

ORIGINAL RESEARCH PAPER

Engineering

A TECHNOLOGICAL OVERVIEW OF AUTONOMOUS VEHICLES IN LANE CHANGING AND EMERGENCY COMMUNICATION

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In today's fast-paced world, when time is valuable, individuals want faster and safer technical solutions to help them save time. Technological enhancement in transportation for various types of vehicles such as unmanned vehicles, autonomous vehicles are gaining importance. The use of these technologies are geographical dependent where the traffic rules varies. Technical breakthroughs such as vehicular adhoc networks (VANET) have enabled the development of autonomous cars, which can drive themselves without human intervention. With the fast increase in vehicle utilization, technology has upgraded to Advanced Driver Assistance System (ADAS) capabilities that assist people in various areas of driving, perhaps reducing human stress while driving. This Paper reviews technological aspects of autonomous vehicular technology. Various algorithms proposed for autonomous vehicles till date are critically reviewed.

INTRODUCTION

Now a days the usage of the vehicles are increasing more. According to the requirement of the humans automobile industries also offering different levels of automations[1]. According to that the cost and speed of the vehicles is also increasing more. In this aspect the traffic safety is a significant social and economic issue these days. The World Health Organization (WHO) estimates that 1.19 million people die annually. Everywhere in the universe, there are road accidents that cause between 20 and 50 million additional non-fatal injuries, many of which lead to disability. Governments are taking more safety measurements but not satisfactory[2]. To reduce the accidents some countries encourages the connected and autonomous vehicles (CAV's). This CAV vehicles can connect with other vehicles and it creates opportunities for new services to emerge and improved driver experience[3]. Reports from the National Highway Traffic Safety Administration (NHTSA) indicate that approximately 400 crashes have place in 2022. On October, 2023 the autonomous car hits the pedestarins in sanfransisco[4]. By using the fundamental principle of MANET, the vehicular adhoc network entered the market in the early 2000s with the goal of ensuring safe driving by enhancing traffic flow and so lowering the number of accidents. Additionally, VANETs often employ on board units (OBUs) and a collection of wireless sensors for short-range communication. With the use of these OBUs, vehicles can communicate wirelessly with other vehicles to transmit and receive messages [5], [6]. The vehicle to vehicle communication will provides information sharing regarding their driving habits, improves the traffic management, Driver assistance, Improved fuel efficiency and optimizes the routes. There are six levels of autonomous vehicles present in today's market. The levels will be depicted below as figure 1.

In basic vehicles which are not having any supporting will belongs to level 0. In level 1 the driver can get the support like reverse parking sensor, seat belt warning system. In level 2 we have the adaptive cruise control system, and also can detect the lane marking system in highways. From the level 3 the technology runs more advanced which can get the conditional automation under conditions. But here in the level 3 the driver must be conscious even in the automation mod also. In the level 4 the driver does want to stay in the vehicle can drive fully autonomously under certain conditions. From level 1 to level 4 vehicles can run in two modes but in the level 5 we are not having the option of steering and it will work only[7].

LEVEL 5

LEVEL 4

LEVEL 3

LEVEL 2

LEVEL 1

LEVEL 0

Level 0 belongs to Non
Autonomous Vehicles
Level 1 belongs to Driver
Assistance like reverse Parking
Sensors
Level 2 belongs to Advanced
Driver Assistance System
Level 3 belongs to Conditional
Driving Automation
Level 4 belongs to High Driving
Automation
Level 5 belongs to Full Driving
Automation

Figure 1: Levels of Automation

Technological Aspects Of Lane Changing Process For AutonomousVehicles:

With the technical enhancement in vehicular technology, the autonomous and emergency vehicles will accommodate with the human driven vehicles in the heterogeneous traffic. For that we have different algorithms discussed in the further sections.

Lane Changing Process

We have 3 types of lane changing models like free lane changing, Forced lane changing and cooperative lane changing. By using the free lane changing model the vehicle doesn't require to interact with the other vehicles which can change the lane easily. By using the forced lane change model, the vehicle need to change the forcefully to clear the traffic easily. In this scenario the subject vehicle will communicate with the adjacent vehicles through the signals. By using the cooperative lane change model, the adjacent vehicle and the subject vehicle will communicate each other and changes the lane easily without creating disturbance to other vehicles. According to simulation results, cooperative lane change models are more stable than forced lane changes [8]. The Decentralized Controller-agnostic cooperative approach algorithm provides the communication between the present lane and the target lane. The subject vehicle will communicate with the adjacent vehicles till the lane changing process is completed. By utilizing the VISSIM software, they simulated the three different types of vehicles like autonomous, networked, and fitted with adaptive cruise control vehicles. With this algorithm the subject vehicles can met only 10% collision upto 26% of the traffic rate. This algorithm unable to captures the pedestrians behaviors[9].

Deep learning-based computer vision algorithms and

models that are trained, the interpreted datasets to precisely predict the line of lanes. To determine the vehicle's location with relation to the center of the lane and its radius of curvature, a sliding window based lane detection method is used. Finally, the vehicle's precise location and the numerical estimate of the lane curvature are displayed together with the lane edge detection [10]. Recurrent Neural Network algorithm creates the Discretionary Lane Change (DLC) approach which can follows the drivers decision on highways. By verifying the real-world outcomes in NS2 and Sumo simulations at 65 mph with 100 cars, the DLC takes a very long 4.3 to 5.2 seconds to change lanes. By using this DLC forced lane change approach will take more time to change lanes. This entire algorithm verified only in highways need to verify in the urban areas[11]. Sentinel, an onboard technology in intelligent vehicles, is designed to direct lane changes during freeway incidents in order to minimize delays and traffic congestion. By seeing the results shows that delay reduces to 37%[12].

The development of an ideal lane detecting system makes use of both LIDAR and visual data is done by collecting the real data from the LIDAR sensor this can handle both the structured and unstructured roads. But high speed vehicles are unable to detect the roads properly and by using the computer vision technology which can find the ROI to detect lanes and changing of lanes [13], [14]. The CARLA simulator can be used to train realistic images. In order to assess the impact of the sim2real conversion with an emphasis on the lane keeping assistance system, Dual Contrastive Learning Generative Adversarial Networks (DCLGAN) are constructed [15]. A random parameters hazard-based duration modeling approach has been used to predict the lane-changing execution time in heterogeneous networks. This approach takes into consideration the panel form of the data and incorporates the unobserved heterogeneity. The results proved that the non-autonomous vehicles lane changes easily when compared to the autonomous vehicles [16]. Numerous edge caching techniques based on Reinforcement Learning (RL) have been proposed to lower the backhaul traffic load. By applying the extensive simulators like nash equilibrium they got nearly 40% data accurately[17]. A standardized architecture called AUTOSAR provides all run-time environments, basic software, device drivers, and communication interfaces. The shape for lane detection and traffic sign detection is detected by a supervised training technique that is based on machine learning. Both of these tasks are programmed in Python using the OpenCV2 and Numpy libraries, and the Hough Detection technique is utilized to identify which traffic light circles are appropriate [18]. The Genetic Algorithm in ant colony optimization (GAACO) technique which can detect both simple and complex traffic scenarios using the SUMO and NS3.2 Simulators. In the simple traffic scenario the PDR for the GAACO algorithm 80% in less vehicles, the ACO algorithm gives 50% and the Particle Swarm Optimization (PSO) algorithm gives 45% only. Again the throughput also high in the GAACO algorithm compared with the ACO and PSO algorithms[19]. To decrease the traffic scenario in urban areas the roundabout roads are developed. Here the lane changing is mandatory for all the vehicles according to their path. In this paper the authors used the SUMO simulator to design and compare 3 different algorithms named as algorithm built in sumo simulator (SUMO); algorithm based on Nash equilibrium (NE); Multivehicle Coordinated Lane Change (MCLC). In both entry and exit points the simulation results shows that the SUMO algorithm shows less interaction between vehicles, whereas the NE algorithm takes more time than the MCLC algorithm. In the entrance scenario the SUMO takes 1.29 sec, NE takes 1.28 sec whereas the MCLC takes 0.85 sec. In the exit scenario the SUMO takes 1.02 sec, NE takes 1.10 sec whereas the MCLC takes 0.77 sec[20].

Autonomous cars must comprehend the movement of human-

driven vehicles by taking into account heterogeneous automobiles. Our autonomous vehicles are seen as lanechanging hints based on changes in ego vehicles' velocity, and a saliency-based approach is used to call attention to the associated vehicle. Next, an intention recognizer based on a Hidden Markov Model (HMM) determines the intention to change lanes. By using the Next Generation Simulation (NGSIM), in urban road situations, the suggested approach has achieved 90.89% in detecting lane changing intention and 88.58% in lane keeping; in highway environments, it has achieved 87.73% and 87.48% in lane changing and lane keeping intentions, respectively. On urban roadways, the proposed system will take an average of 6.67 seconds, while on highway lanes, it will take 7.8 seconds [21]. Due to congested traffic, communication interference, channel fading, and other factors, CAVs operating in this heterogeneous traffic system may experience delays and packet losses in communication links. These events may impair or divert CAVs' ability to drive safely and efficiently. The CAV will try to analyze the HDV's (Human Driven Vehicles) to decrease the traffic dense and accidents while changing lanes. By practical analyze of the heterogeneous traffic, the penetration rate of the autonomous vehicles is 70% and the safety is 81.25% only[22]. By replacing the standard convolution used in YOLOv5 to deformable convolution and simAM is used to detect the objects clearly in the traffic scenario for v2v communication and gets the average accuracy of 64% and 4.6% increased than the original algorithm [23].

InterVehicle Communication:

An efficient simulation model that connects the open-source "VEINS" framework establishes inter-vehicle communication for appropriate traffic management and road safety by utilizing OMNET++ and SUMO simulators. Dedicated shortrange communication up to 300 meters can be provided by VEINS for efficient power management. It lowers the accident rate by reducing the transmit power to 9 mW [24]. By using the road side units and smart traffic lights the vehicle to network communication is created which can reduce the traffic congestion and waiting time [25]. A good opportunity to estimate crash hazards in real time is provided by an invehicle forward collision warning system, which includes time-to-collision and the distance between the leading and trailing vehicles. When predictive warning information is combined with connected automobile technologies, like vehicle-to-vehicle wireless communications, as part of proactive traffic safety management (PSTM), it is expected that more effective crash prevention will be achievable [26]. By using the LoRa and Ultrasonic range sensor technology, the communication is generated between vehicles which can avoids the accidents and ensures safe driving [27]. To encrypt the driving routes and transmit the encrypted data to the fog nodes, a lightweight traffic route management method is developed for fog-based VANETs. The traffic management center (TMC) receives ciphertexts collected by the fog node; it decrypts the acquired data and regulates traffic based on it, without knowing the specific route of each vehicle [28]. Surveillance cameras are used to monitor pedestrian's behaviour. They provide a method for effectively controlling the flow of traffic from self-driving cars at intersections while accounting for pedestrian traffic. By using the smart devices in the road sides, Self-driving vehicles are able to communicate with each other about the road traffic and pedestrians [29], [30].

CAV's in Mixed Traffic:

In the mixed traffic the dynamics if the human driven models are estimated using the recursive least square method. In this paper the author designed the system like in between the two Connected autonomous vehicles one human driven vehicles is done[31]. In this mixed traffic, by developing the long short term memory models which can predict the longitudinal trajectory with a penetration rate of 0.2 [32]. The bidirectional

LSTM is developed which improves the accuracy in predicting the moment of the human driven vehicles by 2.31% [33]. By using the Carsim simulation studies shows that the human centered tracking controller was developed which can estimate the vehicles in different driving situations and can obtain the smooth transient processes of the cut-in scenarios [34]. In the mixed traffic, the emergency vehicles are also present in the real time traffic. In that case by using the CNN to detect the images of the emergency vehicles and can get the accuracy of about 87% and by using the Support Vector Machine classifier algorithms to detect the sirens with the accuracy of about 95% [35].

CONCLUSION

Hence this paper reviews the different vehicular technologies that are in existence till date. Various algorithms used for the autonomous vehicles such as lane changing algorithms, emergency communication in vehicles are presented. This paper is undoubtedly beneficial for the researchers working on the vehicular technology to identify and upgrade with the existing techniques.

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