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Ship navigation via GPS/IMU/LOG integration using adaptive fission particle filter

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ABSTRACT

To achieve a continuous and accurate navigation solution that avoids interruption, GPS is integrated with dead reckoning techniques such as inertial navigation and speed log. A common approach to obtain a low-cost navigation solution is to utilize a multisensor system consisting of MEMS-based inertial measurement unit (IMU), and the whole system is integrated with GPS. However, these sensors provide significant inherent errors because of their complex error characteristics. Particle filter (PF) is considered as a nonlinear filtering technique to accommodate for arbitrary inertial sensor characteristics and motion dynamics. An adaptive fission PF (AFPF) method is proposed to overcome the shortcoming of sample impoverishment problem and improve particle quality. Moreover, further improvement of the MEMS-based IMU/GPS integration navigation system performance during GPS unavailability is achieved by integrating measurement updates from speed log data. The performance of the proposed GPS/IMU/LOG integration using AFPF is evaluated by sea trial, and results indicate that the AFPF solution outperform three different solutions.

1. Introduction

The integration of the Global Positioning System (GPS) and Inertial Navigation Systems (INS) can provide navigation information (position, velocity and attitude) (Chu et al., 2013) and has been widely used for marine navigation applications around the world. In the integrated navigation system, high-precision position and velocity information of ship can be provided by the outputs of GPS, while accurate and reliable attitude information can be provided by INS in the short time. It is clear that integrated navigation system enables to adequately exploit the superiority of the individual systems, such as the consistently high-precision trajectory information of GPS and the short period stability of INS.

GPS/INS integrated navigation is the use of GPS information to correct a solution from INS. However, in hostile environment or serious interference, the GPS satellite signal is non-availability and it is difficult to achieve continuous location. Meanwhile GPS suffers from its own drawbacks and errors. However, it suffers from multipath effects and its signal may easily be blocked or lost under certain environment. Furthermore, INS navigation accuracy degrades rapidly with time on condition that no external aiding source is provided (Georgy et al., 2011). The performance of the INS/GPS navigation solution descended rapidly over time, which lead to severe error growth during periods of GPS unavailability. The three methods to solve this problem are using higher precision INS, adding auxiliary equipment such as speed log and using advanced algorithm and technology. This paper will combine the latter two methods to improve the accuracy.

A low-cost inertial measurement unit (IMU) such as MEMS-based is preferred for ship navigation. These IMUs also have other advantages such as small size, light weight, and low-power consumption. The accuracy of MEMS-based inertial sensors decreases with time, which leads to severe positional error growth in MEMS-IMU/GPS navigation solution during GPS unavailability. The frequently used Linearized KF (LKF), require a linearized system model for the navigation error states, and its effectiveness has been demonstrated in many works (Chen, 2012; Loiola et al., 2011; Roshany-Yamchi et al., 2013). In order to extend KF to the nonlinear system, many modified KFs, e.g., extended KF (EKF) and unscented KF (UKF), have been provided. The commonly used KF-based integration algorithms, Linearized KF and Extended KF (EKF), use linearized system model for the navigation error states. Nevertheless, the performances of these modified KFs depend on the considered system, and poor state estimation results will be obtained for the system with high nonlinearity. These KF-based navigation solutions suffer from divergence during GPS unavailability on account of approximations

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during the linearization process and system mismodeling (Noureldin et al., 2009).

Nonlinear estimating techniques like the particle filter (PF) (Doucet et al., 2000) is not limited to model characteristics and deals with nonlinear problems more effectively. Also, PF can unite prior knowledge and observation information to approximate the optimal filters on condition that a Monte Carlo simulation and recursive Bayesian framework are applied. PF were recently explored to improve the performance of IMU/GPS integration using different approaches (Zhou and Loffeld, 2010; Rigatos, 2012; Georgy et al., 2012; Jwo et al., 2013; Li and Sun, 2014; Yin and Zhu, 2015; Rabbou and Elrabbany, 2015; Xia and Wang, 2016). Owing to its ability to handle with nonlinear non-Gaussian models, PF can adapt any sensor characteristics and motion dynamics. Yet, there are still some serious problems encountered in the general PF, i.e., particle impoverishment. Particle impoverishment is inevitable in virtue of the random particles prediction and re-sampling used in generic PF, such as, under conditions of the likelihood distribution are far away from the generated particles, their particle weights will be close to zero with only a few particles carrying significant weights, making other particles not efficient to produce accurate estimates, causing estimating errors. Intelligent particle filter (IPF) (Yin and Zhu, 2015) is inspired from the genetic algorithm. In IPF, the genetic-operators-based strategy is designed to further improve the particle diversity. But the effectiveness of IPF is influenced by the parameters α and p_M.

With the objective to improve the performance of PF in GPS/INS integrated navigation system, an adaptive fission PF (AFPF) method is proposed to overcome the shortcoming of sample impoverishment problem and improve particle quality. In this approach, the process engenders “offspring” particles, which are called fission. A fission factor that is correlative with the particle weight is applied, making sure that particle diversity is well maintained. The use of this AFPF leads to an enhanced performance.

In addition to the use of AFPF, further improvement of the navigation system performance during GPS unavailability is achieved by integrating measurement updates from other sensors. The first enhancement is due to the use of velocity obtained from the ship's log. The integrated system solution has another advantage, which is that measurement update of the velocities by exploiting the nonholonomic constraints on vessel movements. The second approach to achieve an enhanced solution is to apply with roll and pitch reckoned from the transversal and longitudinal accelerometers readouts together with the speed log readouts as a measurement update in AFPF, so as to updating roll and pitch reckoned from gyroscopes. The updates play the role of aid the IMU and restrict the growth for positional error during GPS degradation or blockage and thus keep a high accuracy navigation solution. The performance of the proposed AFPF based navigation solution by integrating a MEMS-based gyroscope, the speed log, and the GPS is examined by sea trial near Dalian port and compared to other solutions for IMU/LOG/GPS integration on condition that same sources of update as PF and velocity updates during GPS outages, and to KF solution for IMU/GPS integration without any update during GPS unavailability. In this paper, a loosely coupled integration scheme is used.

2. Problem statement

In order to evaluate the state of the vessel x_k at the current time step k, given a group of measurements or observations $Z_k = \{z_0, \ldots, z_k\}$ achieved at time steps 0,1, …,k. x_k is the state vector, which includes the position, velocity, Euler angles, can be defined as

$$x_k = \left[\varphi_k, \lambda_k, h_k, v_k^e, v_k^n, v_k^u, p_k, r_k, A_K\right]^{\mathrm{T}} \tag{1}$$

where φ_k, λ_k, h_k are the latitude, longitude, and altitude, v_k^e, v_k^n, v_k^u are the velocities along east, north, and vertical up directions, and p_k, r_k, A_K are the pitch, roll, and azimuth angles.

The nonlinear system model can be defined as

$$\begin{cases} x_k = f(x_{k-1}, u_{k-1}, w_{k-1}) \\ z_k = h(x_k, v_k) \end{cases} \tag{2}$$

where $u_{k\text{-}1}$ represents the IMU outputs related to the motion between time steps k-1 and k, and $w_{k\text{-}1}$ stands for the process noise, v_k and z_k are measurement noise the measurement vector, respectively. $x_{k\text{-}1}$ is state of the vessel at the time step k-1. The nonlinear model and measurement model are used in GPS measurements when they are available and in speed log measurements during GPS signal non-availability.

The state of the vessel x_k is a vector of stochastic processes, and the aim of this problem is to estimate the probability density function (PDF) $p(x_k|Z_k)$ of the state at each time step k conditioned on the whole set of sensors measurements until time k.

These models are non-linear models and there is no need to linearize them because the technique used can deal with non-linear models. When using EKF, the models need to be linearized, and only the first order terms of the Taylor series are used. This leads to using an error state approach where the KF estimates the error in the navigation states not the states themselves. The system model used by KF is the dynamic error model which is a linearized model and there is a separate INS mechanization used for KF. On the other hand, the approach used in PF is a total state approach not an error state approach as there is no need for linearization. So the system and measurement models used by the integration filter for PF are the total state non-linear models and there is no separate mechanization used.

3. AFPF approach

Before describing the mathematical models used in this integration problem, particle filtering is shortly introduced as well as the adaptive fission particle filter, which is an enhanced version of the PF.

3.1. Particle filter

$x_{0:k} = \{x_0, x_1, \ldots, x_k\}$ and $y_{1:k} = \{y_0, y_1, \ldots, y_k\}$ represent the sequences of states and observations in PF, respectively. Therefore, on the basis of Bayes' theorem, the posterior distribution of the hidden states x_k can be given as:

$$p(x_{0:k}|y_{1:k}) = p(x_{0:k-1}|y_{1:k-1})\frac{p(y_k|x_k)p(x_k|x_{k-1})}{p(y_k|y_{1:k-1})} \tag{3}$$

Owing to $p(y_k|y_{1:k\text{-}1})$ is a normalizing constant, (3) can be expressed by the following equation:

$$p(x_{0:k}|y_{1:k}) \propto p(x_{0:k-1}|y_{1:k-1})p(y_k|x_k)p(x_k|x_{k-1}) \tag{4}$$

where $\propto$ denotes the proportional relation.

As far as nonlinear discrete system (2) is concerned, the analytic solution of posterior distribution $p(x_{0:k}|y_{1:k})$ is hard to be achieved. In place of analytically calculating $p(x_{0:k}|y_{1:k})$, PF approaches it with a mass of particles $x_{0:k}^i (i = 1, 2, \cdots, N)$, in which N is the particle population. The initial particles x_0^i are drawn from initial distribution of states $p(x_0)$.

To cope with the conundrum in the process of sampling from the posterior distribution, the importance sampling technique is proposed. Suppose samples are drawn from an importance distribution that can be easily sampled, as follows:

$$q(x_{0:k}|y_{1:k}) = q(x_{0:k-1}|y_{1:k-1})q(x_k|x_{0:k-1}, y_{1:k}) \tag{5}$$

Combined with (3), the importance weight of particles can be formulated in a recursive form, as follows:

$$w_k^i = \frac{p(x_{0:k}|y_{1:k})}{q(x_{0:k}|y_{1:k})} \propto w_{k-1}^i \frac{p\left(y_k|x_k^i\right)p\left(x_k^i|x_{k-1}^i\right)}{q\left(x_k^i|x_{0:k-1}^i, y_{1:k}\right)} \tag{6}$$

where w_k^i is the importance weight of particle i at a time step k, and $\tilde{w}_k^i$ is