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Design & Control of a 3D Stroke Rehabilitation Platform

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***Abstract*—An upper limb stroke rehabilitation system is developed which combines electrical stimulation with mechanical arm support, to assist patients performing 3D reaching tasks in a virtual reality environment. The Stimulation Assistance through Iterative Learning (SAIL) platform applies electrical stimulation to two muscles in the arm using model-based control schemes which learn from previous trials of the task. This results in accurate movement which maximises the therapeutic effect of treatment. The principal components of the system are described and experimental results confirm its efficacy for clinical use in upper limb stroke rehabilitation.**

Keywords: Stroke rehabilitation; Robotics; Electrical stimulation; Iterative learning control.

I. Introduction

Stroke is the third largest cause of death and largest cause of adult disability in the UK. Of the 15 million people who annually suffer a stroke worldwide, 5 million are left permanently disabled. Conventional therapy to improve upper limb function following stroke is not effective, and only 5% of people who survive a stroke but have severe paralysis regain upper limb function [1]. No conventional therapy is better than another, but intensity has been shown to be important. During the last decade there has been growing evidence for the effectiveness of technologies including rehabilitation robots [2] and electrical stimulation to reduce impairment post-stroke.

Functional electrical stimulation (FES) is a promising method of driving neuroplastic cortical changes to enable recovery, and is motivated by a growing body of clinical evidence [3], and theoretical support from neurophysiology [4] and motor learning research [5]. Evidence shows that its therapeutic benefit is maximized when it is applied co-incidently with a patient's own voluntary intention [6], motivating the precise application of stimulation to accurately assist the completion of tasks. Unfortunately, most of the openloop and triggered FES control schemes employed clinically are insufficiently accurate to fully exploit this association. Although a variety of model-based FES control techniques have been applied for both the lower and upper limbs, few have transferred to clinical practice [7]. One exception is Iterative Learning Control (ILC), a technique more commonly used in robotics, which uses data recorded over previous executions of a task to improve tracking performance on the next attempt. Recently ILC has been used to assist patient's completion of a repeated 2D planar reaching task using a robotic workstation [8], leading to statistically significant results across a range of outcome measures during a clinical trial with 5 stroke patients [9]. Through use of multivariable nonlinear ILC, the system developed in this paper extends the scope of treatment to unconstrained movement using FES applied to multiple muscles. This involves substantial extensions to the underlying dynamic model of the system, and to the ILC schemes used to provide the precise tracking control required. This system is termed SAIL: Stimulation Assistance through Iterative Learning [10], and uses a mechanical platform to support the patient's arm, reflecting the growing interest in combining rehabilitation robots with FES to augment the benefit of each approach and extend the impairment range treated [11]. The FES controllers and other system components developed in this paper can be applied to a wide variety of passive or robotic support system, and hence provide scope for future migration directly into patients' homes.

II. System Overview

The tasks designed for the patient in the rehabilitation process involve tracking a moving object along a preset trajectory using their impaired arm. When providing FES 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. Therefore a commercially available mechanical exoskeleton support structure has been selected. The system employed is a purely passive 'unweighing' device which provides support to overcome gravity via two springs incorporated in the mechanism, allowing patients to focus practice on specific impaired muscles during reaching. To assist the patient's arm in tracking the moving sphere, the controller reads position information from the mechanical support and generates FES control signals. Figure 1 shows a patient's arm supported by the mechanical device and Figure 2 shows the patient trying to track a reaching trajectory during a training session.

The principal system components are now described.

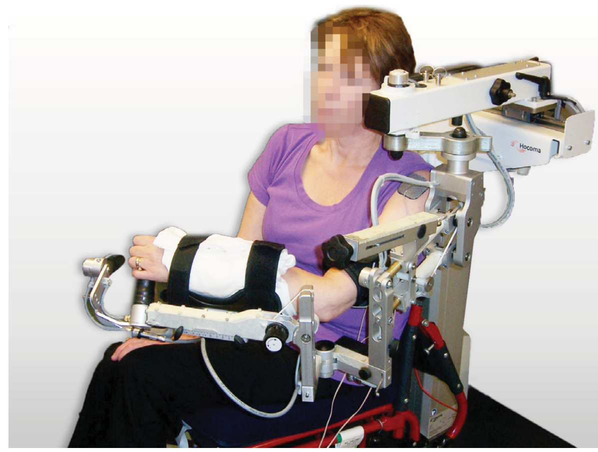


Fig. 1. Stroke patient using SAIL system: mechanical support device.

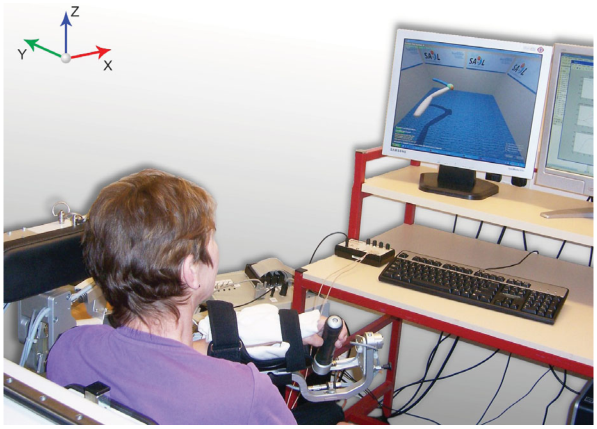


Fig. 2. Patient using SAIL system: tracking task.

A. Mechanical Support

ArmeoSpring® (Hocoma AG, Zurich) is a commercial upper extremity therapy system combining passive arm support with a virtual reality (VR) environment to deliver intensive task-orientated exercise. The device also provides reliable measurement of the human arm position using a resolver at each joint which is aligned in either the horizontal or vertical plane. The diverse range of VR tasks supplied with the system are not suitable for controller evaluation, and hence a custom task display system has been developed.

B. FES Module

Surface electrodes are attached to the patient's anterior deltoid and triceps muscles in accordance with clinical guidelines. The control hardware produces a series of 5V amplitude, 40Hz pulses with the required pulsewidth for each stimulation channel. Each is then optically isolated and fed to the amplification stage of a battery powered commercial stimulator to result in the desired bi-phasic characteristic and voltage amplitude. The amplification level used for each channel is set prior to each treatment session by applying a stimulation signal with pulsewidth 300μs, and slowly increasing the voltage until the maximum comfortable level is reached.

C. System Software

Unlike the 2D case which used a 'real world' task consisting of tracking a moving light spot in the horizontal plane [8], here a virtual tracking task in 3D space is displayed to the patient. This allows a specific trajectory to be displayed clearly, together with the required spot they must track, and the provision of additional visual feedback indicating their current error level. This is achieved using real-time software which reads resolver data from the mechanical support via a real-time control card and outputs the arm position and reference using kinematic models of the human arm and mechanical support systems. These are read by a custom made application developed in C++ with DirectX interface to render the 3D environment. In addition, the realtime software simultaneously implements control schemes for the FES using dynamic models of the combined arm structures. A signal flow diagram is shown in Figure 3.

A monitor is provided for the physiotherapist and another for the patient. The former displays a graphical user interface (GUI) which allows the physiotherapist to customise the parameters which define the task and controllers. Prior to treatment, the physiotherapist assists the patient into the mechanical support and places each surface electrode at a position on the muscle which elicits the maximum appropriate movement. The therapist then sets the FES amplitude, before assisting the patient to extend their arm in several directions in order to define their workspace (used in the calculation of the references). Treatment consists of patients undertaking 6 trials of a range of tracking tasks, using their remaining voluntary control, with the additional assistance of FES. Four tasks will be used at the beginning and end of each treatment session without FES assistance applied, in order to assess improvement in patient's unassisted function.

The screen for patients displays a graphic of their arm in real-time, together with the trajectory tracking task, and is shown in Figure 4. The aim of the tracking task is for the patient to follow a sphere which travels along the trajectory at various speeds. The graphic of the patient's hand changes colour to indicate their current error level. Visual feedback of performance is also given by an error percentage 'score' displayed after each set of trials. A graphic of the initial arm position is displayed to ensure accurate resetting of the system at the start of each trial.

III. Arm Modelling and Control

The dynamic model of the system comprises the biomechanical description of the human arm, coupled with a representation of the mechanical support. The human arm system is time-varying due to changing physiological conditions such as fatigue and spasticity, and includes the presence of the patient's residual voluntary effort. A block diagram of the combined model and controller is shown in Figure 5.

A. Mechanical Support

Figure 6(a) shows the kinematic structure of the exoskeleton mechanical support, where the joint variables $\Theta = [\theta_1, \theta_2, \theta_3, \theta_4, \theta_5]^T$ correspond to the measured joint angles. Note that the parallelogram structure of the upperarm

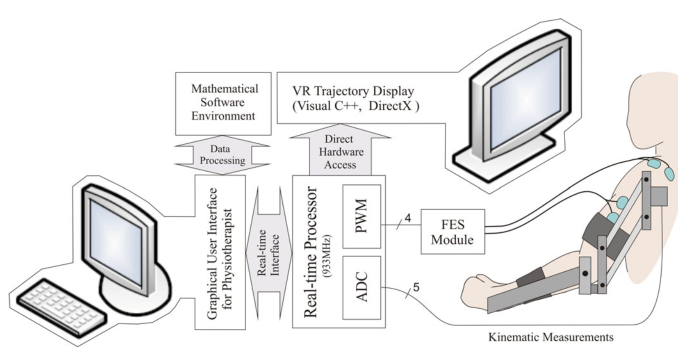


Fig. 3. Signal flow diagram.

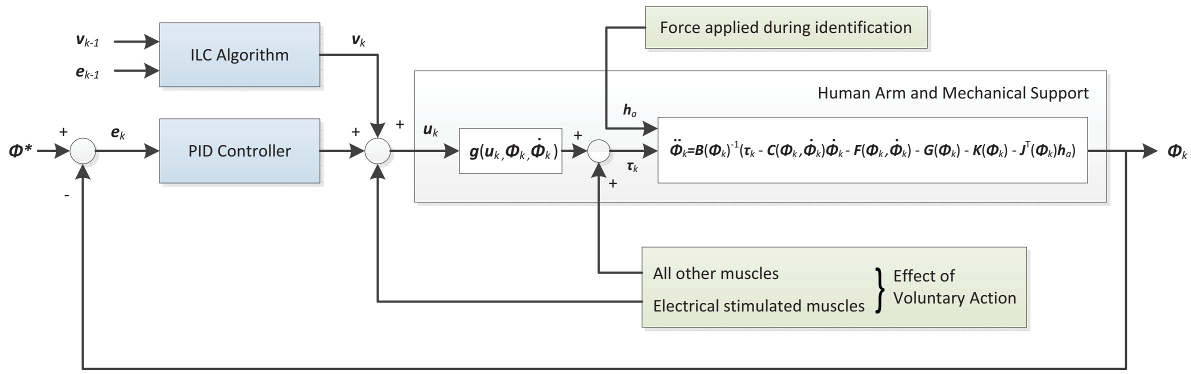


Fig. 5. Block diagram of control scheme showing iterative learning and feedback controllers.

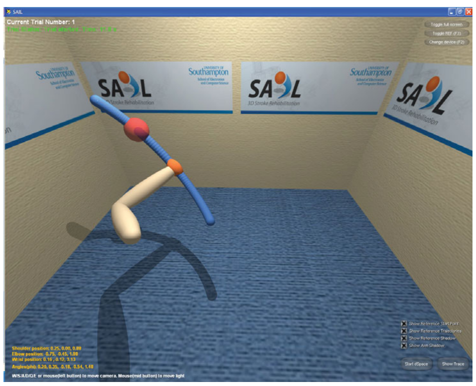


Fig. 4. 3D virtual reality environment for patients.

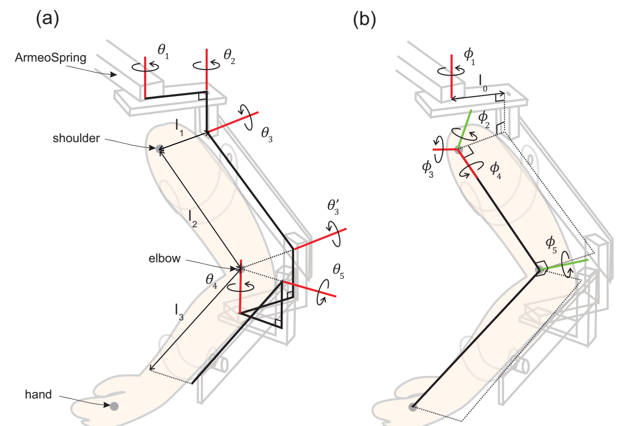


Fig. 6. Kinematic system relationships: (a) measured ArmeoSpring® variables, and (b) anthropomorphic variables.

section results in $\theta_3 = -\theta_3'$. Applying Lagrangian analysis, a dynamic model of the mechanical support is given by

$$B_a(\Theta)\ddot{\Theta} + C_a(\Theta, \dot{\Theta})\dot{\Theta} + F_a(\Theta, \dot{\Theta}) + G_a(\Theta) + K_a(\Theta) = -J_a^T(\Theta)h_a \quad (1)$$

where h_a is a vector of externally applied force and torque, $B_a(\cdot)$ and $C_a(\cdot)$ are 5-by-5 inertial and Corelis matrices respectively. In addition, $J_a(\cdot)$ is the system Jacobian, and $F_a(\cdot)$ and $G_a(\cdot)$ are friction and gravitational vectors. The vector $K_a(\cdot)$ comprises the moments produced through gravity compensation provided by each spring, which are functions of θ_3 and θ_5 respectively, and hence $K_a(\cdot)$ takes the form $[0, 0, k_3(\theta_3), 0, k_5(\theta_5)]^T$.

B. Human Arm

The human arm kinematics are shown in Figure 6(b), and since the arm is strapped to the support, its position can also be described using the same variable set. However to simplify the FES control scheme, it is desirable that those axes about which electrical stimulation produces a moment correspond with joint variables. Spasticity in stroke patients typically produces a resistance to elbow extension during reaching tasks, associated with overactivity of the biceps, and a loss in activity of the triceps and anterior deltoid (this difficulty in performing full elbow extension has been verified experimentally during reaching tasks [12]). These muscles have therefore been selected for stimulation. It is first assumed that application of stimulation to the triceps produces a moment about an axis orthogonal to both the forearm and upperarm, and that FES to the anterior deltoid produced a moment about an axis which is fixed with respect to the shoulder. These anthropomorphically motivated variables are given by $\Phi = [\phi_1, \phi_2, \phi_3, \phi_4, \phi_5]^T$, and are shown in Figure 6(b). The anterior deltoid axis is specified by two constant rotation transformations that are introduced into the human arm kinematic chain, appearing in Figure 7(a). Following initial rotation of the base frame by ϕ_1, the frame is rotated along the z-axis by β and along the x-axis by γ. Identification of the two parameters is described in Section III-C.

The human arm dynamic model can be represented by

$$B_h(\Phi)\ddot{\Phi} + C_h(\Phi, \dot{\Phi})\dot{\Phi} + F_h(\Phi, \dot{\Phi}) + G_h(\Phi) = \tau \quad (2)$$

where τ comprises the moments produced through application of FES, which are of the form $g(u, \Phi, \dot{\Phi}) = [0, g_2(\phi_2, \dot{\phi}_2, u_2), 0, 0, g_5(\phi_5, \dot{\phi}_5, u_5)]^T$. Moreover $u_2(t)$ and $u_5(t)$ are the electrical stimulation applied to the triceps and anterior deltoid muscles respectively, and $u = [0, u_2, 0, 0, u_5]^T$. From [13], each moment can be assumed to be of the form

$$g_i(\phi_i, \dot{\phi}_i, u_i(t)) = h_i(u_i, t) \times F_{m,i}(\phi_i, \dot{\phi}_i) \qquad i \in \{2, 5\} \tag{3}$$

The term, $h_i(u_i, t)$ is a Hammerstein structure incorporating a static non-linearity, $h_{IRC,i}(u_i)$, representing the isometric recruitment curve, cascaded with linear activation dynamics, $h_{LAD,i}(t)$. The term $F_{m,i}(\phi_i, \dot{\phi}_i)$ models the multiplicative effect of the joint angle and joint angular velocity on the active torque developed by the muscle.

The rigid connection between structures means that within the necessary joint ranges, there exists a unique bijective transformation between these coordinate sets, given by $\Phi = k(\Theta)$. The combined model assumes the form

$$\begin{aligned} &B(\Phi)\ddot{\Phi} + C(\Phi, \dot{\Phi})\dot{\Phi} + F(\Phi, \dot{\Phi}) + G(\Phi) + K(\Phi) \\ &= \tau - J^T(\Phi) h_a \end{aligned} \tag{4}$$

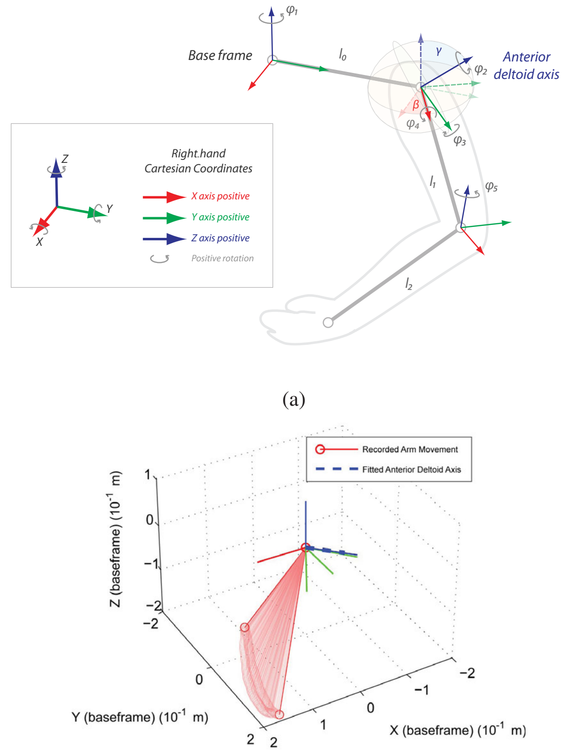
This model is used by the FES control system to produce an input signal that results in accurate tracking of a reference trajectory. Since assistive torque is applied about the ϕ_2 and ϕ_5 axes only, the system is underactuated. When applied during the treatment of patients, the controller assists tracking about ϕ_2 and ϕ_5 alone, and it is assumed that the patient has sufficient control over the remaining axes to adequately perform the task.

C. Model Identification

To deliver precise assistance, the FES controller requires a dynamic model of the combined human arm and mechanical support, and hence identification of all the parameters appearing in (4). These are identified in a series of tests, which, due to variable electrode placement, spasticity, fatigue, environmental and physiological conditions, must be performed prior to each experimentation or treatment session.

The lengths l_1, l_2 are first recorded through direct measurement, then the two parameters, β and γ, defining the anterior deltoid axis are found by applying a 10-second ramp FES input to the anterior deltoid and recording the resulting movement of the patient's elbow. With the assumption that the spring support locally cancels the effect of gravity, and that the movement about ϕ_2 is sufficiently slow to decouple the inertial and Coriolis matrices, such an input only produces movement about the anterior deltoid axis. A plane is therefore fitted to the resulting elbow positions, which then yields β and γ. Figure 7(b) shows an example of the fitted anterior deltoid axis.

A 6-axis force/torque sensor is attached to the underside of the extreme link of the mechanical support to provide the vector of externally applied forces and torques, h_a. The sensor is connected to a short handle with which the therapist can apply force/torque to move the arm. Whilst the arm is held at a fixed position using the handle, stimulation excitation inputs are applied and the corresponding h_a values recorded. The algorithms developed in [13] are employed to identify the isometric properties of each muscle, comprising $h_i(u_i, t)$. To elicit the remaining model parameters in (4), the identification procedure of [14] has been applied.



(a)

(b)

Fig. 7. Identification of anterior deltoid axis: (a) anterior deltoid axis model, and (b) measurement of elbow during identification test.

This involves exciting the mechanical support and human arm system using sufficiently rich kinematic trajectories, achieved by the therapist manually moving the system using the handle. Within (4), the term $F(\Phi, \dot{\Phi})$ is represented in the form of piecewise linear functions, as are the muscle multiplication functions $F_{m,i}(\phi_i, \dot{\phi}_i)$ appearing in (3). Following kinematic excitation, a linear-in-parameter representation of (4) is used to derive the optimal set of parameters using least squares data fitting.

D. FES Control Strategy

The control system structure shown in Figure 5 must assist tracking performance of the supported human arm system through control of the stimulation pulsewidth inputs $u_2(t)$ and $u_5(t)$ which appear in the input vector $u(t)$. The controlled outputs are the components $\phi_2(t)$ and $\phi_5(t)$ of the vector $\Phi(t)$ which must track corresponding components $\phi_2^*(t)$ and $\phi_5^*(t)$ of the reference $\Phi^*(t)$. As described, the remaining joint angles can either be assumed fixed and removed from the system, or treated as a disturbance.

The tasks presented to patients during treatment consist of repeated tracking movements for their affected arm, with a rest period in between during which their arm is returned to the starting position. This structure exactly matches the iterative learning paradigm (see, for example, [15]) and it will hence be applied to control the movement. ILC is a methodology suitable for applications which repeatedly track a fixed reference trajectory over a finite time interval, termed a trial, with resetting to the same initial position between

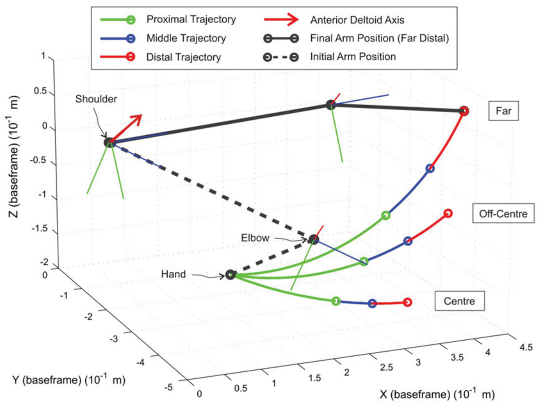


Fig. 8. Generated reference trajectories.

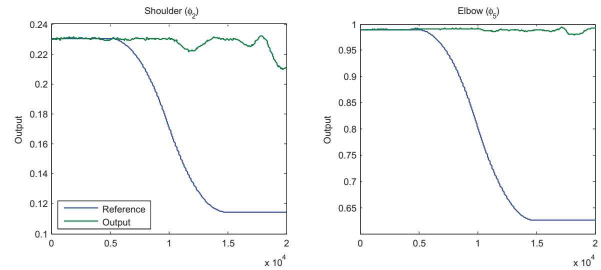


Fig. 9. The tracking performance without FES assistance.

attempts. ILC modifies the control input using the tracking error information from previous trials in order to achieve improved performance for the current and subsequent trials. ILC is often applied in combination with a standard feedback controller to ensure baseline tracking performance and disturbance rejection and in this paper a Proportional plus Integral plus Derivative (PID) controller is employed. Figure 5 shows the full control structure in which an ILC and a PID feedback controller are connected in a parallel layout, where the subscript k denotes the trial number. In this framework voluntary effort of the patient can be treated as an iteration-invariant disturbance and can hence be compensated for [14]. A robust ILC scheme can also deal with significant dynamic changes and model inaccuracy. Here a simple phase-lead ILC algorithm has been selected of the form

$$v_{k+1}(t) = v_k(t) + Le_k(t + \lambda) \qquad (5)$$

where L is a scalar learning gain, and λ is the phase-lead parameter. Full details are given in [16], including optimal selection of λ. Since only ϕ_2 and ϕ_5 variables are controlled, L is multiplied by the matrix diag$\{0, 1, 0, 0, 1\}$.

As stated previously, ILC algorithms require a fixed reference trajectory. Nine such trajectories have been generated that correspond to lifting the upper arm and extending the forearm over a period of 5 or 10 seconds. These are individually selected for each patient by taking the farthest points in their workspace and applying a 3rd order ramp signal to result in a smooth reaching movement to these points. By appropriately scaling each movement, nine tasks of ranging difficultly have been produced, and are shown in Figure 8. Note that variation in the joint angles ϕ_1, ϕ_3 and ϕ_4 is permissible since only ϕ_2 and ϕ_5 are controlled. These 9 tasks are based on clinical need and are easily adjusted by the therapist through alteration of the patient's workspace.

IV. Experimental Results

Following ethical approval, the algorithms have been tested during a preliminary study involving 11 unimpaired participants and 5 stoke patients. The experiments are carried out using sampling frequencies of 1000Hz and 40Hz for capturing the signals and computation of control signals respectively. The patient is first asked to complete 4 unassisted tracking tasks (i.e. without any FES). Figure 9 shows representative unassisted tracking results from one patient who has started clinical trials. Figure 10 shows the patient's tracking performance with assistance from the system. The oscillations observed can be removed through reduction of the PID gains, which are chosen heuristically since it is ILC which drives the tracking. The results confirm that accurate tracking has been achieved for ϕ_5 (elbow movement) and reasonable improvement has been seen for the anterior deltoid. This patient has a very weak anterior deltoid muscle, so that lack of shoulder movement is inevitable, but is expected to improve during treatment. Via the Hebbian Learning effect, the assisted tracking achieved is also expected to transfer to a reduction in impairments during treatment. Full results are given in [17], which includes results using a model-based ILC algorithm based on the Newton method, where the input update is $v_{k+1} = v_k + g'(v_k)^{-1}e_k$ where $g(\cdot)$ is the linearised system model. Figure 11 shows mean squared error plots of the patient's performance in two sessions using different reference trajectories. The results indicate that the ILC performs well for patients with adequate muscle activity.

V. Conclusion

A platform for 3D stroke rehabilitation has been developed, comprising an FES system to achieve precise control of human arm movement in combination with a mechanical support. The technology is designed to help stroke patients train their upper limb muscles during functional tasks using electrical stimulation to augment their remaining movement. ILC algorithms have been applied to improve the performance from trial to trial by precise updating of the FES signals. The subsequent high level of performance maximises the potential for recovery via the Hebbian learning rule. Experimental results show that significant improvement can be achieved within a few trials. Clinical trials have commenced using the system, in which 5 patients each receive 18 treatment sessions of 1 hour duration.

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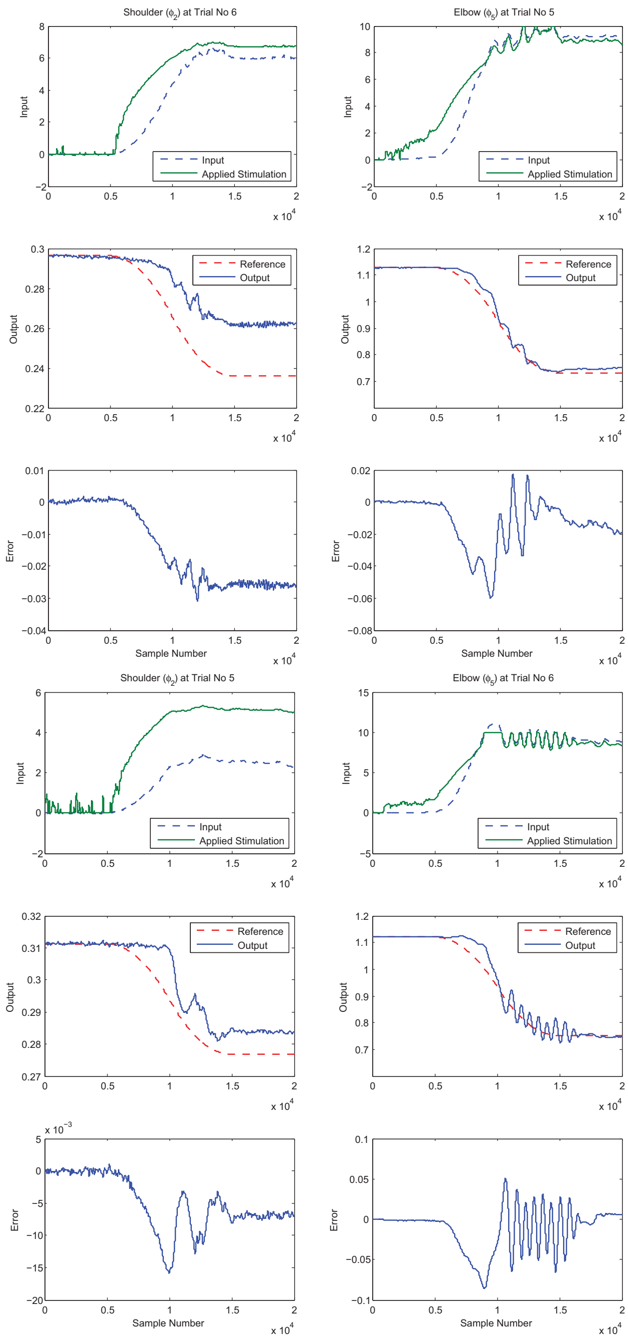
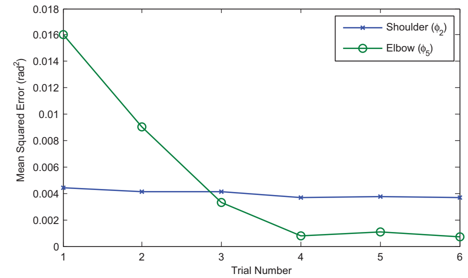
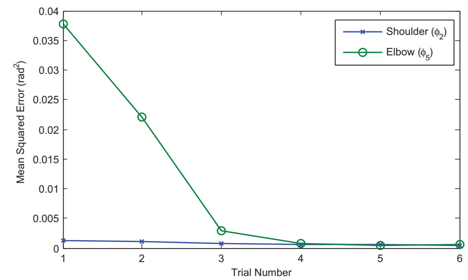


Fig. 10. Stroke patient tracking performance.



(a) Far distal reference



(b) Off-center distal reference

Fig. 11. Stroke patient mean square error plots.

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