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Nonlinear Kalman Filters and Particle Filters for integrated navigation of unmanned aerial vehicles

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ABSTRACT

The paper studies and compares nonlinear Kalman Filtering methods and Particle Filtering methods for estimating the state vector of Unmanned Aerial Vehicles (UAVs) through the fusion of sensor measurements. Next, the paper proposes the use of the estimated state vector in a control loop for autonomous navigation and trajectory tracking by the UAVs. The proposed nonlinear controller is derived according to the flatness-based control theory. The estimation of the UAV's state vector is carried out with the use of (i) Extended Kalman Filtering (EKF), (ii) Sigma-Point Kalman Filtering (SPKF), (iii) Particle Filtering (PF), and (iv) a new nonlinear estimation method which is the Derivative-free nonlinear Kalman Filtering (DKF). The performance of the nonlinear control loop which is based on these nonlinear state estimation methods is evaluated through simulation tests. Comparing the aforementioned filtering methods in terms of estimation accuracy and computation speed, it is shown that the Sigma-Point Kalman Filtering is a reliable and computationally efficient approach to state estimation-based control, while Particle Filtering is well-suited to accommodate non-Gaussian measurements. Moreover, it is shown that the Derivative-free nonlinear Kalman Filter is faster than the rest of the nonlinear filters while also succeeding accurate, in terms of variance, state estimates.

1. Introduction

Nonlinear estimation based on probabilistic inference forms a core component in most modern guidance and navigation systems. The estimator fuses observations from multiple sensors with predictions from a nonlinear dynamic state-space model of the system under control. The most widely used algorithm for multi-sensor fusion is the Extended Kalman Filter (EKF); however this is based on linearization of the system dynamics, which results in a suboptimal application of the recursive estimation of the standard Kalman Filter [1,2]. Moreover, the EKF follows the assumption of Gaussian process/measurement noise which does not always hold. These can seriously affect the performance of the state estimation and even lead to divergence. Consequently, the performance of a control loop that uses an EKF-based estimate of the system's state vector can, in some cases, be unsatisfactory.

To overcome the EKF flaws, two different approaches to state estimation of nonlinear dynamical systems are proposed: (i) Sigma-Point Kalman Filters (SPKF) and particularly the Unscented Kalman Filter (UKF), and (ii) Particle Filters. SPKF methods have proven to be superior to EKF in a wide range of applications. Whereas the EKF can be viewed as a first order linearization method, the UKF achieves higher accuracy, without requiring additional computational effort. Furthermore, implementation of the UKF is substantially easier and unlike the EKF case it does not need any analytic derivation or computation of Jacobian matrices [3–7]. The state distribution in UKF is approximated by a Gaussian random variable, which is represented using a minimal set of suitably chosen weighted sample points. These sigma points are propagated through the true nonlinear system, thus generating the posterior sigma-point set, and the posterior statistics are calculated. The sample points progressively converge to the true mean and covariance of the Gaussian random variable.

The Particle Filter (PF) is a non-parametric state estimator which unlike the EKF does not make any assumption on the probability density function of the measurements [8–11]. The concept of particle filtering comes from Monte-Carlo methods. The Particle Filter has improved performance over the established nonlinear filtering approaches (e.g. the EKF), since it can provide optimal estimation in nonlinear non-Gaussian state-space models. Particle filters can approximate the system's state sufficiently when the number of particles (estimations of the state vectors which evolve in parallel) is large. The PF also avoids the calculations associated with the Jacobians which appear in the EKF equations [12]. The main stages of the PF are prediction (time update), correction (measurement update) and resampling for substituting

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the unsuccessful state vector estimates with those particles that have better approximated the real state vector. Comparing SPKF and PF methods, the latter require more sample points to approximate the state distribution. However, the PF is a non-parametric filter which can be applied to any kind of state distribution, while the SPKF state estimators are still based on the assumption of a Gaussian process and measurement noise.

Aiming also at finding more efficient implementations of nonlinear filtering, in this paper a Derivative-free approach to Kalman Filtering is introduced and applied to state estimation-based control of nonlinear dynamical systems, such as UAVs. In the Derivative-free nonlinear Kalman Filtering method (DKF) the system is first subject to a linearization transformation that is in accordance to the differential flatness theory and next state estimation is performed by applying the standard Kalman Filter recursion to the linearized model. The proposed method provides estimates of the state vector of the nonlinear system without the need for derivatives and Jacobians calculation. By avoiding linearization approximations, the proposed filtering method improves the accuracy of estimation of the system state variables, and results in smooth control signal variations and in minimization of the tracking error of the associated control loop. Moreover, the Derivative-free nonlinear Kalman Filter appears to be faster than the previously mentioned nonlinear filtering methods (i.e. EKF, UKF and PF) while also providing very accurate (in terms of variance) state estimates. The application of the Derivative-free nonlinear Kalman Filter to the UAV model confirms and extends the initial results about the filter's performance given in [13–15].

As a case study, the paper examines the application of the aforementioned nonlinear filtering methods to the problem of sensor fusion-based guidance and navigation of unmanned aerial vehicles (UAVs) [5]. Sensor fusion in land navigation systems has been studied in [16], while typical sensors in UAV navigation systems can be rate-gyros and accelerometers, barometric altimeters and magnetic compasses. GPS position and velocity measurements provide additional information about the UAV's motion. Measurement systems for UAV navigation have been analyzed in [17–20], while different control approaches for UAV flight control have been analyzed in [21–24]. The filtering approaches examined in this paper are used to fuse measurements coming from different sources (measurements from on-board UAV's sensors and/or GPS measurements), thus providing estimates of the state vector of the UAV. The implementation of UAV control through prior estimation of the UAV's state vector from distributed sensor measurements has been analyzed in [17]. Simulation experiments are carried out to evaluate the performance of the nonlinear filters and of the associated state estimation-based UAV control loops.

The structure of the paper is as follows: in Section 2 the principles of flatness-based control are explained and the application of flatness-based control to the UAV model is analyzed. In Section 3 the Extended Kalman Filter is introduced as a basic filtering approach for nonlinear dynamical systems. In Section 4 estimation of the UAV's state vector with the use of Sigma-Point Kalman Filters, when fusing measurements that come from different sensors, is presented. In Section 5 the application of Particle Filtering for estimation of the state vector of the UAV through fusion of distributed sensor measurements is analyzed. In Section 6 it is explained how Derivative-free nonlinear Kalman Filters can be designed in accordance to the differential flatness theory and how they are applied for sensor fusion and state estimation in the UAV case. In Section 7 simulation tests are presented to evaluate the performance of the filtering-based control loops when the UAV's state vector is estimated with the use of the aforementioned nonlinear filters. Finally in Section 8 concluding remarks are stated.

2. Flatness-based control for UAVs

2.1. Differential flatness theory for UAV control

Trajectory tracking by Unmanned Aerial Vehicles with the use of nonlinear control methods is examined first. Various approaches have been proposed for the UAV control among which Lyapunov functions-based control [20,21] and model-based predictive control [19,24]. In this paper it will be shown that flatness-based control is a suitable approach for implementing autonomous navigation of aerial vehicles. Flatness-based control theory stems from differential flatness and has been successfully applied to several nonlinear dynamical systems. Flatness-based control for a UAV helicopter-like model has been developed in [25], assuming that the UAV performs maneuvers at a constant altitude. The same kinematic model has been used in several studies on UAV trajectory tracking and control [22,23].

A dynamical system is considered to be differentially flat if the following properties hold: (i) the so-called flat output exists, i.e. a new variable which is expressed as a function of the system's state variables. The flat output and its derivatives should not be coupled in the form of an ordinary differential equation, (ii) the components of the system (i.e. state variables and control input) can be expressed as functions of the flat output and its derivatives [26,27]. Differential flatness is a property characterizing classes of systems. In certain cases expressing all system variables as functions of the flat output and its derivatives enables transformation to a linearized form for which the design of the controller becomes easier. In other cases by showing that a system is differentially flat one can easily design a reference trajectory as a function of the so-called flat output and can find a control law that assures tracking of this desirable trajectory [27–29].

Flatness-based control has been successfully applied for steering autonomous vehicles and particularly UAVs along desirable trajectories [27,28]. It this paper it is assumed that an helicopter-like UAV, performs maneuvers at a constant altitude. Then, one obtains the following UAV kinematics [25]

$$\begin{aligned} &\dot{x} = v\cos(\theta), \qquad \dot{y} = v\sin(\theta), \qquad \dot{\theta} = \omega = q_1 \\ &\dot{v} = q_2, \qquad \dot{h} = 0 \end{aligned} \tag{1}$$

where (x, y) is the desired inertial position of the UAV, θ is the UAV's heading (angle between the transversal axis of the UAV and axis OX), ω is the UAV's rate of change of the heading angle, v is the UAV's velocity, h is the UAV's altitude, and q_1, q_2 are control inputs constrained by the dynamic capability of the UAVs (namely the heading rate constraint and the acceleration constraint, respectively). There is an equivalence between the UAV's kinematic model and the model of a unicycle robot. The flat output is the cartesian position of the UAV's center of gravity, and is denoted as $\eta = (x, y)$. Then, the flatness-based dynamic compensator is

$$\begin{aligned} &\dot{\xi} = u_1\cos(\theta) + u_2\sin(\theta), \qquad v = \xi \\ &\omega = \frac{u_2\cos(\theta) - u_1\sin(\theta)}{\xi} \end{aligned} \tag{2}$$

where

$$\begin{aligned} u_1 &= \ddot{x}_d + k_{p_1}(x_d - x) + k_{d_1}(\dot{x}_d - \dot{x}) \\ u_2 &= \ddot{y}_d + k_{p_2}(y_d - y) + k_{d_2}(\dot{y}_d - \dot{y}). \end{aligned} \tag{3}$$

It has been shown (see [13,30]) that using the change of coordinates

$$\begin{aligned} &x_1 = x, \qquad x_2 = \dot{x} = \xi\cos(\theta) \\ &x_3 = y, \qquad x_4 = \dot{y} = \xi\sin(\theta) \end{aligned} \tag{4}$$