A Comparative Study: Sensor Fusion of LiDAR and RADAR using Kalman Filter and Extended Kalman Filter

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***Abstract*—The invention of the wheel has changed all our lives in various aspects. It has brought mobility and comfort into our daily lives at ease. But, on the other side, this invention has also increased the chances of accidents and safety threats to our lives. Technology and the innovations has to lead to a various improvements in enhancing the safety after the accident occurs and methods avoiding the chances of the accident happening. Sensors play a vital role in making this happen. The sensors act like the five senses humans have and reduce the probability of the accident. This is made possible with technologies like Advanced Driver Assistance Systems (ADAS). ADAS technology helps in avoiding collisions. Its applications include forward crash warning, lane departure warning, lane change assistance, and emergency brake assistance. In this paper, the two algorithms of sensor fusion for the application of ADAS aimed to enhance safety are compared. Standard Kalman filter cannot be applied to all problem statements. It only suits to linear problems. Results show that the Extended Kalman filter provides better results when compared to the Standard Kalman Filter for various non-linear ADAS applications.**

***Index Terms*—Extended Kalman Filter, Unscented Kalman Filter, ADAS, LiDAR, RADAR, Sensor Fusion**

I. Introduction

AUtomobiles have not only brought many advantages to the humankind but also many disadvantages. Statistics from the WHO show that around 1.2 million people were killed and 50 million people are injured due to road accidents every year [1]. It is also observed that of these car accidents, around 50 percent are due to rear end collisions with no or any braking and 70 percent of the accidents are due to insufficient braking force [1]. One approach to avoid these accidents is to train the drivers effectively, plan and build infrastructure, and adopt new safety rules. Another approach is to make the vehicles smarter [1]. Imagine how many lives could have been saved if the vehicles were smart enough to detect the obstacle and stop before the accident occurred? This important feature is provided by the Advanced Driver Assistance System (ADAS). ADAS provides both active safety and passive safety in a vehicle. ADAS is mainly focused on providing active safety in the vehicle. The passive safety approach deals with the safety aspects of the driver and vehicle once the accident occurred or starts to occur. This includes the opening of airbags, tightening of seat belts, etc. [2]. While active safety mainly deals with taking actions to avoid accidents from happening. This includes the prediction of the accident before happening and braking the vehicle at a safe distance and safe position. Active safety measures include electronic stability control (ESC), anti-lock braking systems (ABS), and other ADAS like intersection collision avoidance (ICA) and lane keeping assistant (LKA)[2]. For enabling these features and predict the behaviors of vehicles in the environment, many sensor are used. The sensors like Lidar, Radar, Camera, and ultrasonic allows the vehicle to become smarter and get a better understanding of its surroundings[1]. All these sensors help the vehicle in sensing the behavior of the vehicles around it and take the best decision to save the life of the driver [2]. This paper illustrates the modern sensors which are used for enabling the ADAS features and the various methods for processing the data from these sensors collectively to make a decision. This paper further focuses on the ADAS technologies available today in the prevention of longitudinal, lateral, and reverse collisions. There are majorly two main goals of driver assistance systems. One major goal is to have a system that focuses on the activities of the driver and the other major goal is to keep track and have control over the behavior of the vehicle in the live scenario [3]. If viewed from a birds-eye, these two requirements are entirely different and require a lot of separate features. But in the ADAS, both are viewed from the same perspective [3]. The main objectives of the driver assistance systems are knowing what the driver is doing, improving his knowledge over what is happening around, giving necessary and critical information to the driver, and enhancing his comfort while driving [1]. The applications of these units include prevention of crash, forward and cornering control, and vehicle condition observation [1]. The function of ADAS varies from simple sensors to complex systems that can drive a vehicle for a long duration of time [1]. The most important aspect of ADAS is to enhance vehicle safety on the road, to cover collision, and have better steering capacity. There are many ways in which collisions can occur [1]. Majorly they occur when two vehicles crash into each other due to various reasons. Some common scenarios are, head-on collisions, crash with an automobile passing along by side, crash with a car going on the other lane, collision with a car taking a turn, etc.[1] Figures from the past show that in Germany the major reason for truck accidents is incorrect velocity, not maintaining the required gap between vehicles, during taking a turn or cornering/U-turn/ backing/starting [1].

Various sensors and frameworks are utilized for navigation and control of the self-driving vehicle. Amongst them, LiDAR, RADAR and Stereo Camera are the most commonly used ones. This section deals with the working principle advantages and limitations of each of these sensors.

LiDAR (Light Detection and Ranging) transmits light pulses (Infrared rays or visible / ultraviolet (UV) waves) from a revolving mirror, some portion of that light will reflect back to the sensor to recognize surfaces or objects. The distance between is calculated as speed of light times the measured time period at multiple angles. In Rain, dust and foggy environments, the performance of LiDAR is very poor.

RADAR (Radio Detection and Ranging) sends electromagnetic waves to detect objects. Based on the speed of the objects the frequencies of the sensed echoes get varied. The computing resource requirement of RADAR is relatively less when compared to LiDAR and Stereo Camera. RADAR is very poor at classification of the object. The Stereo camera uses two cameras to capture images similar to human eyes. Since the object distance is calculated from two different views, it helps in calculating more accurate distance between camera and the object surface. This is not feasible with a mono camera system. Similar to LiDAR, performance of stereo camera is very poor in rain, dust and foggy environment.

From above, it is very clear that we cannot entirely depend on single sensor for the calibration parameters as each of these sensors have limitations. So, it is necessary to take advantage of the capabilities of each sensor and fuse them to get optimized result for our applications.

II. Parameters to be considered for choosing LiDAR and RADAR

The rapid growth of technology and manufacturing processes has led to the rapid rise in the development of automotive sensors for ADAS applications. Especially, huge prospects are being seen in the area of sensing and perception for autonomous vehicles and due to this factor the automotive LiDAR and RADAR industry is expected to grow substantially. The cumulative annual growth rate of LiDAR for ADAS applications is expected to increase by 113% from 0.04 billion in 2020 to 1.7 billion in 2025 [4]. In addition the CAGR of RADAR for ADAS applications is also expected to increase by 19% from 3.8 billion in 2020 to 9.1 billion in 2025 [4]. The

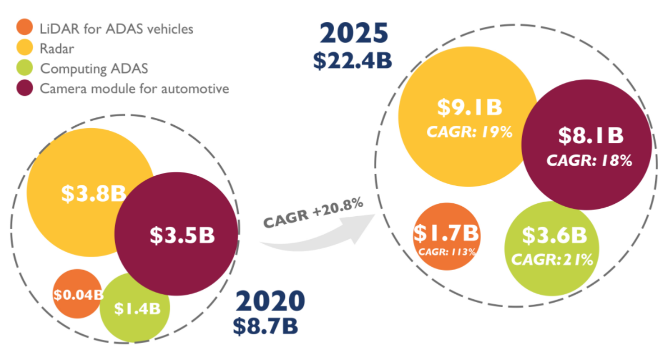

Fig. 1: Market Forecast of Different Sensors in ADAS Vehicles. [4]

sensor which is responsible for enabling the ADAS features in an automobile includes LiDAR and RADAR. Both these sensors have their uniqueness and strengths. But there are also several challenges implicated while handling these sensors [5]. These consist of reducing the consumption of energy, adjusting to changing weather conditions, lowering the response latency, and security [5]. The main goal is to take advantage of their individual sensor's strength and combine them to get the best result [5].

A. Selection of LiDAR

LiDAR works by shooting a laser beam at a distant object and measuring the time taken for this beam to return at the receiver end to calculate the distance of the object. All points which are gathered together from the objects are referred to as point cloud data [6]. These point cloud data is capable of capturing high resolution of 3D images of the surrounding and function for longer distances than camera sensors. The angle of measurement might vary from sensor to sensor [7]. Some sensors have 360 degrees angle possibility with help of rotating sensor on the mounting, whereas others might cover only 120 degrees. It varies from manufacturer to manufacturer and application to application [8]. The parameters which have to be considered while choosing a LiDAR for an autonomous vehicle are horizontal and vertical field of view, range, and data processing capacity [8]. Several functional models have been developed describing the advantages of LiDAR [8]. In Fig. 2 [9] LiDAR and its components are shown. Usually, the LiDAR range can vary up to 100 meters[10]. Applications of a LiDAR sensor include automatic braking, object recognition, and collision avoidance. Unlike Camera, as LiDAR is an active sensor, it has no difference between the day or night scenario in efficiency [10]. LiDARs have disadvantages as well. They are costly and have more weight when compared to other sensors [11]. In addition to that, changing weather conditions like fog or extreme rain can affect the efficiency of the system functionality [10]. New technological development in LiDAR is the entry of solid-state LiDAR which is not only more powerful but also more compact [10]. LiDAR is usually placed on the top of the vehicle to achieve maximum visibility and capture maximum range possible [9].

1) Range: Range is an important factor to be considered for LiDAR. It is mainly influenced by the diffuse reflectance from the target surface, power of the laser, and the target surface ambient light. In order to mask the noise due to the ambient light a minimum threshold is set within the detector and the reflected light from the laser should be of appropriate energy in order to trigger the detector. Under extreme circumstances some returns might be missed and a 50% probability of detection when the probability of detection due to a false positive remains low is one such measure for maximum range. Moreover it also makes sense to include target reflectance since the reflected light captured by the detector decreases with the distance square. Also, there needs to be a compromise between the maximizing the probability of pulse detection versus minimizing the

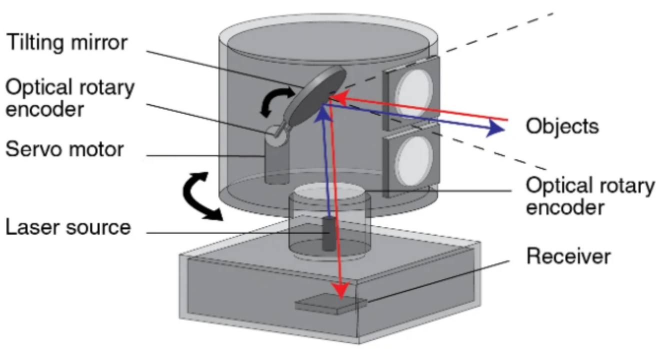

Fig. 2: Image of the LiDAR. [9]

false positive probability. Based on this reasoning, different applications use different thresholds for signal detection. For instance, some applications may require highly reliable data whereas other applications may utilize highest detection sensitivity but may be able to tolerate and filter out the erroneous signals in a software. All these features in some or the other way finally boil down to the cost associated with a sensor and the variation of Range with cost for different LiDARs based on the collected data is represented in Fig. 3(a).

2) Points per second: The set of all LiDAR reflections that is being measured constitutes a point cloud. Since each laser beam is tight in diameter a beam going to an object and getting reflected creates a point. The laser scans the environment every second at a particular frequency in order to generate the complete representation of the environment. Number of points per second play a major role especially for object classification since a higher number of points would lead to a better estimation of the point. But there also comes an attached burden on the costs aspects due to the high amount of processing techniques required when there are more number of data points. In Fig. 3(b) a cost based variation of data points per second for different LiDARs has been depicted.

3) Accuracy: The diameter of the LiDAR beam and the divergence affect the accuracy. To get accurate image formations we need good know-how regarding the platform motion due to the time taken by the LiDAR to obtain images. The existence of non-circular beams and divergence in beam profile puts a limitation laser light falling on a faraway object but this can be amended by making the initial beam diameter larger but then is a negative effect of a large spot size for measurements in short ranges. Considering these parameters, it has been observed that the sensitivity and range for a LiDAR are reduced due to higher levels of ambient light. Moreover, the usage of pinholes or small detectors to pass only concentrated beam from the source tends to reduce the ambient light effects due to the reduction in the area at the receiver. However, solid state or fiber lasers fire symmetric beams of circular shape which can be configured to transmit high energy as well as maintain tight diameters over long distances in order to enable their measurement. Keeping these things in mind a plot of angular accuracy versus the cost for various LiDARs are shown in Fig. 3(c)

4) Overall Score: In order to asses the variation of weights were assigned to each parameter and based on the computation of the weighted average, scores were assigned. The LiDAR with the best overall score had the best performance. The plots of the Overall scores versus the cost for various LiDARs are as depicted in Fig. 3(d).

B. Selection of RADAR

Radar emits radio waves of microwaves and directly estimates the speed and distance of the object through a change in the frequency by Doppler shift method [11]. The radar can detect objects even at very long distances because it uses microwaves which has very high wavelength [11]. This high wavelength helps in traveling and detecting target objects at very long distances. Radar can function very well in any given weather condition which sets this apart from Lidar [11]. In Fig. 4 [12] the Radar and its components are shown. RADARs can be classified into three categories based on the distance up to which they can cover. That is into long-range, medium-range, and short-range RADARs [8]. The long-range sensors range from 80 to 200 meters. Medium range sensors range from 30 to 80 meters and short-range sensors range from 1 to 30 meters [8]. Applications of the RADAR sensor includes inter traffic alerts and blind-spot recognition. RADARs are usually located at the corner position in a vehicle [8]. Nowadays, the main focus of the RADAR application is to optimize the cost and performance of the RADAR sensor for achieving long-range [8]. Capability of a radar to resolve two targets based on differences in their distance, angle and velocity is very critical for an accurate perception.

1) Range Resolution: It is the capability of the radar to distinguish between two targets that are very close to each other in range. If a radar has range resolution of 4 meters then it cannot separate on range basis a pedestrian standing $1\mathrm{m}$ away from the car. The range resolution is solely dependent on the bandwidth of the chirp B_{sweep} and is given in Fig. 5 [13, Fig.1]

$$d_{res} = \frac{c}{2B_{sweep}} \tag{1}$$

Where *c* = velocity of light in m/s ; d_{res} = angular resolution as a distance between two targets; B_{sweep} = bandwidth of the chirp in GHz

2) Velocity Resolution: If two targets have the same range they can still be resolved if they are traveling at different velocities. The velocity resolution is dependent on the number of chirps.A higher number of chirps increases the velocity resolution, but it also takes longer to process the signal.

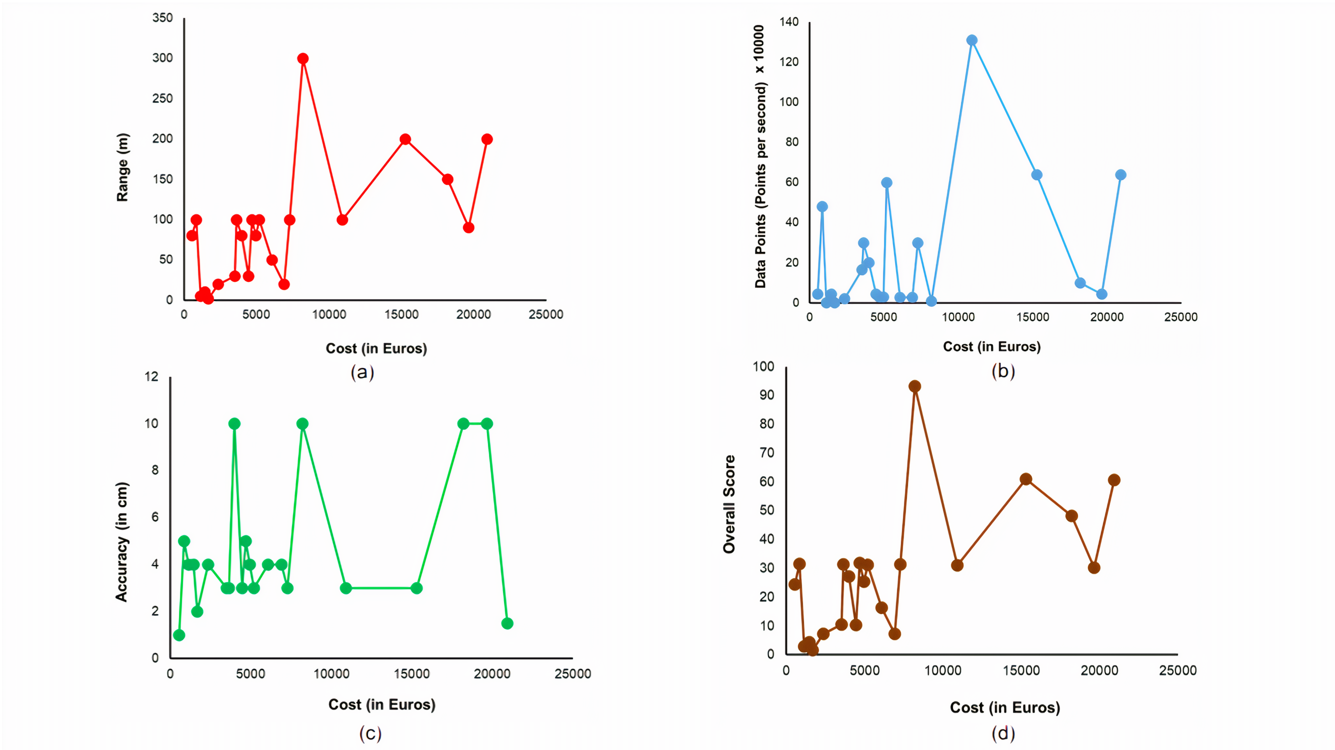

Fig. 3: Cost based comparison of LiDARs a) Range b) Points per second c) Accuracy and d) Overall Score

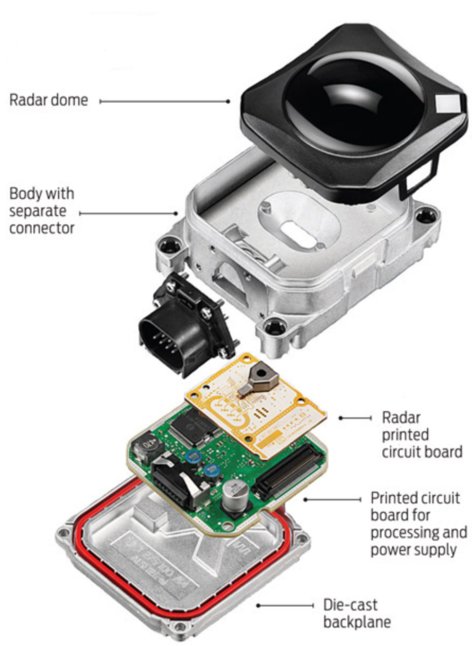

Fig. 4: Image of RADAR.[12]

3) Angle Resolution: Radar is capable of separating two targets spatially. If two targets are at similar range travelling at same velocities, then they can still be resolved based on their angle in radar coordinate system. For defining angular resolution based on antenna beam width limits, the half power points of the radiation pattern for the antenna needs to be specified. For two equally large targets at the same the range, the angular resolution is given as:

$$S_A \geq 2R \cdot \sin \frac{\Theta}{2} \tag{2}$$

Where Θ = antenna beamwidth (Theta); S_A = angular resolution as a distance between two targets; R = Slant range aim - antenna [m]

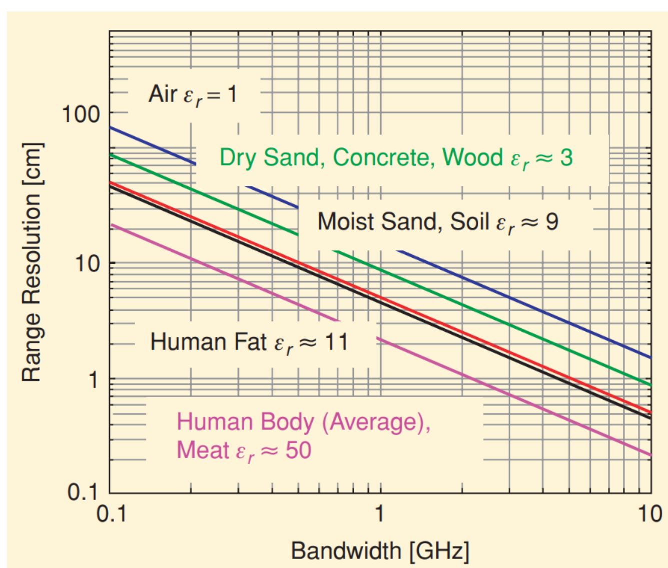

Fig. 5: Range resolution variation for a short range RADAR.[13, Fig.1]

III. Selection of Method for Sensor Fusion

Sensor fusion has been a fast developing area of research since recent years. With the increasing need of automation and development of different types of sensors the need to manage the increasing quantity of data has made it a necessity for the data to be easily perceived by Humans. Sensor Fusion is being used in various areas of research and Automotive automation is one such field. Through the integration of sensors we assure a correct prediction of value and has a certain advantage over output from one sensor. For accurate fusion of these sensor value algorithms like Kalman Filter, or Bayesian filter are used which help us overcome certain inherent problems like sensor uncertainty, ambiguities of the environment and other problems related to data management. It has the following advantages like Certainty, Representation, Accuracy and completeness.

A. Kalman Filter

As stated by [14] Kalman filter is an ideal statistical recursive data processing algorithm which continuously calculates an estimate of a continuous valued state based on periodic observations of the state. It uses an explicit statistical model of how x(t) changes over time and an explicit statistical model of how observations z(t) which are made related. [14]

In Kalman filter the estimation is done using feedback control.The state of the system is predicted using filter at a particular time and then obtains feedback based on measurement [14].

A linear stochastic equation governs the time update (prediction) function of basic Kalman filter. As every iteration requires almost the same effort, the Kalman filter is well adapted for real-time usage [14]. We first define a model for the states to be estimated in the standard space-time form:

$$\dot{x}(t) = \mathrm{A}(t)x(t) + B(t)u(t) + n(t) \tag{3}$$

where x(t) is the state vector of interest, A(t) is the transition matrix, B(t) is the control matrix, u(t) is a known control input. The observations equation defined in standard spacetime model:

$$z(t) = H(t)x(t) + v(t)[14] \tag{4}$$

where H(t) is the measurement matrix, z(t) is the observation vector. n(t) and v(t) are random zero-mean Gaussian variable describes uncertainty as state evolves, with covariance matrices Q(t) and R(t) respectively. From this, the Kalman filter proceeds in two stages, prediction and update A prediction $\hat{x}(k|k-1)$ of the state at time k is given as

$$\hat{x}(k|k-1) = A(k)x(k-1|k-1) + B(k)u(k) \tag{5}$$

The covariance $\mathrm{P(k|k-1)}$ is also computed as

$$P(k|k-1) = A(k)P(k-1|k-1)A^T(k) + Q(k) \tag{6}$$

At time k, and observation z(k) is made and the estimate $\hat{x}(k|k)$ update of state x(k). Together with the updated state estimate covariance matrix $\mathrm{P(k|k)}$, are computed from the state prediction and observation by

$$\hat{x}(k|k) = \hat{x}(k|k-1) + K(k)[z(k) - H(k)\hat{x}(k|k-1)] \tag{7}$$

TABLE I: Extended Kalman Filter Time and Measurement update equations [15]

Time Update (Predict)
$\hat{\mathbf{x}}_k^- = \mathbf{f}\left(\hat{\mathbf{x}}_{k-1}, \mathbf{0}\right)$
$\mathbf{P}_k^- = \mathbf{F}\mathbf{P}_{k-1}\mathbf{F}^\mathbf{T} + \mathbf{W_k}\mathbf{Q}_{k-1}\mathbf{W}_k^T$

Measurement Update (Correct)
$\mathbf{K}_k = \mathbf{P}_k^-\mathbf{H}^\mathrm{T}\left(\mathbf{H}\mathbf{P}_k^-\mathbf{H}^\mathrm{T} + \mathbf{V}_k\mathbf{R}_k\mathbf{V}_k^T\right)^{-1}$
$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k\left(\mathbf{z}_k - \mathbf{h}\left(\hat{\mathbf{x}}_k^-, \mathbf{0}\right)\right)$
$\mathbf{P}_k = \left(\mathbf{I} - \mathbf{K}_k\mathbf{H}\right)\mathbf{P}_k^-$

$$P(k|k) = [I - K(k)H(k)]P(k|k-1)[15] \tag{8}$$

K(k) is the Kalman gain matrix that is a measure of the relative confidence of the past estimates and the latest observation. The Kalman gain is chosen to minimize the a prior state estimate covariance. [15]

B. Extended Kalman Filter

An Extended Kalman Filter is used to solve the problems in which state functions or measurement functions are nonlinear as stated by [15]. In a realworld scenario, it is very common to come across the nonlinear problems. When we apply a linear problem on the standard Gaussian distribution of Kalman Filter, it would result in a Gaussian distribution [15]. But, when we apply a nonlinear function on the Gaussian distribution, then it would result in non-Gaussian distribution[16]. Therefore, it is very much difficult to solve nonlinear problems with the standard Kalman filters. Hence Extended Kalman filter is introduced which converts the nonlinear problem statement into a linear one and then applies the mathematical formulas to get the desired Gaussian distribution. An Extended Kalman Filter is used to solve the problems in which state functions or measurement functions are nonlinear. After the nonlinear transformation, the Kalman filter noise is no longer normal. The equations are mentioned in [Table 1]. [15]

C. Unscented Kalman Filter

As explaied in [15] UKF uses the concept of Sigma Points. We take some points on source Gaussian and map them on target Gaussian after passing points through some non linear function and then the new mean and variance of transformed Gaussian is calculated. Since the system output or the sensor output in real time from LiDAR and RADAR is Non- linear we will be using extended Kalman filter which will help in better prediction than Basic Kalman filter and is less complex than UKF. [15]

D. Use of Deep Learning for Sensor Fusion

A deep learning based sensor fusion system can be used to fuse two independent, multi-modal sensor outputs as explaied by [17]. This system is shown to successfully learn the complex capabilities of an existing state-of-the-art sensor fusion system and generalize well to new sensor fusion datasets. It has high precision and recall with minimal error or confusion after training on millions of examples of labeled multi-modal sensor data. It is robust, has a sustainable training time, and has real-time response capabilities on a deep learning PC with a single NVIDIA GeForce GTX 980Ti graphical processing unit (GPU). [17]

IV. Sensor Fusion of LiDAR and RADAR using Extended Kalman Filter

Functional safety is an important aspects of Autonomous vehicles, this shows how with the use of multiple sensors are used to attaing the level of safety required [18]. Multiple sensors are employed to overcome the flaws or drawbacks of individual sensors. For example, RADAR measures distances with accuracy while camera is beneficial for object detection and classification. hence by fusion multiple properties we get a better and accurate perception of the surrounding. [18]

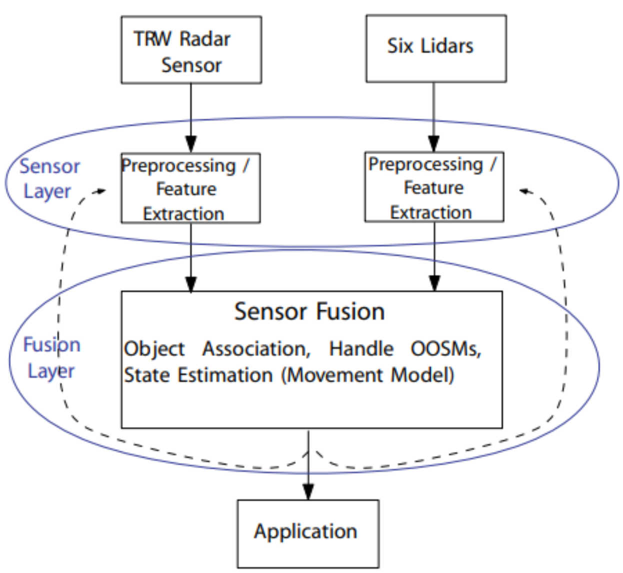

Fig. 6: Fusion Architecture of LiDAR and RADAR.[19]

This system is based on processing the data shown by Mukhtar et al. [20] obtained by LiDAR and RADAR to track the object and predict its position and velocity. Using Bayesian methods like Extended Kalman or Particle Filter as mentioned were used by Mukhtar et al. [20] which improved the tracking considerably. The Fig. 6 above represents a sensor fusion algorithm implemented on python processing inputs form a dataset of RADAR and LiDAR. [20]

V. Results and Discussion

In summary, this paper addresses and compares the Kalman filter and Extended Kalman filter for its application in Sensor fusion.In this paper we have compared the predictions of Kalman and Extended Kalman using RADAR and LiDAR as signal inputs

By comparing Fig. 7 and Fig. 8 we can see that there is a huge difference between the prediction accuracy of a Kalman

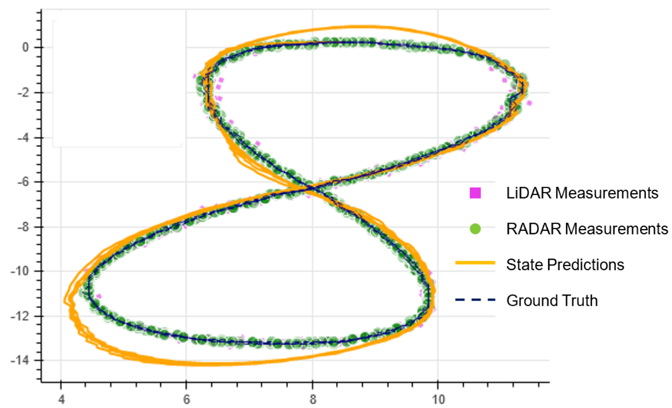

Fig. 7: Kalman Filter Predictions vs Ground Truth

and an Extended Kalman Filter. It is seen that Extended Kalman filter has better prediction capabilities and can be used for applications such as steering wheel control, acceleration and braking depending on the values taken as input from the sensor.

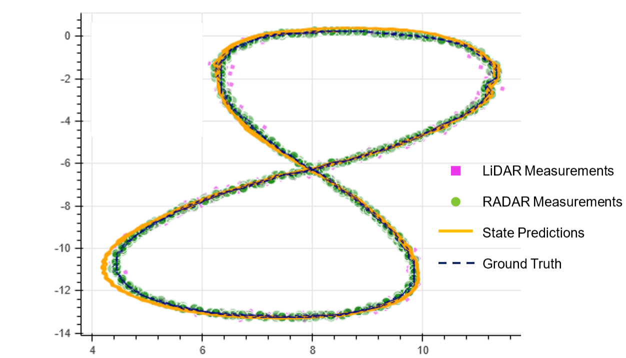

Fig. 8: Extended Kalman Filter Predictions vs Ground Truth

Vehicles are becoming more smart and safe by the integration of sensors into them. Sensors help the vehicle to assess its environment in a better fashion and take informed decisions. But, each sensor has its own advantages and limitations. For example, as the camera is a passive sensor, it is very difficult to work with the observations from this sensor during the night times. So the camera sensor plays a vital role in the recognition of symbols and traffic signs like no other sensor. The active sensors like LiDAR and RADAR can be useful during the low light scenarios. There exists no sensor in the market which acts as a solution for all the existing problems. Therefore it is very important to understand the potential of each sensor in a given condition and work with them to make the best predictions and estimates. Methods like Standard Kalman, Extended Kalman, and Unscented Kalman are used to perform the task of fusion. These methods have their own limitations. Kalman filter is a very powerful tool that is helpful in making predictions from the given information. The advantage of the Kalman filter is that it has the least power requirement for the computation. But, the Kalman filter gives the best results only when the data is in linear form. When the linear data is mapped on to the Gaussian curve, it results in Gaussian distribution. Whereas, when nonlinear data is fed along with the Gaussian curve, it results in a Non-Gaussian curve. It can be seen that all the real-world scenarios are non-linear problems that are non-Gaussian in nature. To solve those problems with more accuracy either extended Kalman or Unscented Kalman filters can be used. In both of these methods, the nonlinear data is converted to the linear data and mapped with Gaussian distribution to get better results. Unscented Kalman filter gives the best results when compared to all the other methods, due to its large sample size while computing the mean. Whereas, the Extended Kalman filter takes only one point into consideration. The disadvantage of the Unscented Kalman filter is that it involves higher computational power. This is a drawback of the Unscented Kalman filter when compared to the Extended Kalman filter. Therefore these methods can be used to fuse the data from various sensors for various applications.

VI. Conclusion and Future Work

In summary, the method for sensor fusion by combining LiDAR and RADAR was analyzed and compared. Extended Kalman filter is the ideal fusion technique when compared to others due to its high accuracy and low computational power requirements. These sensors and fusion techniques can be used for application aimed at improving safety and avoiding a crash in all directions. Technologies like artificial intelligence and machine learning can be incorporated into these sensor applications of the automobile to enhance driver safety. As the number of users of the vehicle is very large, it is very easy to collect and train the neural network which can take better decisions in crash situations and improve driver safety.

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