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Newton-method based iterative learning control for robot-assisted rehabilitation using FES

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ABSTRACT

Precise control of useful movement is critical in providing effective upper limb stroke rehabilitation using functional electrical stimulation (FES). To address the lack of accuracy currently available in clinical practice, this paper develops a general framework based on iterative learning control (ILC), an approach that has been successfully employed in three clinical treatment trials. An upper limb model is first developed to encompass unconstrained movements of the upper arm. In line with clinical need, additional assistance is then incorporated via a general class of robotic support mechanism. An iterative learning scheme is then developed to enable a subset of joint angles to be controlled via stimulation of an arbitrary set of muscles. This scheme is the first ILC approach which explicitly addresses coupled multivariable nonlinear dynamics in upper-limb rehabilitation, enforcing convergence over multiple executions of a reaching task. Experiments with six participants confirm practical utility and performance.

1. Introduction

Stroke is the leading cause of disability in the UK with 150,000 new cases each year. Half of all acute stroke patients have a significant impairment of one arm, of whom only 14% regain useful function. Current treatments are of limited effectiveness and only 5% of survivors with severe paralysis regain upper limb function [1]. In recent years new technologies have emerged to reduce impairment post-stroke, including rehabilitation robots [2] and electrical stimulation [3], which facilitate intense practice of movement in a motivating environment.

Rehabilitation robots are active or passive supporting devices that allow patients to practice tasks [4]. The sensory feedback gained through repetition enables cortical reorganization in the brain that can bring about functional recovery. Similarly, functional electrical stimulation (FES) directly activates weak or paralyzed muscles, and is another method of driving neuroplastic cortical changes to enable recovery. FES is supported by a growing body of clinical evidence [5], and theoretical support from neurophysiology [6] and motor learning [7] which shows that the therapeutic benefit increases when it is applied co-incidently with a patient's own voluntary intention [8]. Hence FES must precisely assist the patient's own voluntary task completion, in order to maximize functional recovery.

A large number of FES control techniques have been applied to the upper limb, but few that are capable of providing high accuracy have transferred to trials with patients [9]. Here model-based feedback approaches are crucial to address the highly complex, time-varying dynamics, but in the clinical domain there is substantial difficulty in obtaining an accurate model, minimal set-up or identification time, and reduced control over environmental factors. In upper limb patient trials the applied control signal remains mostly open-loop, triggered [10], or is based on electromyographic (EMG) [11,12] or electroencephalographic (EEG) feedback [13,14] to provide a measure of patients' voluntary intention. Closed-loop control of upper limb movement has transferred to clinical practice in only a small number of cases, and most do not use a model of the biomechanical system [15,9]. Used mainly with spinal cord injury patients, one of the few advanced methods comprises artificial neural networks (ANNs), which create a mapping between muscle activity and kinematic variables [16–18]. However such model-free approaches have limited ability to adapt to changing physiological conditions, must be re-trained for use with different movements (requiring kinematic and EMG data collected from unimpaired participants performing similar movements), and do not permit detailed performance and stability analysis.

Iterative learning control (ILC) is one model-based approach that has been applied in three clinical rehabilitation trials with stroke patients. In the first, FES was applied to the triceps muscle to assist patients' completion of a reaching task. In particular, the patients' hand was strapped to a robot and they attempted to

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follow a target moving along an illuminated elliptical track. The patients attempted this task six times, and between each one the ILC algorithm updated the stimulation to be applied on the next attempt using a dynamic model of the arm [19,20]. The use of a model replaces the need for unimpaired participant data to map between intended movement and required control action, as in the case of ANN approaches. A second rehabilitation platform, shown in Fig. 1, was developed to extend the approach to assist 3D arm movements. This system presented virtual reality tracking tasks to the patient, and applied FES to two muscles in the arm and shoulder [21]. Here a commercially available passive mechanism provided support against gravity. For each system unparalleled levels of tracking accuracy were achieved by ILC [20,21], which translated into statistically significant results across a range of outcome measures when used in clinical trials with stroke patients spanning 18–25 treatment sessions [22,23].

The controllers previously used have combined partial linearization with linear single-input, single-output (SISO) ILC schemes that neglected the dynamics of unstimulated joints. In constrast, this paper applies a multivariable, nonlinear ILC scheme within FES-based stroke rehabilitation for the first time. The generality of the underlying system representation enables widespread application across different supports and choice of stimulated muscles. It also encorporates the effects of uncontrolled joints to improve tracking accuracy of the controlled ones, as well as providing conditions for the stability of the uncontrolled joints. The ILC approach employed in this paper extends Newton method based ILC to multiple-input, multiple-output (MIMO) continuous-time dynamics. It also embed for the first time the ability to track subsets of outputs using subsets of inputs. The contents is arranged as follows: Section 2 develops a model of the upper limb and robotic support. Sections 3 and 4 contain ILC algorithm derivation and experimental results respectively, and conclusions are given in Section 5.

2. Model of supported upper limb with FES

When providing assistance during upper limb reaching movements, stimulation must be applied within a controlled environment to ensure safety and comfort across a broad spectrum of patient ability. This may be provided by a passive/orthotic support device such as a simple sling, hinged mechanism, or orthosis, or by a robotic mechanism, of which many designs are available [24]. FES should be provided to assist muscles that have experienced a loss of activity as a result of stroke, such as the triceps, anterior deltoid, wrist and finger extensors [5,6,25]. This is in contrast to overactivity of muscles such as the biceps, wrist and finger flexors, which typically produce a resistance to arm extension as a result of spasticity. In this section a suitable model of the combined human arm and support that has general application across upper limb rehabilitation is derived for use in the ILC algorithms of Section 3.

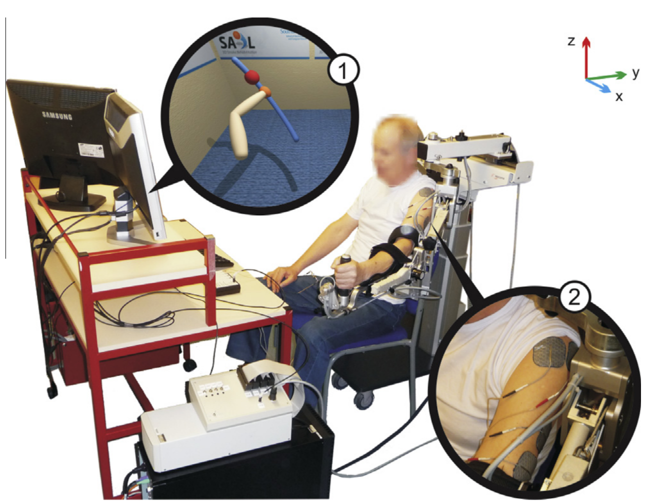

Fig. 1. Experimental system showing participant with their arm in the mechanical support. Close-up views of (1) realtime 3D graphic environment for the patient and (2) surface electrodes on triceps and anterior deltoid.

2.1. Mechanical support

A general dynamic model of the support structure which assumes rigid links is given by

$$\boldsymbol{B}_a(\boldsymbol{\Theta})\ddot{\boldsymbol{\Theta}} + \boldsymbol{C}_a(\boldsymbol{\Theta},\dot{\boldsymbol{\Theta}})\dot{\boldsymbol{\Theta}} + \boldsymbol{F}_a(\boldsymbol{\Theta},\dot{\boldsymbol{\Theta}}) + \boldsymbol{G}_a(\boldsymbol{\Theta}) + \boldsymbol{K}_a(\boldsymbol{\Theta}) = -\boldsymbol{J}_a^T(\boldsymbol{\Theta})\boldsymbol{h} \quad (1)$$

where $\boldsymbol{\Theta} = [\theta_1,\ldots,\theta_q]^T$ is a vector of q joint angles, $\boldsymbol{h}$ is a $q \times 1$ vector of externally applied force, and $\boldsymbol{B}_a(\cdot)$ and $\boldsymbol{C}_a(\cdot)$ are $q \times q$ inertial and Coriolis matrices respectively. In addition, $\boldsymbol{J}_a(\cdot)$ is the system Jacobian, and $\boldsymbol{F}_a(\cdot)$ and $\boldsymbol{G}_a(\cdot)$ are friction and gravitational $q \times 1$ vectors respectively. The vector $\boldsymbol{K}_a(\cdot)$ comprises the $q \times 1$ moments produced by the assistive action of the support mechanism.

2.2. Human arm

A dynamic model of the human arm can be represented by

$$\boldsymbol{B}_h(\boldsymbol{\Phi})\ddot{\boldsymbol{\Phi}} + \boldsymbol{C}_h(\boldsymbol{\Phi},\dot{\boldsymbol{\Phi}})\dot{\boldsymbol{\Phi}} + \boldsymbol{F}_h(\boldsymbol{\Phi},\dot{\boldsymbol{\Phi}}) + \boldsymbol{G}_h(\boldsymbol{\Phi}) = \boldsymbol{\tau}(\boldsymbol{u},\boldsymbol{\Phi},\dot{\boldsymbol{\Phi}}) \quad (2)$$

in which $\boldsymbol{\Phi} = [\phi_1,\ldots,\phi_p]^T$, with inertial and Coriolis matrices $\boldsymbol{B}_h(\cdot)$ and $\boldsymbol{C}_h(\cdot)$ respectively of compatible dimension. Friction and gravitational $p \times 1$ vectors are respectively $\boldsymbol{F}_h$ and $\boldsymbol{G}_h$. If effects such as spasticity in bi-articular elbow/shoulder muscles are sufficiently mild, biomechanical coupling between joints can be omitted [26], and the former takes the form

$$\boldsymbol{F}_h(\boldsymbol{\Phi},\dot{\boldsymbol{\Phi}}) = \mathrm{diag}\left\{F_{v,1}(\dot{\phi}_1) + F_{s,1}(\phi_1),\ldots,F_{v,p}(\dot{\phi}_p) + F_{s,p}(\phi_p)\right\} \quad (3)$$

as confirmed experimentally in [19]. The term $\boldsymbol{\tau}(\boldsymbol{u},\boldsymbol{\Phi},\dot{\boldsymbol{\Phi}})$ comprises the moments generated through application of FES, so that if m muscles are assumed to actuate the system, $\boldsymbol{u}(t) = [u_1(t),\ldots,u_m(t)]^T$. The ith element of the muscle torque vector $\boldsymbol{\tau}(\cdot)$ is the sum of moments generated by each of the m muscles that may each impart a moment about the ith joint.

2.3. Muscle selection and modeling

Modeling the force/moment generated by electrically stimulated muscle is a well explored area, but clear divisions exist between modeling for analysis and for direct model-based control application. Models used for experimental motion control primarily comprise anarticular muscles, and assume the muscle operates about a fixed axis [15]. These contrast with more complex models that encompass muscles with multiple attachment points, often biarticular structure, and movement over pre-defined sliding surfaces [27,28]. However, such simplification opens up a route for parameter identification, yielding tractable control solutions, and is therefore the approach taken in this paper. From [29] the moment generated about the ith joint by the jth muscle can be represented as a Hill-type model of the form

$$\tau_{i,j}\Big(u_j(t),\theta_i(t),\dot{\theta}_i(t)\Big) = h_j(u_j(t),t) \times F_{M,i,j}\Big(\theta_i(t),\dot{\theta}_i(t)\Big) \quad (4)$$

where $h_j(u_j(t),t)$ is a Hammerstein structure incorporating a static non-linearity, $h_{IRC,j}(u_j(t))$, representing the isometric recruitment curve, cascaded with linear activation dynamics, $h_{LAD,j}(t)$. The multiplicative effect of the joint angle and joint angular velocity on the active torque developed by the muscle is captured by the term