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Journal of the Franklin Institute 351 (2014) 4672–4687

Journal of The Franklin Institute

www.elsevier.com/locate/jfranklin

Estimation fusion of nonlinear cost functions with application to multisensory Kalman filtering

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Received 27 November 2013; received in revised form 22 April 2014; accepted 15 July 2014
Available online 29 July 2014

Abstract

This paper focuses on four fusion algorithms for the estimation of nonlinear cost function (NCF) in a multisensory environment. In multisensory filtering and control problems, NCF represents a nonlinear multivariate functional of state variables, which can indicate useful information of the target systems for automatic control. To estimate the NCF using multisensory information, we propose one centralized and three decentralized estimation fusion algorithms. For multivariate polynomial NCFs, we propose a simple closed-form computation procedure. For general NCFs, the most popular procedure for the evaluation of their estimates is based on the unscented transformation. The effectiveness and estimation accuracy of the proposed fusion algorithms are demonstrated with theoretical and numerical examples.

1. Introduction

Multisensory data fusion techniques are a topic of current interest as a means of increasing the accuracy of parameter and state estimates. In a range of scenarios, as system states or targets are

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http://dx.doi.org/10.1016/j.jfranklin.2014.07.011

measured using multi-sensors, this interest has been motivated by the increased availability of different types of sensor and thus, data fusion has the potential for widespread application. Consequently, several distributed fusion architectures and corresponding techniques have been presented [1–4], most notably for linear distributed fusion estimation algorithms. However, optimal mean-square linear fusion formulas, for an arbitrary number of local estimates with matrix and scalar weights, have also been reported [5–10] (also see references therein).

If a central processor receives the measurement data of all local sensors directly and processes them in real time, the correlative result is known as the centralized estimation process. However, this process has some serious disadvantages, including bad reliability and survivability, as well as heavy communication and computational burdens, especially when system dimension is high. Thus, a distributed estimation fusion process and the fusion of local estimates are required for saving computational resources. To achieve distributed fusion filtering, Bar-Shalom and Li discussed the specific architectures and techniques for data fusion [1,5]. Furthermore, Shin, Sun and Zhou developed and presented both explicit and implicit linear fusion formulas for finding the best linear combinations of local estimates weighted by scalars and matrices [5–10]. In the linear fusion formulas, the local cross-covariance, as statistical information between local estimates, is used to obtain high estimation accuracy. The formulas have been used widely for linear [1,3,4,7–12] and nonlinear dynamic state-space models based on the Kalman filter and different variants of suboptimal nonlinear filters, such as the unscented Kalman filter, the extended Kalman filter, the central difference Kalman filter and their extensions, in order to enhance the performance of the nonlinear estimation in sensor fusion problems [13–21].

However, some applications require the estimation fusion of nonlinear functionals of state variables, representing useful information for system control, for example, a quadratic form of a state vector, which can be interpreted as a current distance between targets or as the energy of an object [1]. We refer to the nonlinear functional as the nonlinear cost function (NCF). Aside from the aforementioned papers, most authors have not focused on the estimation of the NCF, considering instead only a state estimation (filtering). To the best of our knowledge, there are no methods reported in the literature for estimation fusion of NCFs in a multisensory environment.

Therefore, in this paper, the estimation fusion problem of NCFs of state variables is considered under a multisensory environment. Centralized and decentralized estimation fusion algorithms are proposed and their accuracies compared.

This paper is organized as follows. Section 2 presents a statement of the estimation fusion problem for NCFs. In Section 3, the centralized global optimal estimator is derived. Section 4 describes the linear fusion formulas within the Kalman filter framework. In Section 5, we propose three nonlinear decentralized estimation fusion algorithms for NCFs. In Section 6, the unscented transformation is introduced and its application for estimation of NCFs proposed. In Section 7, we study the comparative analysis of the proposed fusion estimators via a theoretical example. In Section 8, the efficiency of the fusion estimators is studied for the case of an unmanned marine prober system and other examples. Finally, we conclude our results in Section 9.

2. Problem statement

The general Kalman multisensory framework involves estimation of the state of a discrete-time linear dynamic system

$$\begin{aligned} &x_{k+1} = F_k x_k + G_k w_k, \quad k = 0, 1, 2, \ldots, x_0 \sim \mathbf{N}(\bar{x}_0, P_0), \\ &y_k^{(i)} = H_k^{(i)} x_k + v_k^{(i)}, \quad i = 1, \ldots, L, \end{aligned} \tag{1}$$