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# Online Identification of Electrically Stimulated Muscle Models

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*Abstract*— **Online identification of electrically stimulated muscle under isometric conditions, modeled as a Hammerstein structure, is investigated in this paper. Motivated by the significant time-varying properties of muscle, a novel recursive algorithm for Hammerstein structure is developed. 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 Recursive Least Squares (RLS) algorithm applied to the over-parametric representations of the Hammerstein structure, ARLS exhibits superior performance on experimental data from electrically stimulated muscles and a faster computational time for a single updating step. Performance is further augmented through use of two separate forgetting factors.**

## I. Introduction

As a result of the tradeoff between the complexity of general nonlinear systems identification and the interpretability of linear dynamical systems, Hammerstein structures have received considerable attention, and have been used in various areas to, for example, model chemical [24], biological [10] and electrical [26] processes. The Hammerstein structure consists of a memoryless nonlinear block followed by a linear dynamic system, and the difficulty is that the inner signal is not measurable, that is, only input-output data measurements can be used to separate the nonlinear component from the linear one. There are many identification methods applicable to Hammerstein models and in general they can be roughly classified into two categories: iterative, for example, [21] and [10] with application to stretch reflex electromyogram, and non-iterative methods, for example, an equation-error parameter estimation method in [6], an optimal two-stage algorithm in [1], and decoupling methods in [2]. However, after reviewing the existing techniques, limitations were encountered when identifying an input-output model of electrically stimulated muscles with incomplete paralysis. Consequently [20] developed two iterative algorithms for the identification of electrically stimulated muscles, and their efficacy was demonstrated through application to experimentally measured data.

The algorithms developed in [20] represent significant progress in the identification of electrically stimulated muscles, but the models were only verified over a short time interval (20 sec duration). However, when applied to stroke rehabilitation, stimulation must be applied during intensive, goal orientated practice tasks in order to maximise improvement in motor control [23]. In clinical trials this translates to sustained application of stimulation during each treatment session of between 30 minutes and 1 hour duration [9]. In this case, slowly time-varying properties of the muscle system arise due to fatigue, changing physiological conditions or spasticity [14]. Motivated by this, online identification will be considered in this paper where in this approach, the model parameters are updated once new data is available. Only a few of the existing identification methods are recursive, and can be divided into three categories.

The first category is the recently developed recursive subspace identification method [4]. Firstly, the Markov parameters of the system are estimated by least squares support vector machines (LS-SVM) regression and over-parameterizations. This is followed by recursive estimation of state-space model matrices by a propagator-based subspace identification method. 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 comprises stochastic approximation [15] where algorithms with expanding truncations are developed for recursive identification of Hammerstein systems. Two major issues with this method are the rather slow rates of convergence, and the lack of information on how to select the optional parameters in the algorithm for problems from different areas.

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 [1] and [6]. After this step, the RLS or ERLS method can be applied [5].

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 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 [8] and [22].

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- Most of the test signals used comprise random noise in order to guarantee persistent excitation, even when applied to the human muscle [22], and use pseudo-random 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 [3]. In [8] a test consisting of 25 pulses is used, each of which is of 1 second 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 [8] 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 showing the prediction error, the posteriori estimated output without constraints is better than the one with constraints. Thus, the idea of adding constraints to RLS, leading to increased computational load, is well worth considering.

Overall, RLS is the most promising technique for application to electrically stimulated muscle. This algorithm is implemented here but due to ignorance of the rank constraint in the over-parametric vector, the performance is not wholly satisfactory, especially in noisy environments, so another recursive algorithm is developed in Section II-B. Moreover, a long-period test signal needs to be designed for our application, which is persistently exciting and also gradually recruits the motor units. This problem is addressed in Section III.

## II. Problem Statement and Solution Methods

### A. Problem Statement

Consider the discrete-time SISO Hammerstein model, shown in Fig. 1.

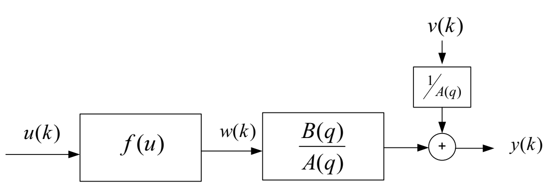



Fig. 1. Hammerstein System.

The linear block is represented by the ARX model:

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

where

$$B(q) = b_0 q^{-d} + b_1 q^{-(d+1)} + \cdots + b_n q^{-(n+d)} \tag{2}$$

$$A(q) = 1 + a_1 q^{-1} + \cdots + a_l q^{-l} \tag{3}$$

$q^{-1}$ 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 function $f_1, f_2, \ldots, f_m$ and a bias:

$$w(k) = f(u(k)) = \beta_0 + \sum_{i=1}^{m} \beta_i f_i(u(k)) \tag{4}$$

The considered recursive identification problem 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 (2,3) and the nonlinear parameters $[\beta_0, \ldots, \beta_m]$ in (4).

### B. ARLS Algorithm

A recursive identification method is developed which avoids over-parameterization by instead splitting the model into nonlinear and linear components, where each is identified independently using a parallel implementation. This method builds on [20] in which two iterative algorithms were developed for Hammerstein systems with differing noise models, and in each case nonlinear and linear parameters were alternately optimized by different projection algorithms. Whilst both involved LS optimization for offline identification, and therefore extend naturally to the online case through application of RLS, the one with simpler implementation and faster computation time will be taken as a starting point. By invoking certain approximations, this algorithm can be implemented recursively as follows:

- Recursive identification of linear parameters

  The parameters of the ARX model can be separated into linear and nonlinear parameter vectors

$$\theta_n = [\beta_0 \quad \cdots \quad \beta_m]^T \tag{5}$$

$$\theta_l = [a_1 \quad \cdots \quad a_l \quad b_0 \quad \cdots \quad b_n]^T \tag{6}$$

$y(k)$ can be expressed as a function of linear parameters $a_1(k), \ldots, a_l(k), b_0(k), \ldots, b_n(k)$ only, if the nonlinear parameter vector $\theta_n$ is known

$$\begin{aligned} y(k) = & -a_1(k)y(k-1) - \cdots - a_l(k)y(k-l) \\ & + b_0(k) f(u(k-d), \theta_n) \\ & \vdots \\ & + b_n(k) f(u(k-d-n), \theta_n) + v(k) \end{aligned} \tag{7}$$

or

$$y(k) = \phi_l^T(k, \theta_n)\theta_l(k) + v(k) \tag{8}$$

where

$$\begin{aligned} \phi_l^T(k, \theta_n) = & [-y(k-1) \quad \cdots \quad -y(k-l) \\ & f(u(k-d), \theta_n) \quad \cdots \quad f(u(k-d-n), \theta_n)] \end{aligned} \tag{9}$$

A forgetting factor $\lambda_l$ is used in the recursive least squares algorithm to minimize the criterion

$$V_l(\theta_l, k) = \frac{1}{2} \sum_{i=1}^{k} \lambda_l^{k-i} \left( y(k) - \phi_l^T(k, \hat{\theta}_n(k-1))\theta_l(k) \right)^2 \tag{10}$$

where the nonlinear parameter vector is approximated by the estimated value at the previous time instant $k-1$.

The recursive algorithm for the linear parameter vector $\theta_l(k)$ is

$$P_l(k) = \frac{1}{\lambda_l}\left(P_l(k-1) - \frac{P_l(k-1)\phi_l(k,\hat{\theta}_n(k-1))\phi_l^T(k,\hat{\theta}_n(k-1))P_l(k-1)}{\lambda_l I + \phi_l^T(k,\hat{\theta}_n(k-1))P_l(k-1)\phi_l(k,\hat{\theta}_n(k-1))}\right) \quad (11)$$

$$\hat{\theta}_l(k) = \hat{\theta}_l(k-1) + P_l(k)\phi_l^T(k,\hat{\theta}_n(k-1))\left(y(k) - \phi_l^T(k,\hat{\theta}_n(k-1))\hat{\theta}_l(k-1)\right) \quad (12)$$

- Recursive identification for the nonlinear parameter vector Similarly, it is first assumed that the linear parameter vector $\theta_l$ is known, which leads to a system equation linear in nonlinear parameters,

$$A(q,\theta_l)y(k) = \phi_n^T(k,\theta_l)\theta_n(k) + v(k) \quad (13)$$

where

$$A(q,\theta_l)y(k) = y(k) + a_1 y(k-1) + \cdots + a_l y(k-l) \quad (14)$$

and

$$\phi_n^T(k,\theta_l) = [\sum_{i=0}^{n} b_i \quad \sum_{i=0}^{n} b_i f_1(u(k-d-i)) \quad \cdots \quad \sum_{i=0}^{n} b_i f_m(u(k-d-i))] \quad (15)$$

and then the linear parameter vector is substituted by the estimated value from the previous time instant, resulting in a recursive algorithm for the nonlinear parameter vector

$$P_n(k) = \frac{1}{\lambda_n}\left(P_n(k-1) - \frac{P_n(k-1)\phi_n(k,\hat{\theta}_l(k-1))\phi_n^T(k,\hat{\theta}_l(k-1))P_n(k-1)}{\lambda_n I + \phi_n^T(k,\hat{\theta}_l(k-1))P_n(k-1)\phi_n(k,\hat{\theta}_l(k-1))}\right) \quad (16)$$

$$\begin{aligned}\hat{\theta}_n(k) = {} & \hat{\theta}_n(k-1) \\ & + P_n(k)\phi_n^T(k,\hat{\theta}_l(k-1))\left(A(q,\hat{\theta}_l(k-1))y(k) - \phi_n^T(k,\hat{\theta}_l(k-1))\hat{\theta}_n(k-1)\right)\end{aligned} \quad (17)$$

## III. Application to Electrically Stimulated Muscle

In this section, the two recursive algorithms are applied to online identification of the response of electrically stimulated muscle.

### A. Modelling of electrically stimulated muscle

The most widely assumed structure used in model-based control of electrically stimulated muscle is the Hill-type model [16]. 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. The first two account for passive elastic and viscous properties of the muscle and comprise static functions of the muscle length and velocity [19], [12]. The activation dynamics capture the active properties of the muscle, and are almost uniformly represented by a Hammerstein structure. This comprises 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.

The non-linearity has been parametrized in a number of ways, taking the form of a simple gain with saturation [11] or a piecewise linear function [19], [18]. The linear dynamics have been assumed to be first order in [19], critically damped second order in [25] or second order with possible transport delay in [18].

In the tests which follow, the linear block is represented by an ARX model described by (1), (2), and (3), with the parameters $l = 2, n = 2, d = 1$. To provide a smooth function with continuous derivatives suitable for subsequent control, the nonlinear function $f(u)$ is represented by the cubic spline

$$f(u) = \beta_0 + \beta_1 u + \beta_2 u^2 + \beta_3 u^3 + \sum_{i=4}^{m+3} \beta_i |u - u_{i-3}|^3 \quad (18)$$

where $u_{\min} = u_1 < u_2 < u_3 < \cdots < u_m = u_{\max}$ are the spline knots.

### B. Experimental Setup

Experimental tests have been carried out using a workstation which has been developed as a platform for upper limb stroke rehabilitation. It incorporates a five-link planar robotic arm which includes a six axis force/torque sensor in its extreme link, and an overhead projector used to display trajectories to patients. The system has been used in a clinical trial in which electrical stimulation was applied to the patient's triceps to assist their completion of trajectory tracking tasks. Full details of the system are provided in [13] which includes experimental validation of the sensor and stimulation hardware.

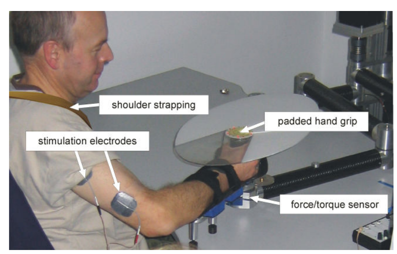
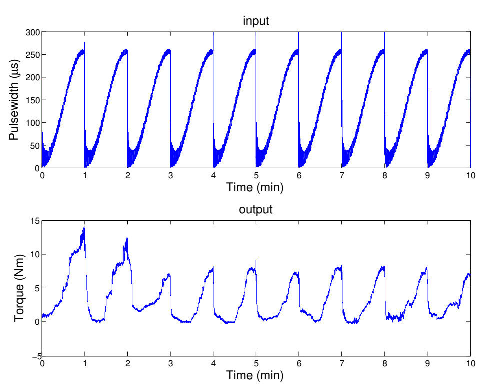


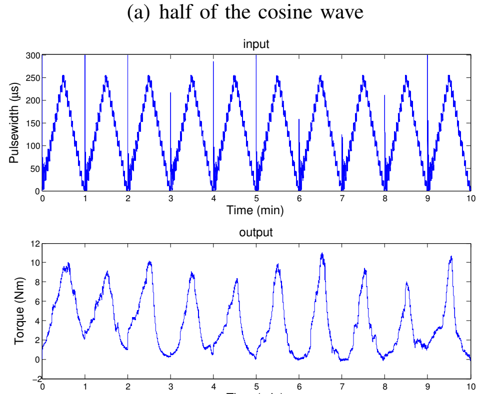

Fig. 2. Robotic workstation

Recursive identification tests were performed on a single unimpaired subject, and took place on several independent days. The participant's upper arm and forearm lengths were first taken, they were then seated in the workstation and their right arm was strapped to the extreme link of the robotic arm. Straps were applied about the upper torso to prevent shoulder and trunk movement (as shown in Fig. 2). The subject's upper limb was then moved over as large an area as possible and a kinematic model of the arm produced using the recorded measurements. This was used to transform the force recorded by the force/torque sensor to torque acting about the elbow (see [13]). The electrodes were then positioned on the lateral head of triceps and adjusted so that the applied stimulation generated maximum forearm movement. The stimulation consists of a series of bi-phasic pulses at 40 $Hz$, whose pulsewidth is variable from 0 to 300 $\mu s$ with a resolution of 1 $\mu s$. The amplitude, which is fixed throughout all subsequent tests, is determined by setting the pulsewidth equal to 300 $\mu s$ and slowly increasing the applied voltage until a maximum comfortable limit is reached. A sample frequency of 1.6 $KHz$ is used by the real-time hardware.

The position of the robotic arm was then fixed at an elbow extension angle of approximately $\pi/2$ rads using a locking pin. This removes the non-isometric components of the biomechanical model, so that the resulting system corresponds to a Hammerstein structure (comprising the muscle model with the addition of passive elastic torque from the remaining arm which may also vary in time). The model's input is the stimulation pulsewidth, and its output is the torque about the elbow. The recursive identification tests last for 10 min, comprising 10 repeated waves of either a half-cosine function, or a staircase signal, added to which the diminishing excitation technique [7] has been used to make the input signals persistently exciting. Although the white noise input signal is widely used in recursive identification, it is unsuitable for the present application as previously noted. Both the half-cosine and staircase input signals have similar characteristics to those used in rehabilitation (see [17]) and the corresponding output signals are plotted in Fig. 3.




(a) half of the cosine wave




(b) staircase wave

Fig. 3. The input and output signals for recursive identification tests

### C. Results

The two recursive algorithms, RLS and ARLS, are compared in the following aspects:

- One-step ahead prediction

In order to evaluate the accuracy of the recursive algorithms, the measured torque outputs $y$ are compared with the one-step ahead predicted outputs $\hat{y}$ in terms of best fit rate defined as:

$$Best\ Fit = \left(1 - \frac{\|y-\hat{y}\|_2}{\|y-\bar{y}\|_2}\right) \times 100$$

and $\hat{y}$ is defined as

$$\hat{y}(k+1) = G(q, \hat{\theta}_l(k)) f(u, \hat{\theta}_n(k))$$

which is a one-step ahead prediction, using the updated model at the time instant $k$ to predict the output at the next time instant $k+1$.

Table I lists the best fit rates for half cosine and staircase wave inputs respectively, and considers both the whole 10-minute dataset and the first 1-minute dataset, the latter of which contains less time-varying information. The corresponding fitting plots are shown in Fig. 4.

TABLE I

MUSCLE TESTS: BEST FIT RATES BETWEEN THE MEASURED OUTPUTS AND THE ONE-STEP AHEAD PREDICTED OUTPUTS FROM THE TWO RECURSIVE ALGORITHMS

| | half cosine wave input | | staircase wave input | |
|---|---|---|---|---|
| | RLS | ARLS | RLS | ARLS |
| 1 min | -10.0244 | 87.9188 | -130.4187 | 80.3162 |
| 10 min | -52.3874 | 61.3267 | -408.2148 | 57.4049 |

- Computational Time

Since the algorithms are intended for online implementation in real-time, their computation time is an important factor. The time taken to perform a single updating step for both recursive algorithms is listed in Table. II.

TABLE II

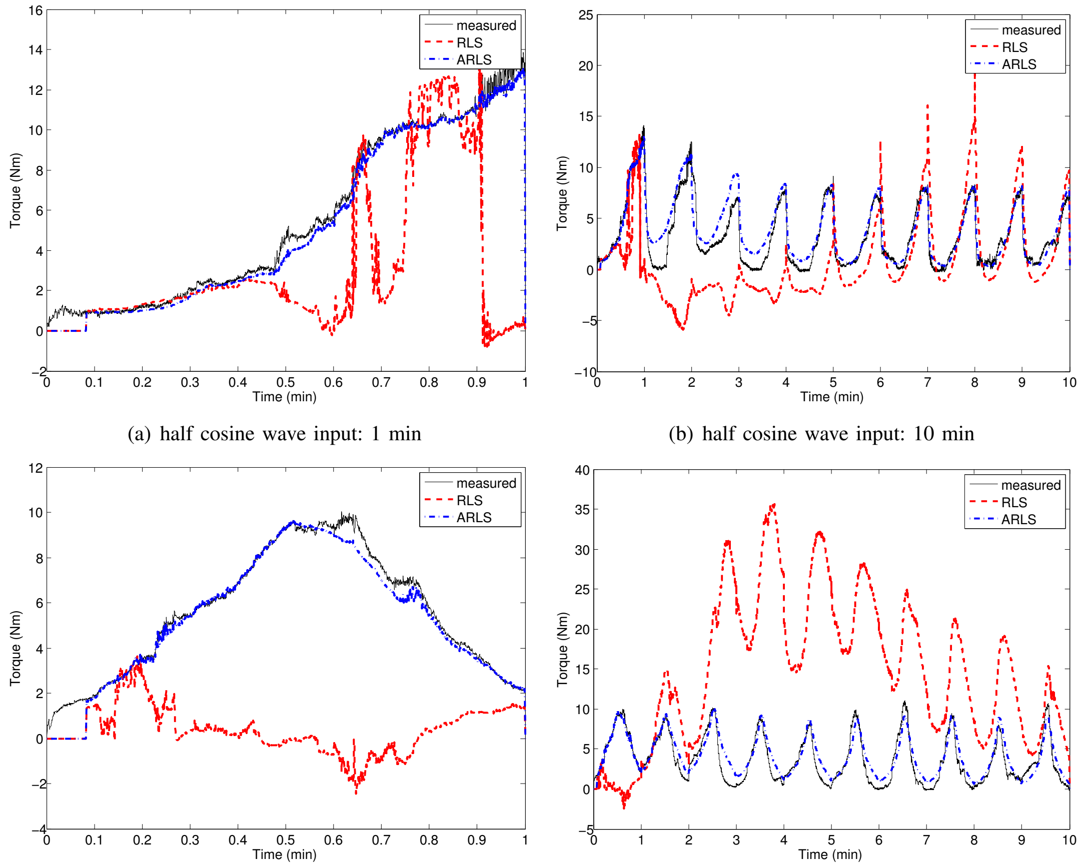
MUSCLE TESTS: COMPUTATIONAL TIME IN SECONDS FOR A SINGLE UPDATING STEP FOR THE TWO RECURSIVE ALGORITHMS

| | RLS | ARLS |
|---|---|---|
| computational time | 0.0019 | $1.0989 \times 10^{-4}$ |

### D. Discussion

First of all, the input and output signals, plotted in Fig. 3, clearly exhibit time-varying properties of the electrical stimulated muscle system, that is, the responses to the same input slowly change with time. This is in accord with the assumptions made in this paper and also strongly supports the need for online identification.

From the results, it is clear that ARLS is far superior to RLS. The reason is the over-parametrization method from which RLS arises already suffers from the problem of an implicit rank constraint, that is, the newly defined parameter vector should have a rank constraint, which is often ignored.




(a) half cosine wave input: 1 min

(b) half cosine wave input: 10 min

(c) staircase wave input: 1 min

(d) staircase wave input: 10 min

Fig. 4. Muscle Tests: the fitting plot between the measured outputs and the one-step ahead predicted outputs from the RLS and ARLS algorithms.

Consequently, the performances are not satisfactory, for example, in [27], the over-parametrization method shows sensitivity to noise, when compared with the iterative and numerical methods. Hence, after implementation in a recursive fashion, the estimates from RLS are likely to be worse, especially for the noise contaminated experimental data. ARLS overcomes this problem by avoiding over-parameterizations and splitting the parameters into linear and nonlinear parts, each of which has their own information states and updating algorithms. With respect to the experimental results, for 1 minute data, one-step ahead prediction can track the output well, shown in Fig. 4(a) and 4(c) and for 10 minute data, it also can capture long term variation in the muscle properties, as illustrated by Fig. 4(b) and 4(d).

Moreover, ARLS is even faster than RLS, because ARLS splits the algorithm into two parallel ones, each of which entails low-dimensional matrix multiplication.

Another advantage of ARLS is that it has two separate weights for linear and nonlinear parameters, $\lambda_l$ and $\lambda_n$. In the real muscle system, the linear and nonlinear parameters represent two different mechanisms (muscle activation and recruitment respectively) which change over time at different rates. The ability to choose individual weights for each mechanism provides clear selection and performance advantages over a single $\lambda$ parameter.

In the previous recursive process, the weighting parameters $\lambda$, $\lambda_l$ and $\lambda_n$ are fixed at 1, and the implications of this choice are now considered using Tables III and IV. For RLS, there is no improvement when tuning the $\lambda$ parameter, while for ARLS, the fitting rate reaches 70% for $\lambda_l = 0.9995$ and $\lambda_n = 0.9997$.

TABLE III

10 MIN DATA OF HALF COSINE WAVE INPUT: BEST FIT RATES BETWEEN MEASURED AND ONE-STEP AHEAD PREDICTED OUTPUTS FROM RLS WITH DIFFERENT $\lambda$

| $\lambda$ | Best Fit Rate (%) |
|---|---|
| 1 | -52.3874 |
| 0.9999 | -109.1885 |
| 0.9998 | -141.6934 |
| 0.9997 | -103.2831 |
| 0.9990 | -64.0752 |

Fig. 5 shows the time trajectory of the estimated values for the linear and nonlinear parameters from ARLS. These illustrate the underlying physiological changes in the muscle system over time.

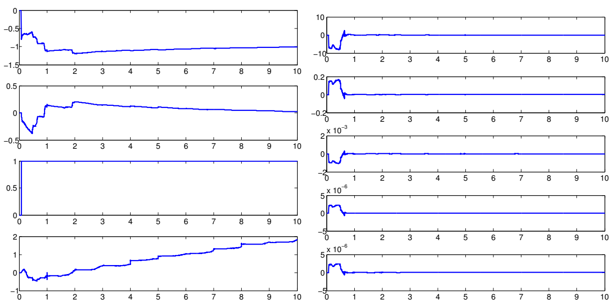
## IV. CONCLUSIONS

A novel recursive identification algorithm has been developed for Hammerstein structures, in which the linear

TABLE IV

10 MIN DATA OF HALF OF COSINE WAVE INPUT: BEST FIT RATES BETWEEN MEASURED AND ONE-STEP AHEAD PREDICTED OUTPUTS FROM ARLS WITH DIFFERENT $\lambda_l$ AND $\lambda_n$

| $\lambda_l$ | $\lambda_n$ | Best Fit Rate (%) |
|---|---|---|
| 1 | 1 | 61.3267 |
| 0.9999 | 0.9999 | 63.6053 |
| 0.9998 | 0.9999 | 65.8187 |
| 0.9997 | 0.9999 | 67.6394 |
| 0.9996 | 0.9998 | 68.7207 |
| 0.9995 | 0.9997 | 70.8437 |
| 0.9994 | 0.9996 | 43.0805 |



(a) linear parameters (b) nonlinear parameters

Fig. 5. Muscle tests: the time trajectory of the estimated values of the linear and nonlinear parameters from ARLS.

and nonlinear parameters are recursively identified in a parallel manner. The proposed algorithm has been shown to outperform the leading RLS alternative when applied to the experimental identification of electrically stimulated muscle. The identification procedure will be shortly utilised in clinical trials with stroke patients for the purpose of rehabilitation.

## V. ACKNOWLEDGMENTS

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