Mechanical Systems and Signal Processing 114 (2019) 571–578

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

Sensor fusion and rotational motion reconstruction via nonlinear state-observers

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ARTICLE INFO

Article history:
Received 9 August 2017
Received in revised form 12 April 2018
Accepted 12 May 2018

Keywords:
Sensor fusion
Rotational motion reconstruction
State estimator
Extended Kalman Filter
Sliding-Mode Observer

ABSTRACT

Despite the ease to instrument and record body accelerations and angular velocities of a body moving in space, the reconstruction from these measurements of rotational displacement is not a trivial task. Given that these quantities need to be integrated in order to define a displacement quantity the noise present in those signal can significantly disturb the results and limit the deployment of the technique in industrial applications, moreover the nonlinear kinematics that constrains the problem can be a challenge to the commonly used noise filtering techniques, such as linear state-estimators (Kalman filter). This paper aims to elaborate on the topic, by providing a concise formulation to the problem under rigid-body body assumptions and explore the use of nonlinear state-estimators to address the conditioning of the measured data, data fusion and reconstruction of the body motion. A comparison is drawn between an extended linear approach (EKF) and the proposed methodology, paying particular attention to the conditions that affect the performance of both methodologies. The paper compares results from numerical experiments using to better illustrate the differences between methodologies.

1. Introduction

The problem of angular motion reconstruction is in quite old and many of the aerospace structures build since the 50th required automatic orientation (satellites, aircrafts, etc). Several estimation algorithms have been developed since then [1]. Gyroscope is one of the most convenient angular velocity sensor to support the estimation of angular position of a body in space (*e.i.* define its attitude). However, the direct integration of its signal leads to the accumulation of noise error and a subsequent drift in the angle predictions. A common solution is the use state estimators/observers to minimize the measurement noise [2] and improve its integration.

Given that the integration of angular velocity signal does not have an absolute reference, both residual noise and poor initial conditions can lead to prediction errors. One alternative, is to use a set of accelerometers to calculate the body attitude through the relative acceleration [3]. In this approach the direction of gravity can also be used as a reference for two of the angular components (roll and pitch), significantly improving attitude determination for low translational acceleration applications. Nevertheless, this approach faces some fundamental challenges given the high sensitivity to sensor orientation and measurement noise [4].

Nowadays, attitude estimation for low-cost application, such as recreational aviation and UAVs [5], puts more strain in the process, as sensors and onboard processing have poor performances. In these instances, the development focus on

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https://doi.org/10.1016/j.ymssp.2018.05.021
0888-3270/

efficient algorithms that are robust to all these physical and practical limitations [6]. Most of these applications makes use of an estimation process that was originally created for linear system and is adapted to nonlinear system (*i.e.* Extended Kalman Filter – EKF) [5,7,8]. Although several commercially available solutions deploy variants of EKF algorithms, this solution have limited performance when structured uncertainties (e.g. sensor misalignment) and high nonlinearity (large angular accelerations) are present in the system.

To address these issues, a nonlinear attitude state estimator is proposed in this paper that allows for a robust elimination of noise and structured uncertainties. Moreover, the nonlinear nature of the estimator allows for the good estimation even in highly nonlinear operation. The concept is based on sliding mode observers (SMO) developed in [9] and properly expressed in terms of the angular motion dynamics, also allowing for the fusion of sensor information from accelerometers and gyroscopes.

It is important to note that several other nonlinear estimation methods are available, as pointed by Crassidis et al. [8]. Several variants of EKF, particle filters, adaptive and nonlinear estimators/observers are described together with the assumptions on the systems measurement dynamics, noise profile and convergence criteria that applies for each. Nevertheless, the use of SMO for the problem being considered in this paper is suitable given the its property to address structured uncertainties and do not required linearized versions of the dynamic model.

In the following sections the development of the attitude estimator/observer is further detailed. The dynamic framework at which the nonlinear estimator will be designed upon is described in the detail through Section 2. Section 3 will explore the design of linear and nonlinear state estimators for this problem, followed by a numerical example in Section 4 and a brief discussion and conclusion on the results at Section 5.

2. Preliminaries

Assume the existence of a rigid body on space, with motion described in an inertial reference frame (I). At the center of gravity of the body (point O), a local coordinate system is established (see Fig. 1).

The motion of points located at the rigid body (A, B and C) can be expressed with respect to its center of gravity (O), considering that all vectorial quantities are expressed in the body coordinate system:

$$\mathbf{a}_X = \mathbf{a}_O + \boldsymbol{\alpha} \times \mathbf{r}_{XO} + \boldsymbol{\omega} \times (\boldsymbol{\omega} \times \mathbf{r}_{XO}), \tag{1}$$

where $\mathbf{a}_X$ represent the accelerations of a point (either A, B or C), $\mathbf{a}_O$ the acceleration at the center of gravity, $\boldsymbol{\alpha}$ the angular acceleration of the body, $\boldsymbol{\omega}$ the angular velocity and $\mathbf{r}_{XO}$ the relative position between a body point (either A, B or C) to the center of gravity (O). By manipulating Eq. (1) for the point A, one can isolate the acceleration at point O,

$$\mathbf{a}_O = \mathbf{a}_A - \boldsymbol{\alpha} \times \mathbf{r}_{AO} - \boldsymbol{\omega} \times (\boldsymbol{\omega} \times \mathbf{r}_{AO}). \tag{2}$$

By inserting Eq. (2) back into Eq. (1), for the components B and C one can obtain,

$$\begin{aligned} \mathbf{a}_B &= \mathbf{a}_A - \boldsymbol{\alpha} \times \mathbf{r}_{AO} - \boldsymbol{\omega} \times (\boldsymbol{\omega} \times \mathbf{r}_{AO}) + \boldsymbol{\alpha} \times \mathbf{r}_{BO} + \boldsymbol{\omega} \times (\boldsymbol{\omega} \times \mathbf{r}_{BO}) \\ \mathbf{a}_C &= \mathbf{a}_A - \boldsymbol{\alpha} \times \mathbf{r}_{AO} - \boldsymbol{\omega} \times (\boldsymbol{\omega} \times \mathbf{r}_{AO}) + \boldsymbol{\alpha} \times \mathbf{r}_{CO} + \boldsymbol{\omega} \times (\boldsymbol{\omega} \times \mathbf{r}_{CO}) \end{aligned} \tag{3}$$

Eq. (3) can be manipulated to assume the following form:

$$\begin{bmatrix} -\mathbf{r}_{AB} \times \boldsymbol{\alpha} \\ -\mathbf{r}_{AC} \times \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} \mathbf{a}_{AB} - \boldsymbol{\omega} \times (\boldsymbol{\omega} \times \mathbf{r}_{AB}) \\ \mathbf{a}_{AC} - \boldsymbol{\omega} \times (\boldsymbol{\omega} \times \mathbf{r}_{AC}) \end{bmatrix}, \tag{4}$$

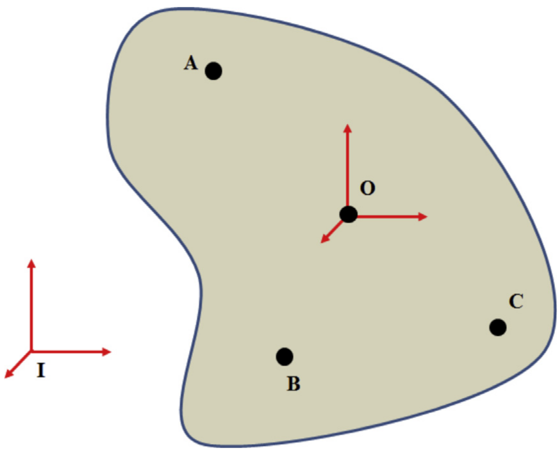

Fig. 1. Arbitrary body under special motion with the definition of different reference frames.