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Speech and rotor flux estimation of induction machines using a two-stage extended Kalman filter☆

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ABSTRACT

This paper presents an effective implementation of an extended Kalman filter used for the estimation of both rotor flux and rotor velocity of an induction motor. An algorithm proposed by Hsieh and Chen in [Hsieh, C.S., & Chen, F.C. (1999). Optimal solution of the two-stage Kalman estimator. *IEEE Transactions on automatic control*, *44*(1), 194–199] for linear parameter estimation is extended to non-linear estimation, where parameters such as the velocity of an induction machine are present in the transition matrix and in the augmented state space. Compared to a straightforward implementation of an extended Kalman filter, our modified optimal two-stage Kalman estimator reduces the number of arithmetic operations by 25%, allowing higher sampling rate or the use of a cheaper microcontroller.

1. Introduction

Variable speed control of AC machines based on direct field oriented control requires an evaluation of the instantaneous magnetic flux of the rotor and the knowledge of the relative rotor shaft position. Since rotational sensors are expensive and delicate, their removal may result in a lower cost as well as increased system reliability. Therefore, many research efforts have been made in the last two decades to estimate the rotor speed and position from the stator voltages and currents.

The resulting methods can be put into two classes. The first consists in estimating the stator harmonic frequencies produced by the rotor saliency when the rotor turns. These currents contain encoded speed information which could be retrieved by digital signal processing estimators. Related works are Aller, Habetler, Harley, Tallamm, and Lee (2002), Bharadwaj, Parlos, and Toliyat (2004), Ferrah et al. (1998), Hilairet and Auger (2001), Hurst and Habetler (1996), Hurst, Habetler, Griva, Profumo, and Jansen (1997) and Morand, Lin-Shi, Retif, and Llor (2004), where real-time adaptive digital filtering techniques are well suited for speed estimation because new recorded data provide updated frequency estimation compared to other alternatives (Blasco-Giménez, 1997). This approach has been used frequently because of a high accuracy estimation in the steady state. But this method suffers from speed tracking error during transients and is prone to instability.

The second is based on the rotor back electromotive force (EMF) which contains the velocity information. Non-linear state observers such as extended Luenberger observers (Du, 1993; Du, Vas, & Stronach, 1994, 1995; Kim, Hyun, & Shin, 2004; Song, Lee, Song, Choy, & Kim, 2000), extended stochastic observers (EKF) (Atkinson, Acarnley, & Finch, 1991; El Hassan, Von Westerholt, Roboam, & De Fornel, 2000; Hilairet, Auger, & Darengosse, 2000; Kim et al., 2004; Von Westerholt, Pietrzak-David, & de Fornel, 1992) or adaptive estimators (Bowes, Sevin, & Holliday, 2004; Kubota, Matsuse, & Nakano, 1993; Kwon & Kim, 2004; Marino, Tomei, & Verrelli, 2004; Purwoadi, 1996; Siala & Terrien, 2003) can be used to estimate this back EMF from the stator currents and voltages. These observers are parameter dependent, making the estimates sensitive to parameter variations. Compared to the first method, these observers give an accurate speed estimation during transient operations, as well as during the steady state. For this reason, these methods are commonly used in practice.

Generally, the main subject of the papers mentioned above is the determination of gain matrices based on different approaches such as dynamics and/or stability assignment, or insensitivity to parameter uncertainties. But the improvement in the implementation of these observers is seldom studied. The main goal of our

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paper is to present an effective implementation of extended Kalman filters (EKFs) for mechanical speed estimation of an induction machine in order to reduce the traditional EKF computational algorithm complexity. The linear algorithm developed in Hsieh and Chen (1999) is adapted to a restricted class of non-linear systems. A two-stage Kalman estimator has the advantage of reducing the computational complexity compared to the classical EKF. The complete equations of this filter are presented and compared with a rough implementation of the classical EKF equations.

The paper is organized in two sections. In Section 2, the non-linear two-stage Kalman estimator equations are developed. In Section 3, this modified two-stage extended Kalman filter is used for speed estimation. The continuous and discretized model of the induction machine are recalled. In the same section, the algorithm complexity of the estimator is compared to a rough implementation of the classical matrix equations for the general case. Finally, simulation and experimental results are provided in this section to demonstrate the effectiveness of this observer.

2. Extended Kalman filter

2.1. Effective algorithm

The problem of estimating the state, parameters and unknown inputs generally leads to an augmented state system that is commonly treated with an augmented state Kalman filter, whose implementation is in practice computationally intensive. To reduce the computational cost, Friedland (1969) introduced for the first time a two-stage Kalman estimator. The main idea is to decouple the Kalman filter into two parallel filters: a full-order filter and another one for the augmented state. Friedland's filter is devoted to estimating the state of a linear process in the presence of a constant but unknown bias vector. Moreover, this filter is not exactly like the classical Kalman filter, so many researchers have contributed to this area. Related works are Hsieh and Chen (1999), Ignagni (2000), Keller (1997), Keller and Darouach (1999), Kim, Jee, and Song (2008) and Tanaka (1975).

In 1999, Hsieh and Chen (1999) proposed an optimal two-stage Kalman estimator (OTSKE) that recovered the performance of the classical Kalman filter. This modified Kalman filter is "optimal" in the sense that the filter gives the minimum mean square error of the system state. This optimality is recovered because the equations are mathematically equivalent to the classical equations of the Kalman filter. The system is described by the linear discrete-time state space model:

$$\begin{cases} X[k+1] = A[k]X[k] + B^{\Theta}[k]\Theta[k] + W^{x}[k] \\ \Theta[k+1] = G[k]\Theta[k] + W^{\Theta}[k] \\ Y[k] = C[k]X[k] + D^{\Theta}[k]\Theta[k] + \eta[k] \end{cases} \tag{1}$$

where $X[k] \in R^n$ is the system state, $\Theta[k] \in R^p$ is seen as a dynamical bias that enters linearly in the system, and the measurement vector is $Y[k] \in R^m$. The matrices $A[k]$, $B^{\Theta}[k]$, $G[k]$, $D^{\Theta}[k]$ and $C[k]$ are of appropriate dimensions with the assumption that $G[k]$ is invertible. The process noises $W^x[k]$, $W^{\Theta}[k]$ and the measurement noise $\eta[k]$ are random noise sequences uncorrelated with each other, such that the first and second moments (mean and variance) are

$$\begin{cases} E(W^{x}[k]W^{x^{t}}[k-\tau]) = Q^{x}[k]\delta[\tau] \\ E(W^{\Theta}[k]W^{\Theta^{t}}[k-\tau]) = Q^{\Theta}[k]\delta[\tau] \\ E(W^{x}[k]W^{\Theta^{t}}[k-\tau]) = Q^{x\Theta}[k]\delta[\tau] \\ E(\eta[k]\eta^{t}[k-\tau]) = R[k]\delta[\tau] \\ E(W^{x}[k]\eta^{t}[k-\tau]) = 0 \\ E(W^{\Theta}[k]\eta^{t}[k-\tau]) = 0. \end{cases}$$

This linear state space model is a general case, where the matrices B^{Θ} and D^{Θ} give the action of the unknown input Θ in the dynamical system or in the measurement input equations. If only the measurement inputs are biased, the matrix B^{Θ} is zero. Similarly, D^{Θ} is equal to zero only when the dynamics of the system are biased.

It is known that many practical processes require non-linear observers. Parameter estimation for diagnosis, disturbance observers, speed and position estimation for sensorless control of electrical machines leads to a non-linear system where these variables to be estimated are present in the augmented vector and in the transition matrix. Some past works (Mendel, 1976; Zhou, Sun, Xi, & Zhang, 1993) have focused on estimating the state X and biases Θ of a non-linear system where the unknown inputs Θ are constant and enter linearly in the system:

$$\begin{cases} \dot{X}(t) = f(X(t)) + \Lambda_1\Theta(t) + W(t) \\ Y(t) = h(X(t)) + \Lambda_2\Theta(t) + \eta(t). \end{cases}$$

This class of non-linear systems restricts the application of the two-stage Kalman filter. The general two-stage extended Kalman filters (GTSEKFs) introduced in Hsieh (2003) extend the two-stage Kalman filter to non-linear systems. In the paper, they show how to choose two functions ϕ and ψ to apply a new two-stage transformation. However, the issues of choosing the non-linear functions ϕ and ψ are still an open problem for discrete-time systems. To solve this problem, the authors propose to apply a backward difference equation, despite the fact that this operator introduces approximation. In this work a particular case of the GTSEKF is presented for the estimation of the parameters of a linear parameter varying system. This shows a practical application of this important contribution to estimation theory in a real situation.

Following the same approach as given in Hsieh and Chen (1999), this paper describes a transformation for non-linear discrete-time systems where the variables to be estimated are present in the augmented vector and in the transition matrix. Moreover, some systems have a deterministic input vector $U[k]$; for classical AC electrical machines (induction and synchronous machines), this vector represents the stator voltages. So our problem is described by the non-linear discretized state space model:

$$\begin{cases} X[k+1] = A(\Theta[k])X[k] + B^{\Theta}(\Theta[k])\Theta[k] \\ \qquad + B^{u}(\Theta[k])U[k] + W^{x}[k] \\ \Theta[k+1] = G[k]\Theta[k] + W^{\Theta}[k] \\ Y[k] = C(\Theta[k])X[k] + D^{\Theta}(\Theta[k])\Theta[k] \\ \qquad + D^{u}(\Theta[k])U[k] + \eta[k]. \end{cases} \tag{2}$$

The differences between our equations and those of Hsieh and Chen (1999) are as follows:

- Our system is non-linear because of the product between the state vector X and the augmented state Θ,
- A deterministic input vector U is added, and
- A matrix $D^u(\Theta[k])$ is added in order to use this modified OTSKE in more general systems.

Treating $X[k]$ as the full-order state and $\Theta[k]$ as the augmented system state (parameters or unknown inputs to be estimated), the state space model is described by

$$\begin{cases} X^{a}[k+1] = \overline{A}(\Theta[k])X^{a}[k] + \overline{B}(\Theta[k])\,U[k] + W[k] \\ Y[k] = \overline{H}(\Theta[k])X^{a}[k] + D^{u}(\Theta[k])\,U[k] + \eta[k] \end{cases} \tag{3}$$

with

$$X^{a}[k] = \begin{bmatrix} X[k] \\ \Theta[k] \end{bmatrix} \qquad \overline{A}[k] = \begin{bmatrix} A(\Theta[k]) & B^{\Theta}(\Theta[k]) \\ 0 & G[k] \end{bmatrix}$$

$$\overline{B}[k] = \begin{bmatrix} B^{u}(\Theta[k]) \\ 0 \end{bmatrix}$$

$$\overline{H}[k] = \begin{bmatrix} C(\Theta[k]) & D^{\Theta}(\Theta[k]) \end{bmatrix} \qquad W[k] = \begin{bmatrix} W^{x}[k] \\ W^{\Theta}[k] \end{bmatrix}$$