Survey and Analysis of Filtering Methodologies used in Localization applicable in Connected and Autonomous Vehicles

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Abstract— **Filtering is considered as a methodology that could be used in the process of enhancement of the image so as to highlight its strong lines as well as to either emphasize specific features or remove them from the image frame. These specifics are required as a computer vision application towards autonomous vehicles as detecting specific objects and mapping/localization play an important role in the software used in self-driving cars. There are two main approaches when it comes to mapping and localization also commonly known as simultaneous localization and mapping (SLAM) in terms of autonomous vehicles and robots, Kalman and Particle filters. In this survey and analysis project, we shall discuss these approaches that play a significant role in image processing as well as provide an overall support system to autonomous vehicles by discussing and analyzing the prior research done on the topic.**

I. INTRODUCTION

For an autonomous vehicle, localization with the help of computer vision or computational photography is a major challenge, especially in situations where the sensors lack GPS and inertia. Efficient and fast key point localization for vehicles in these contexts is a challenging endeavor since enhanced precision typically results in lower performance and likewise. Related applications like ballistic weapon tracking and control systems as well as industrial sectors like interfaces that deal with virtual reality, machine vision, etc., make autonomous recognition and surveillance fascinating fields for research. Kalman filters may closely combine visual feature observations with additional data from the mentioned sensors in machine vision-aided navigation that permits precise descent. The filter provides real-time, resource-adaptive estimations of the landscape orientation and acceleration with respect to the position of the vehicle. In order to achieve maximum performance in an autonomous vehicle, effective navigation seems necessary in localization of the moving vehicle with respect to the surroundings. An autonomous vehicle has the capacity to locate itself on a grid with a few units of measurement of precision is vital. Since it can locate itself with more accuracy, an autonomous vehicle may be conscious of its surrounding environment while driving, including road features and edges of the road. This helps the vehicle recognize lane changes and enable safe navigation. The accurate localization of the car becomes vital to automatic driving whenever the vehicle is operated in an urban layout. Also, it must be extremely dependable to prevent any mishaps.

II. BACKGROUND MOTIVATION

The study of processing and retrieving information from image frames either in live streams of cameras or from videos that could be used by computer vision systems is known as "image processing." While images represent unstructured data, processing images is much more difficult than studying sorted relevant data, like tables or spreadsheets. Depending on the intended use, image processing can be applied in a wide range of fields by employing a wide range of methods and algorithms. It is a prominent and developing area of computer vision that is utilized in many fields, such as medicine, video processing, statistical pattern recognition, bio-metrics, self-driving cars and autonomous vehicles, etc.. The way filtering of data eliminates the data that is not required to go along with the overall implementation of the system in either of the development of the machine learning model or the training of the system, the same way filtering an image allows a better view from the image frame. The effect of filtration helps in the quality of the image especially in increasing or decreasing the sharpness of the outline of the entity or even in increasing the overall contrast levels of the image. So, in other words, we can define filtering as the methodology in altering image frames in terms of the size, depth. brightness, contrast, smoothness, etc. which allows an overall alteration of pixels in the image for transformation into its desired form by means of various graphical editing approaches. Some common and mostly used filters include the Gaussian filter, Box filter and the bilateral filter, all these filters can be used in de-blurring and smoothing in the image frame.

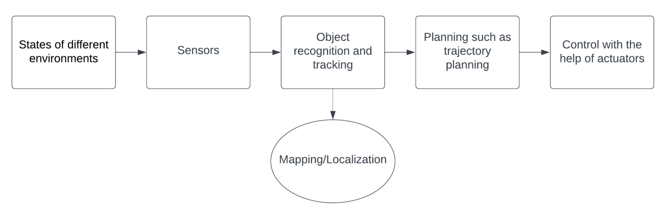

Fig 1. Brief software architecture of a connected and autonomous vehicle

III. FILTERING TECHNIQUES

In this section, we shall discuss the different types of filters and how they can be used in the modification of the image frame so as to provide the essential key-points required in autonomous vehicles. Based on the number of filters that could be used such as the particle filter, the Kalman filter plays a vital role in connected and autonomous vehicles.

A. *KALMAN FILTERS*

The Kalman filter is divided into two main stages that allow the prediction of the states, and the computation of the gain using Kalman filters. In step one, the filter has to compute a prediction for the new values based on the original value that was given. It also has to predict the error as well as the variance to the different noise that is present in the system. Noise in this case can be assumed as the change in the value of the acceleration of the vehicle when it is moving on the roadway. The second stage includes taking the measured value from the remote sensing systems such as the LiDAR sensor. The difference between the value which was predicted and the value that was measured before results in a value that allows us to get the overall Kalman gain. By that gain, we can then compute the new value and finally the uncertainty too. The result we get is then fed again to the first stage (the prediction stage) and the cycle continues until we get the difference between the value that was predicted and the value we measured before, almost equivalent to 0. The value, which was calculated is also known as the predictive value given as a result by the Kalman filter.

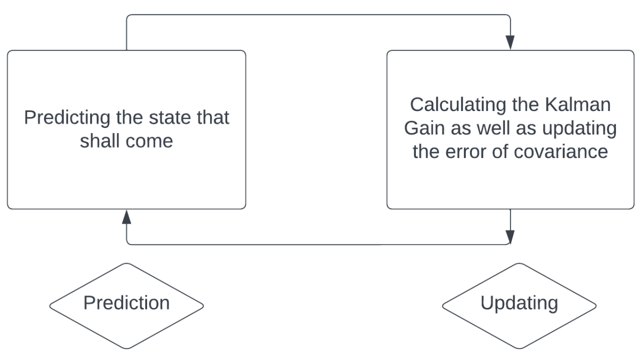

Fig 2. How the Kalman filter works?

In 1994, Alonzo Kelly et al. [1] developed a filter based on the state space of Kalman's initial research findings to tackle the problem of the position estimation in vehicles.

A group of researchers [2], developed a sensor fusion system that acted as a guidance system for connected and autonomous vehicles while driving through alleyways. They had a sensor based system that had the purpose of providing the eyes of the machine and for localization used a laser radar. They also used an inertial measurement unit for the detection of the amount of tilt that was done by the vehicle as well as found out the speed of the car while traveling via the speed sensor used. They used the combination of the Kalman filter and the fuzzy logic algorithm for the data fusion from the speed sensor and the laser radar that was used. The overall guidance system using sensor fusion was further tested on alleyways and they observed that their overall system was almost as good as a human driving a car.

N Murakami et al. [3], used a Kalman filter to build an object detection and recognition system for an agriculture based tractor. A 180 degree arc of up to eight meters in radius may be laterally scanned with a 1 degree resolution using the object recognition technology, which was designed using a real-time kinematic positioning GPS, inertial measurement units, as well as a laser range detector.

The inertial measurement unit is basically an electronic measurement for the force applied on a body, the magnetic field and finally the angular rate. Usually, these IMUs are made of 3 accelerometers, magnetometers and finally gyroscopes for providing the balance. There are some factors in the Kalman filter that have an adverse effect when it comes to image processing in autonomous vehicles. It could be in this case the processed noise, which is simply the consideration of the entity's trajectory would probably not correspond to the evaluation of the motion of wind and temperature. For example, in an autonomous vehicle, surroundings play a major role in the overall system. When the surroundings are clear, the system shall agree that it is safe to move in the direction it was intended to move. However, if the lane is quite busy, the system will not be able to accurately read every individual either crossing the road or minor vehicles such as bikes that pass by the vehicle. Other distractions such as weather conditions play a vital role too. Another factor that should be considered is the measurement noise, which has one flaw, that is the sensor which was used for the tracking of the system might not have been calibrated correctly, leading to errors in calculation.

Some researchers [4], used a mixture of Kalman filters to provide an estimation of vehicle densities as well as the modes when the congestion was at peak at locations where the measurement was kept unknown on a highway. They used the Kalman filter to solve the complex problem with the help of the switching state of the space model, a discrete state of unknown proportions. They prove that efficient filtering can be achieved if we utilize minimal or maximum number of sampling sequences. In a study done by some other researchers [5], they have used this similar type of approach however as an extension as they considered the characteristics of speed as well as they used a particle filter for the overall estimation of density and the overall flow speed.

Ramviyas Parasuraman et al. [6], proposed an online framework based on the Kalman filter that allows for the estimation of "spatial wireless connectivity" with respect to the the signal strength it was received which is based out of the path loss as well as the variance from the shadow fading performed on the wireless channel in connected and autonomous vehicles. They used the path loss to provide an estimation based on the minimum squaring method as well as predicted the shadowing effect based on the "exponential/empirical variogram". In order to combine the two models via fusion they used a discrete Kalman filter. They compared their approach with other state-of-the-art approaches made in the field and yielded a hearty accuracy of around 96 percent for the prediction of the received signal strength at a distance of 20m in front of the trajectory of the robot.

Yiyang Wang et al. [7], proposed a methodology where the safety and security of a CAV was taken into consideration. They used signal filtering techniques as well as anomaly detection based approaches in the overall process. Further on, they used the extended version of the Kalman filter also known as the adaptive extended Kalman filter [9] so as to provide an overall smooth reading of the sensor used in a nonlinear vehicle following the model of a CAV.

State of the Art Methods using Kalman Filters in CAV			
Authors	Application	Approach used	Accuracy/AUC value
[6]	Estimation of ”spatial wireless connectivity” in CAV	Discrete Kalman filter + ”Exponential/Empirical Variogram” + Path loss	96%
[7]	Anomaly Detection and Recovery in CAV Sensors	Adaptive Extended Kalman filter + One Class Support Vector Machine on Intelligent Driver Model	With time = 0 second: AUC = 0.98, With time = 0.5 second: AUC = 0.9793, With time = 1.5 seconds: AUC = 0.9782
[8]	Anomaly Detection and Identification in Automated Vehicles	Convolutional neural networks + x^2 detector + Kalman filtering	AUC: 0.96

In order for a precise detection of anomalies, they used one class support vector machine models that were previously trained to detect such types of anomalies. Based on the methodology they used, they allowed the extended version of the Kalman filter to provide an estimation of the localization as well as the speed of the vehicle by taking into account the factor of surrounding ongoing traffic. In doing so, they were able to achieve a far better overall anomaly detection in terms of performance when compared to an adaptive extended Kalman filter that had a traditional x^2 - detector.

B. PARTICLE FILTERS

Particle filters have the main purpose of the task of localization of specific landmarks during the use of self-driving vehicles. The filter allows the system to give an overview of the updated version of the specific position based on the sensor that has been used in the development of the CAV. It also helps in providing the system a high definition mapping of the updated position. If a multiple layered light detection and ranging sensor was to be used in the autonomous system then the extraction of line characteristics would be the main role of the particle filter. [25] If we were to consider a self-driving vehicle driving in a neighborhood surrounded by some specific landmarks, then the sensors used on the car for example the multiple layered LiDAR could help in calculating the distance between the vehicle and the landmarks that surround the vehicle whilst in motion. As a start move the initialization of several infinite based points are localized at the vehicles current location. The principle of particle filtering of the vehicle works on the fact that every time the vehicle is in motion, the distance values that come from the actual vehicle and the distance values that come from the infinite based particles of the assumption of the vehicle shall give us the posterior probability of every particle that is the actual vehicle. Hence, giving us the filtered version where there are no irrelevant particles to be seen. [25] A particle filter is based on the generation of the particles that will be considered as the dataset, calculating as well as evaluating the particle's probability of every particle which is basically the actual vehicle, re-sampling completely only on the condition of the weight value in the calculation of the probability and finally repeating the move to make sure that the system reaches the specific orientation within the given time. Sometimes in the calculation of the probability you might need to use Gaussian distribution for N-1 number of dimensions to find the optimal solution. A great illustration on how the particle filter works can be seen in the block diagram below.

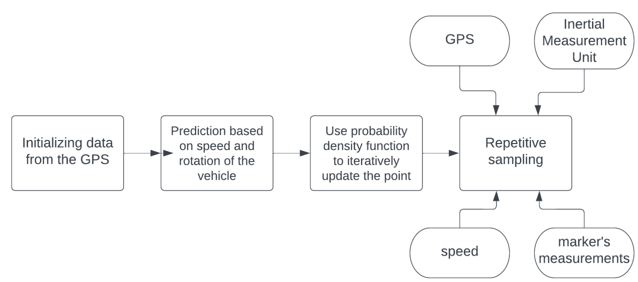

Fig 3. How the Particle filter works?

Particle filters, also referred to as sequential Monte Carlo methods [1] , are a type of algorithm used for state estimation in dynamic systems. [15] They are particularly useful when direct observation of the system's state is not possible, and instead, inference is made based on a series of noisy observations. The fundamental concept of particle filters involves representing the probability distribution of the system's state through a collection of particles, each of which denotes a possible state. These particles are propagated forward in time based on the system's dynamics at each time step, and weighted according to how closely they correspond to the observed data. The particles with the highest weights are then resampled to generate a new set of particles for the next time step. [27] [29]

In the realm of autonomous vehicles, particle filters are widely utilized for state estimation, which involves estimating the current state of the vehicle based on sensor measurements. They can be employed for various tasks

such as localization, where the objective is to estimate the vehicle's position on a map, or for object tracking, where the goal is to estimate the position and motion of other vehicles, pedestrians, or objects in the environment. [28]
Paul A. Brasnett et al. [11], designed a methodology in the overall analysis of entity recognition and its tracking by the help of the concept of particle filtering to process specific features and characteristics that were identified using the splits of videos also known as the video frames. They developed two specific filters for the overall system keeping specifics into consideration such as the color and the texture that are well outlined in nonlinear models. With the help of various cues that could be used in the comparison of different tracking scenarios, they showed the advantages of an overall increase in the accuracy as well as the increase in overall strength in the detection of those entities based on natural as well as synthetic video successions.
They made the overall system [12] a bit more less sophisticated by embedding the initialization of the track without the need of including the entity recognition schema as they had done earlier as well as extended the work to add in more number of entities hence making it useful for multiple number of entities at the same time.
Particle filters can easily integrate measurements from multiple sensors such as cameras, LiDAR and radar etc. This way the algorithm produces more accurate and precise estimates of the vehicle's stare. This improves the vehicle's overall safety and reliability. [26] Sometimes autonomous vehicles operate in unpredictable and uncertain environments and particle filters are fitting to handle this kind of uncertainty. Particle filters have the capability to account for uncertainty and provide more reliable state estimates. [26]

State of the Art Methods using Particle Filters in CAV		
Authors	Application	Approach used
[16]	Object Tracking	Multi-Task Correlation Particle Filter
[18]	Pose Tracking of Entities	Counter hypothetical likelihood function + Particle Filter
[19]	Tracking and Localizing Entities in Re-detection	Kernalized Correlation Filter ("particle filter redetection based tracking approach")

Metrics of State of Art methods	
Authors	Accuracy
[16]	AUC: 0.545
[18]	Using RGB encoder: AUC: 81.2 and When Using RGB-D encoder: AUC: 88.2
[19]	Success Plot Ranking Score: 0.584 and Precision Ranking Score: 0.821

There are many applications of the Particle filter that can be used in the connected and autonomous vehicle industry, some of the major applications are listed below:

- Localization: One of the best ways to localize a vehicle within known map is to use particle filters combined with sensor movements and with an understanding of the surrounding environment.

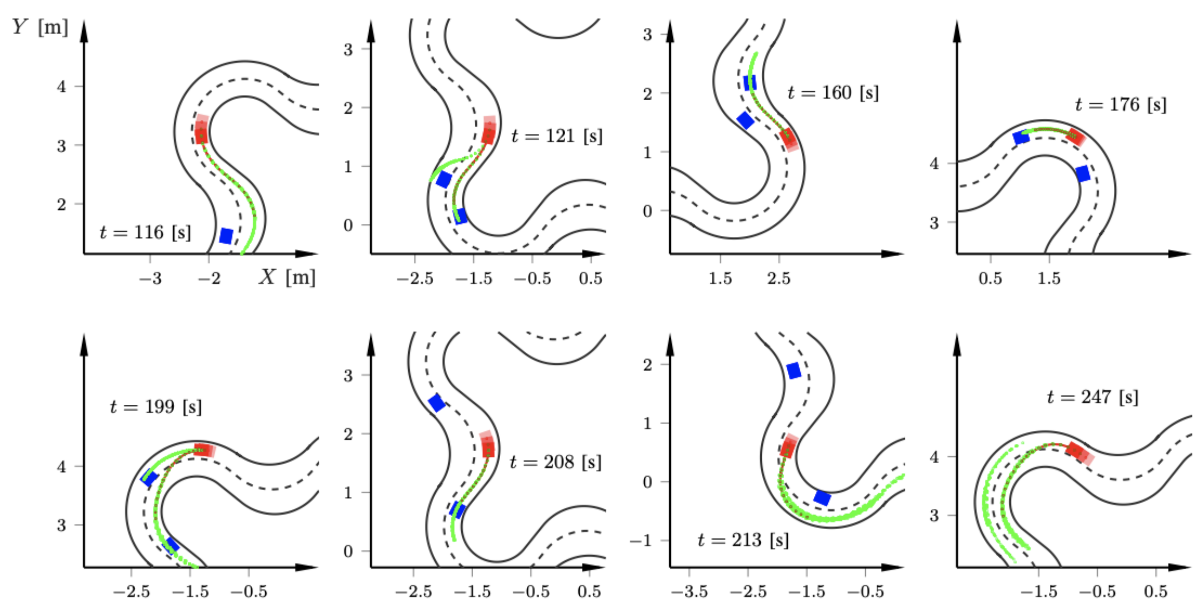

Fig 4. An Illustartion of validation of how the Particle filter works using an ego vehicle that can be denoted using the red square, obstacles are denoted by the blue square and the particles that are based from the particle filter are the green linings
*Fig 4. has been taken from [10]

This can be done by using particle filters to analyze the vehicle's pose (position and orientation) by integrating data from the sensors (GPS, IMU, LiDAR, and cameras).

Particle filters can also estimate the uncertainty of the vehicle's pose which is important for autonomous driving tasks such as planning and control.

- Object tracking: Particle filters can be used for tracking objects in the surrounding such as vehicles/pedestrians and obstacles. This is achieved by generating a set of particles that represent the possible trajectories of the object and then weighing them based on parameters like the observed measurements from sensors such as LiDAR and cameras and how they match them. The particle filter can then predict its future behavior by estimating its current state such as position, velocity, size, and shape.
- Sensor fusion: Particle filters also can fuse the data from multiple sensors in order to improve the accuracy and robustness of localization and object tracking. For example, a particle filter can combine measurements from GPS, IMU etc. to estimate the vehicle39;s pose with higher accuracy than would be possible by using an individual sensor alone.
- Computational Efficiency: A very important concept of particle filters in autonomous vehicles is using computational efficiency to balance accuracy. They can become more expensive as the complexity of the state space and the number of particles begin to increase. However various techniques have been developed to improve the efficiency of particle filters such as importance resampling, adaptive sampling, and parallelization.

For mobile robot navigation, T Fukao et al. [13] created a self-localizing method consisting of a 2D laser range finder depending on the particle filter. In order for the vehicle to balance while moving on more difficult terrain, a trajectory generation method and a sturdy controlling mechanism are integrated with the localization approach. When unanticipated entities or barriers showed up on the grid, the researchers stated that the particle filter was used instead of the Extended Kalman Filter to manage sensory uncertainty.

Using the help of a navigation methodology via particle filters, Santosh A. Hiremath et al. [14] created an autonomous guidance methodology for a robot fitted with a row-based light detection and ranging sensor over a labyrinth sector. In order to assess the robot-environment condition, the established particle filter based algorithm was utilized. This included estimating the robotic orientation, horizontal variation, spacing between plant rows, and separation at the ends of rows too. The robot was guided and steered using these approximations. The acquired data revealed that the frontal side and view of the robot as well as the lateral deviations had RMSE values of ”2.4 degrees and 0.04 m”, correspondingly.

To use a particle filter in autonomous vehicles, a set of particles representing potential vehicle states is initialized, and as the vehicle moves and sensors provide new measurements, the particles are updated and resampled to reflect the current state of the vehicle. This enables the filter to converge on the most probable state estimate based on the available data.

Particle filters are valuable in autonomous vehicles since they can handle non-linear and non-Gaussian systems that are prevalent in real-world scenarios. Furthermore, they can incorporate multiple sources of sensor data and can handle measurement uncertainty. Consequently, particle filters are a prevalent choice for state estimation in autonomous vehicles.

IV. WHAT MAKE SLAM BASED APPROACHES VULNERABLE AND SIGNIFICANT AT TIMES?

Despite the fact that the Kalman filter and the Particle filter having so many applicable uses, they have some problems that are hard to follow at times. Some of the advantages that make Kalman filter very advantageous are:

- When it comes to minimizing the estimate's mean square error, Kalman filters are the best estimators.
- Since Kalman filters can operate in real-time, they are appropriate for applications that need prompt and precise updates. [20] [21]
- Extended Kalman filters can tackle non-linear systems and make Kalman filters resilient to noisy data.
- Many uses for Kalman filters exist, such as monitoring, positioning, automation as well as signal processing. Kalman filters are appropriate for embedded technologies as well as other applications with limited means since they only need a small amount of computational capacity. [20] [21]
- Iterative upgrades are used by Kalman filters, which means that upgrading the estimation has a relatively low computational cost yet does not become more expensive as more data is added. [21] [23]

However, there are times when the Kalman filter might prove a bit out of bound allowing it to me quite disadvantageous at times like:

- The linearity of the dynamic systems and estimation methodologies is the foundation of Kalman filters. The Kalman filter might not be able to produce precise projections if the system is incredibly nonlinear. [24]
- The state noise plus the measurement noise are presumed to be Gaussian in Kalman filters. The Kalman filter could give predictions that are not ideal if the distortion is non-Gaussian. [24]
- Kalman filters do not keep track of previous predictions; instead, they just retain the present estimation and the erroneous covariance matrix. Multiple target tracking or processing various assumptions about the state of the system are not instances where Kalman filters dominate. [20] [24]

Now when it comes to the Particle filters, they have the same case as we had for the Kalman filters. There are times when the Particle filters might prove useful such as:

- Particle filters give out high versatility as well as they can be utilized with various other sensors so as to make

them an important tool in autonomous vehicles that depend on various sensor inputs. [23]
- Particle filters offer real-time estimation, which is crucial in autonomous vehicles where quick decision-making is essential. [23]
- They can continue to provide an estimation of a vehicle's state even though one or more sensors fail in the process, hence increasing the overall robustness of the autonomous driving system. [23]

Now, if we were to see how these filters were to be proven as not helpful and not reliable, we would have to check the overall cons of using these filters such as:

- For real-time implementation in vehicles, particle filters can be computationally costly, particularly when working with high state spaces. [22] [23]
- Since particle filters are susceptible to evaluation noise, a great deal of noise can produce predictions of the state of the vehicle that are inaccurate. [22]

V. CONCLUSIONS AND FUTURE WORK

Based on the research work that have been discussed, we can conclude that Kalman filters and Particle filters both have advantages and disadvantages but are applicable in certain applications in autonomous driving. Again, we have discussed the pros and cons of these filters based on the characteristics of the filters that differ them against each other. We have also discussed the state-of-the-art of methods as well as created an outline in the form of a table where we have compared the results based on the area under the curve (AUC) and the accuracy that was achieved when the researchers tested there overall system.

In the future, a brief and thorough study of the approaches that SLAM uses in robotics also known as (ROS) such as Hector SLAM, Cartographer, RTAB-Map, etc., could be done. These are some interesting applications that can be used in the application of autonomous driving too and have a significant demand in terms of technology and innovation.

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CONTRIBUTIONS

There are a lot of topics that come along when it comes to the applications of connected and autonomous vehicles. We chose the approaches that could be used in CAV specifically as it could give use a brief idea of how localization and mapping have an influence in autonomous driving.

In doing so, I contributed to the deep thorough survey analysis of the Kalman filter and my colleague Adheik Dominic contributed in providing a thorough survey analysis of the Particle filter. Together we discussed on how influential these approaches are in terms of both self driving vehicles as well as robotics.