System Identification of Muscle Dynamics for ILC-based Stroke Rehabilitation

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***Abstract*—In this paper results are presented for the identification of electrically stimulated muscle dynamics in stroke patients. This research forms a critical component in the model-based control of electrically stimulated upper-limb movement, which, in turn, is necessary to maximise improvement in sensory-motor function during rehabilitation with electrical stimulation.**

An overview is firstly provided of an experimental test facility that has been developed for stroke rehabilitation. During treatment stroke participants use this system to track elliptical trajectories projected onto a target above their arm, assisted by electrical stimulation applied to their triceps. The control approach used to apply stimulation is summarised, and the structure of the muscle model within the scheme is described. A novel iterative identification scheme is then introduced for the muscle dynamics of stroke patients, and experimental results are presented to confirm its performance and suitability in the proposed rehabilitation context.

***Index Terms*— Identification, Muscles, Iterative methods, Biomedical engineering**

I. INTRODUCTION

Each year there are approximately 100,000 new cases of stroke in the UK. One third of patients will not survive the first year and another third will make a full recovery. Half of all acute stroke patients starting rehabilitation will have a marked impairment of function of one arm of whom only about 14% will regain useful sensory-motor function [1], [2]. It has been argued that arm and hand function is more important than mobility in achieving independence following stroke [2]. Impaired motor control means that stroke patients cannot learn new skills though practice. As a consequence of the inevitable disuse, neuroplastic changes within the motor cortex areas previously responsible for control of the paralysed limb form new connections with local areas that retain voluntary control [3]. This ‘learned disuse’ is believed to be a significant barrier to recovery of sensory-motor function. The problem may be limited through use of Functional Electrical Stimulation (FES) which provides the experience for the patient of moving, and has been used with some success to improve recovery of upper limb motor control [4]. However FES may also have a direct effect on excitability of the central nervous system: greater improvement has been observed when stimulation is associated with a voluntary attempt to move the limb [4], [5], and the ‘Hebbian Learning Rule’ hypothesis has been proposed to explain this enhanced motor learning [6]. Triggering of stimulation through voluntary activity has been demonstrated [7], but has not been able to provide the precise control necessary.

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A workstation has been designed and constructed in order to test the ‘Hebbian Learning Rule’ by providing a reaching task for the patient to perform using their remaining voluntary action, whilst simultaneously applying FES using advanced control schemes to aid its completion. Recent clinical trials with 5 stroke participants comprising between 18 and 25 treatment sessions gave rise to results indicating statistically significant improvement in several areas, including their level of unassisted tracking [8].

The need for a high level of tracking accuracy means that advanced model-based control schemes have been implemented for the application of stimulation. In particular Iterative Learning Control (ILC) has been used, a technique that is applicable to systems operating in a cyclical mode. Using information from previous trials of the task, ILC produces a correction term that is added to the reference in order to reduce the tracking error over the next trial (see, for example, [9]). When accurate tracking of the reference trajectory is achieved, the stimulation is reduced to promote sustained voluntary effort by the subject. The performance of the control approach, however, is highly dependent on the model of the underlying system, and, in particular, the dynamics of electrically stimulated muscle. This paper focuses on the identification of stimulated muscle in stroke patients, which is necessary to increase the tracking accuracy of the controller, and hence the potential of the system for rehabilitation.

II. ROBOTIC WORKSTATION OVERVIEW

The task presented to the seated patient is to track trajectories using their impaired arm. So that the objective is presented with maximum clarity, only trajectories in a fixed horizontal plane are used and the patient’s forearm is constrained to move in this plane by a custom-built robot. A data projector mounted above the subject is used to shine an image of the entire trajectory path, as well as a moving spot to indicate the current point that they must follow, onto a target mounted above the subject’s hand. A cross-hair on the target clearly shows that point which is intended to follow the moving spot as it progresses along the trajectory path. Fig. 1 shows a subject using the workstation. The elements comprising the workstation are now summarised (full details can be found in [10]).

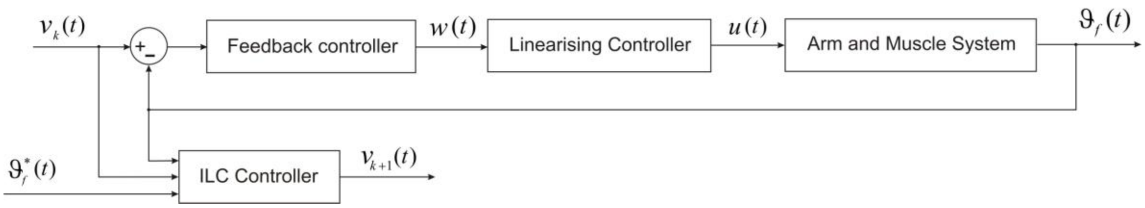


Fig.3 Stimulation Control Scheme

Fig. 1 Subject using robotic workstation to perform a tracking task

A. Software Overview

A custom made Graphical User Interface (GUI) initiates all identification procedures and tracking tasks, and uses a real-time interface and set of function libraries to access the control hardware. A Visual C++ application using the OpenGL interface, together with C libraries for direct access to the control hardware, clearly displays the tracking tasks to the participant.

B. Stimulation System

Four channels of stimulation are supported, each comprising a sequence of bi-phasic pulses at 40Hz. The frequency, amplitude, pulsewidth range and bi-phasic characteristic have been chosen to achieve a smooth muscle contraction [10]. The control hardware uses digital outputs to produce a binary stimulation pulsewidth demand for each channel in the range μs to 350μs (resolution 1μs). Each is then optically isolated and a microcontroller is used to generate a series of 5V amplitude, 40Hz pulses with the required pulsewidth for each channel. The desired bi-phasic characteristic and voltage amplitude is produced using the amplification stage of a commercial stimulator.

C. Robotic Arm System

The subject's arm is strapped to a five-bar robotic arm providing support and constraining it to lie in a horizontal plane, as illustrated in Fig. 2. The robotic arm is actuated using two DC brushless servomotors which are driven by modular PWM amplifiers running in torque mode using Hall effect feedback. A 4000-line encoder is mounted on each motor shaft, and on the link to which the subject's arm is strapped. A six axis force/torque sensor is situated between the penultimate and final links to measure forces applied by the subject. This force has components F_x and F_y, in the directions of the base co-ordinate vectors $\boldsymbol{x}$ and $\boldsymbol{y}$ respectively.

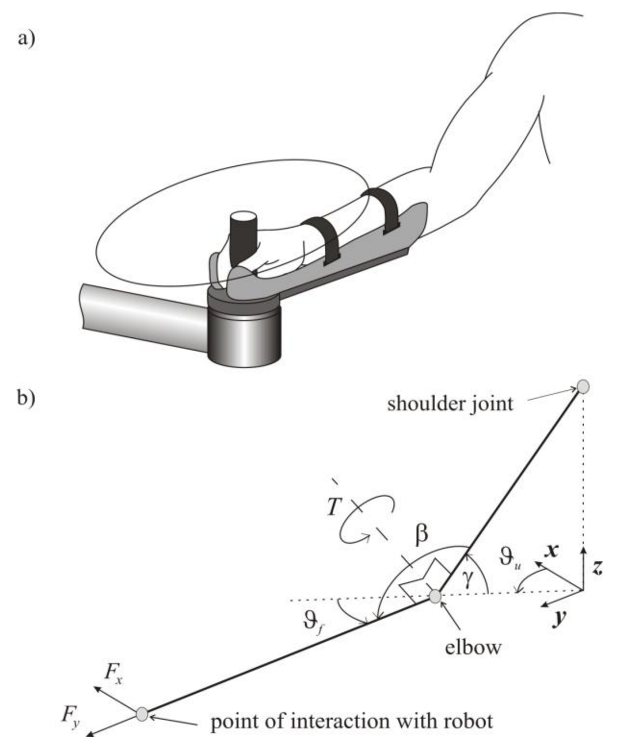


Fig.2 Stimulated human arm system a) schematic, and b) underlying geometry

The upper arm and forearm angles are denoted by ϑ_u and ϑ_f respectively, and similarly the elbow angle and upper arm elevation angles are given by β and γ. The torque resulting from the electrically stimulated triceps muscle is denoted by T.

III. Control Approach

The patient's arm is a complex non-linear time-varying system which is influenced by i) the robot (through F_x and F_y), ii) the electrical stimulation, and iii) the subject's remaining voluntary effort. Since FES has only yet been applied to the triceps in the clinical trials undertaken, the robotic control scheme has been developed to provide assistive torque purely about the upper arm. Around the forearm axis, the robot simply produces the effect that the patient is moving a point mass of 1Kg with damping of 10N/m^{-1}s. If the higher derivatives of the reference are assumed to be sufficiently small, the system dynamics about the upper arm are decoupled from those about the actuated forearm, and a SISO system results (see [12] for details). This system comprises a model of the electrically stimulated muscle, followed by a non-linear system representing the arm dynamics. This latter system describes the relationship between the torque produced through FES, T, and the resulting forearm angle, ϑ_f (full details can be found in [12]). The control system adopted for this system is shown in Fig. 3 and consists of a linearising controller, followed by a feedback controller, the input to which is updated using a linear ILC scheme. Here $u(t)$ denotes the stimulation pulsewidth, ϑ_f^* the forearm reference trajectory, and $w(t)$, $v(t)$ are intermediary signals.

This control scheme has been used during clinical trials with 5 stroke patients, and has led to accurate tracking, which has in turn resulted in improvement in unassisted tracking [8]. Although identification techniques have been implemented for both the muscle model and arm system dynamics (see [13] for details), it is the muscle model which presents the more challenging identification problem, since it varies significantly due to physiological effects, such as fatigue and spasticity, and is extremely sensitive to electrode placement and environmental conditions. The accuracy of the model of muscle dynamics is therefore of paramount importance, and motivates the novel iterative identification scheme proposed in the next section.

IV. Muscle Model

The task is to model the response of muscles to the applied electrical stimulation. The torque generated at the elbow joint and the stimulation pulse-width applied to the triceps are chosen as the output and input variables, respectively. The most widely assumed structure is the Hill-type model which describes the output as the product of three independent experimentally measured factors: the force-length property, the force-velocity property and the activation dynamics of the stimulation input. The activation dynamics, the most dominant factor when typically slow, controlled motions are presented, is investigated here.

A Hammerstein system is chosen to represent the isometric muscle dynamics due to correspondence with biophysics: the static nonlinearity $f(u)$ represents the Isometric Recruitment Curve (IRC), which is defined as the static gain relation between stimulus activation level and output torque when the muscle is held at a fixed length and the Linear Dynamics, $G(q)$, represents the dynamic response of electrically stimulated muscle, see Fig. 3.

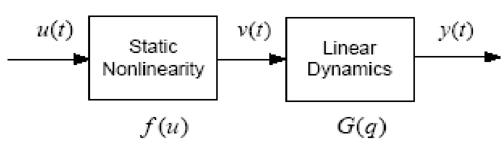


Fig. 3. Hammerstein Structure

V. Test Design

As distinct from many engineering systems, the tests are not applied to a mechanical or physical process, but to a human being, in particular to a stroke patient, so that they require special care in order to ensure the tests are productive, minimize unnecessary discomfort and also the presence of unwanted physiological effects (such as involuntary muscle contractions).

Several important issues have been considered for designing tests for identifying electrically stimulated muscles:

1) Signal Amplitude Distribution: uniformly distributed test signals are recommended.
2) Duration of Test: 20-30s
3) Stimulation Pattern: It is preferred to use gradually exciting signals, although abruptly exciting ones are considered as well.

Based on the investigations undertaken, four candidate tests are proposed: Triangular Ramp (TR) Test, Staircase Test, Filtered Random Noise (FRN) Test, and Pseudo-Random Multi-level Sequences (PRMS) Test, see Fig. 5 for examples of these.

VI. Identification

A. *Problem Statement*

A nonlinear discrete-time Hammerstein model is shown in Fig. 4. The system input, output and noise are denoted by $u(k)$, $y(k)$ and $v(k)$, respectively. The internal signal $w(k)$ is not measurable.

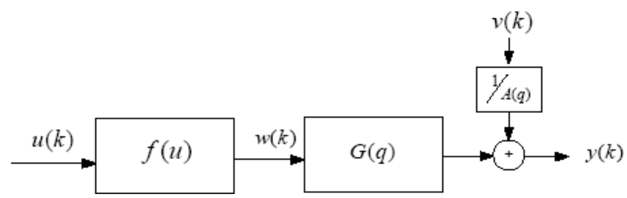


Fig. 4. A Discrete-time Hammerstein Model

The linear system is represented by

$$G(q) = \frac{B(q)}{A(q)} = \frac{b_0 q^{-1} + b_1 q^{-2}}{1 + a_1 q^{-1} + a_2 q^{-2}}$$

The nonlinearity $f(u)$ is represented by the cubic splines

$$f(u) = \sum_{i=1}^{m-2} \beta_i \left| u - u_{i+1} \right|^3 + \beta_{m-1} + \beta_m u + \beta_{m+1} u^2 + \beta_{m+2} u^3$$

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

B. *Iterative Algorithm*

In this paper, an Iterative Algorithm is proposed for identification of the Hammerstein system. The idea behind it is to divide the parameters into a linear component $\theta_l = [a_1, a_2, b_0, b_1]$ and a non- linear component $\theta_n = [\beta_1, \beta_2, \ldots, \beta_m]$, and then update the linear and non-linear parts at each iteration in a least squares sense.

The procedure is briefly described as follows:

1) Use the values of the linear parameters estimated

from Triangular Ramp Deconvolution method as the initial guess θ_l^0 (this was the identification method used during clinical trials with the workstation, see [12] for details).

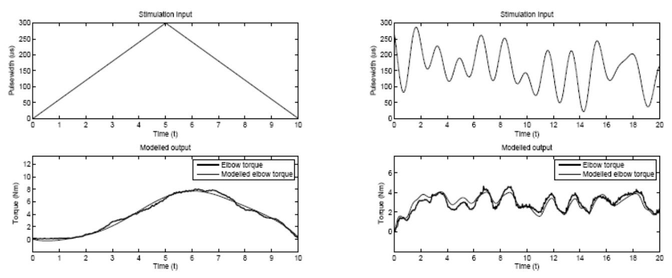
2) Recover the intermediate signal *w(k)* by using the linear parameters from the last iteration, and update the non-linear parameters by fitting cubic splines in a least squares sense.

$$\theta_n = \arg\min_{\theta_n} \sum_{k=1}^{N} (w(k) - f(u(k), \theta_n))^2$$

3) Optimize the linear parameters by using the non-linear parameters estimated in 2), which is simply a linear system identification problem.
4) Go back to 2). Stop when convergence occurs.

VII. Experimental Results

Ten trials for four candidate tests have so far been carried out using a single unimpaired human participant. The Hammerstein model identified using the proposed Iterative Algorithm has been compared with a wide range of other model structures and algorithms using the same experimental data. Furthermore, validation analysis for the same type of candidate tests and cross-validation analysis among four candidate tests has also been conducted. Fig. 5 shows an example of modeled output produced using the proposed Iterative Algorithm for the four candidate tests.



(a) Triangular Ramp test (b) Filtered Random Noise test

(c) Staircase test (d) Pseudo-Random Multi-level test

Fig. 5. An example of four candidate test inputs and modeled outputs

VIII. Conclusion and Future work

A summary has been presented of work undertaken in the identification of electrically stimulated muscle under isometric conditions in order to increase the accuracy of models used for rehabilitation using electrical stimulation. Four candidate tests have been carried out on human subjects and several model structures and algorithms have been compared using experimental data. The proposed Iterative Algorithm for Hammerstein model identification out-performs all others in terms of identification and validation performance. The staircase test has been used for the first time in this area, and exhibits a superior predictive ability compared with the other three considered when using different stimulation patterns.

Future research will extend this work by enrolling more unimpaired subjects for experimental tests, before recruiting stroke participants for further tests. The model identified using the proposed Iterative Algorithm will then be incorporated into the ILC control scheme to further improve the accuracy of tracking tasks. Finally, online identification and adaptive control will be implemented in order to address the problem of time-varying changes in the dynamics of electrically stimulated muscle.

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