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Anti-Jamming Vehicle To Vehicle Communication For Intelligent Transport System Using Fuster's Paradigm

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Abstract - Connected and Autonomous Vehicles (CAV) has the ability of sensing its current circumstance and moving securely with practically no human information. The anti-jamming Vehicle to Vehicle (V2V) transmission in CAV networks for Intelligent Transport System (ITS) utilizing fuster's paradigm. Cognitive Dynamic System (CDS) that builds rules of behavior consisting of five principles of human cognition known as Fuster's paradigm which embodies perception-action cycle (PCA), memory, attention, intelligence, and language. The lane features are obtained from the images obtained through feature extraction process. The obtained images through sensors are sampled for object detection. The reinforcement learning of the vehicles environment where the vehicles learn about the existing world and the action. The key optimization process during the simulation is to get the accumulated reward and not just simultaneous reward. The accurate distance between the vehicles and interpretation of the inter-system relationship between radar tracking and vehicular communication is achieved. V2V communication for autonomous vehicles receives messages as a local or global message based on the message received the action taken. Thus, the V2V communications in intelligent transport system achieves average accuracy 97.04% without any loss of communications overcoming the jamming to avoid collision between vehicles.

Keywords--Autonomous Vehicles, Perception, Cognition, Reward, Anti-Jamming

I. Introduction

Advanced control frameworks interpret sensory data to recognize suitable route paths, as well as obstructions and relevant signage [12]. Smart vehicles are additionally called autonomous vehicles, driverless vehicles, or self- driving vehicles. A smart vehicle enables a vehicle to work independently by sensing the climate and executing a responsive action. It incorporates four key advances: environment condition perception and modeling, localization and map building, path planning and dynamic decision-making, and movement control.

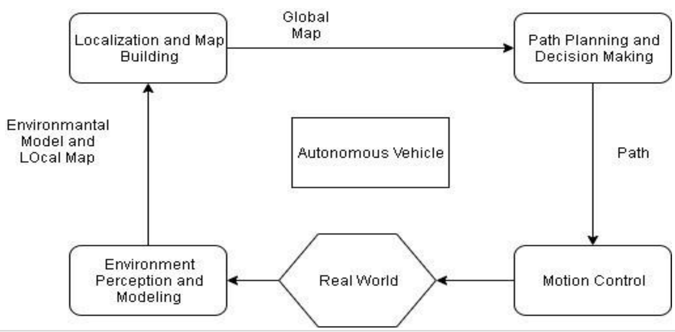

Fig. 1 Four fundamental technologies of intelligent vehicle

An Intelligent Transportation System (ITS) shown in Fig. 1 is a high-level application which focus to offer inventive types of assistance identifying with various methods of transport and traffic management and enable clients to be better informed and make more secure, more organized, and smarter utilization of transport networks [2].

II. Literature Survey

A detailed survey of various literatures pertaining to lane detection and lane change, path planning and decision-making. Recent advances in self-driving vehicle communications are introduced. Cognitive Dynamic framework [14] proposed the anti-jamming V2V communication in CAV networks by power control related to channel determination. CRC is used to examine and address the jamming issue. A study of anti-jamming defense problems from a multi-domain perspective, which encompass both the power domain and spectrum domain, and a Multi-Domain Anti-Jamming scheme (MDAS) [9]. An anti-jamming deep reinforcement learning calculation to get the ideal anti-jamming procedures [18]. A recursive convolutional neural network to deal with the complex intuitive decision-making issue with an unbounded number of states [13]. An adversarial machine learning to design an intelligent jamming attack on wireless communications and presented a defense scheme against the jamming attack [17][20].

A outline of exploration ICT-based support and assistance administrations for security of future connected vehicles. General order and a brief description of vehicle discovery, street location, path recognition, person on foot identification, drowsiness recognition, and crash avoidance [2]. A model consisting of a back-propagation neural network model optimized by a Particle Swarm Optimization (PSO) algorithm, and a continuous identification model is developed based on the results obtained of naturalistic on- road tests utilizing millimeter-wave radar information [3]. A novel path changing choice model for self-driven vehicles dependent on deep autoencoder organization and XGBoost [15]. Path change move calculation with a pragmatic way to deal with decide a between vehicle traffic hole and time case to make out the move [8].

A motion planning and tracking system for independent vehicles by utilizing the resistance organization and MPC for self-sufficient vehicles [6]. A steering control calculation and its closed-loop framework examination and test approval for precise, smooth, and computationally economical path track of automated vehicles [16]. Movement prediction [10][19] estimation for multi-way turn congregations using a Long Short-Term Memory (LSTM) - based Recurrent Neural Network (RNN). Model Predictive Control [4][7] dependent on fuzzy adaptive weight control is proposed to settle the issue of intelligent vehicle during the cycle of path track and path change in motion planning with a combination of probabilistic and deterministic expectation for robotized driving under complex driving conditions. An ongoing in-vehicle video investigation to recognize and follow vehicles ahead for wellbeing, auto- driving, and target following. The Hidden Markov Model (HMM) is utilized to isolate target vehicles from the foundation and track them probabilistically [1]. A plan, execution, and assessment of a virtual objective based surpassing choice, movement arranging, and control calculation for self-governing vehicles [5][11].

III. **Cognitive Risk Control**

IV.

$$R(\pi,r)=E\pi[\sum t=0\ \gamma tr(st,at)]$$
------------(1)

where R is reward ,γ is the discount factor of the reward , $\prod$ is policy to optimize the reward, st is state of the vehicle, at is action of the vehicle

A smart vehicle is a vehicle of detecting its current circumstance and working without human association. A new method based on CRC is designed for anti-jamming V2V communications in CAV networks [14]. The structure of CRC tailored for anti-jamming V2V communications is illustrated in Fig. 2. The basic framework of CDS, which comprises of the perceptor, the feedback channel, the executive and jammer. These tasks are classified into 3 sub- tasks: (i)The object detection, object identification or recognition, object classification, (ii)The Object Localization and (iii)Prediction of Movement

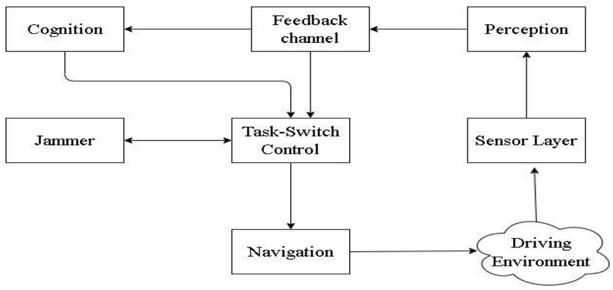

Fig. 2 Architectural Structure of Cognitive Risk Control Tailored for Anti-Jamming V2V Communications

A. Perception

The purpose of sensing is to build a 360-degree environmental model around the vehicle for the detection of different kinds of objects and the perceptor in CDS is to perceive the dynamic and uncertain environment so that informed decisions can be made later in the executive on a cyclic basis. The perception cycle comprising path planning, decision making, vehicle control, environment, perception, localizing and mapping.

B. Feedback Channel

The feedback channel occupies a distinctive place within the CDS in that it has the perceptor on its right-hand side and the executive on its left-hand side; hence, it sits in the middle of the CDS as given in Fig. 3. Most importantly, the feedback channel is fully occupied by internal rewards, whose primary function not only involves the perceptor on the right but also the executive on the left.

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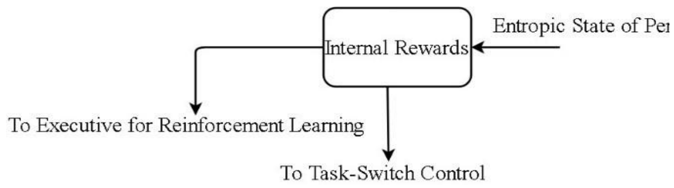

Fig. 3 Feedback Channel

During the learning process the framework moves from state to state, by making a move. Activity could be delayed down, change the path, or delayed down and state is a current and current circumstance the vehicles are in and the framework is getting a reward. The reward is a criticism to the framework to make sense of whether that made a decent move or not. With access to the state s and reward capacity r, the purpose of reinforcement learning is to locate the ideal approach π∗ which optimize the expected future total rewards:

Algorithm: Reinforcement Learning
//Input : State of the Vehicle (Agent) in the particular environment
//Output: Reward is obtained based on the State-Action Pair
//A-Agent
//E-Environment
//St-State
//At-Action
//Rt-Reward

Learning process
for t = 1,2,…. A observes St
A decides on At E provides Rt
E moves A to next state St+1
if result = postive
every state && action pair = rewarded e**lse** every state && action pair = punished
end if
end for

The above algorithm specifies the reinforcement learning of the vehicles in the environment. The vehicles learn about the existing world and the action.

C. Cognition

There are two basic components involved in cognitive control:

(i) Planner, the function of which is to extract a set of prospective actions from the action-space, which are continually improved under the influence of attention from one shunt to the next.
(ii) Policy, the function which leads to decision- making based on the choice of the optimal cognitive action derived from the set of prospective actions computed by the planner.

1) Steer Controller

At a given time t, the steering angle depends on the Cross-Track Error (CTE), and the time derivative of the CTE. The CTE is the distance between the focal point of mass of the vehicle, and the ideal direction. The regulator should be adjusted, i.e., it depends upon to choice made for sthe coefficients kp and kd such that the car drives (relatively) smoothly.

Steer(t) = kp CTE(t) + kd (dCTE(t)/dt) ....(2)

2) Distance Calculation

The distance between the vehicles is illustrated in eq (3.5)

Distance = sqrt(l.x - t.location.x) ** 2 + (l.y - t.location.y) ** 2 + (l.z - t.location.z) ** 2)) (3)

D. Anti - Jamming

Jamming includes bombarding recipients with noise—signals or messages that cause interference. Sending a signal of adequately high power on the similar frequency as another signal can cause interference and is neither complicated nor expensive to execute. This strategy can prevent independent vehicle communication frameworks from receiving intended messages clearly, and sometimes, even altogether.

1) Procedure to Change Route

V2V communication for autonomous vehicles receives messages as a local or global message. The action is taken based on the message received and the route is changed accordingly. If there is any loss of communication which may lead to the collision of vehicles as illustrated in Fig. 4.

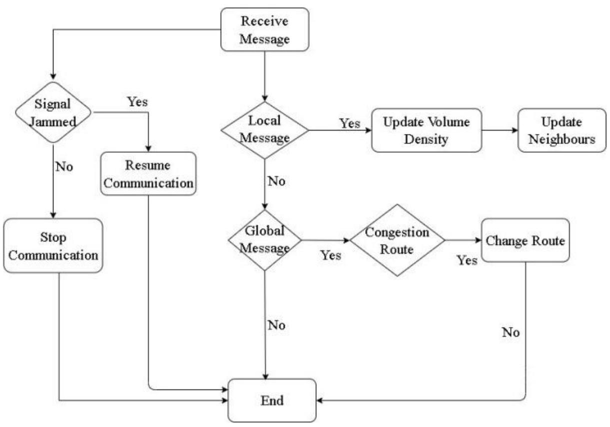

Fig. 4 Flowchart for Route Change

Algorithm: Route Change to overcome jamming attacks

//Input : Vehicles connected in V2V network i=1 to n

//Output : Detect jamming attack and change route message

= = received

for each vehicle i=1 to n

if message = = received
if received message = = local message
update volume density && update neighbors
else received message = = global message
if route = congestion change route
else end
else if received message = = not received && signal jammed resume communication
else collision occurs && stop
end if end if
end if end for

Each vehicle in the V2V network communicates with each other. The messages received may be local or global. Based on the received message the corresponding vehicle changes the route to the destination.

V. Implementation and Results

The necessary setup of the system is done for its real-time implementation which yielded the results. The executions and results are examined in the following sections

A. Data Collection and Processing

The driving test system would save outlines from three front-facing cameras recording information from the vehicle's perspective; just as different driving statistics like speed, throttle and steering angle. The camera data is used as model input and expect it to predict the steering angle in the [-1, 1] range. A minimal adaptation of self-driving vehicle is assembled. At that point Deep Learning calculation in PC predicts the controlling point to evade a wide range of crashes. Predicting steering angle can be considered as a regression issue. Model will take in the steering point from the according to the turns in the picture and will at last predicts steering angle for obscure pictures.

Φ is the minimum steering angle required to align the vehicle at the mid-line of the lane calculated using the equation 4. The other essential parameter is the perpendicular steering distance μ.

$$\Phi = \theta 1 - \theta 2 \qquad \text{--------------(4)}$$

A negative μ indicates rightward drag of the vehicle and the steering angle is denoted by Φ to align it along the mid-line of lane. Similarly, a positive μ and Φ indicate leftward drag as illustrated in Table I.

Table I Conditions for Different Road Scenarios

Scenario	Steer Straight	Steer Right	Steer Left
μ	$-1<\mu<1$	$\mu < 1$	$\mu > 1$

Φ	$\theta 1 - \theta 2 = 0$	$\theta 2 > \theta 1$ Φ=negative	$\theta 2 < \theta 1$ Φ=positive

A threshold value of 1 for μ is assigned, in order to tackle sudden fluctuations in steering due to noise. A function to load all the pictures just as the steering wheel point esteems in a numpy array.

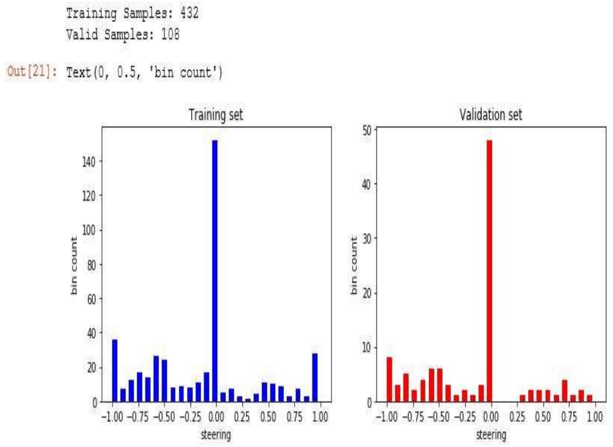

Fig. 5 Training Set vs Validation Set

The following stage was to split the information utilizing the 80–20 rule which means utilizing 80% of the information for training while the rest for testing the model on unseen pictures. Plotted the sample training and validation steering point distributions as shown in Fig. 5 above.

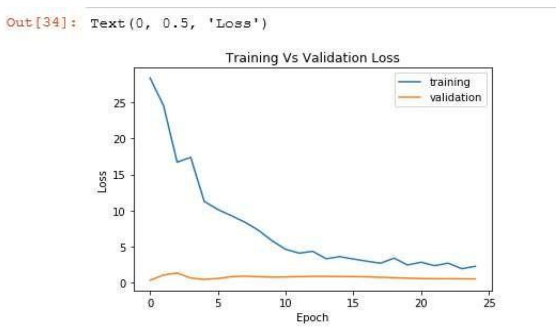

Fig. 6 Loss vs Epoch

Trained the model for 25 epochs with a group size of 128. Additionally, plotted the training and the validation loss as a component of epochs. The model is combining very acceptable in only 25 epochs. It implies that it is learning a genuinely good strategy to direct a vehicle on inconspicuous street conditions. The Fig. 6 gives the training and validation models.

B. Carla Simulation

In-order to prevent the loss of transmission to avoid collision, the input given is autonomous vehicles with sensors. CARLA reenacts a dynamic world and gives a key interface between the agent and environment i.e., surrounding that helps out the world. To help this functionality, CARLA is coordinated as a client-server

framework, where the server runs the simulation and renders the scene. The customer API is executed in python and is liable for the transmission between the independent agent and the server by methods for sockets.

1) Experiments

The network output is trained to group every pixel in the picture into one of the accompanying semantic classifications: A = {sideway, road, dynamic object, lane marking, miscellaneous static}. The probability distributions given by the network are utilized to assess the inner self path dependent out and about road and the lane markings. The network yield is used to figure an obstacle mask that expects to incorporate people on foot, vehicles, and different hazards. Three strategies are assessed modular pipeline (MP), and reinforcement learning (RL) – on two progressively difficult driving errands, in every one of the two accessible towns. The errands are defined up as objective coordinated route: an agent is instated somewhere in town and needs to arrive at a destination point. In these experiments, the agent is allowed to ignore speed limits and traffic lights.

Table II Quantitative evaluation of two autonomous driving systems on goal-directed navigation tasks

Task	Training Condition s		New Town		New Weather		New Town & New Weather	
	MP	RL	MP	RL	MP	RL	MP	RL
Straight	98	89	92	0.23	100	86	50	68
One turn	82	34	61	0.23	95	16	50	20
Navigation	80	14	24	0.41	94	2	47	6
Navigation Dynamic	77	7	24	2	89	2	44	4

Table II reports the level of effectively finished scenes under four different conditions. The first is the training condition: Town 1, Training Weather Set. The beginning and finish areas are not quite the same as those utilized during training: just the overall climate and surrounding conditions are the equivalent. The other three test conditions test more aggressive theory: to the generally concealed Town 2 and to already un encountered atmosphere from the Test Weather Set. Generally, the presentation of all techniques is not perfect even on the least complex assignment of driving in an orderly fashion, and the achievement rate further decreases for more difficult tasks. The table reports the level of effectively finished scenes in each condition. Quantitative assessment of normal distance travelled by the vehicles in training condition and new town, higher is better as given in Table III.

RL collides with pedestrians least often, which could be clarified by the huge negative reward incurred about by such impacts. These outcomes include the susceptibility of end-to-end ways to deal with manage uncommon events: splitting or turning to remain from a passerby is an uncommon occasion during training.

Table III Average distance (in kilometers) traveled

Task	Training Conditions		New Town		New Weather		New Town & New Weather	
	MP	RL	MP	RL	MP	RL	MP	RL
Opposite Lane	10.2	0.18	0.45	0.23	16.1	0.09	0.40	0.21
Collision-Static	10.0	0.75	0.44	0.23	16.1	0.72	0.45	0.25
Collision-Vehicle	16.4	0.58	0.51	0.41	20.2	0.24	0.47	0.37
Collision-Pedestrian	18.9	17.8	1.40	2.55	20.4	0.85	1.46	2.99

While CARLA can be used to assemble the recurrence of such events during training to help end-to-end approaches, further advances in learning estimations and model structures might be mandatory for significant improvements in robustness.

VI. Conclusion and Future Work

A. Conclusion

The anti-jamming V2V communication in CAV networks smart vehicle framework utilizing fuster's paradigm is accomplished with a precision of 97.04%. Assessment of the distance between self-governing vehicles is determined. Interpretation of the inter-systematic connection between radar tracking and vehicular transmission. V2V communication for smart vehicles gets messages as a local or global message. The move is made dependent on the message received. If there is any chance that there is any loss of communication which may prompt the impact/collision of vehicles. The calculation for changing the route based dependent on the messages received from self-governing vehicles associated with the transmission

B. Future Work

The performance of proposed approach in a large- scale and complex network ought to be considered. At present, this methodology predominantly focuses on a confined region(area). With more vehicles joining the communication, the jamming condition will turn out to be considerably more convoluted, the channel model may should be modified because of high vehicle portability, and each exclusively made decision will affect any other vehicles in the area. Depending on the most impressive biological entity that is ever known, there is an incredible chance to progress and overhaul the current plan of cognitive anti-jamming V2V transmission, among numerous other designing applications that is in urgent requirement for cognitive or intelligent abilities.

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