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Recursive identification of Hammerstein systems with application to electrically stimulated muscle

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A B S T R A C T

Modeling of electrically stimulated muscle is considered in this paper where a Hammerstein structure is selected to represent the isometric response. Motivated by the slowly time-varying properties of the muscle system, recursive identification of Hammerstein structures is investigated. A recursive algorithm is then developed to address limitations in the approaches currently available. The linear and nonlinear parameters are separated and estimated recursively in a parallel manner, with each updating algorithm using the most up-to-date estimation produced by the other algorithm at each time instant. Hence the procedure is termed the alternately recursive least square (ARLS) algorithm. When compared with the leading approach in this application area, ARLS exhibits superior performance in both numerical simulations and experimental tests with electrically stimulated muscle.

1. Introduction

Modelling of electrically stimulated muscle has been a widely investigated area and plays an important role in the analysis of motor control and the design of motor system neuroprostheses. Muscle representations are also necessary in the development of increasingly effective rehabilitation systems for patients (de Kroon, Ijzerman, Chae, Lankhorst, & Zilvold, 2005). There exist a large number of models developed for different aspects of muscle contraction under both isometric, e.g. Bernotas, Crago, and Chizeck (1986) and non-isometric conditions, e.g. Durfee and Palmer (1994), considering the modulation of the output force by varying either the number of active muscle fibers, e.g. Chizeck, Crago, and Kofman (1988) or the frequency of the activation, e.g. Bai, Cai, Dudley-Javorosk, and Shields (2009) and Cai, Bai, and Shields (2010). The most widely assumed structure used in model-based control of electrically stimulated muscle is the Hill-type model (Hill, 1938). This describes the output force as the product of three independent experimentally measured factors: the force–length property, the force–velocity property and the nonlinear muscle activation dynamics under isometric conditions respectively, termed simply activation dynamics (AD) of the stimulation input. The first two account for passive elastic and viscous properties of the muscle and comprise static functions of the muscle length and velocity (Freeman et al., 2009a; Jezernik, Wassink, & Keller, 2004; Lan, 2002; Schauer et al., 2005; Riener & Fuhr, 1998). The activation dynamics capture the active properties of the muscle, and are almost uniformly represented by a Hammerstein structure.

This structure is a crucial component of the muscle model since in most applications joint ranges and velocities are small so that the isometric behavior of muscle dominates. The widespread use of a Hammerstein structure to represent the activation dynamics is due to correspondence with biophysics: the static nonlinearity represents the isometric recruitment curve (IRC), which is the static gain relation between stimulus activation level, and steady-state output torque when the muscle is held at a fixed length. The linear dynamics represents the muscle contraction dynamics, which combines with the IRC to give the overall torque generated.

There are many identification methods applicable to Hammerstein models and in general they can be classified into two categories: iterative, for example, Narendra and Gallman (1966), Zhu (2000) and Westwick and Kearney (2001), and Dempsey and Westwick (2004) with application to stretch reflex electromyogram, and non-iterative methods, for example, an equation-error parameter estimation method in Chang and Luus (1971), an optimal two-stage algorithm in Bai (1998), a blind approach in Bai (2002) and decoupling methods in Bai (2004). However, after reviewing the existing techniques, limitations were encountered when identifying an input–output model of electrically stimulated muscles with incomplete paralysis. These drawbacks were associated with both the structure of the linear and nonlinear Hammerstein components, and the form of the excitation inputs employed. Consequently Le, Markovsky, Freeman, and Rogers (2010) developed two iterative algorithms suitable for

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the identification of electrically stimulated muscles in subjects with incomplete paralysis, and their efficacy was demonstrated through application to experimentally measured data.

The algorithms developed in Le et al. (2010) represent significant progress in the identification of electrically stimulated muscles, but the models were only verified over a short time interval (20 s duration). However, when applied to stroke rehabilitation, stimulation must be applied during intensive, goal orientated tasks in order to maximize improvement in motor control (Schmidt & Lee, 1998). In clinical trials this translates to sustained application of stimulation during each treatment session between 30 min and 1 h duration (de Kroon et al., 2005). In this case, slowly time-varying properties of the muscle system arise due to fatigue, changing physiological conditions or spasticity (Graham, Thrasher, & Popovic, 2006). Motivated by this, online, also termed recursive, identification will be considered in this paper, in which the model parameters are updated once new data is available. Only a few of the existing identification methods for Hammerstein structures are recursive, and can be divided into three categories.

The first category is the recently developed recursive subspace identification method by Bako, Mercere, Lecoeuche, and Lovera (2009), where the nonlinear function is first recursively estimated by over-parameterizations and component-wise least squares support vector machines (LS-SVM). This is followed by estimation of the Markov parameters by recursive least squares and then a propagator-based method is used to recursively estimate system state-space model matrices from these parameters. This procedure does not have sparsity due to the LS-SVM model, and the resulting computational load makes it unsuitable for real-time implementation.

The second category is stochastic approximation (Chen, 2004; Greblicki, 2002) where a stochastic approximation algorithm with expanding truncations is developed for recursive identification of Hammerstein systems. Two major issues with this method are the rather slow convergence rates, and the lack of information on how to select the optional parameters in the algorithm.

The third category is recursive least squares (RLS) or extended recursive least squares (ERLS). The RLS algorithm is a well known method for recursive identification of linear-in-parameter models and if the data is generated by correlated noise, the parameters describing the model of the correlation can be estimated by ERLS. Here, a typical way to use these two algorithms is to treat each of the cross-product terms in the Hammerstein system equations as an unknown parameter. This procedure, which results in an increased number of unknowns, is usually referred to as the over-parameterization method (Bai, 1998; Chang & Luus, 1971). After this step, the RLS or ERLS method can be applied (Boutayeb & Darouach, 1995; Boutayeb, Aubry, & Darouach, 1996; Zhao & Chen, 2009).

The limitations of current algorithms are stated next and used to justify some of the critical choices necessary for this work to progress.

- The first two categories have only been applied in simulation and the stochastic approximation has not the considered time-varying linear dynamics. This, together with the drawbacks described above, is the reason for not considering them further for the application treated in this paper. The third category is the most promising as it has already been applied to electrically stimulated muscle in Chia, Chow, and Chizeck (1991) and Ponikvar and Munih (2001).
- Most of the test signals used comprise random noise in order to guarantee persistent excitation, even when applied to the human muscle (Ponikvar & Munih, 2001), and use pseudorandom binary sequences. However, this type of signal, which excites the motor units abruptly, will cause patient discomfort and may elicit an involuntary response, as reported in Baker, McNeal, Benton, Bowman, and Waters (1993). In Chia et al. (1991) a test consisting of 25 pulses is used, each of which is of 1 s duration in the form of a noisy triangular wave. This test meets our requirements but is too short to exhibit time-varying properties.
- The most relevant previous work is Chia et al. (1991) where the system considered had linear constraints and RLS was developed for constrained systems. However, the results given do not establish that the constraints are achieved. For example, even when considering the prediction error, the posteriori estimated output without constraints is superior to the one with constraints. Thus, the idea of adding constraints to RLS, leading to increased computational load, still merits consideration.

Overall, RLS has the greatest potential for application to electrically stimulated muscle, but the problem of consistent estimation must be resolved (Chen, 2004; Chia et al., 1991). The deficiency of RLS is illustrated in Section 3, where noise and excitation inputs that correspond with those encountered in the rehabilitation application domain are employed, and confirm its unsatisfactory performance. This motivates development of an alternative recursive algorithm in Section 2.3, as well as the design of a long-period test signal which is persistently exciting and also gradually recruits the motor units, and hence is suitable for application to patients. This problem is addressed in Section 4.

2. Problem statement and solution methods

2.1. Problem statement

Consider the discrete-time SISO Hammerstein model shown in Fig. 1. The linear block is represented by ARX model:

$$y(k) = \frac{B(q)}{A(q)} w(k) + \frac{1}{A(q)} v(k) \tag{1}$$

where

$$B(q) = b_0 q^{-d} + b_1 q^{-(d+1)} + \cdots + b_n q^{-(n+d)} \quad \text{and}$$
$$A(q) = 1 + a_1 q^{-1} + \cdots + a_l q^{-l} \tag{2}$$

q^{-1} is the delay operator and n, l and d are the number of zeros, poles and the time delay order, respectively. The parameters n, l and d are assumed to be known. The nonlinearity is represented by a sum of the known nonlinear functions $f_1, f_2, \ldots, f_m$ and a bias:

$$w(k) = f(u(k)) = \beta_0 + \sum_{i=1}^{m} \beta_i f_i(u(k)) \tag{3}$$

The identification problem considered is:

Given N consecutive input–output data measurements $\{u(k), y(k)\}$ estimate recursively the linear parameters $[a_1, \ldots, a_l, b_0, \ldots, b_n]$ in (2) and the nonlinear parameters $[\beta_0, \ldots, \beta_m]$ in (3).

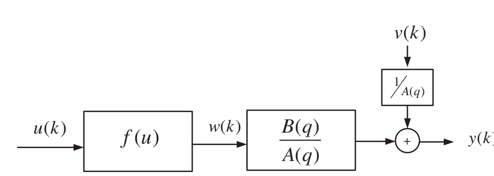

Fig. 1. Hammerstein system.