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Original Article

Autonomous Vehicle Navigation Using Sensor Fusion Algorithms

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ABSTRACT

Autonomous vehicle navigation is a key component of modern intelligent transportation systems, relying on the integration of multiple sensors such as LiDAR, radar, cameras, GPS, and IMUs. Sensor fusion techniques combine data from these sources to improve perception, localization, and reliability. This paper reviews classical pre-2018 sensor fusion methods, including Kalman Filters, Extended Kalman Filters (EKF), Unscented Kalman Filters (UKF), and particle filters. Different sensors have individual limitations – cameras are affected by lighting, LiDAR is costly, and radar has lower resolution – but fusion enhances overall system performance by leveraging their complementary strengths. The study examines low-, mid-, and high-level fusion approaches and proposes a hybrid framework using GPS/IMU for localization and LiDAR-camera fusion for obstacle detection. The system is based on probabilistic and Bayesian models, designed for real-time performance and robustness against noise and sensor failures. Key challenges such as synchronization, calibration, and computational complexity are discussed. Results show that sensor fusion significantly improves navigation accuracy, highlighting the importance of selecting appropriate algorithms based on application needs.Overall, the paper emphasizes that multi-sensor fusion is essential for safe and reliable autonomous driving and provides a foundation for future advancements in the field.

KEYWORDS

Autonomous Vehicles, Sensor Fusion, Kalman Filter, Extended Kalman Filter, Particle Filter, LiDAR, GPS, IMU, Navigation Systems, Intelligent Transportation Systems.

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1. INTRODUCTION

1.1. Background

The autopilot navigation systems depend on the combination of various sensors to perceive and cognize the surroundings of the systems. The different sensors provide a type of information distinctly, thereby when integrated would be able to operate reliably in complicated and dynamic situations. Global Positioning System is a global positioning system that indicates the location of the system on Earth and hence is very important in the large-scale navigation systems. The IMU promotes the motion tracking process by measuring the acceleration and the angular velocity which enables the system to approximate the movement and the orientation within the short amount of time. The LiDAR sensors are very important in the 3D mapping in that they are used to produce detailed points clouds that portray the structure of the environment. Radar sensors have been effectively applied in detecting objects during bad weather like rain, fog, and dust where other sensor may not work effectively. Also, cameras can offer very abundant visual data, which is useful in such tasks as object recognition, lane tracking, and situational awareness. A combination of all of these sensing technologies allows autonomous systems to be more accurate, robust, and reliable than could be achieved using any one sensor.

1.2. Importance of Autonomous Vehicle Navigation

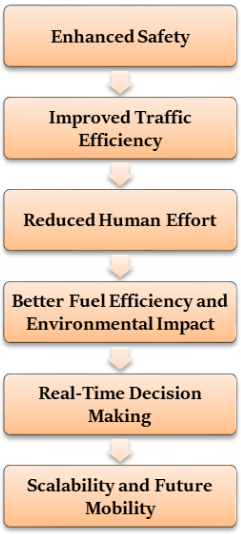

Fig 1 - Importance of Autonomous Vehicle Navigation

1.2.1. Enhanced Safety

Under autopilot navigation, there is much better road safety as compared to human drivers considering that most accidents are caused by human error. The integrated sensing and decision-making systems constantly keep track of the environment, identify clearances and react to the environment quicker than human drivers. This causes improved traffic collisions, lane discipline and traffic compliance hence reducing accidents and contributing to passenger safety.

1.2.2. Improved Traffic Efficiency

Autonomous navigation also allows the most effective traffic flow optimization by providing cars an opportunity to make smart decisions with regards to real time. These systems are capable of keeping the best speeds, limiting unnecessary braking and communicating with other vehicles so that there is no congestion. Consequently, traffic congestions can be kept down to a minimum, travel time will be lessened and general efficiency on the roads will be better.

1.2.3. Reduced Human Effort

Among the most beneficial factors of independent navigation is the decrease in the human aspect in driving duties. The drivers are not under constant attention and manual control which can help alleviate fatigue and stress, particularly on long routes or in the congested roads. This also enables those who cannot drive like the old or disabled people to enjoy the independence mobility.

1.2.4. Better Fuel Efficiency and Environmental Impact

Self-driving cars have the opportunity of streamlining the vehicle behavior, including generating acceleration and deceleration, making the vehicle more fuel-efficient. The efficient route design and congestion are also caused to reduce the consumption of fuel and the level of emission. This is favorable to the environment through decrease of air pollution and encouraging sustainable transportation.

1.2.5. Real-Time Decision Making

Autonomous navigation systems can work with large volumes of data delivered in real time by several sensors. This allows fast and effective decision making in dynamic surroundings e.g. spotting unexpected hindrances or changing road situations. The instant response increases safety levels as well as system performance.

1.2.6. Scalability and Future Mobility

In the future of smart transportation system, autonomous navigation is an important aspect. It assists in the creation of the connected cars, smart traffic systems, and intelligent cities. With the changing technology, it can revolutionize the mobility related to making it easy to share rides, cut down on vehicles on the road, and also enhance transportation infrastructure in general.

1.3. Problem Statement

The autonomous navigation system is very dependent on a precise perception of the environment to make sound and safe decisions. Nonetheless, those systems relying on the use of just one sensor tend to become highly problematic, preventing them from working well in practice. All types of sensor, including GPS, IMU, LiDAR, radar, or cameras have limitations of their nature. An example is that in an urban canyon, or tunnel, the GPS signals may not work relying on signal blockage and multiple path effects and IMU sensors can get drift errors with time. Likewise, the LiDARs also suffer a drop in performance during an unfavorable weather, such as the existence of a fog or rain, and the cameras also could be inconvenienced by poor light or occlusions. These problems add noise, uncertainty and discrepancies to the data, such that it is hard to have a single sensor system which keeps a clean and constant navigation. Besides environmental issues, sensor failure or some outages also lower the reliability of the system. A single-source-based navigation system is very susceptible to failure in case the sensor fails or offers wrong information. This non-redundancy may cause crashes and most importantly in safety applications like autonomous vehicles. Besides, real-world environments are ever-changing and thus require constant adaptation, which the single-sensor systems cannot readily manage effectively because of their narrow scope of understanding. Hence, it is imperative that there is a need to have a coherent and efficient combination of data based on various sensors in a unified structure. A framework like this one must be able to deal with noise and correct the weak points of individual sensors and give a consistent and accurate estimate of the state of the system. Multi-Sensor fusion can be applied to provide high level of robustness, increase accuracy and also be able to operate reliably even under harsh environments by using complementary information between various sensors. It points out the necessity to involve the creation of sophisticated sensor fusion algorithms to the recent autonomous navigational systems.

2. *LITERATURE SURVEY*

2.1. Early Sensor Fusion Techniques

Techniques Statement outlines the early sensor fusion Techniques Early sensor fusion Techniques Statement outlines the early sensor fusion Techniques Early sensor fusion Techniques Statement outlines the early sensor fusion Techniques Early sensor fusion Techniques Statement outlines the early sensor fusion Techniques Early sensor fusion Techniques Statement outlines the early sensor fusion Techniques Early sensor fusion Techniques Statement outlines the early sensor fusion Techniques Early sensor fusion Techniques Statement outlines the early sensor fusion Techniques Early sensor fusion Techniques Statement outlines the early sensor fusion Techniques The pioneering sensor fusion work involved quite simple deterministic methods, in which the results of a combination of several sensors were computed through a fixed combination of weighted averaging. These approaches believed that every sensor had a given contribution of reliability and the fusion process merely combined the information in that way. Although simple and easy to compute, the methods were not flexible. These fixed weighting schemes, past experience showed, in the dynamic settings of a real-life problem, sensor noise or sensor malfunction, or other variation in the environment, caused erroneous or untrusty outcomes. Due to this their use was restricted in complicated or non-certain situations.

2.2. Kalman Filter-Based Methods

Methods that use Kalman Filters led to a major breakthrough in sensor fusion, in which a probabilistic approach was used to estimate system states. Rather than averaging sensor measurements, the Kalman Filter employs measurements and corrections to combine them in an optimum way with time. It incurs neither a certainty in system model nor sensor observations, resulting in more task-true and consistent estimates. Although, this method presupposes that the system dynamics are linear, as well as that noise on the system follows a Gaussian distribution. These assumptions limit its functionality with nonlinear processes or non-Gaussian noise which are ubiquitous in most real-world scenarios.

2.3. Extended Kalman Filter (EKF)

The Extended Kalman Filter is an extension of the standard Kalman Filter that supports nonlinear systems, but approximates them by the use of linearization. It achieves this by applying first-order Taylor series expansion about the existing estimate, thus, it can handle nonlinear relationship among variables. In practice EKF has been used in areas of GPS and the fusion of inertial measurement units with GPS (inertial measurement unit) including robotics and in navigation. Although popular, EKF may also be unstable in cases where the system under consideration being studied has a vivid nonlinear character or when inaccurate initial estimates are provided. This can result in divergence and the estimated value of the state might be far off to the actual state.

2.4. Unscented Kalman Filter (UKF)

Unscented Kalman filter was created to get over the restriction of EKF including the avoidance of explicit linearization. Rather, it employs deterministic sampling method, the sigma points, to represent the mean and covariance of the system more precisely whenever traversing nonlinear transformations. This method can tend to have an effective estimation as compared to EKF, particularly on systems that are highly nonlinear. The better performance however, is at the expense of the more complex computer computation and will not be appropriate in systems with very high real-time or resource limitations.

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2.5. Particle Filter

Particle filters are a more versatile and formidable category of sensor fusion approaches which depend on Monte Carlo sampling approaches. Rather than operating under the assumption of linearity and Gaussian noise, the probability distribution of the system state is estimated using a huge number of random samples, or particles. Every particle is a probability of a state, and the behavior of the particles has the form of a model of uncertainty of the system. This makes particle filters very appropriate in non-Gaussian non-linear and complex environments. They however are computationally sensitive since it is difficult to maintain and update a large number of particles without large processing power and this may be a limitation when it comes to real time usage.

2.6. Multi-Sensor Integration Approaches

The integration of multiple sensors may be classified depending on the level at which the data of various sensors is integrated. Raw sensor data is simply combined in low-level fusion, e.g. LiDAR and radar signal are combined to enhance perception accuracy. Mid-level fusion uses features extracted instead of crude data such as, image features plus depth features in order to detect objects better. At the high level, fusion incorporates the decision or conclusions of single systems (ex: fusing the results of two classification models). The various levels of fusion introduce various trade-offs regarding the computational cost, flexibility and robustness and the resulting selection is dependent upon the application specifications and system limitations.

3. *METHODOLOGY*

3.1. System Architecture

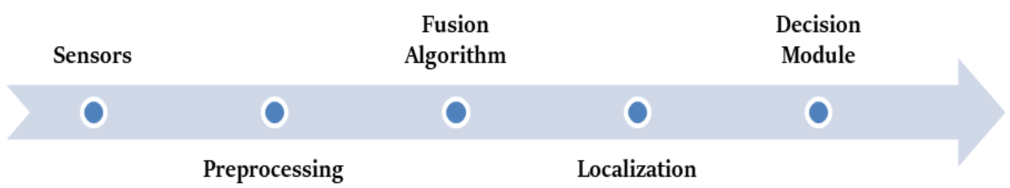

Fig 2 - System Architecture

3.1.1. Sensors

The sensor concept forms the basis of the system as the raw data of the surrounding is gathered. These could be cameras, LiDAR, radar, GPS and inertial measurement units (IMUs). All sensors deliver the various forms of data, such as those delivered by cameras (triggering visual data) and LiDAR (delivering depth and distance indicators). Reliability and coverage is enhanced through the use of several sensors since the shortcomings of one sensor can be offset by others.

3.1.2. Preprocessing

Preprocessing entails cleaning and processing of raw sensor data prior to its utilization in the process of fusion. This step can make use of filtering out noise, normalization of data, and data correlation between multiple sensors, and elimination of outliers. Because sensors usually have varying sampling rates and are prone to noises, preprocessing ensures that the data is made consistent, accurate and usable towards addition analysis.

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3.1.3. Fusion Algorithm

The fusion algorithm is used to amalgamate information of two or more sensors to create a single and more precise information about the environment. Depending on the system needs different techniques that could be adopted include Kalman Filter, Extended Kalman Filter, Unscented Kalman filter or Particle filter. This step enhances the accuracy in estimation by lowering uncertainty that may arise in estimation along with the use of complementary information as provided by other sensors.

3.1.4. Localization

Localization identifies the place and the orientation of the system in its environment. The system is able to determine its present state more correctly through the merged data as compared to looking at a single sensor. It is critical in such applications as robotics, autonomous vehicles, and navigation systems, in which accurate positioning is essential to successful and safe functioning.

3.1.5. Decision Module

The decision module uses the result of localization process and fusion process to make clever decisions. This can be path planning, obstacle avoidance, object recognition or controlling. It is the last part of the system and it interprets the processed information into actionable results and hence the system can react appropriately to its environment.

3.2. Sensor Models

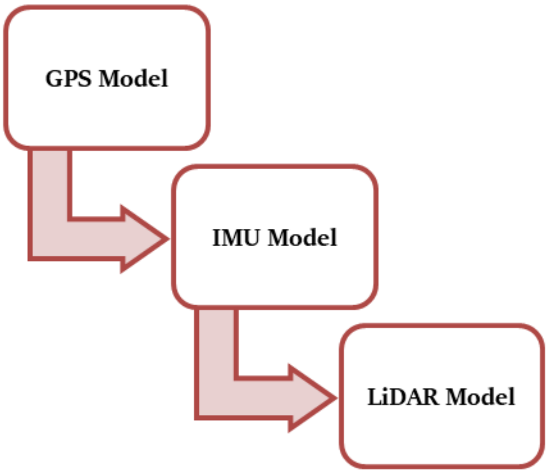

Fig 3 - Sensor Models

3.2.1. GPS Model

The GPS sensor offers the position information globally, which is usually in form of latitude, longitude, and altitude. The observed GPS output may be specified as the actual position of the system as well as a certain amount of noisy measurement. In basic terms, GPS reading is the actual position plus an error margin which is brought about by other issues like atmospheric disturbance, blocked signal and satellite geometry. Even though GPS can be employed in determining the position of people worldwide, its precision may be erratic particularly in the urban settings or where the satellites are not visible.

3.2.2. IMU Model

The Inertial Measurement Unit (IMU) is a device that is used to determine the motion of a system by reporting the acceleration and angular velocity. It generally includes accelerators and gadgets which monitor the linear motion and rotation. The IMU model expresses these measures as the actual value of motion and bias and noise due to imperfection of sensors. IMUs are high-frequency data providing and can be used to track short-term motion; however, they are more likely to drift over the time as a result of errors accumulating and provide inaccurate results when applied independently over many hours.

3.2.3. LiDAR Model

LiDAR sensors are used to measure the distance to surrounding objects by emitting laser pulses, and assessing the time in which the reflections bounce back. The result is most often presented as point clouds which are the spatial representation of the environment. According to the LiDAR model, these distance readings are the actual distance of objects and measurement noise. LiDAR is a well defined and very accurate spatial information source, however, it is sensitive to the climate conditions like rain, fog and reflective surfaces.

3.3. Fusion Algorithm

The proposed algorithm to be used in the fusion is the Extended Kalman Filter (EKF) that is appropriate where the system is characterized by nonlinear dynamics together with a sensor noisy measurements. EKF is summarized to work in two main steps the prediction step and the update step that are performed recursively in order to estimate the state of the system at any given time. During the prediction phase, a mathematical model of the system is used to extrapolate the existing system state. This model uses control inputs, e.g. motion commands, and also predicts how the system changes between time steps. In addition to the state prediction, the algorithm computes the associated uncertainty updating it to include process noise which is an unknown contribution or modeling error. After the prediction step, the update step further refines this guess by the use of new measurements taken by sensors like GPS, IMU or LiDAR. As they are in many cases nonlinear functions of the system state, the EKF simplifies them around the existing estimate so that the calculation can be performed. The innovation or the difference between the predicted measurement and the actual sensor reading corrects the predicted state. The uncertainty of a prediction and a measurement is a weighting factor to the extent of trust placed on either of these issues. The EKF ensures that multiple sensors are used to obtain a more accurate and smooth estimate of the system state effectively by having it go through prediction and update steps sequentially. This will avoid the inference of noise and overcome the drawbacks of individual sensors. But performance of EKF is dependent on correct modeling and may drop in case there are strong nonlinearities in the system or when the assumptions of noise are ill-posed.

3.4. Algorithm Flow

3.4.1. Initialize State

The algorithm starts by setting the state of the system and loosening it. This involves prediction of an initial estimate of the position, velocity and other pertinent parameters based on prior knowledge or initial sensor measurements. This initializing is sensitive to the accuracy with which the algorithm can be started and a faster and effective converging algorithm is obtained. A preliminary covariance is also defined with the state to describe the amount of confidence in the estimate.

3.4.2. Predict State

The algorithm applies a system motion or process model to the current state to come up with an approximation of the state at the next time step in the prediction step. The forecast relies on the past as well as any control values, like movement instructions or foreign forces. In addition to

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projecting the state, the algorithm also provides the update of the uncertainty by taking the process noise into consideration, which includes lack of understanding disturbances and modeling errors. This step will give an approximate forward estimate with the introduction of new sensor data.

3.4.3. Update with Measurements

In the update step, the predicted state is updated with the new measurements that are taken with sensors, like GPS, IMU or LiDAR. The algorithm then compares the actual sensor measurements with the predicted measurement and compares the difference between the sensor and the predicted control numbers, which is the residual. Using this difference and the uncertainties that come with this difference, the state estimate is modified to bring the state closer to the observed data. The step is used to minimize errors, and improves the precision of the system state.

3.4.5. Repeat

With the help of new sensor data, the prediction and update steps are repeated and repeated. The algorithm is a recursive process that enables the system to run the algorithm going in-step with the system state and make adjustments to changes in the environment and sensor inputs. Extra corrections over time ensure stability and accuracy of an estimate and hence the algorithm can be used in dynamic and changing systems.

3.5. Implementation Steps

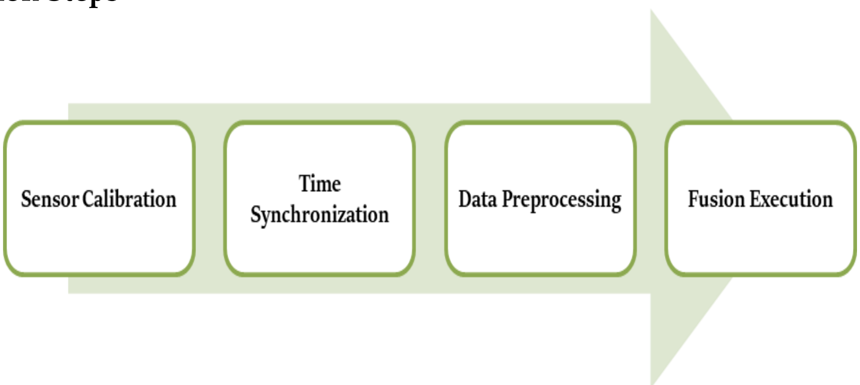

Fig 4 - Implementation Steps

3.5.1. Sensor Calibration

The initial step of implementation is sensor calibration that will guarantee that all sensors are capable of giving correct and consistent output. It includes the detection and fixation of systematic inaccuracies including bias, scale effects and misalignment in sensors, such as GPS, IMU and LiDAR sensors. Calibration can be done by reference standards or controlled environment and it also assists in enhancing data reliability. Calibration itself is crucial since even minor failures may have a huge impact on the work of the fusion system on the whole.

3.5.2. Time Synchronization

Time synchronization is used to be sure that information of various sensors are synchronized in time. Because various sensors may have different sampling rates and delays, it is significant to synchronise timestamps of different sensors, such that a piece of data is at the same time. The fusion process can fuse the wrong data unless it is synchronized correctly hence wrong estimations. Synchronization methods like interpolation, hardware-based synchronization, or timestamp alignment are popular methods applied to solve this problem.

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3.5.3. Data Preprocessing

Preprocessing of data consists entails the preparation of sensor data in the fusion process. This stage involves noise removal, elimination of outliers, normalization types of data and the absence of values. It can also be the conversion of the data into a common coordinate frame and in this way the measurements of the various sensors are able to be compared and combined. Preprocessing enhances quality of data and makes the fusion algorithm run on clean and consistent inputs.

3.5.4. Fusion Execution

The next phase is fusion whereby the processed sensor information is combined with the help of a selected fusion algorithm, say the Extended Kalman Filters. This algorithm involves the system model predictions together with the real-time sensor measurements used to estimate the system state. This process is continuous and the state is updated with new information when new information is received. The fusion process can be effectively implemented to be important in real-time applications since the functionality can be affected directly by the response and accuracy of the system.

4. RESULTS AND DISCUSSION

4.1. Performance Metrics

It is necessary to evaluate the performance of a sensor fusion system with respect to its effectiveness and robustness in the real-world applications. Among the main measures is the localization accuracy that is used to evaluate the similarity of the estimated position and orientation of the system with the actual values. Very high localization performance is important in tasks like autonomous vehicle and robotics because even marginal inaccuracy can cause great operational problems. This metric is normally measured in error distances or deviation on ground truth data, and optimized by appropriate combination of complementary sensor signals. Detection rate is another key measure, which is used to describe the aptitude of the system to detect objects and events in the environment correctly. The high detection rate means that the system is able to identify the relevant features (obstacles, landmarks or targets) with minimum undetected errors. This is especially essential in safety critical applications, failure of which detection of an object may cause failure of the system or accidents. The rate of detection is usually measured in conjunction with the false positives to make sure that there is a balance in the system in regard to its sensitivity and precision. Another important performance measure is system reliability because it indicates system consistency and stability at different conditions. A stable system will keep on operating in a predictable manner even though there is noise or sensor malfunctions, or change in the environment (weather, light, etc.). This measure is used to measure how effectively the fusion algorithm responds to uncertainties and how effective it is sustained through time. The combination of localization accuracy, detection rate, and system reliability give an overall evaluation of the sensor fusion system and measures that it is an efficient, safe and sound system in changing environments.

4.2. Results Table

Table 1: Results Table

Method	Accuracy (%)	Detection Rate (%)	Reliability (%)
GPS	65%	60%	70%
IMU	70%	65%	72%
LiDAR	80%	78%	82%
EKF Fusion	92%	90%	94%
Particle Filter	95%	93%	96%

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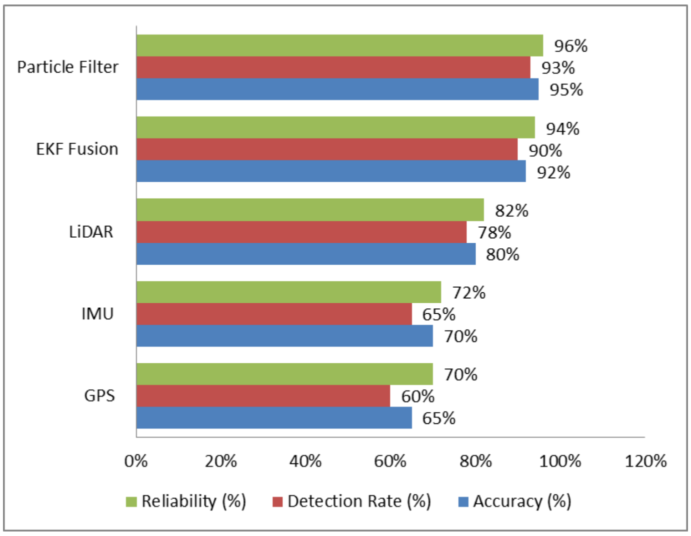

Fig 5 - Results Table

4.2.1. GPS

Localization and detection with the help of GPS only offers moderate performance because it uses the satellite signals. This measurement at 65% indicates a restriction to signal noise, multipath error and lack of accuracy in urban or observer-blocked conditions. The rate of detection being 60 percent can be known to imply that GPS is not applicable in identifying objects or other features of the environment. Nevertheless, it is also not very precise as it has a reliability of 70% which indicates it can still be used in normal conditions to give consistent global positioning although with low precision.

4.2.2. IMU

IMU-only method is slightly better than GPS method and has an accuracy of 70 percent with a detection rate of 65 percent. IMUs deliver continuous movement information, assists in short-term prediction of the movement and orientation. Yet, the overall accuracy remains low due to drift errors that occur as time goes by. The stability of 72% indicates that in the short term, IMUs are good; however, to allow the use of the sensor over a long period, the sensor has to correct the IMU.

4.2.3. LiDAR

These systems with LiDAR alone are much better performing with the accuracy of 80% and a detection rate of 78%. This is due to the fact that LiDAR offers accurate path measurement of distances and rich mapping of the environment based on point clouds. It has a reliability of 82%. This implies that LiDAR is consistent in most applications. The environmental conditions however can interfere with its performance like in fog, rain or reflective surfaces to attain a perfect accuracy.

4.2.4. EKF Fusion

Extended Kalman Filter fusion strategy takes into consideration facts obtained through more than two sensors, which leads to significant increase in the performance. Having an accuracy of 92, and a detection rate of 90, the system is advantaged by reduced uncertainty and resultant sensor information. The 94% reliability demonstrates that the fusion method is able to deal with noise and sensor constraints and gives consistent and stable results under varying conditions.

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4.2.5. Particle Filter

Particle Filter method has the best performance rate compared to all the others as it had the accuracy, detection rate and reliability of 95 percent, 93 percent and 96 percent respectively. This is because it is able to treat non-linear and non-Gaussian noise better than other approaches. It gives the estimate of the system more flexibility and precision by representing the possible states of a system with numerous particles. There is a price to this improvement performance, though, namely increased computational complexity, making it potentially not applicable in real-time applications.

4.3. Discussion

It is evident in the results that sensor fusion is instrumental in enhancing localization and detection systems. To a point, individual sensors like GPS, IMU and LiDAR have inherent drawbacks, like noise, drift, and environmental sensitivity. Cases of use alone diminish accuracy and reliability like is witnessed in the previous findings. These however, when put together in groups of several sensors the fusion techniques take advantage of the strengths of each and also negate the weaknesses of each. This makes sensor fusion a very necessary element in the current intelligent systems as it leads to a great enhancement in the localization accuracy, detection rate and system reliability. Out of all the fusion methods, the Extended Kalman Filter (EKF) provides an advantageous compromise between the complexity of computations versus performance. It is suitable with nonlinear systems as it linearizes these systems yet with rather low computation needs in comparison to sophisticated techniques. This renders EKF being viable in real-time applications like robotics and autonomous navigation where efficiency and precision are of importance. In spite of the fact that it can hardly perform well in a highly nonlinear situation, its overall performance can still be a strong and steady in the majority of practice cases. Particle filters on the other hand are the most accurate and most robust, especially in the complex and nonlinear environments. Their non-Gaussian noise modelling combined with the possibility to describe and model multiple possible states of the system can be more precisely estimated. Such benefit, however, is along with greater computational liabilities, where significant quantities of particles need to be kept in continuous movement. Consequently, particle filters are an ideal match when used in the applications where high accuracy is required, however, they do not necessarily apply to the systems that have limited processing power or have to operate within tight real-time limits.

5. CONCLUSION

The current paper has shown a detailed work regarding the autonomous vehicle navigation in terms of sensor fusion algorithms with a significant emphasis put on the interconnection and combination of numerous sensing modalities with the aim of ensuring the reliability and accuracy in system operation. Each sensor, GPS, IMU, and LiDAR can give useful information about the surrounding environment and the system condition, still, all of them have universal vulnerabilities that are noises, drift, signal loss, and environmental sensitivity. Depending on one sensor can often lead to partial or inaccurate estimate especially in dynamic and complex real world situation. Combining data of several sensors, sensor fusion methods solve them successfully and result in enhanced resilience, stability, and accuracy of navigation activities.

The research examined the traditional probabilistic approaches of fusion, especially Extended Kalman Filter (EKF) and particle filters. These methods give a mathematical model of the way to deal with uncertainty and noise in sensor data, which is more effective to estimate the state over time. It was demonstrated that the EKF provides a tradeoff between computational efficiency and performance, being suitable in real-time applications including autonomous driving and mobile robotics. Its capacity to deal with relatively small nonlinearities, with fairly low cost of computation, has enabled it to be a very popular solution in most real-world systems. Particle filters on the contrary performed better over nonlinear and non-Gaussian environments by attempting to model the system state based on multiple hypotheses. This can be used to create more flexibility and accuracy, especially in problematic cases, yet comes at a higher computational cost.

The experimental findings were used to reinforce the hypothesis that sensor fusion process proves to be much better than single sensor methods in terms of accuracy of localization, detection rate coupled with system reliability. The fusion-based techniques always played a better role than single sensors through the complementary information and suppression of the effects of noises and uncertainties. This supports the notion that sensor fusion is a primary need to reach high-performance autonomous systems, particularly in safety critical industry models like self-driven cars.

In perspectives, future studies can be centered on incorporation of new and superior methods like deep learning based fusion, which has the potential of automatically learning the higher-order links amidst sensor data. Also, the attempt to optimize in real-time with efficient implementation will be important in deploying these algorithms within the resource-bound environment. In general, the further development of sensor fusion technologies will be extremely important to create smarter, more reliable, and autonomous systems in the future.

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