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COOPERATIVE ROAD AND LANE AWARE V2I COMMUNICATION FOR COLLISION AVOIDANCE IN AUTONOMOUS SELF-DRIVING VEHICLES

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Autonomous self-driving vehicles are becoming more essential in research due to its features and implementation. Vehicle to Infrastructure (V2I) is a critical component in autonomous self-driving cars. With the proper implementation of V2I communication many road accidents can be prevented. The proposed work implements new cooperative algorithm that embeds road classification, lane marking detection and classification. The proposed algorithm uses Road Side Unit (RSU) and Dedicated Short Range Communication (DSRC) for V2I communication. This algorithm enhances the safety in lane changing with the incorporation of lane marking detection. The results clearly demonstrate the implementation of V2I communication with an acceptable efficiency of 99% that enhances the road safety.

Keywords: Lane detection, lane marking classification, inter vehicular communication, self-driving cars, V2I communication, DSRC

1. Introduction

Recent advancements in the field of Autonomous vehicles implements various features to improve the road safety. Various levels of autonomous vehicles varying from level-0 to level-5 are reported in Ahangar *et al.* (2021), Prakash (2024), Nurliyana *et al.* (2023), Petrovic *et al.* (2020). According to Moujahid *et al.* (2018), level-2 autonomous vehicle implementation currently exists in India. A noticeable feature of autonomous vehicles grabbing the attention of the researchers is Advanced Driving Assistance System (ADAS) technology. This ADAS technology includes the techniques such as adaptive cruise control, forward collision avoidance warning system, Anti-Lock Braking System (ABS), Lane Keeping Assistance System (LKAS), and Lane Departure Warning System (LDWS) described in Eichelberger and McCartt (2016), Brookhuis *et al.* (2019), Grove *et al.* (2015), Moujahid *et al.* (2018), Wang *et al.* (2018).

In addition to the existing ADAS features, road classification and lane marking detection and classification system provides more security to the self-driving cars. Various Convolutional Neural Network (CNN) algorithms such as Xceptionnet, ResNet-50, MobileNet-V2 attains acceptable accuracy are reported in Srilalith (2024). The Indian Road Congress (IRC) and the Ministry of Road Transport and Highways (MoRTH) maintain a uniform set of guidelines for lane and colour markings. Two distinct colours, such as yellow and white, are used to display the lane markings. Lane markings are classified as Continuous and Dashed according to the length. The yellow divides the opposing lanes, while white indicates traffic moving in the same direction. If the markings are dashed, the vehicle can change lanes; if the markings are continuous, lane changes are not advised. The Enhanced ENet-B0 algorithm is implemented in Prakash *et al.* (2024) to recognize lane markings. Further the concept of lane marking detection with better accuracy using Deep convolutional Neural Networks is reported in Tian *et al.* (2018). To further improve the features of lane marking boundaries are detected using linear parabolic and Gaussian mixture is elaborated in De Paula and Jung (2015). A conditional random field approach for detecting the lane marking are reported in Mathibela *et al.* (2015). As demonstrated in Yang *et al.* (2018), the goal of lane marking detection and classification is to integrate this into the ADAS. Additionally, Zhou *et al.* (2017), Chen *et al.* (2021), Pan *et al.* (2020), Puphal *et al.* (2022) report on the integration of above concept with other aspects like traffic, lead vehicle position, target lane clearance and Cooperative lane changing systems. By incorporating the Vision based perception algorithm with histogram analysis both straight and curved lanes are detected properly (Muthalagu *et al.*, 2020). To establish the signalling system in the

autonomous vehicles using the lane marking classification includes several parameters as reported in Aledhari *et al.* (2025), Qu *et al.* (2022), Jula *et al.* (2000), Saranya *et al.* (2022), Suh *et al.* (2018).

Inter Vehicular Communication (IVC) technology allows the vehicles to exchange information wirelessly. The IVC can predict the moment of surrounding vehicles more accurately than the sensors presented in vehicles. Different Inter Vehicular Communication models for lane changing is elaborated in Li *et al.* (2020), Li *et al.* (2021), Yao and Li (2021). The lane changing process is categorized as Discretionary Lane Change (DLC) and Mandatory Lane Change (MLC). The DLC aims to better road clearance and safe manoeuvring. The MLC happen in the complex environments and can reaches the planned destination by following the prescribed path. The Recurrent Neural Network (RNN) algorithm is designed for DLC based high speed mobility and lane changing is analysed and achieves lane changing operation in 4.3 to 5.2 seconds for highway scenarios reported in Naskath *et al.* (2022). For the same lane changing model a concept of neural network has been implemented in Sharma *et al.* (2022). Different features such as location sharing and traffic clearance are incorporated in IVC to reduce the frequency of road accidents are reported in D'Orey and Ferreira (2014). The Dedicated Short Range Communication (DSRC) is a wireless local area network broadcasts the information without any external hardware (S *et al.*, 2025). The Road Side Units (RSU's) are designed to assist the self-driving cars dynamically provides traffic efficiency and road safety (Barskar and Chawla, 2015).

The Proposed system integrates the DSRC based Inter vehicular communication (IVC) with Road Side Unit (RSU)-assisted Vehicle-to-Infrastructure (V2I) communication supports the decentralized decision-making system.

2. Proposed system

The Inter Vehicular Communication (IVC) is a critical component of autonomous vehicles in today's scenario and ongoing research. Several researcher results are incorporated to improve various elements of the IVC. The road classification, lane marking detection and classification system are incorporated to avoid accidents and improve the efficiency. The flowchart of the proposed work is depicted in Figure 1.

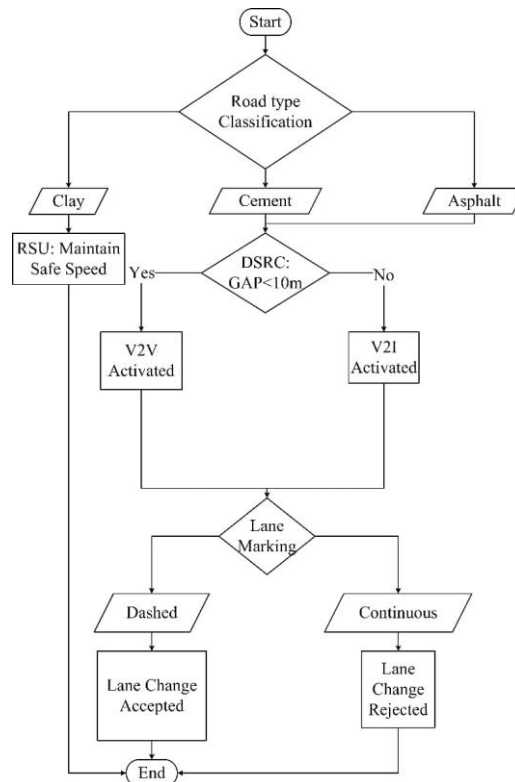


Figure.1. Flowchart of the proposed algorithm

Initially the road has been classified via asphalt, cement and clay. Depending upon the road type lane marking detection and classification is performed for asphalt and cement roads. Upon the lane identification the IVC is established for lane crossing.

2.1. Road classification

Three types of roads are generally used in India such as Asphalt, Cement and Clay. Asphalt roads are used for Highways. Cement roads are used in villages or towns and clay roads are used in remote locations. With these different roads, the autonomous cars need to adopt the practical situations in real-time. Three different roads are designed as edges namely E_{asphalt} , E_{cement} , E_{clay} connected with a junctions $\bar{N}$. The algorithm is implemented in microscopic traffic simulator to classify roads. The Road Side Unit (RSU's) is incorporated in infrastructure to support the Vehicle-to-Infrastructure (V2I) communication monitors traffic conditions and broadcast road level control advisories.

RSU Deployment: The Road Side Unit (RSU's) are deployed as infrastructure nodes fixed at predefined locations along each road segment. Each RSU is deployed at a fixed position covers a spatial interval represented in Eq.1.

$$RSU_k = (r_k, r_k + l_k), \quad (1)$$

where r_k = RSU position,

l_k = detection length.

When a vehicle (v_i) enters into the RSU covering zone, then controller retrieves the current state and represented by a state vector $S_i(t)$ shown in Eq.2.

$$S_i(t) = [x_i(t), v_i(t), l_i(t)]^T, \quad (2)$$

where $x_i(t)$ = vehicle Position,

$v_i(t)$ = speed of the Vehicle,

$l_i(t)$ = lane Index.

Road Type Identification: The RSU determines the road segments using Edge ID and mapped it to a semantic road class will be expressed as Eq.3. This mapping enables the RSU to associate each vehicle with corresponding road conditions.

$$R(E) \in \{Asphalt, Cement, Clay\}. \quad (3)$$

DSRC-Based V2V Communication: The Vehicular networks designs the Dedicated Short Range Communication (DSRC) to enable the direct communication between vehicles (V2V) and V2I. Every vehicle periodically broadcast the detected road type to near vehicles. Mathematically the distance based connectivity constraint represented as Eq.4.

$$\|x_i(t) - x_j(t)\| \leq r_{DSRC}, \quad (4)$$

where $x_i(t), x_j(t)$ = positions of vehicles i and j ,

r_{DSRC} = DSRC communication range.

Basic Safety Message (BSM) Generation: Each vehicle v_i broadcast its instantaneous driving state as a Basic Safety Message (BSM) represented in Eq.5. The BSM consists of Vehicle Identifier, Vehicle Position, Lane Index Speed, Road Type.

$$BSM_i(t) = \{ID_i, x_i(t), l_i(t), v_i(t), R_i(t)\}, \quad (5)$$

where ID_i = Vehicle Identifier,

$x_i(t)$ = Vehicle Position,

$l_i(t)$ = Lane Index,

$v_i(t)$ = Speed,

$R_i(t)$ = Road Types.

The BSM message is broadcast to all surrounding vehicles. Any vehicles with in the range of the DSRC can receive that messages. Mathematically the neighbour set of vehicle i can be represented as Eq.6.

$$N_i(t) = \{v_j \in V \mid j \neq i \mid \|x_i(t) - x_j(t)\| \leq r_{DSRC}\}. \quad (6)$$

Each vehicle aggregates received BSMs from neighbouring vehicles to form a cooperative perception of the driving environment. Road type information shared by nearby vehicles enables early awareness of road conditions ahead, even before physically entering the corresponding road segment. The perceived road condition $\bar{R}_i(t)$ for vehicle i is computed as shown in Eq.7.

$$\bar{R}_i(t) = \text{mode}(\{R_j(t) \mid v_j \in N_i(t)\}). \quad (7)$$

This proposed algorithm describes a rule-based road-aware vehicle behavior algorithm that was developed using the Simulation of Urban Mobility (SUMO) platform integrated with the Traffic Control Interface (TraCI), as illustrated in Figure 2. As a result, the categorized road type has been successfully included into the IVC, as illustrated in Figure 3.

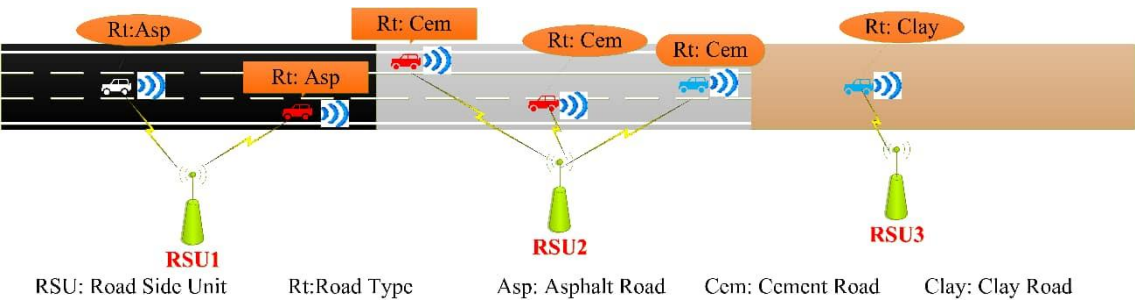


Figure 2. Road classification via DSRC and RSU

```
Select Command Prompt - python v2x_controller.py
Microsoft Windows [Version 10.0.19045.6466]
(c) Microsoft Corporation. All rights reserved.

C:\Users\Rama>cd C:\Users\Rama\Desktop\R1_Outputs\14

C:\Users\Rama\Desktop\R1_Outputs\14>netconvert -n road.nod.xml -e road.edg.xml -o road.net.xml
Success.

C:\Users\Rama\Desktop\R1_Outputs\14>sumo-gui road.sumocfg

C:\Users\Rama\Desktop\R1_Outputs\14>python v2x_controller.py

===== DSRC + RSU ROAD TYPE BROADCAST =====
[t=003] veh1 | Actual=ASPHALT | Perceived=ASPHALT | RSU=ASPHALT | DSRC=['ASPHALT']
[t=005] veh2 | Actual=ASPHALT | Perceived=ASPHALT | RSU=ASPHALT | DSRC=['ASPHALT']
[t=023] veh3 | Actual=CEMENT | Perceived=CEMENT | RSU=CEMENT | DSRC=['CEMENT']
[t=024] veh4 | Actual=CEMENT | Perceived=CEMENT | RSU=CEMENT | DSRC=['CEMENT', 'CEMENT']
[t=028] veh5 | Actual=CEMENT | Perceived=CEMENT | RSU=CEMENT | DSRC=['CEMENT', 'CEMENT']
[t=039] veh6 | Actual=CLAY | Perceived=CLAY | RSU=CLAY | DSRC=['CLAY']
```

Figure 3. Console output of road classification

The above simulated results shown in Figure 3 are practically implemented by considering the three different images as shown in below Figure 4. The proposed road classification algorithm works with an accuracy of $\cong 99\%$ as shown in Figure 4a. The detailed analysis of the road classification algorithm is presented in Prakash *et al.* (2024). Hence the road classification algorithm work for the real-time roads with acceptable accuracy.



Figure 4. Different road classification

2.2. Lane marking detection and classification system

Along with the road classification, the lane marking detection and classification system enhances road safety. With a proper detection and classification of lane markings aids the ADAS system to incorporate an important mechanism called Lane Changing System (LCS). Each vehicle detects the lane markings presented on roads. In the present work for the existing lane marking detection system, the feature of LCS is incorporated with specific parameters such as LC. The values for these parameters are selected based on the guidelines of National Highway Authority of India (NHAI), as the algorithm focuses on the road conditions in India.

Each road segment consists of N_l number of lanes and L_i lane index. Each vehicle detects the left and right lane markings presented on roads represented in Eq.8. If no adjacent lane exists on either side, then the corresponding lane marking is represented as NONE.

$$L_l = \begin{cases} 1, & i < N_l - 1 \\ 0, & \text{Otherwise} \end{cases} \quad (8a)$$

$$L_r = \begin{cases} 1, & L_i > 0 \\ 0, & \text{Otherwise} \end{cases} \quad (8b)$$

$$L_s = 0 \Rightarrow M_s = \text{NONE}, \quad (8c)$$

where L_l and L_r = Left and Right Lane Markings.

In addition to the lane marking detection the lane marking need to classify as Continuous or dashed. According to National Highway Traffic Safety Administration (NHTSA), the straight roads can have the both dashed and continuous lane markings whereas the curved roads are preferring the continuous lanes due to low visibility and vehicle instability. The length of the lane marking will be calculated with k . if k crosses the threshold value then the lane marking is classified as continuous. The RSU will also classify the lane markings as continuous when it detects the hazardous zone such as School Zone, Intersections which ensures the safety.

$$S_{RSU} = 1 \Rightarrow \begin{cases} M_l = \text{Continuous} \\ M_r = \text{Continuous} \end{cases} \quad (9)$$

where M represents the message from RSU.

The proposed algorithm is fed to the Simulator to detect left and right lane markings properly which is depicted in Figure 5. In the simulator the Road ID's are considered as A, B, C. Along with Road ID every road having different Lane ID's.

```

Microsoft Windows [Version 10.0.19045.6466]
(c) Microsoft Corporation. All rights reserved.

C:\Users\Rama>cd C:\Users\Rama\Desktop\R1_Outputs\Final Outputs\15.5
C:\Users\Rama\Desktop\R1_Outputs\Final Outputs\15.5>python build_net.py
Building network...
Success.
Network built successfully

C:\Users\Rama\Desktop\R1_Outputs\Final Outputs\15.5>python run_simulation.py
Starting SUMO Simulation...

[t=007] veh1 | Road=ASPHALT | Lane=E1_1 | Speed=13.46 m/s | Status: Left=DASHED, Right=DASHED
[t=009] veh2 | Road=ASPHALT | Lane=E1_0 | Speed=9.72 m/s | Status: Left=CONTINUOUS, Right=DASHED
[t=030] veh3 | Road=CEMENT | Lane=E2_2 | Speed=12.79 m/s | Status: Left=DASHED, Right=CONTINUOUS
[t=058] veh4 | Road=CEMENT | Lane=E2_0 | Speed=0.23 m/s | Status: Left=CONTINUOUS, Right=DASHED
[t=058] veh5 | Road=CEMENT | Lane=E2_1 | Speed=7.26 m/s | Status: Left=DASHED, Right=DASHED
[t=073] veh6 | Road=CLAY | Lane=E3_0 | Speed=3.86 m/s | Status: Left=NONE, Right=NONE

```

Figure 5. Console Output for lane classification

The practical scenario of the lane marking detection with asphalt and cement roads are shown in Figure 6. According to Indian Road Congress (IRC) lanes are classified as continuous and dashed. Initially the algorithm is applied on images to justify the lane markings and borders as depicted in Figure 6. The binary thresholding is applied to the grayscale images to isolate lane markings. The left and right lane markings are extracted from the binary regions using the contour detection. With the contour height analysis, the lane markings are classified as depicted in Figure 7.



Figure 6. Lane markings justified (a) asphalt road, dashed and continuous lane markings are present (b) cement road, borders are present



Figure 7. Output image of lane classification

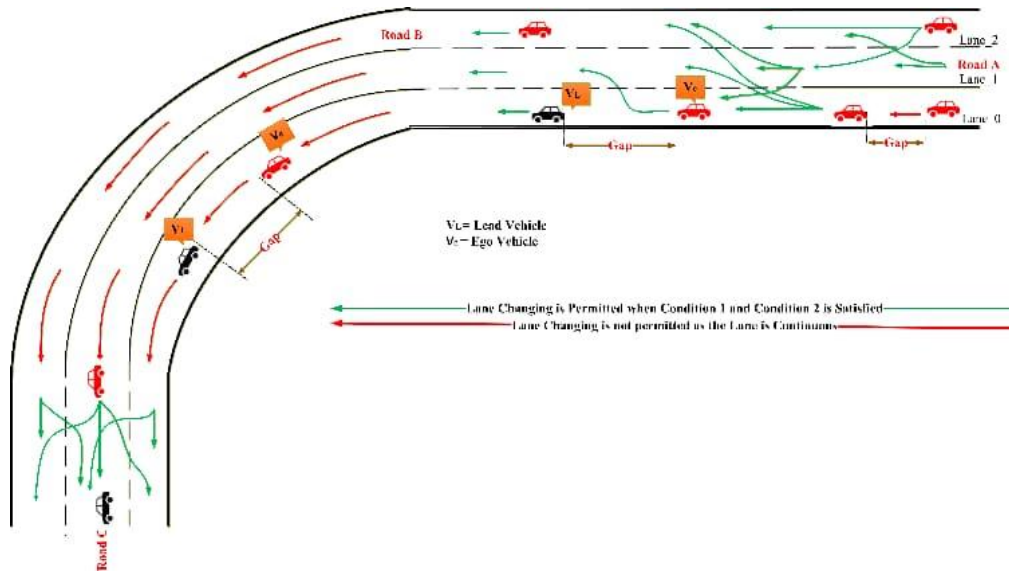
3. Incorporation of lane markings system in the IVC

The Inter Vehicular Communication (IVC) is a critical component of autonomous vehicles in today's scenario and ongoing research. Several researcher results are incorporated to improve various elements of the IVC. The Lane Marking classification function would be more useful if included in the IVC. In the existing literature IVC is established between the autonomous vehicles based on the gap between the vehicles. On establishment of IVC Vehicles broadcast Road ID, Lane ID, Speed and Gap which predominantly verifies the vehicles present in the same lane. The gap between the lead and ego vehicles are calculated using the x-coordinate positions as shown in Eq.10.

$$D = X_{lead} - X_{ego}, \quad (10)$$

where D = Gap between the vehicles,
 X_{lead} = Position of lead vehicle,
 X_{ego} = Position of ego vehicle.

A threshold value of 10 m is set, and the choice for lane marking is made using Eq.10. To improve safety, lane marking classification has been added to the current system. Figure 8 (b) shows the overall output of the proposed algorithm.



(a)

```

C:\Users\Rama\Desktop\R1_Outputs\16.2>python build_net.py
Building network...
Success.
Network built successfully

C:\Users\Rama\Desktop\R1_Outputs\16.2>
C:\Users\Rama\Desktop\R1_Outputs\16.2>python run_simulation.py

Vehicle: veh3 | Road: ASPHALT | Lane: E1_0 | Speed: 2.60 m/s
Lane Markings -> Left: CONTINUOUS, Right: DASHED
Gap to Lead Vehicle (veh1): 9.98 m
[ ] IVC ACTIVATED
[ ] veh3 -> [ ] veh1 : Overtake Request
[ ] veh1 -> [ ] veh3 : OVERTAKE REJECTED
[ ] Right lane blocked by veh2, gap = 5.12 m
[ ] Ego slowing down

Vehicle: veh5 | Road: ASPHALT | Lane: E1_2 | Speed: 3.00 m/s
Lane Markings -> Left: DASHED, Right: CONTINUOUS
Gap to Lead Vehicle (veh6): 6.61 m
[ ] IVC ACTIVATED
[ ] veh5 -> [ ] veh6 : Overtake Request
[ ] veh6 -> [ ] veh5 : OVERTAKE REJECTED
[ ] Ego slowing down

Vehicle: veh4 | Road: CEMENT | Lane: E2_0 | Speed: 4.00 m/s
Lane Markings -> Left: CONTINUOUS, Right: DASHED
Gap to Lead Vehicle (veh2): 10.30 m

Vehicle: veh6 | Road: CEMENT | Lane: E2_2 | Speed: 4.15 m/s
Lane Markings -> Left: DASHED, Right: CONTINUOUS
Gap to Lead Vehicle (veh2): 8.79 m
[ ] IVC ACTIVATED
[ ] veh6 -> [ ] veh2 : Overtake Request
[ ] veh2 -> [ ] veh6 : OVERTAKE REJECTED
[ ] Ego slowing down

Vehicle: veh6 | Road: CLAY | Lane: E3_0 | Speed: 1.66 m/s
Lane Markings -> Left: NONE, Right: NONE
[ ] ALERT: CLAY ROAD -> GO SLOW REQUIRED

```

(b)

Figure 8. (a) Road scenario with different lane markings and IVC; (b) overall console output of the proposed algorithm

For the above simulation outputs, the following code has been incorporated in the simulator.

Code for the Proposed Lane marking classification algorithm:

```
def broadcast_v2v(vehicle_id, edge_id, lane_Marking_id, gap, message):
    log_message = (f"[V2V] Vehicle: {vehicle_id}, Edge: {edge_id}, Lane: {Lc}, Gap: {gap:.2f} m,
    f"Message: {message}")
    print(log_message)
    def get_left_Marking_lane_id(vehicle_id, Lc):
        road_id = traci.vehicle.getRoadID(vehicle_id)
        lane_index= traci.vehicle.getLaneMarkingIndex(vehicle_id)
        if (lane_index > 0 && Lc :
            return f"{road_id}_{lane_Marking_index}"
        return None
    def get_right_Marking_lane_id(vehicle_id):
        road_id = traci.vehicle.getRoadID(vehicle_id)
        lane_index= traci.vehicle.getLaneMarkingIndex(vehicle_id)
        num_lanes = traci.edge.getLaneNumber(road_id)
        if( lane_index < 0 && Lc:
            return f"{road_id}_{lane_Marking_index}"
        return None
    def check_lane_markings(vehicle_id, Lc):
        # For simplicity, if an adjacent lane exists then we assume its marking is "Dashed".
        left_lane_id = get_left_Marking_lane_id(vehicle_id,Lc)
        right_lane_id = get_right_Marking_lane_id(vehicle_id, Lc)
        left_marking = If Lc is Continuous then "Display as Continuous" else "Display as Dashed"
        right_marking = If Lc is Continuous then "Display as Continuous" else "Display as Dashed"
        return left_marking, right_marking
```

The above code clearly shows the definition of the modules for lane marking detection and implementation in the IVC. Initially from the proposed algorithm left lane markings and right lane markings are identified. These ID's are passed as parameters for IVC method. Further lane marking classification condition is combined with existing IVC technique (which is not shown for brevity). Hence with the proposed algorithm the simulator checks both the existing parameters i.e., gap between the vehicles and proposed lane marking classification for established the IVC.

If the condition is satisfied, then the lane changing is allowed. If any one of the criteria is not satisfied, lead vehicle rejects to change lane. Then the ego vehicle reduces its speed with a rate of 20% of the current speed till 1m/s. as in Eq.11.

$$S_n = \text{Max}(0.8 * S_o, 1), \quad (11)$$

where S_n = New Speed;

S_o = Old Speed.

The proposed algorithm consists of three parts:

- (i) Road classification as discussed in section 2.1.
- (ii) Lane marking detection and classification in section 2.2 and
- (iii) Incorporation of IVC feature whether to change the lane or not depending on the lane marking classification.

The practical usage of first two parts of this algorithm are clearly depicted with acceptable accuracies in the preceding sections 2.1 and 2.2. Hence the authors clearly suggest that the incorporation of cooperative lane changing feature can be implemented practically and can be added as new ADAS feature.

4. Conclusion

In the current study, road classification is performed first and with satisfactory accuracy. The same algorithm has been extended to recognize various lane markings. Depending on the lane marking classification, the algorithm is executed and decision is made for lane changing. This work may be extended to include more road safety considerations and self-driving cars.

Declaration of Generative AI and AI-assisted technologies in the writing process:

During the preparation of this manuscript the authors did not used Generative AI and AI-assisted technologies and take full responsibility for this declaration.

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