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Comparison of Kalman Filter and Particle Filter Used for Localization of an Underwater Vehicle

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Abstract - This paper compares filtering methods used for localization of an underwater robot: Kalman filter and particle filter. Kalman filter and particle filter are major filters for estimation of robot pose on the ground. They are adapted for underwater robot localization. While Kalman filter can be used for linear or linearized processes and measurement system, the particle filter can be used for nonlinear systems. Also, the uncertainty of Kalman filter is restricted to Gaussian distribution, while the particle filter can deal with non-Gaussian noise distribution. In cases where abrupt sensor noise is rarely observed, both filters work fairly well. However, when sensor noise exhibits jerky error, Kalman filter results in location estimation with hopping while particle filter still produces robust localization. The paper also compares performance of these filters under various measurement uncertainty and process uncertainty. The methods are compared and verified through experiments.

Keywords - Underwater robot, Localization, Particle filter, Kalman filter, Filtering method

1. Introduction

Localization is one of the oldest and most extensively worked on research area in the underwater robotics. Nevertheless it is still the hottest topic of investigation and crucial factor for successful navigation and operation of an underwater robot. This paper focuses on two of the most promising localization methods: Kalman filter[1, 2] and particle filter[3, 4] method. These methods are based on Bayes filtering approach[5] which incorporates internal system state transition information and measurement information. The measurement information reflects the state with respect to external references, such as the distance and bearing with respect to external beacons or landmarks whose locations are given.

Some of the methods which use only the external measurement information are trilateration and triangulation[6-8]. They usually use least squares method to obtain the most probable location of a robot as well as to eliminate the mismatch of the measurements due to sensor uncertainty. Since they rely only on external sensing for localization, they are prone to produce wild answers leading to volatile location estimation. Internal state transition information added to the external measurement data enhances robustness and precision of the location estimation in cases of Kalman filter and particle filter.

A particle of the particle filter corresponds to an estimated state. Particle filter uses multiple particles to represent the distribution of estimation. So in case of localization in an underwater environment the particle is a vector of six elements: three for rectangular coordinates and three for heading angle in three dimensional space. The particle distribution depicts the actual distribution more closely as the number of particles increases. However, more particles require more computation time. The number of particles is determined by trading the update rate off the precision and reliability of the estimation.

This paper compares and verifies the performance and features of the KF and PF method through experiments. The experiment uses indoor mobile robot instead of underwater robot. To bring about the effect of acoustic range measurement in underwater environment, the measurement of range from beacons which emits ultrasonic signal is used. To keep the experiment compatible with the test in underwater environment, ranges from beacons are used as the sensor measurements which correspond to the range data from acoustic underwater beacons. The motion commands of surge rate and yaw rate are available in the experiment.

Section 2 summarizes the EKF method and particle filter method used for localization. Section 3 compares the methods using experiments. Section 4 concludes the results and suggests further researches.

2. Kalman filter and particle filter used for localization

The Kalman filter and particle filter method are based on Bayes filter approach which is depicted on Figure 1. At every sampling time, the methods predict the state estimation using internal information such as surge and yaw rate measured by encoders or speedometer. Then they correct the predicted state estimation by incorporating the external measurement information such as the distance to beacons or range and bearing to landmarks. The algorithm of Kalman filter and particle filter for localization are well described in reference by Sebastian[9].

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Localization $KF(\boldsymbol{X}_{t-1|t-1}, z_t^{in}, z_t^{out})$

1. $\overline{\boldsymbol{X}}_t$ = *Time update*$(\boldsymbol{X}_{t-1}, z_t^{in})$
2. $\boldsymbol{X}_t$ = *Measurement update*$(\overline{\boldsymbol{X}}_t, z_t^{out})$
3. *return* $\boldsymbol{X}_t$

Fig. 1. Fusion of internal and external information by Bayes filter approach.

Kalman filter has some restriction on system model and features of uncertainty in application. It can be usually applied when state develops according to linear transition equations and the measurement is linearly related to states. In addition, the uncertainty in state transition and measurement is supposed to be Gaussian. On the contrary, particle filter can deal with arbitrary state transition and measurement. Also, uncertainty in state transition and measurement may not be Gaussian. So, the particle filter can be more widely applicable than the Kalman filter.

Figure 2 shows an example of estimation result and uncertainty distribution of Kalman filter and particle filter estimation. Kalman filter yields one estimation result and its uncertainty is described by the error covariance which is shown as an ellipsoid. Particle filter provides particle distribution as the result for estimation and uncertainty distribution.

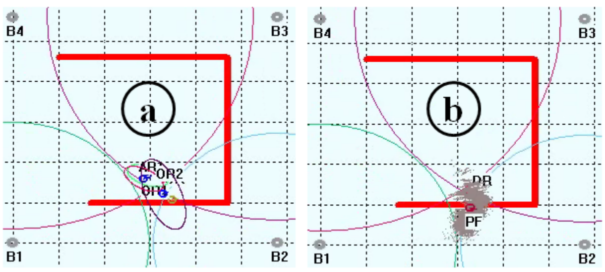

Fig. 2. Estimation and uncertainty distribution of Kalman filter and particle filter.

3. Experiments

The experiment uses a differential drive robot and four beacons for range measurement. A beacon emits ultrasound signal and the robot receives the signal and calculates the distance using the time difference between the transmission and reception of the signal. Table 1 shows the location of the four beacons and the way points of the robot motion. The robot makes six round-trips from the way point 1 to way point 4 in sequence.

Table 1. Way points and the location of four beacons.

	Way points(m)	Beacons(m)
1	(1.7, 1.0)	(0.0, 0.0)
2	(4.7, 1.0)	(5.8, 0.0)
3	(4.7, 4.6)	(5.8, 5.6)
4	(1.0, 4.6)	(0.0, 5.6)

Figure 3 shows the localization result by the dead-reckoning. Figure 4 and Figure 5 show the result for the extended Kalman filter and particle filter respectively. The Kalman filter method requires computation time of 7.956×10^{-5}sec while the particle filter requires 4.445×10^{-2}sec on average with the number of particles 15,000. As shown on the figure, though it is not so remarkably noticeable, particle filter estimation results in smoother and robust trajectory than does the extended Kalman filter.

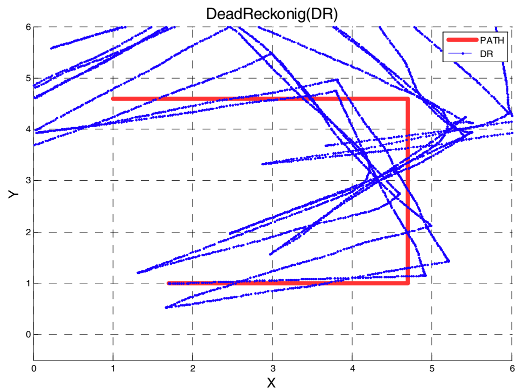

Fig. 3. Trajectory estimation using dead-reckoning method.

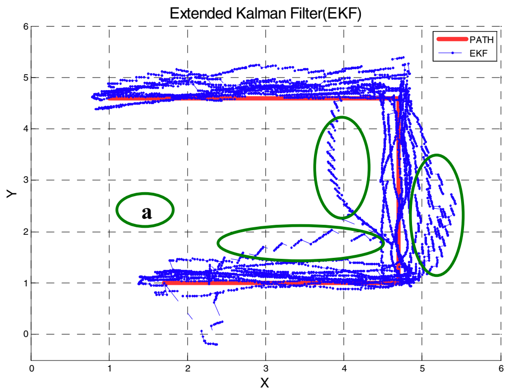

Fig. 4. Trajectory estimation using extended Kalman filter method.

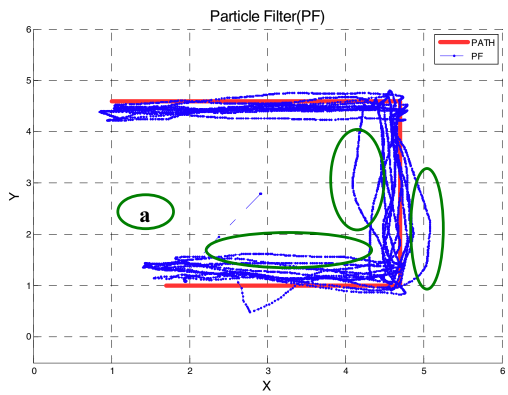

Fig. 5. Trajectory estimation using particle filter method.

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4. Conclusions

This paper compares the performance of the Kalman filter and particle filter in location estimation of an underwater robot. Both of the methods result in much better performance than the trilateration, triangulation, and least squares method. Though the particle filter results in smoother and more robust trajectory estimation, it consumes longer computation time than the extended Kalman filter. The result can be used for selection of proper localization method for underwater robot navigation. For further research it is required to investigate the topic in real underwater environment which facilitates six dimensional motion and considerations on hydrodynamic effects.

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