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Multi-Sensor Fusion and Simulation-Based Software Test Coverage Criteria For Autonomous Vehicles

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Abstract

In this paper, we have reviewed various simulation methods of testing software oriented intelligent behavior of cars and proposed a lidar based simulation for better test path coverage that provides confidence to test vehicles instead of road testing. Apart from the simulation techniques, the multi-sensor fusion architectures have also been reviewed which are vital for any type of ADAS frameworks.In this work, LIDAR sensor modelling and simulation using MATLAB's automated driving tool is performed.

INTRODUCTION

The research and development in the fields of automotive software design and test generation is gaining widespread momentum worldwide[1]. Intelligent driving systems are the recent explorative fields getting attention in both academia as well as industries in terms of computer vision, human computer interaction, machine learning and deep learning based neural networks[2]. The growing challenge of ever-increasing system complexity due to hundreds of operating units being integrated in autonomous cars to process the output data in real-time is inevitable. Self-piloted cars have to make decisions in fractions of seconds to avoid imminent crashes[3]. Developing smarter ways of testing and evaluating the upcoming driver assistance functions that lead to the path of fully autonomous vehiclesare the chief concerns of several automotive industries[4]. Pertaining to the advanced level of automation added into the new framework, necessary testing and validation approach will be discussed for evaluating the intelligent features. This paper thus includes exploiting deep neural networks in the field of automotive software modelling as well.

As ADAS functions become more prevalent, industries will face more problems to scale the technology to mid-tier segments[5]. There is still no standardization available for modelling and validating data processing of vehicle sensors. There is a multitude of sensing resources equipped in a single car ranging from cameras, radars, Lidars, ultrasonic sensors[6]. The communication between them results into plenty of information that must be processed timely to control vehicle's orientation.

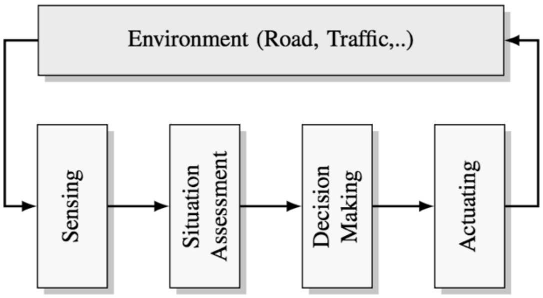

Figure 1: Process of environment perception by automated vehicles

Safety critical software systems embedded onto the vehicles must operate robustly and consistently in various unpredictable environments. Testing them in real world situations may lead to serious damage to the environment that is generally not feasible. Therefore, developing and verifying the safety of the system's components using virtual testing methods is highly recommended by various manufacturers[7]. Moreover, it is a highly costly affair to test them on roads which usually needs millions of kilometers driving to conform their suitability and safety[8].

There is a strong emergence to simulate the behavior of the system not on actual roads but on computer based simulation[9].

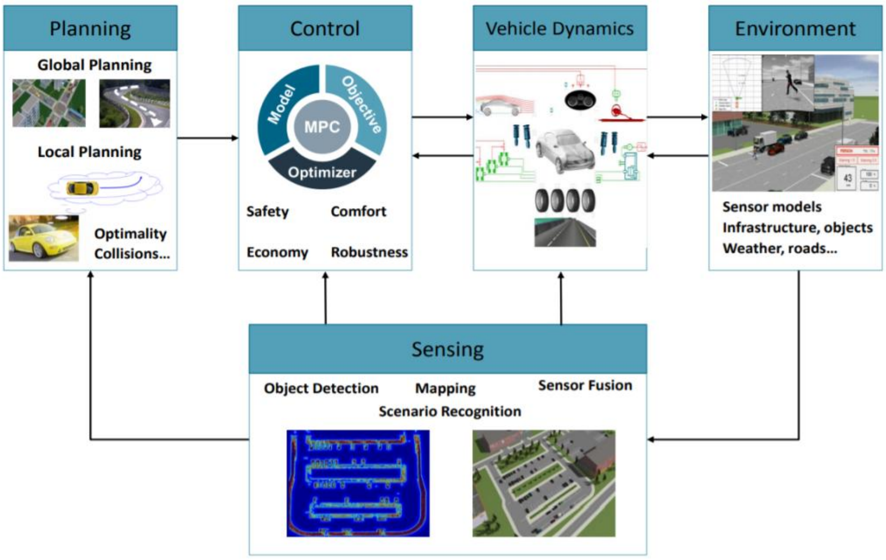

Figure 2: Simulation Architecture as described in [10]

The primary building blocks of any autonomous driving architecture includes sensing, planning, controlling, vehicular dynamics setting and motion as per the planned trajectories.

Related Work

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LIDAR based sensor model as presented by [11] consists of five different types of models such as object model, geometric model, physical model, vehicle model and environmental model. The authors have done verification of these models in the PANOSIM environment using the application of autonomous emergency braking system. The entire process is performed on the virtual simulation platforms. Sensor vision volume is also explained in this research work. Every model described by the authors is validated with the physical ground truth values also.

The results have been highlighted in the figure as well.

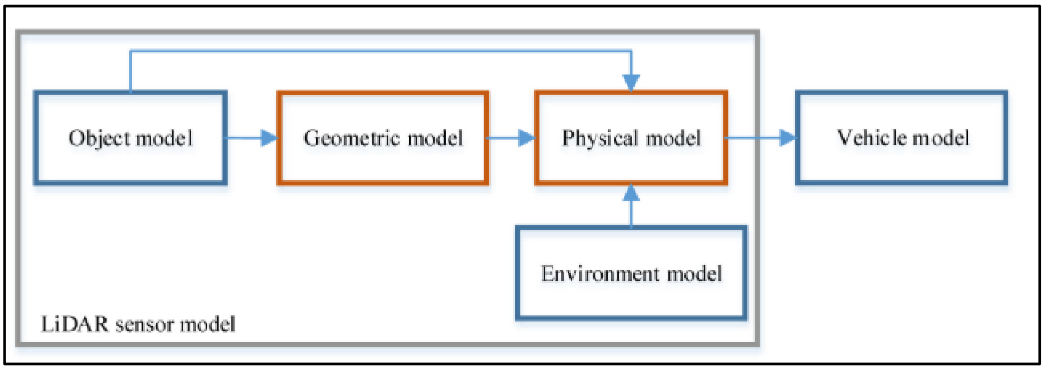


Figure 3: Sensor Modelling of LIDAR automotive sensor

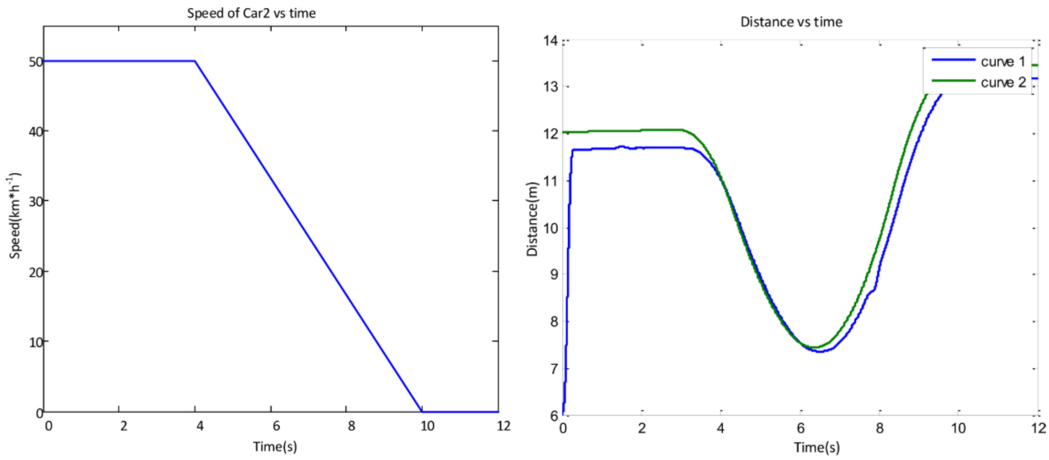
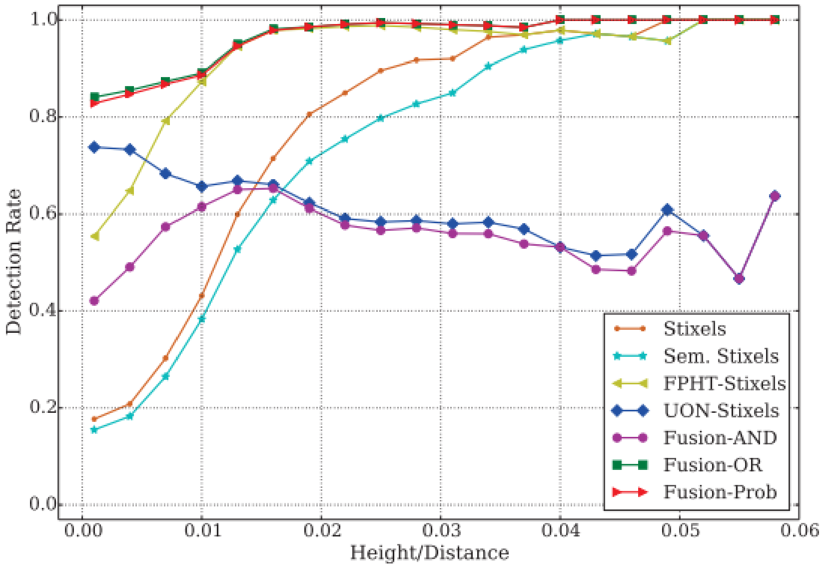


Figure 4: Results of Simulation of AEB

Authors in [12] presented a novel Bayesian network framework to detect objects and other road hazards by the self-driving cars. They have utilized "stixel" based representation to identify obstacles in the way of vehicle motion. A probabilistic function approach has been provided which is integrated with the learning based technique of CNN i.e. deep learning methods. Approximately 28% more accuracy has been reported by the researchers using this methodology. Results of this techniques have been provided in the figure below where the proposed method "stixel" has reported maximum detection rate as compared to other approaches.



Another Research work [13] proposes a framework of developing an adaptive cruise control system using 4 different layers i.e. sampler layer, profiler layer, tutor layer and performer layer. The sampler layer signifies a car-following model which ensures that at each time step, the distance maintained by the follower car is equivalent to human-like safety distance threshold. The final output is then expressed in terms of acceleration and smooth distance maintenance.

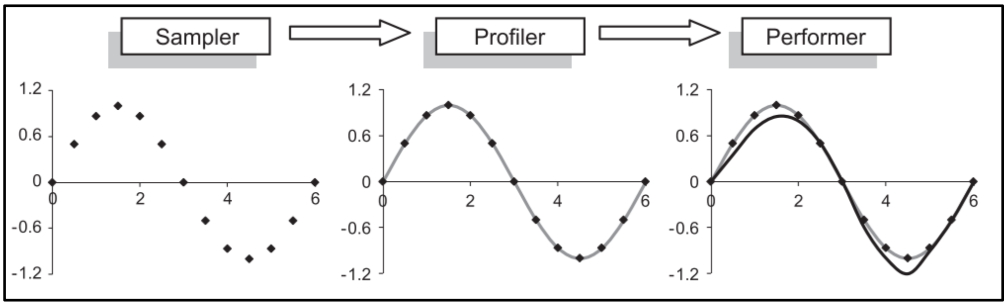


Figure 5: Layers of the ACC framework

The next table adapted from [13] shows the calibration results obtained after the proposed algorithm is executed.

Table 1: Results as obtained in the [13]

Calibration result.

	Current trajectory	Other trajectories			
		Min	Max	Mean	Std.Dev.
β_0	0.0762	0.0202	0.0928	0.0389	0.0179
β_1	0.9725	0.9631	0.997	0.9826	0.0135
β_2	0.5382	0.5034	0.6398	0.4908	0.0745
β_3	0.0265	0.0153	0.1806	0.0129	0.0672
Calibration time (s)	67.20	30.00	219.6	65.66	68.66
$\beta_0/(1-\beta_1)$	2.7709	0.5469	20.07	5.3110	6.8490
$\beta_3/(1-\beta_1)$	0.9636	0.0333	1.000	0.6620	0.3352

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The research work by [14] discusses effective world modelling paradigms to be used for trajectory planning by the autonomous cars. Basically, this research work emphasizes the concept of multi-sensor fusion required to execute by the different sensors which perceive the external environment. The techniques used in the process includes Bayesian filter, particle filters, Global nearest neighbor (GNN), sequential monte-carlo (SCM) based methods.

The authors in [15] proposed multi-sensor fusion architecture based on the embedded system of Texas Instrument's automotive SOC. For SAE levels 3 and 4, sensor fusion can be done by single DSP only. The performance of the technique is evaluated individually both for prediction steps and update steps as shown in the figure below.

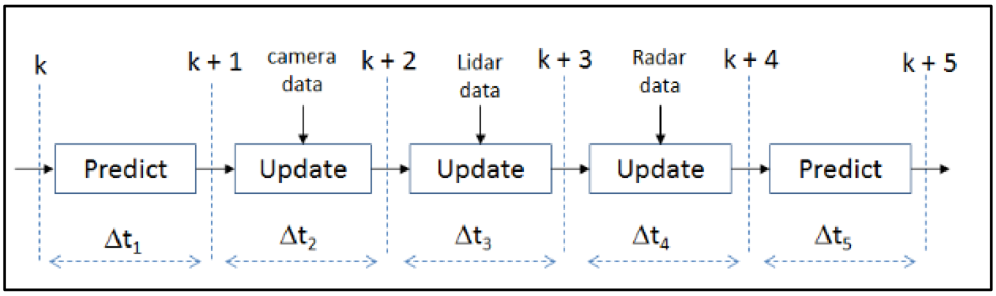

Figure 6: Update and predict steps in automotive sensing

The research work [16] focused on the development of ADAS using artificial vision and 3D-laser sensor equipment to improve both safety and reliability in difficult traffic environments. It mainly deals with inter-urban scenarios where systems such as collision avoidance and adaptive cruise control are studied and explored.

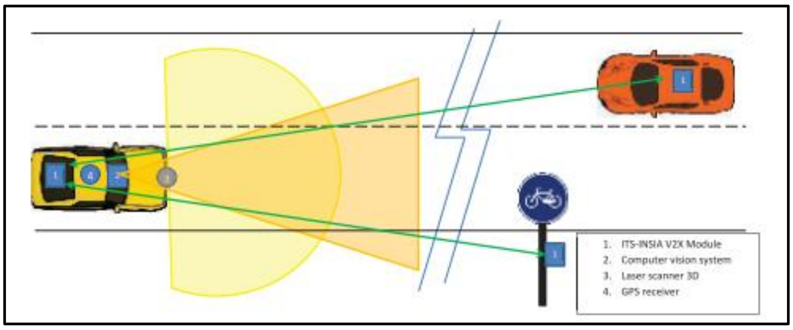

Figure 7: ADAS architecture and scenario building

The initial steps of obstacle detection consist of laser generated PC points which are then considered as clusters. The clusters are then validated against stored dataset of clusters.

Proposed Work

There is a multitude of testing tools available but still no standardized benchmark is present confirming to ISO 26262 protocols. In this proposed method, lidar based simulation is proposed where a point cloud is firmed as shown in the figure.

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Autonomous vehicles or driverless cars particularly can sense closetraffic scenariosby means ofanarrayof technologies such as LiDAR, RADAR, odometry, GPS etc. According to SAE's automobilecategorization[17], beginning from L0 (level zero)where absolutely no automation is present however, as we escalate in the top most levels towards more automation, in level 5 except starting the vehicle rest all controls are very well handled by the system itself [18]. A plethora of sensing devices which are mounted onto the car exhibit the task of driving autonomously across the planned trajectory of the motion. Once the data is acquired by the sensors, the next step is to make decisions for either brakes application, steering or acceleration accordingly. During this step, the vehicle has to perform very critical tasks of object detection, recognition which can include either static objects such as road infrastructures of moving objects such as vehicles and pedestrians etc[19].

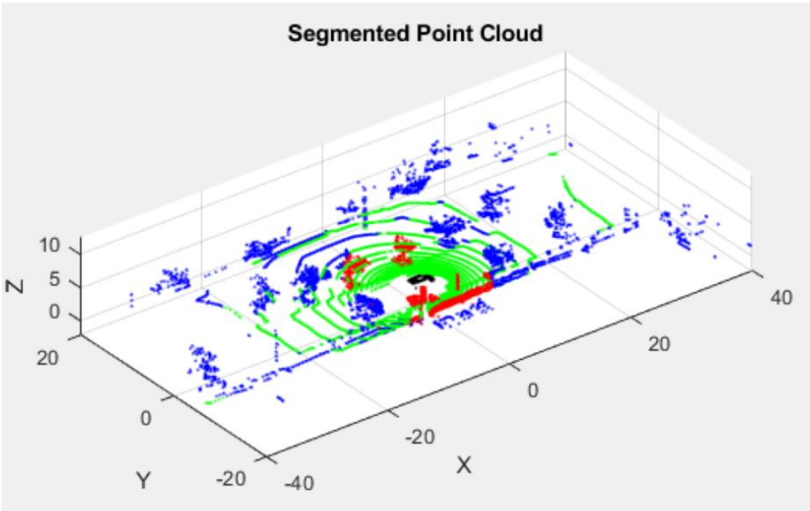

Figure 8: LIDAR Point cloud

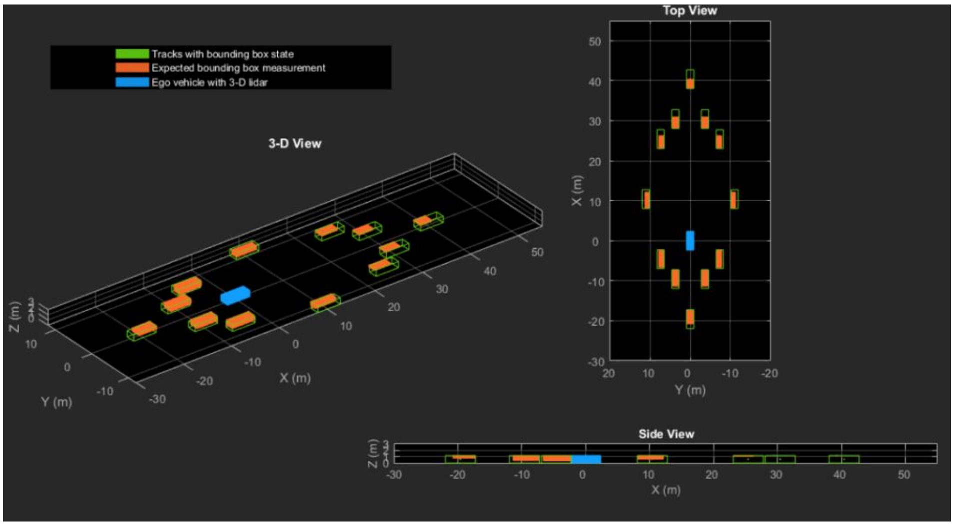

Figure 9: LIDAR based simulated traffic environment

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Results and Analysis

The Figures 10, 11 and 12 provide the results of obstacle detection using LIDAR during multi-sensor fusion algorithm. As can be seen in the Figure 10. We have used worl coordinate systems to generate the vehicular and world traffic models.

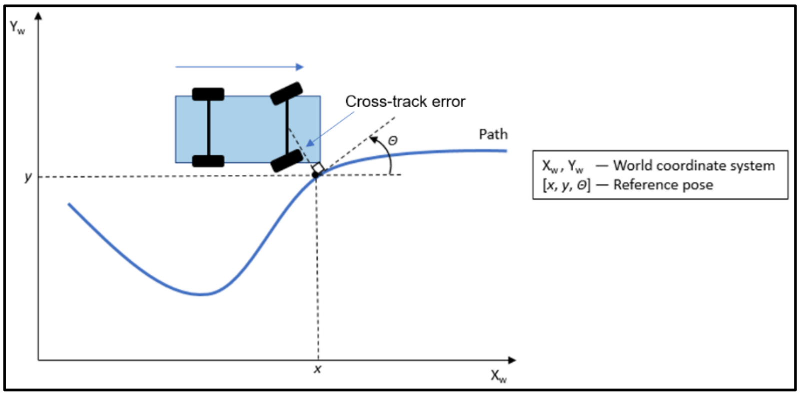

Figure 10: World coordinate system used during simulation

The Figure 11 and 12 gives an overview of the tracks identified by the LIDAR obstacle detection which gives better accuracy as compared to previous methods studied. T4, T5, T11 and T7 indicates that there is an object in this lane and helps to take appropriate actions by the automated systems.

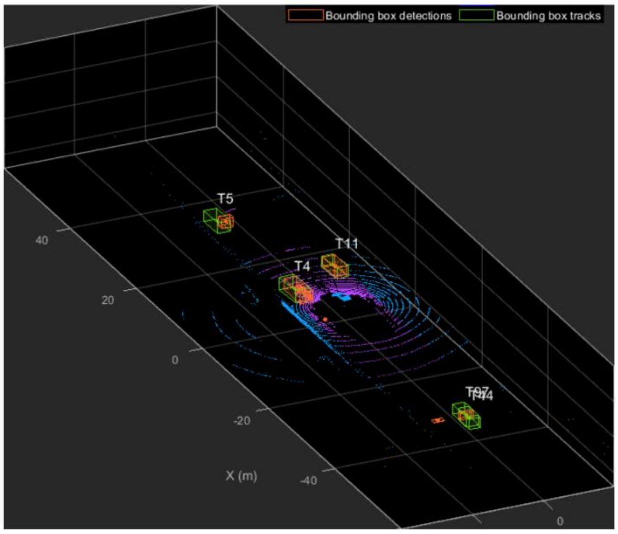

Figure 11: Total no. of tracks detection and association

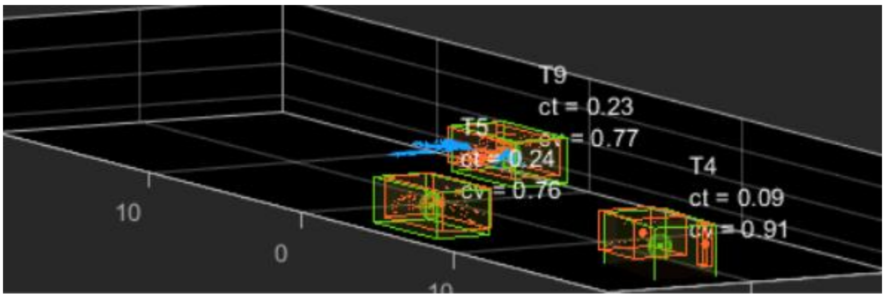

Figure 12: Object classification and detection by LIDAR sensors

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Conclusion

For performing multi-sensor fusion of radar and camera, there might not arise any challenge to detect an object and take timely decisions. However, for LIDAR based detection, appropriate simulation as to be carried out in order to prove the applied method suitable and safe for the autonomous systems to be safe and secure on roads in real time. Thus, this paper reviews and proposed improved simulation strategies for handling the tasks of object detection and decision making by an automated driving system.

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