## Regularized particle filter with roughening for gyros bias and attitude estimation using simulated measurements

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This work describes the attitude determination and the gyros drift estimation using the Regularized Particle Filter with Roughening for nonlinear systems. The Particle Filter (PF) is a statistical, brute-force approach to state estimation that often works well for problems that are difficult for conventional nonlinear filters. The Regularized Particle Filter (RPF) was used for preventing the sample impoverishment, as this problem occur when the region of state space in which the posteriori probability density function has significant values does not overlap with the a priori probability density function. This means that if all of our a priori particles are distributed according to a priori probability density function, and one computes the posteriori probability density function, and one computes the posteriori probability density functions.

The Particle Filter has some similarities with the Unscented Kalman Filter which transforms a set of points (cloud) through known nonlinear equations and combines the results to estimate the moments (mean and covariance) of the state [1,2]. However, in the Particle Filter the points (particles cloud) are chosen randomly, whereas in the Unscented Kalman Filter the points are carefully picked up based on a very specific criterion [3]. In this way, the number of points (particles) used in a Particle Filter generally needs to be much greater than the number of points (sigma-points) in an Unscented Kalman Filter.

The application of the Regularized Particle Filter in this work uses simulated measurements of a real satellite CBERS-2 (China Brazil Earth Resources Satellite 2) which was at a polar sunsynchronous orbit with an altitude of 778km, crossing Equator at 10:30am in descending direction, frozen eccentricity and perigee at 90 degrees, and provided global coverage of the world every 26 days [1]. These simulated measurements were yielded by the package PROPAT, a Satellite Attitude and Orbit Toolbox for Matlab available in-house.

The attitude dynamical model for CBERS-2 is described by nonlinear equations involving the Euler angles. The attitude sensors available are two DSS (Digital Sun Sensors), two IRES (Infra-Red Earth Sensor), and one triad of mechanical gyros. Gyros are very important sensors, as they provide direct incremental angles or angular velocities. They can sense instantaneous variations of velocities (accelerations). Therefore, an important feature is that it allows the replacement of complex models (several different torques acting on the space environment) by using their measurements to turn the dynamical equations into simple kinematic equations. However gyros present sources of errors of which the drift is the most troublesome. Such drifts yield along time an accumulation of errors which must thus be accounted for in the attitude determination process.

In this work, attitude dynamics as well as sensors measurements are simulated to reproduce realistic scenarios with low or high sampling rates, or different levels of accuracy. Then the RPF is run and attitude determination results in typical conditions are generated. The results are compared with a former implementation of an Unscented Kalman Filter (UKF).

## References

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