turned on, limiting the time for download drastically. Amount of data download varies according to time and network condition. Reason accounts to the fact that the car may spend varying time under a particular network at different times of day. Resources are in the form of a block called as the physical resource block (PRB). Different physical resource blocks are allocated at different period of time as the need calls for.

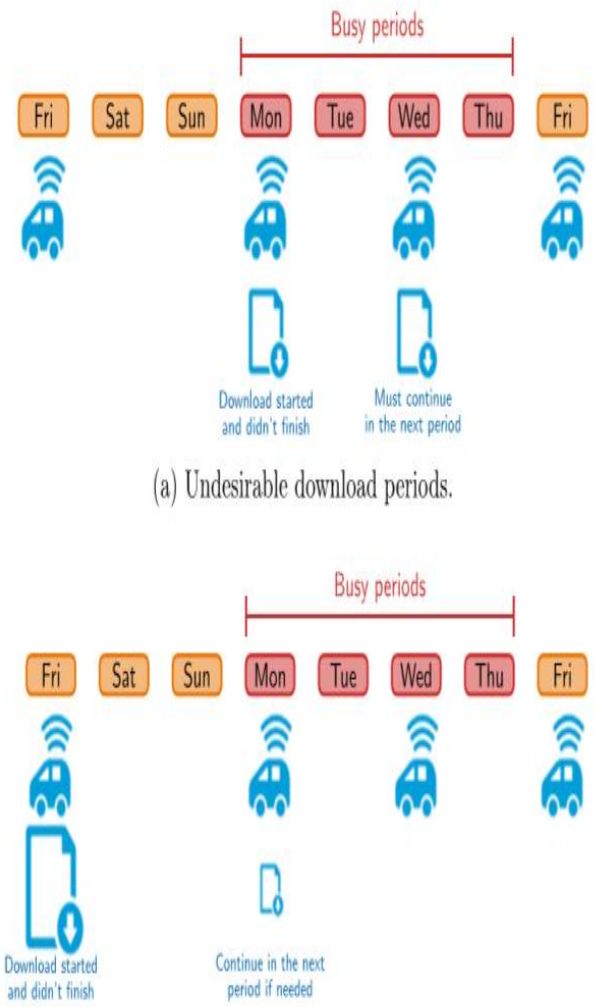

Fig. 5.Example of Experimental setup of Periodic Software Download (Carlose E. Andrade et al.,).

Figure 5 shows the experimental setup of periodic software download. In this paper authors have proposed genetic algorithm-Time- and Machine- Dependent Scheduling Problem. In this for each job starting from a particular period until all the demand is satisfied there are some constraints to be followed all the capacity required for each job must be less than that of machine job requirement. .Machine capacity must be less than the actual requirement. Maximum global resource utilization must be less than maximum resource consumption. Maximum number of jobs per period must be less than maximum resource consumption. In such a situation if all these constraints are followed the demand of the job is given. In real application, some jobs may appear very late, and it is not uncommon that a job defines the make span which is the time when all jobs are finished. Authors of this paper has proposed scheduling software updates for connected cars with limited availability.

Feng Wen et al., has proposed a hybrid temporal association rules mining method for traffic congestion prediction Traffic congestion is one of the largest traffic problems and one solution is a prediction of its generation. Traffic congestion comes from three phases order: the free travel phase, the meta-stability phase, and the traffic congestion phase. Therefore, it can be considered that if the meta-stability phase can be detected, forecasting traffic congestion becomes possible. This paper proposes a driver model that forecasts traffic congestion based on changes in driving behavior and that does not rely on traffic flow monitoring infrastructure. As a result of evaluation in driving simulators, it was understood that the distribution of steering, throttle and speed input frequency changes based on changes in the travel phase. It is possible to distinguish these changes using support vector machines as shown in Figure 1, and it is possible to make this into a driver model that predicts traffic congestion. Traffic congestion has been predicted by using neural network as in Figure 6.Neural Network has three layers

a. input layer
b. hidden layer
c. output layer

The author has proposed this traffic congestion prediction using Density-based spatial clustering of application with Noise in this algorithm neighborhood radius and a minimum number of points have been used. So for this algorithm, Neighborhood radius and minimum number of points are given as an input. The output is the cluster result. So iteration begins with initialization of a cluster id if the size of the neighborhood point is less than the minimum number of points then the point is a noise else the point is added to the cluster. This iteration follows until the size of the neighborhood is not null. So this algorithm has been used in this paper by the authors to predict the congestion. Then authors have proposed region Query algorithm in which NP is the output. Here the input is database, points, neighborhood radius and minimum number of points. Here distance is calculated if the distance is less than the neighborhood radius in such a case the point is assigned to the NP which stores the point of neighborhood radius. Traffic congestion is changing continuously in such a situation temporal association rule mining

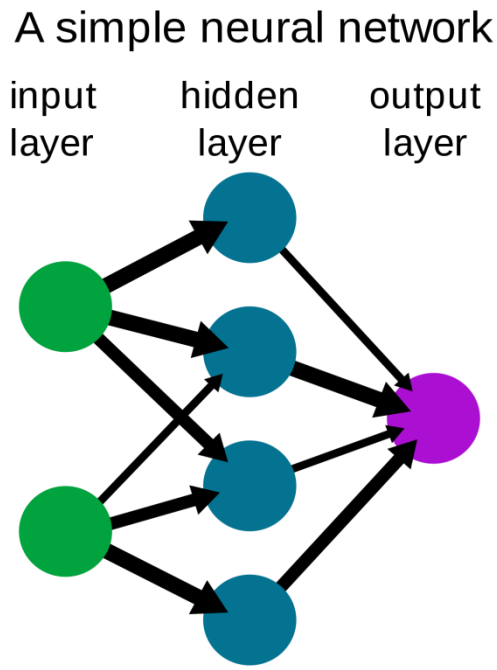

Fig. 6. Example of Neural Network.

is used. Where initial population is compared with the total population with a parent and offspring's are generated from which the chromosome of the parent is being analyzed.

After generating the chromosome the crossover is done in which. The set of parent chromosome is given as an input where the two chromosomes are stored in anticlis and conselist and then the crossover is done. Figure 7 shows the cross-over.

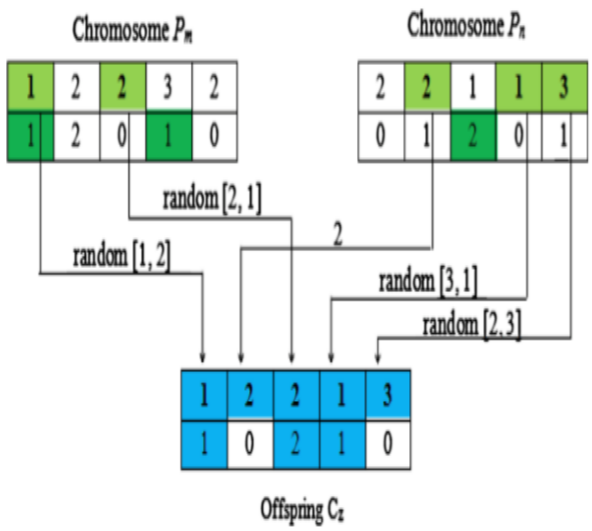

Fig. 7.Example shows the crossover (Feng Wen et al.,).

After this mutation is done and then the rules are extracted and Classification is done at the point of which the classifier is build. So as an experimental result data description is done and data preprocessing and then experimental set up is being done in this paper. In this manner the authors have successfully determined a hybrid temporal association rules mining method for traffic congestion prediction.

Seng W. Loke et al., has proposed an cooperative car parking using vehicle to vehicle communication which is an agent based analysis. In this paper a cooperative car parking algorithm has been used which is used to determine adept way to find an parking lot that is free enough to park a vehicle. Vehicles vstreaming to a car park area at peak hour is commonly associated with significant time consumed time consumed due to traffic congestion induced by vehicles circulating. Figure 8 shows different parking lot.

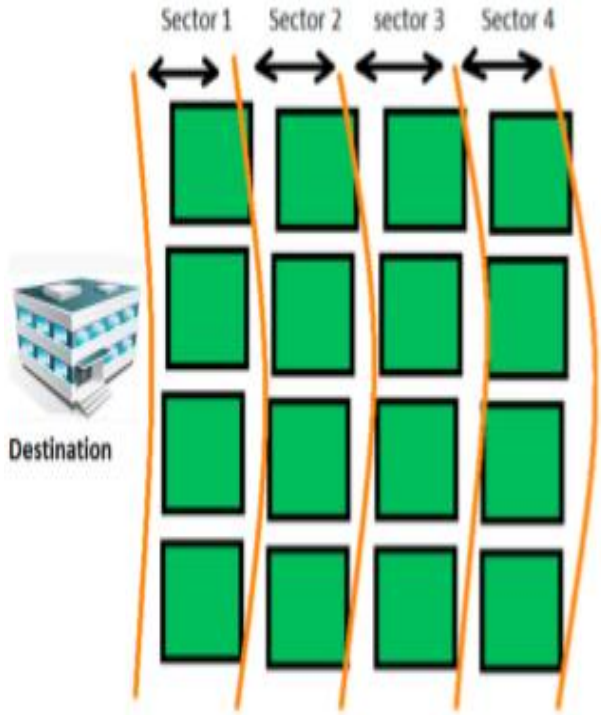

Fig. 8.Example of vehicle parking sector lot (Seng W. Loke et al.,).

There are a different slots in a parking lot in which a vehicle has to decide to select which slot this slot is decided by using vehicle-to-vehicle communication. This can be determined by using Cooperative car parking Greedy Search algorithm (CoPark GD) and Cooperative car parking Walking distance and searching time (CoPark WS).CoPark-GD aims to model the situation of vehicles (which we also call agent, interchangeably) all striving to find parking slots near to the building entry to reduce walking. The vehicles grant the highest priority to the parking slots nearest to the building entry. Each vehicle sorts the sub-areas, which obtained as initial information, in an ascending order based on the distance to the building entry and then selects the first slot at the nearer sub-area as its current target slot (which it then heads towards). During the vehicle's way to the target slot, it shares its intention with other vehicles it comes within DSRC range with by disseminating a message (named INFO message) containing the vehicle ID, position and the (current) target slot (i.e., its current destination). A vehicle receiving the INFO message from the sending vehicle can then determine its potential of getting that parking slot by comparing its own distance to the target slot with the distance of the sending vehicle to the same slot (in the situation where both vehicles have the intent to go to the same parking slot). A vehicle can alter its target slot and select the next successive slot (in its sorted list) in case it realizes that there is one (or more) other vehicle(s) nearer to its target slot.

CoPark-WS

The CoPark-WS algorithm is another approach to cooperative car parking that aims to find parking close to the building entry while also aiming to reduce searching time.

It can be viewed as an enhanced version of CoPark-GD. Similar to CoPark-GD, each agent then sorts the sub-areas based on their distances to the building entry. The parking slot in the area nearest to the building entry, optimistically, is selected as the currently preferred slot by the agent who then moves towards it. The vehicle also periodically broadcasts INFO messages to share its intentions with other cars as in CoPark-GD. Furthermore, vehicles in CoPark-WS gather knowledge about the demand (for parking slots) of areas. A vehicle could change its target slot if it realizes that the slot is now occupied or has been selected by another agent nearer to the slot. In case the area (where its target slot is)has another free slot, based on the agent's knowledge, the agent would select that as the next target. Otherwise, a new assessment of the utilityof the remaining available areas is computed based on the utility function below. The agent selects the area of highest utility to move towards, i.e., a slot of this highest utility area would be selected as the new target slot. Note that we use the term *decision point* to mean the time that the vehicle realizes (or decides) that it would not have any chance to park at the current target area, and so needs to reassess the areas based on a utility function below to select a new target area (containing another target slot). A vehicle can decide to alter its target search area at different time slots based on when it recognizes the lack of chance to park at the current target area. That can happen either when the vehicle is far away or inside the target area. A vehicle (or agent) computes the utility value $Ui(k)$ of area i at a decision point k based on messages received from other vehicles so far, its own position and its current knowledge of the number of available areas. The utility function is used to assess the utility of areas taking into account the distance of the area to the building entry and distance of the area to the vehicle itself. Note that the distance metric we used in this paper is the Euclidean distance so that our approach is heuristic (though other metrics such as travel distance might also be used). We suppose there are M initial number of areas (each area containing a collection of parking lots) and $O(k)$ is the number of areas at time k which the agent has found to be totally occupied (no free slots in the area), and considered "lost" to the agent. $O(k)$ is determined based on the vehicle's detection of the situation of areas that it has passed through during its journey and areas are lost to the agent due to the competition from others. $V(k)$ represents the availability ratio of areas: $V(k) = M\ O\ k$. In addition, Ii and $Ji(k)$ are weights representing the value to the agent of an area i being near to the building entry, and near to the vehicle position, respectively; e.g., having a high Ii means that an area is near the building entry (and does not vary with k) and a high $Ji(k)$ means that the area is near to the vehicle's current position (and sovaries with k). The vehicle's decision to select an area that is far from or near to the building entry depends also on the levels of demand on the areas and the current number of available areas (areas not yet lost). The level of demand on an area i, denoted by $Di(k)$computed as follows:$i(k)=MAX\{0,(\omega i-\tau i(k)-\rho i(k))/\omega i\}$ where ωi is the initial number of slots in area i (as obtained by the vehicle at a car park entrance), $\tau i(k)$.

Ching Nok TO et al., has proposed an autonomous vehicle control strategy wherein they have taken into consideration the Road Curvature Center, Kinematics and dynamic vehicle rotation centers. and an autonomous control system.

Sunan Huang et al., has proposed a paper based on Evaluation of remote pedestrian sensor system based on the analysis of car- pedestrian accident scenarios. Here data is collected, knowledge is developed, Estimation of the pedestrians' speeds, Estimation of cars velocity, Estimation of impact locations, Mathematical model and a sensor evaluation is done. Figure 9 shows vehicle and pedestrian system that specifies how to escape an accident scenario.

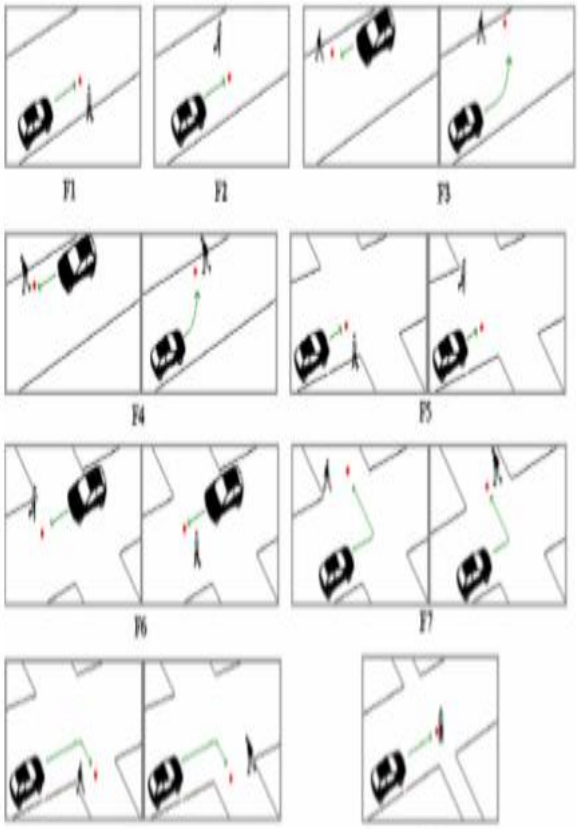

Fig. 9.Example of navigation system to avoid accident scenario with a pedestrian. (Sunan Huang et al.,)

Carlos Melende et al., Accurate car positioning on the Earth's surface is required for many state of the art automotive applications. Through a Navigation satellite system, deployed globally, position of the car can be determined.

III. RESULTS AND DISCUSSIONS

Table1 Car Following Model-spacing

	DDPGvRT	DDPGv	DDPGs	IDM	RNN	Loess	NNa
Intra-Driver Validation error	5.05	7.34	11.32	8.08	8.08	10.36	14.03
Inter driver validation error	6.03	7.7	12.9	10.03	7.06	12.08	14.28

Table2 Car Following Model-Speed

	DDPGvRT	DDPGv	DDPGs	IDM	RNN	Loess	NNa
intra-driver validation error	17.09	17.52	21.67	20.76	22.09	29.78	35.97
Inter-driver validation error	20.98	27.78	30.78	26.24	23.98	30.45	43.89

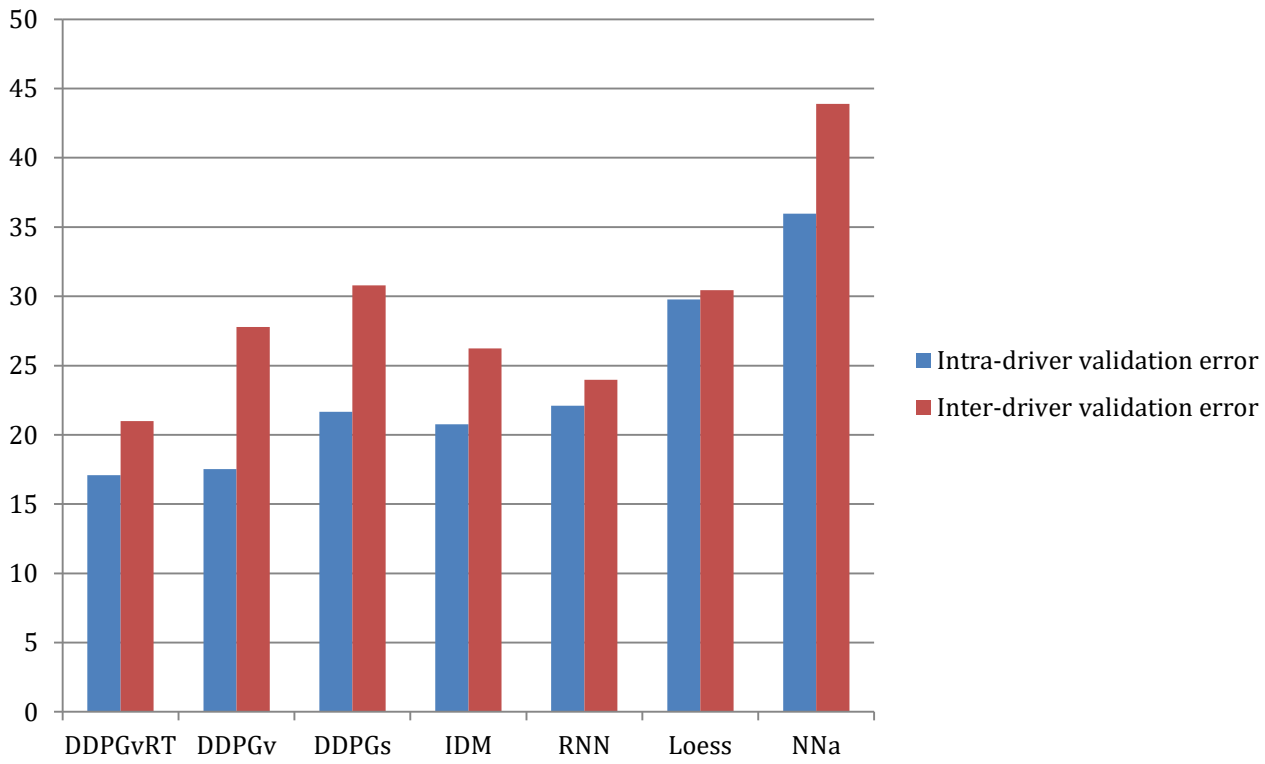

Figure11 Car Following Model-spacing

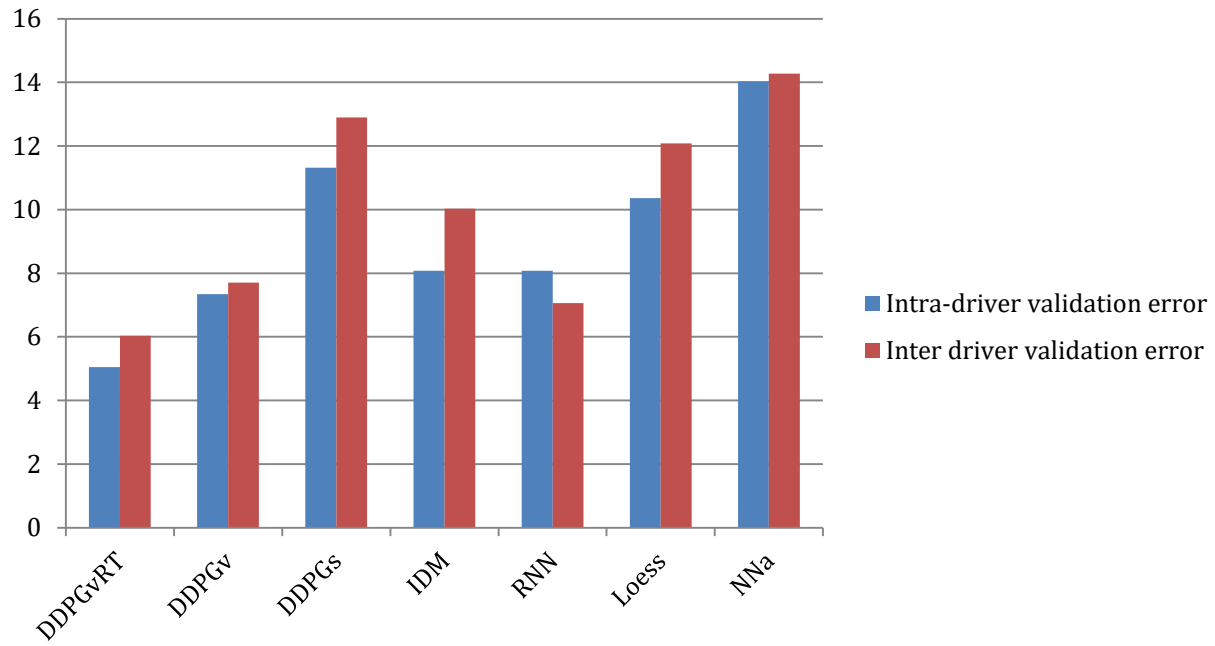

Figure12 Car Following Model-Speed

Table 3 Description of the investigated car-following models.

Model	Description
DDPGs	Deep deterministic policy gradient (DDPG) model with spacing deviation as reward function, without reaction delay.
DDPGv	DDPG model with speed (velocity) deviation as reward function, without reaction delay.
DDPGvRT	DDPG model with speed deviation as a reward function, considering a reaction delay of 1s.
IDM	Intelligent driver model, Representing traditional car following models
RNN	Car-following model base on recurrent neural network.
Loess	Car following model based on locally weighted regression, representing data-driven nonparametric model.
NNa	Car-following model that predicts follower acceleration, representing data-driven conventional neural network-based models.

Table1 and Table 2 show the tabular representation of speed and spacing of a car following model. And pictorial representation of the car following model of its spacing and speed is depicted by Figure 1 and 2 respectively. Table 3 shows the description of the investigated car-following models.

IV. CONCLUSION

So in this way it can be said that an intelligent decision support system can be incorporated to have an intelligent driver model system.

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