Estimation of position and velocity of simulated ball using Sensor Fusion techniques

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***Abstract*—Paper investigates use case of Kalman and Particle filters to estimate the trajectory of a thrown ball. These Filter is powerful techniques for sensor fusion to estimate the states of any system, and commonly used in various fields. They work by using the simulated model and observations over time to iteratively estimate the state of the system. Both sensor fusion algorithms have been implemented on a commonly used ball-throwing example to estimate the position and velocity states of the ball from the noisy observation samples. In this paper, I will explain basic use of the Kalman and Particle filter, as well as the assumptions made during their realization. In addition, this paper also examines filter's robustness to sensor measurement dropout, when the system state temporarily fails for a certain period of time leading to missing observations.**

***Index Terms*—kalman filter, particle filter, state estimation, projectile motion, ballistic trajectory**

I. Introduction

What is the topic and why is it worth studying? The Introduction commonly describes the topic under investigation, summarizes or discusses relevant prior research, identifies open questions and problems and provides an overview of the research that is to be described in greater detail in the sections to follow. - Using the powerful tools to estimate the state of the object updating the over time on simple examples can help us to understand behaviour of fusion system.

Example: Ballistic trajectory estimation is a common problem in physics and engineering. It is a fundamental task that arises in a variety of applications, such as missile guidance, rocket flight, and sports analytics. The aim of this study is to leverage the strengths of Kalman and Particle filters in state estimation, as well as understanding how they cope with measurement noise and dropout periods.

The Kalman Filter is a powerful tool for state estimation and has been widely used in various fields such as control, navigation, and signal processing. It works by using a system model and measurements to iteratively estimate the state of a system. In particular, it can estimate the state of a linear system with Gaussian noise optimally, given a set of assumptions about the system and measurement models. However, these assumptions may not always hold in practice, and the filter's performance may degrade significantly in the presence of non-linearities, non-Gaussian noise, and model uncertainties. Additionally, it may not perform well in scenarios where measurements are incomplete or missing, which can be common in real-world applications.

The Particle Filter, on the other hand, is a non-parametric filter that can handle non-linear and non-Gaussian models. It works by representing the posterior distribution of the state using a set of weighted particles, which are propagated through the system model and resampled based on the likelihood of the measurements. Unlike the Kalman Filter, it does not make any assumptions about the system or measurement models, and can handle arbitrary non-linearities and non-Gaussian noise. However, it can be computationally expensive and may suffer from particle degeneracy, especially in high-dimensional state spaces.

In this paper, we will provide an overview of these two filters and their mathematical basis, as well as the assumptions made in their implementation. We will also investigate their performance in estimating the trajectory of a thrown ball under various levels of measurement noise and dropout periods. Our results will demonstrate the effectiveness of these filters in state estimation and shed light on their behavior in scenarios where measurements may be incomplete, noisy, or non-linear. We will also discuss the implications of our findings for real-world applications, and suggest possible directions for future research.

Overall, this paper provides a comprehensive analysis of the Kalman and Particle filters' implementation for trajectory estimation and their robustness to measurement noise and dropout. Our results demonstrate the effectiveness of these filters in estimating the trajectory of a thrown ball and shed light on their behavior in scenarios where measurements may be incomplete, noisy, or non-linear. This study will contribute to the understanding of state estimation techniques and their applications in various fields.

II. Sensor Fusion Methodology

We conducted experiments to investigate the performance of the Kalman Filter and Particle Filter in estimating the trajectory of a thrown ball. The experiment involves a hypothetical scenario of two balls launched from different heights, and with distinct velocities, modeled with both the Kalman Filter and the Particle Filter.

A. Kalman Filter

What did you do? A section which details how the work was performed. It typically features a description of the methods that were involved. A rule of thumb is that this section should be sufficiently detailed for another researcher to duplicate your research. You should also address the theoretical background of your specific problem solutions for the task at hand, taking into account the issues raised above.

//The methodology for the Kalman Filter involves a discrete white noise model to represent the inherent noise in the model prediction and the measurements. We estimate the trajectory of the thrown ball using the Kalman Filter and evaluate its performance under various levels of measurement noise and dropout periods.//

B. Particle Filter

What did you do? A section which details how the work was performed. It typically features a description of the methods that were involved. A rule of thumb is that this section should be sufficiently detailed for another researcher to duplicate your research. You should also address the theoretical background of your specific problem solutions for the task at hand, taking into account the issues raised above.

//In the case of the Particle Filter, a set of particles, each representing a possible state of the system, is initiated. These particles are then propagated over time based on the laws of physics, with random noise added to mimic the inherent uncertainty in the real-world scenario. Each particle's state is observed with added noise, representing the measurement process's inaccuracy. The Particle Filter provides a set of probable system states, considering all particles' states. We estimate the trajectory of the thrown ball using the Particle Filter and evaluate its performance under various levels of measurement noise and dropout periods.//

III. Experiment Results

How well does it work? The evaluation must show that your implementation works correctly. Use appropriate datasets to represent specific properties of the algorithm and discuss them. Evaluate the accuracy of your implementation's estimation accuracy and explain your results with respect to the following parameters: - Different launch positions, launch directions and launch velocities of the ball(s). - Different time intervals between observations. Experiment also with the complete failure of the observations of different duration. How do you model this failure? - Different initial parameters.

A. Kalman Filter

The Kalman Filter demonstrates excellent performance in estimating the projectiles' trajectories, even during periods of measurement dropout. Our findings demonstrate that the Kalman Filter is not affected significantly by measurement dropout, and it can still provide accurate estimates of the projectile's trajectory.

B. Particle Filter

//The Particle Filter effectively provides a representation of the possible states, considering the uncertainty in the system's dynamics and measurements. Our findings show that the Particle Filter can estimate the trajectory of the thrown ball even in the presence of significant measurement noise and dropout periods. Furthermore, a plot comparing the particles at different time steps illustrates the filter's effectiveness in tracking the balls' trajectories.//

C. Evaluation

//The findings of our study underline the remarkable robustness of both the Kalman Filter and the Particle Filter when dealing with measurement noise and dropout. Both filters utilize the system's dynamics to predict future states during the dropout period, maintaining an acceptable error margin and providing accurate trajectory estimates. The results of our experiments demonstrate the effectiveness of these filters in estimating the trajectory of a thrown ball and shed light on their behavior in scenarios where measurements may be incomplete, noisy, or non-linear.//

IV. Conclusion

A brief summary and outlook of questions to be explored in the future. //This comprehensive application of the Kalman Filter and Particle Filter in a ballistic motion context offers enlightening insights into these filters' potential and limitations. The study reinforces their position as powerful tools in managing state estimation problems involving uncertainties and measurement dropouts. Our future research will probe into investigating advanced filter tuning methodologies, employing non-linear models, and scrutinizing the filters' performance under various types of measurement noise models. Further, we intend to explore more advanced sequential Monte Carlo methods, such as the Rao-Blackwellized Particle Filter.//

References

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References

[1] R. E. Kalman, "A new approach to linear filtering and prediction problems," Journal of Basic Engineering, vol. 82, no. 1, pp. 35–45, Mar. 1960.

[2] A. Doucet, N. de Freitas, and N. Gordon, Eds., Sequential Monte Carlo Methods in Practice. New York, NY, USA: Springer-Verlag New York, Inc., 2001.

[3] A. Doucet, S. Godsill, and C. Andrieu, "On sequential Monte Carlo sampling methods for Bayesian filtering," Statistics and Computing, vol. 10, no. 3, pp. 197–208, Jul. 2000.

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