Chapter 3
Methodology for Model-Based Fuzzy Kalman Filter Design via Singular Spectral Analysis of Experimental Data

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ABSTRACT

This chapter presents a methodology for designing of fuzzy Kalman filter (FKF) via spectral decomposition of the experimental data. The adopted methodology consists in the parametric estimation of local state-space linear submodels of a fuzzy model of the dynamic system, by means of a fuzzy algorithm based on least squares, as well as in the estimation of FKF gains from the fuzzy model, using the parallel and distributed compensation (PDC) method. The partitioning of experimental data is performed by the fuzzy C-Means (FCM) clustering algorithm, for the definition of the rule base as well as the nonlinear FKF characteristic. Considering the PDC method, the Kalman gains in the consequent of each FKF rule are updated as a function of the unobservable components resulting from the spectral decomposition of noisy experimental data. Computational and experimental results illustrate the good performance of the methodology presented when compared to relevant approaches from the literature.

INTRODUCTION

In sciences and engineering is very common the solution of problems with stochastic nature such as prediction, separation, and detection of signals in the presence of random noise(Kasasbeh, Viswanathan, & Cao, 2017)(Woodbridge, Elidan, & Wiesel, 2017)(Zhu, Wang, Bao, Hu, & Li, 2019). Kalman filter (KF) is the most well known and used mathematical tool for stochastic estimation from noisy measurements.

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It was proposed by Rudolph E. Kalman in 1960, who published his famous paper "A New Approach to Linear Filtering and Prediction Problems"(Kalman, 1960), describing a recursive solution to discrete-time linear filtering problem, and becoming a standard approach for optimal estimation. Since the time of its introduction, the Kalman filter has been the subject of extensive research and applications in the fields of orbit calculation, target tracking, integrated navigation, dynamic positioning, sensor data fusion, microeconomics, control, modeling, digital image processing, pattern recognition, image segmentation and image edge detection, and others (Serra, 2018). This broad interest in FK is due to its optimality, convenient form for online real-time processing, easy formulation, and implementation.

The problem of state estimation of a dynamic system is present in many engineering applications(Wan, Sharma, & Sutton, 2018)(Grotas, Yakoby, Gera, & Routtenberg, 2019)(Zhao, 2017). There is great interest in estimating these states as they provide an internal representation of system conditions over time. One of the main reasons for state estimation is that, in many cases, it is not possible to measure them using sensors, i.e., they are not observable. Over the years, several state estimation algorithms have been proposed. Among them, the Kalman filter emerged from continuous-time filtering studies developed in the 1940s, which was based on the minimization of the mean square error. However, Kalman formulated the problem considering noisy measurements as a discrete sequence in time and used the representation of systems by state-space models, which allowed its application in the context of multiple inputs and multiple-output systems.In addition, the use of state-space representation of the system made it possible to recursively estimate the internal states of the dynamic system. The Kalman filter calculatesrecursively the optimal state with a predictor-corrector structure, where a state prediction is made based only on system dynamics before its observation is available, and updates this prediction when its observation is available at the current time instant. These two distinct steps are known as the propagation step and the assimilation or update step. The idea of KF is to perform filtering and state estimation by combining system dynamics information through a state space model and sensor measurements. Currently, the Kalman filter is one of the most popular estimation algorithms applied and has been applied in many search fields(Evangelista & Serra, 2019)(Bouzera, Oussalah, Mezhood, & Khireddine, 2017)(Yang & Sun, 2018)(Zhou & Hou, 2019).

Once most of the practical dynamic systems are nonlinear, several researchers have dedicated themselves to adapting Kalman's filtering theory to nonlinear systems. One of the solutions for applying KF to nonlinear dynamic systems is the Extended Kalman Filter (EKF), which is based on the linearization of models, initially proposed by Stanley F. Schmidt in 1962 (Smith, Schmidt, & Mcgee, 1962). The EKF depends on approximations by linear functions, and the use of linearization techniques, so that this task can become computationally infeasible in highly nonlinear dynamic systems, compromising the performance of EKF. Therefore, another alternative for implementing KF to nonlinear dynamic systems was proposed in 1995 by Julier and Uhlmann (Julier & Uhlmann, 1997), the so-called Unscented Kalman Filter (UKF), which treats the nonlinearities of a dynamic system through of sampling technique called Unscented Transformation (UT). This type of transformation propagates statistical information of the nonlinear dynamic system in a recursive way so that the UKF does not depend on approximations by linear functions like EKF(Chang, Xu, & Wang, 2016)(Serra, 2018).

In the last years, fuzzy systems have been widely used in applications such as modeling and control of dynamic systems. Due to its structure based on rules, where the antecedent propositions of the rules define fuzzy operation regions and the consequent describes a corresponding physical behavior in those regions, they are capable of approaching functions, nonlinearities and uncertainties(Serra, 2012)(Ferreira & Serra, 2011). Initially proposed by Lotfi A. Zadeh in 1965 (Zadeh, 1965), the fuzzy system theory