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A COMPARATIVE STUDY OF KALMAN FILTERS AND PARTICLE FILTERS FOR LOCALIZATION IN DYNAMIC SETTINGS FOR SLAM IN UNKNOWN ENVIRONMENTS

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Abstract

Simultaneous Mapping and Localization (SLAM) is a technique used by autonomous vehicles to navigate in GPS denied environments. Two of the most used methods for state estimation in SLAM are Kalman Filter (KF) and Particle filter (PF). Kalman filter is used for estimation in linear systems with Gaussian noise. Few examples of KF applications are autonomous vehicles, aircraft navigation, industrial automation, etc. Particle filters are essential for nonlinear systems with nonlinear Gaussian noise. Few examples of PF application are sensor fusion, start tracking, aircraft navigation. In this paper we discuss an experiment to compare the 2 filers and conclude on which is better and more efficient method for navigation.
Index Terms— Navigation, Localization, Simultaneous Localization and Mapping (SLAM), sensor fusion, Particle Filter (PF), Kalman Filter (KF), Laplace

I. INTRODUCTION

SLAM is used by autonomous vehicles to create a dynamic map and locate the robot relative to the map. This map keeps updating as the robot moves forward and explores further. Kalman Filters and Particle Filters are commonly used for state estimation in SLAM. Each method has distinct strengths and limitations. This study compares their performance in dynamic settings, evaluating which is more suited to robust localization in real-world applications.

1.1 Overview of Kalman and Particle Filters

1.1.1 Kalman filter: Kalman Filter is a mathematical algorithm that is used for state estimation in linear dynamic systems with Gaussian noise. The filter algorithm works in stages, prediction and update. In the prediction phase, the filter forecasts the system's next state, and its associated uncertainty based on a known state transition model and control input. This step provides a prior estimate of the system's state. In the update phase, the Kalman Filter corrects this estimate using new measurements from sensors, accounting for their associated noise. The correction is weighted by the Kalman gain, which determines how much trust to place in the prediction versus the observation. This recursive process continues, refining the state estimate over time. The Kalman

Filter is widely used in fields such as robotics, autonomous vehicles, and aerospace for tasks like navigation, target tracking, and sensor fusion.

1.1.2 Particle Filter: The Particle Filter (PF) is a Bayesian estimation technique designed for non-linear with non-Gaussian systems, making it particularly useful in applications where the Kalman Filter (KF) fails. It operates by representing the system's state distribution using a set of particles, each representing a possible state hypothesis. These particles are propagated over time using the system's dynamic model, and their weights are updated based on how well they align with new observations. The filter uses a process called resampling to focus computational resources on the most probable states, eliminating particles with low weights and duplicating those with high weights. This enables PF to handle multi-modal distributions, where there are multiple likely state estimates. Particle Filters are widely used in robotics, particularly for SLAM (Simultaneous Localization and Mapping), as they can effectively estimate a robot's position in environments with ambiguous or incomplete sensor data. They are also applied in target tracking for defense systems and financial modeling for systems with complex, stochastic behaviors. Despite their flexibility, PFs can be computationally expensive, as accuracy depends on the number of particles used. They may also suffer from particle depletion, where all but a few particles have negligible weights, reducing estimation quality. Nonetheless, their ability to model highly non-linear and non-Gaussian systems makes them indispensable in many real-world scenarios.

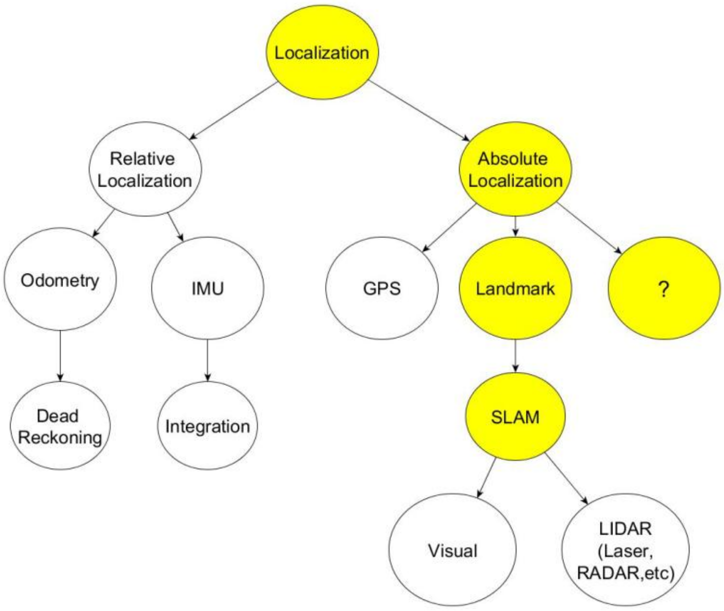

Fig1: Sensor Fusion Flowchart

II. METHODOLOGY

A SLAM environment is simulated in MATLAB with varying Levels of noise for the sensor outputs, dynamic objects and non-linearity. A dynamic model of a ground robot is developed using equations of motion and Laplace theorem of energy. A trajectory following control model is developed using PID for the robot to follow to certain trajectories like circular, eclipse. The robot's actual position is calculated by a dead reckoning method with incorporating noise to imitate a real-life scenario. The robot's states are then estimated using the KF and PF and then the results are analysed. Accuracy is measured by the Root Mean Square Error (RMSE). The robustness is assessed by the filter's ability to handle noises and dynamic objects.

III. LIMITATIONS AND CHALLENGES

Kalman filters and Particle filters have their own positives and negatives. A few pros of Kalman filters are they have faster computing abilities as compared to particle filters. They provide good estimation where the system has gaussian noise and can be linearized around some points. The drawback of Kalman filter is it becomes unreliable in nonlinear environments. The drawback of particle filters is that require high computational time and memory. They also require a change of data throughout the sampling time. A few pros of particle filter are they work efficiently in highly nonlinear environments with non-Gaussian errors which makes it suitable for nonlinear environments.

IV. RESULTS

The Kalman Filter outperformed the Particle Filter in both accuracy and computational efficiency when the environment was linear with Gaussian noise, when non-linear dynamics or non-Gaussian noise were increased the environment, the Particle Filter's performance outshined the KF. Its ability to model complex distributions enables it to maintain accurate state estimates even in challenging conditions. With increased accuracy comes increased computational time and resources for the PF

V. CONCLUSION

1. Both the filters work efficiently depending on the specific situation.
2. KF is ideal for systems with linear dynamics and Gaussian noise, offering computational efficiency and optimal state estimation.
3. In contrast, PF provides a more flexible and robust solution for non-linear, non-Gaussian systems, albeit at a higher computational cost.

REFERENCES

1. Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. Journal of Basic Engineering, 82(1), 35-45.
2. Doucet, A., de Freitas, N., & Gordon, N. (2001). Sequential Monte Carlo Methods in Practice. Springer.
3. Julier, S. J., & Uhlmann, J. K. (1997). A new extension of the Kalman filter to nonlinear systems. Proceedings of AeroSense: The 11th International Symposium on Aerospace/Defense Sensing, Simulation, and Controls.
4. Fox, D., Burgard, W., & Thrun, S. (1999). Markov localization for mobile robots in dynamic environments. Journal of Artificial Intelligence Research, 11, 391-427.

5. Van der Merwe, R., & Wan, E. A. (2001). The square-root unscented Kalman filter for state and parameter-estimation. Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing.
6. Montemerlo, M., Thrun, S., Koller, D., & Wegbreit, B. (2002). FastSLAM: A factored solution to the simultaneous localization and mapping problem. Proceedings of the AAAI National Conference on Artificial Intelligence.