DISCRETE TIME SYSTEMS

Edited by **Mario A. Jordán**
and **Jorge L. Bustamante**

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Published by InTech
Janeza Trdine 9, 51000 Rijeka, Croatia

Publishing Process Manager Ivana Lorkovic
Technical Editor Teodora Smiljanic
Cover Designer Martina Sirotic
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First published March, 2011
Printed in India

A free online edition of this book is available at www.intechopen.com
Additional hard copies can be obtained from orders@intechweb.org

Discrete Time Systems, Edited by Mario A. Jordán and Jorge L. Bustamante
p. cm.
ISBN 978-953-307-200-5

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Preface

Discrete-Time Systems comprehend an important and broad research field. The consolidation of digital-based computational means in the present, pushes a technological tool into the field with a tremendous impact in areas like Control, Signal Processing, Communications, System Modelling and related Applications. This fact has enabled numerous contributions and developments which are either genuinely original as discrete-time systems or are mirrors from their counterparts of previously existing continuous-time systems.

This book attempts to give a scope of the present state-of-the-art in the area of Discrete-Time Systems from selected international research groups which were specially convoked to give expressions to their expertise in the field.

The works are presented in a uniform framework and with a formal mathematical context.

In order to facilitate the scope and global comprehension of the book, the chapters were grouped conveniently in sections according to their affinity in 5 significant areas.

The first group focuses the problem of Filtering that encloses above all designs of State Observers, Estimators, Predictors and Smoothers. It comprises Chapters 1 to 6.

The second group is dedicated to the design of Fixed Control Systems (Chapters 7 to 12). Herein it appears designs for Tracking Control, Fault-Tolerant Control, Robust Control, and designs using LMI- and mixed LQR/Hoo techniques.

The third group includes Adaptive Control Systems (Chapter 13 to 15) oriented to the specialities of Predictive, Decentralized and Perturbed Control Systems.

The fourth group collects works that address Stability Problems (Chapter 16 to 20). They involve for instance Uncertain Systems with Multiple and Time-Varying Delays and Switched Linear Systems.

Finally, the fifth group concerns miscellaneous applications (Chapter 21 to 27). They cover topics in Multitone Modulation and Equalisation, Image Processing, Fault Diagnosis, Event-Based Dynamics and Analysis of Deterministic/Stochastic and Multidimensional Dynamics.

We think that the contribution in the book, which does not have the intention to be all-embracing, enlarges the field of the Discrete-Time Systems with signification in the present state-of-the-art. Despite the vertiginous advance in the field, we think also that the topics described here allow us also to look through some main tendencies in the next years in the research area.

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Part 1

Discrete-Time Filtering

1

Real-time Recursive State Estimation for Nonlinear Discrete Dynamic Systems with Gaussian or non-Gaussian Noise

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1. Introduction

Many systems in the real world are more accurately described by nonlinear models. Since the original work of Kalman (Kalman, 1960; Kalman & Busy, 1961), which introduces the Kalman filter for linear models, extensive research has been going on state estimation of nonlinear models; but there do not yet exist any optimum estimation approaches for all nonlinear models, except for certain classes of nonlinear models; on the other hand, different suboptimum nonlinear estimation approaches have been proposed in the literature (Daum, 2005). These suboptimum approaches produce estimates by using some sorts of approximations for nonlinear models. The performances and implementation complexities of these suboptimum approaches surely depend upon the types of approximations which are used for nonlinear models. Model approximation errors are an important parameter which affects the performances of suboptimum estimation approaches. The performance of a nonlinear suboptimum estimation approach is better than the other estimation approaches for specific models considered, that is, the performance of a suboptimum estimation approach is model-dependent.

The most commonly used recursive nonlinear estimation approaches are the extended Kalman filter (EKF) and particle filters. The EKF linearizes nonlinear models by Taylor series expansion (Sage & Melsa, 1971) and the unscented Kalman filter (UKF) approximates *a posteriori* densities by a set of weighted and deterministically chosen points (Julier, 2004). Particle filters approximates *a posterior* densities by a large set of weighted and randomly selected points (called particles) in the state space (Arulampalam et al., 2002; Doucet et al., 2001; Ristic et al., 2004). In the nonlinear estimation approaches proposed in (Demirbaş, 1982; 1984; Demirbaş & Leondes, 1985; 1986; Demirbaş, 1988; 1989; 1990; 2007; 2010): the disturbance noise and initial state are first approximated by a discrete noise and a discrete initial state whose distribution functions the best approximate the distribution functions of the disturbance noise and initial state, states are quantized, and then multiple hypothesis testing is used for state estimation; whereas Grid-based approaches approximate *a posteriori* densities by discrete densities, which are determined by predefined gates (cells) in the predefined state space; if the state space is not finite in extent, then the state space necessitates some truncation of the state space; and grid-based estimation approaches assume the availability of the state transition density $p(x(k)|x(k-1))$, which may not easily be calculated for state models with nonlinear disturbance noise (Arulampalam et al., 2002; Ristic et al., 2004). The Demirbaş estimation approaches are more general than grid-based approaches since 1) the state space need not to be truncated, 2) the state transition density is not needed, 3) state models can be any nonlinear functions of the disturbance noise.

This chapter presents an online recursive nonlinear state filtering and prediction scheme for nonlinear dynamic systems. This scheme is recently proposed in (Demirbaş, 2010) and is referred to as the DF throughout this chapter. The DF is very suitable for state estimation of nonlinear dynamic systems under either missing observations or constraints imposed on state estimates. There exist many nonlinear dynamic systems for which the DF outperforms the extended Kalman filter (EKF), sampling importance resampling (SIR) particle filter (which is sometimes called the bootstrap filter), and auxiliary sampling importance resampling (ASIR) particle filter. Section 2 states the estimation problem. Section 3 first discusses discrete noises which approximate the disturbance noise and initial state, and then presents approximate state and observation models. Section 4 discusses optimum state estimation of approximate dynamic models. Section 5 presents the DF. Section 6 yields simulation results of two examples for which the DF outperforms the EKF, SIR, and ASIR particle filters. Section 7 concludes the chapter.

2. Problem statement

This section defines state estimation problem for nonlinear discrete dynamic systems. These dynamic systems are described by

$$\begin{aligned}
&\text{State Model}\\
&x(k+1) = f(k, x(k), w(k)) \qquad (1)\\
&\text{Observation Model}\\
&z(k) = g(k, x(k), v(k)), \qquad (2)
\end{aligned}$$

where k stands for the discrete time index; $f : \mathbb{R}x\mathbb{R}^m x\mathbb{R}^n \to \mathbb{R}^m$ is the state transition function; $\mathbb{R}^m$ is the m-dimensional Euclidean space; $w(k) \in \mathbb{R}^n$ is the disturbance noise vector at time k; $x(k) \in \mathbb{R}^m$ is the state vector at time k; $g : \mathbb{R}x\mathbb{R}^m x\mathbb{R}^p \to \mathbb{R}^r$ is the observation function; $v(k) \in \mathbb{R}^p$ is the observation noise vector at time k; $z(k) \in \mathbb{R}^r$ is the observation vector at time k; $x(0)$, $w(k)$, and $v(k)$ are all assumed to be independent with known distribution functions. Moreover, it is assumed that there exist some constraints imposed on state estimates. The DF recursively yields a predicted value $\hat{x}(k|k-1)$ of the state $x(k)$ given the observation sequence from time one to time $k-1$, that is, $Z^{k-1} \triangleq \{z(1),\ z(2), \ldots, z(k-1)\}$; and a filtered value $\hat{x}(k|k)$ of the state $x(k)$ given the observation sequence from time one to time k, that is, Z^k. Estimation is accomplished by first approximating the disturbance noise and initial state with discrete random noises, quantizing the state, that is, representing the state model with a time varying state machine, and an online suboptimum implementation of multiple hypothesis testing.

3. Approximation

This section first discusses an approximate discrete random vector which approximates a random vector, and then presents approximate models of nonlinear dynamic systems.

3.1 Approximate discrete random noise

In this subsection: an approximate discrete random vector with n possible values of a random vector is defined; approximate discrete random vectors are used to approximate the disturbance noise and initial state throughout the chapter; moreover, a set of equations which must be satisfied by an approximate discrete random variable with n possible values of an absolutely continuous random variable is given (Demirbaş, 1982; 1984; 2010); finally, the approximate discrete random variables of a Gaussian random variable are tabulated.

Let w be an m-dimensional random vector. **An approximate discrete random vector with n possible values** of w, denoted by w_d, is defined as an m-dimensional discrete random vector with n possible values whose distribution function the best approximates the distribution function of w over the distribution functions of all m-dimensional discrete random vectors with n possible values, that is

$$w_d = \min_{y \epsilon D}^{-1} \{ \int_{\mathbb{R}^n} [F_y(a) - F_w(a)]^2 da \} \tag{3}$$

where D is the set of all m-dimensional discrete random vectors with n possible values, $F_y(a)$ is the distribution function of the discrete random vector y, $F_w(a)$ is the distribution function of the random vector w, and $\mathbb{R}^m$ is the m-dimensional Euclidean space. An approximate discrete random vector w_d is, in general, numerically, offline-calculated, stored and then used for estimation. The possible values of w_d are denoted by w_{d1}, w_{d2}, ..., and w_{dn} ; and the occurrence probability of the possible value w_{di} is denoted by $P_{w_{di}}$, that is

$$P_{w_{di}} \triangleq Prob\{w_d = w_{di}\}. \tag{4}$$

where $Prob\{w_d(0) = w_{di}\}$ is the occurrence probability of w_{di}.

Let us now consider the case that w is an absolutely continuous random variable. Then, w_d is an approximate discrete random variable with n possible values whose distribution function the best approximates the distribution function $F_w(a)$ of w over the distribution functions of all discrete random variables with n possible values, that is

$$w_d = \min_{y \epsilon D}^{-1} \{ J(F_y(a)) \}$$

in which the distribution error function (the objective function) $J(F_y(a))$ is defined by

$$J(F_y(a)) \triangleq \int_{\mathbb{R}} [F_y(a) - F_w(a)]^2 da$$

where D is the set of all discrete random variables with n possible values, $F_y(a)$ is the distribution function of the discrete random variable y, $F_w(a)$ is the distribution function of the absolutely continuous random variable w, and $\mathbb{R}$ is the real line. Let the distribution function $F_y(a)$ of a discrete random variable y be given by

$$F_y(a) \triangleq \begin{cases} 0 & \text{if } a < y_1 \\ F_{y_i} & \text{if } y_i \le a < y_{i+1},\ i = 1,\ 2,\ \ldots, n-1 \\ 1 & \text{if } a \ge y_n. \end{cases}$$

Then the distribution error function $J(F_y(a))$ can be written as

$$J(F_y(a)) = \int_{-\infty}^{y_1} F_w^2(a) da + \sum_{i=1}^{n-1} \int_{y_i}^{y_{i+1}} [F_{y_i} - F_w(a)]^2 da + \int_{y_n}^{\infty} [1 - F_w(a)]^2 da.$$