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Orbit determination via adaptive Gaussian swarm optimization

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Abstract

Accurate orbit determination (OD) is vital for every space mission. This paper proposes a novel heuristic filter based on adaptive sample-size Gaussian swarm optimization (AGSF). The proposed estimator considers the OD as a stochastic dynamic optimization problem that utilizes a swarm of particles in order to find the best estimation at every time step. One of the key contributions of this paper is the adaptation of the swarm size using a weighted variance approach. The proposed strategy is simulated for a low Earth orbit (LEO) OD problem utilizing geomagnetic field measurements at 700 km altitude. The performance of the proposed AGSF is verified using Monte Carlo simulation whose results are compared with other advanced sample based nonlinear filters. It is demonstrated that the adopted filter achieves about 2.5 km accuracy in position estimation that fulfills the essential requirements of accuracy and convergence time for OD problem.

Keywords: Orbit determination; Gaussian swarm optimization; Adaptive heuristic filter; Weighted variance

1. Introduction

Autonomous navigation has always been the center of attention since the beginning of its concept. Rapid growth of space traffic has also turned orbit determination (OD) to an important problem in the past few decades and a subject of continuous research. The basic ingredients of effective determination of the trajectory of an orbiter over time include observation or sensor data, valid mathematical models for the vehicle dynamics and measurements as well as an effective filtering method. Characteristics such as accuracy, rapidity and automation are the important factors to compare the performance of various space navigation systems. Global positioning system (GPS) (Kuang et al., 2008), Doppler orbitography and radio positioning integrated by satellite (DORIS) (Jayles et al., 2010), three-axis-magnetometers (TAM) (Shorshi and Bar-Itzhack, 1992; Kim and Chun, 2000), sun sensors, horizon sensors, radars (Sato et al., 2001), etc. are among some of the more conventional approaches utilized to estimate the position and velocity of a space vehicle.

Extracting orbital information out of the available measured data has been studied using various methods. The simplest method for OD is based on the batch least square that requires the whole amount of information obtained in a finite time for OD (Psiaki, 1999), which is not suitable for on-line processing. The capability of on-line processing is one of the important characteristics required for autonomous systems. In this regard, recursive methods also known as filters have been initiated as a substitute.

Extended Kalman filter (EKF) is the simplest, most well-known and widely utilized filtering method for OD problem (Morton et al., 2004; Shorshi and Bar-Itzhack, 1992). The EKF is an analytical filter based on first-order linearization of nonlinear dynamic systems and measurement models.

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However, the intensity of nonlinearities usually degrades the accuracy of EKF and propels it to divergence. To overcome the EKF shortcomings, unscented Kalman filter (UKF) was introduced in 1995 (Julier et al., 1995). UKF is a sampling-based method that uses some deterministically determined samples known as sigma points to describe a Gaussian posteriori probability density function (PDF). Forecasting and data assimilation of sigma points provide an estimation of the nonlinear system states. UKF is accurate just up to the second order moment, so it is not reliable for state estimation of nonlinear non-Gaussian stochastic systems. On the contrary, Particle filter (PF) can estimate arbitrary nonlinear non-Gaussian dynamic systems (Gordon et al., 1993). PF determines the required posterior PDF by using a set of weighted random samples (particles). In the simplest basic form of the PF, the particles are propagated through the dynamic model and then weighted according to the likelihood function that determines how closely the particles match the measurements. The particles that best match the measurements are multiplied and the remaining ones are discarded. The performance of the PF heavily depends on whether the particles are located in the significant regions of the state space or whether the significant regions are covered by the particles.

Nevertheless, the PF algorithm still suffers from some difficulties of its own. It is proven that after some iterations, most of the particles are zero weighted and thus do not take part in estimation process any longer. To solve this issue, a re-sampling step is suggested to discard the insignificant particles and copy the fittest ones based on their weights. Unfortunately, this strategy results in a gradual loss of diversity in particles. To remedy, various techniques have also been introduced to cope with the diversity issue. These include different kinds of re-sampling methods, combining PF with other filters like EKF, UKF, or Gaussian sum filter (GSF), embedding PF with heuristic optimization methods like the ant colony optimization (ACO), particle swarm optimization (PSO), genetic algorithm (GA) or simulated annealing (SA). It needs to be mentioned that the number of participating particles in PF is constant over time, but as the number of particles increases in an application, the representation of the required PDF becomes more accurate.

Kim and Chun (2000) has simulated a circular Keplerian orbit and a bootstrap particle filter to estimate some parameters of the translational dynamic system. Crassidis and Lightsey (2000) and Deutschmann et al. (2000) have utilized GPS measurements to determine orbital elements. Xu and Shen (2010) delivered a different work focused on GEO orbit determination. He developed a pseudo range measurement equation using seven Earth based observation stations. Besides estimation of the satellite position and velocity, he also considered the thrust force as a disturbance to be estimated using EKF. Choi et al. (2010) estimated the position and velocity utilizing UKF and based on GPS C/A code pseudo range. Psiaki and Hinks (2007) has also investigated the problem of estimating the position and velocity vectors of a spacecraft in a lunar orbit based on measurement of star occultation/rising times behind moon.

Mashiku et al. (2012) used PF to estimate the trajectory of space objects for collision avoidance based on the Earth or space based range measurements. It is shown that PF can represent the full PDF of the random orbit state more accurately than EKF and Splitting Gaussian Mixture algorithm.

Wang et al. (2012) have used a fusion of Earth sensor and star sensors to OD of a satellite using unscented particle filter (UPF). An Earth correction term (based on star sensor measurement) has been also used to improve the precision of OD. It is shown that their proposed method achieves higher accuracy and a more stable filter characteristic than that of the standard PF and UKF.

From a new point of view, state estimation can be also regarded as a stochastic dynamic optimization problem. Recently, various optimization methods have been utilized to solve this kind of optimization problems. Ansalone and Curti (2013) introduced an initial orbit determination by GA, and simulated the method assuming space-based observation. In following, Hinagawa et al. (2014) proposed an initial OD method by Lambert's problem with a GA based on optical observations. They demonstrated that the proposed method outperforms Gauss and Escobal's methods.

Stochastic methods are also referred to as evolutionary algorithms and are usually inspired by natural phenomena. Evolutionary computation techniques initially exploit a population of individuals (particles) that represent possible solutions to the problem of interest. The optimal solution is searched through cooperation and competition among individual particles. The most popular class of these techniques is the genetic algorithm (GA) based on Darwin's principle of survival of the fittest. Ant-colony optimization (ACO) is the other evolutionary method inspired ants behavior, and simulated annealing algorithm mimics the equilibrium of the large numbers of atoms during an annealing process. The particle swarm optimization (PSO) method was first suggested by Eberhart and Kennedy (1995). It belongs to the category of swarm intelligence method. It mimics unpredictable behavior of bird flocks while searching for food, trying to take advantage of the mechanism of information sharing that affects the overall behavior of the swarm.

According to Tan et al. (2001), an appropriate initial population size plays a key role in the effectiveness and efficiency in the performance of evolutionary algorithms. Therefore, a new method is proposed in this study to set the number of needed particles adaptively. In this regard, the sample size is determined based on weighted variance of the participating particles.

The structure of this paper is organized as follow. First, the orbital kinematics and dynamics are described in Section 2. Then, the measurement model is introduced in Section 3. Section 4 is devoted to the development of the

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