Multiple Model Adaptive ILC for Human Movement Assistance

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Abstract—A switched multiple model iterative learning control framework is developed which guarantees robust stability and performance bounds under the assumption that the true plant belongs to a plant uncertainty set that is specified by the designer. In addition, the framework automatically adapts the reference trajectory according to the action of an existing internal control loop that is assumed to be embedded in the plant structure. The framework is inspired by the needs of stroke rehabilitation where assistive technology must support the remaining, weak volitional effort of the patient. Exploiting the multiple model based switching between models and reference trajectories, the framework is also able to potentially eliminate the need for identification and tuning and hence meet the demanding needs of clinical application.

I. INTRODUCTION

Iterative learning control (ILC) is an approach formulated for systems that track the same output trajectory over multiple attempts, termed trials. Numerous algorithms have been proposed that update the control input in the reset interval between trials, with the aim of sequentially reducing the tracking error. A rich theoretical framework has emerged, together with a wide range of application fields. In particular, ILC has been successfully used by many groups to assist lower limb motion [19], [16], [2], [1]. ILC was first applied to upper limb stroke rehabilitation in [11], where it controlled the functional electrical stimulation (FES) applied to artificially activate patients’ muscles. The movement accuracy produced by ILC led to statistically significant results in a clinical trial. ILC has since been used in further clinical trials to assist more complex movements involving the arm, wrist and hand [11], [15], [14], again producing statistically significant improvements in function.

While ILC can accurately assist completion of a predefined motion trajectory, the framework has not been able to respond to the voluntary effort contribution of each stroke participant. Not only does this cause the tracking accuracy to degrade, but any mismatch between voluntary intention and assisted movement also reduces the rehabilitation effectiveness [6]. Clinical application also restricts the time available for model identification and controller tuning, necessitating greater robust performance over a wide uncertainty space.

This paper addresses both issues by developing the first ILC framework to automatically adapt the reference trajectory in response to the residual capability of user, while simultaneously ensuring convergence to the intended task. This means that it can achieve high accuracy tracking of the motion that the participant is themselves attempting and thereby maximizes clinical outcomes. The framework is built on the estimation based multiple model switched adaptive control developed in [3], [4] and further extended for ILC in [8] to become estimation based multiple model ILC (EMMILC). These use a bank of Kalman filters to assess the performance of a set of candidate plant models, and the controller corresponding to the most suitable plant model is then switched into closed-loop. Given sufficient candidate models, the framework is able to guarantee robust performance. This feature is highly attractive within stroke rehabilitation since it theoretically removes the need for time-consuming model identification and control tuning.

II. PROBLEM FORMULATION

Many models have been proposed for human motor control, usually splitting the action of the central nervous system (CNS) into path planning and subsequent tracking stages. Approaches can be divided into those that attempt to simulate the internal feedback/forward mechanisms present in the CNS, and those that try only to model the resulting kinematic motion at the task level. The latter typically pose reaching tasks as optimization problems, involving, e.g., the minimization of jerk [5], torque change [20], variance [10], interaction torques or a combination [17]. These forms can be represented by first defining a motion ‘kernel’ \( \tilde{r} \) that captures the essential features of the known task. This comprises a sequence of \( p \) desired joint positions/velocities that must occur at isolated, potentially unknown, time points or intervals in a finite duration. Hence \( \tilde{r} \in \mathbb{R}^{n_1} \times \cdots \times \mathbb{R}^{n_p} \). This is translated to an ideal movement of \( o \) joints specified over a sufficiently long sampling interval \( [0, T] \), \( T \in \mathbb{N} \), by operator \( \bar{B} : \mathbb{R}^{n_1} \times \cdots \times \mathbb{R}^{n_p} \to l^2_1[0, T] \). CNS feedforward and feedback action can be modelled by operators \( \bar{K}_B : l^2_1[0, T] \to l^2_2[0, T], \bar{K}_F : l^2_2[0, T] \to l^2_2[0, T] \) respectively which produce electrical nerve signal \( \tilde{v} \) that is transmitted to the musculoskeletal system represented by operator \( \bar{F} : l^2_2[0, T] \to l^2_2[0, T] \). In this paper FES is assumed to be

![Fig. 1](image-url)

a) ‘along the trial’ model of stimulated arm with volitional effort and applied assistance, b) equivalent system with controller \( \hat{C} \).

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FES to assist the $m$ muscles involved in the movement is represented by additive signal $\tilde{u}$, as shown in Fig. 1a). These combine in a static manner [13] which may be assumed to be linear [12]. These forms can be expressed as the general structure of Fig. 1b) by setting $\tilde{H} = \tilde{K}_R \tilde{D}, \tilde{G} = (I + F \tilde{K}_R)^{-1} F$. It follows that $\tilde{G}$ can be expressed by the causal linear time-invariant (LTI) state-space system $(A_G, B_G, C_G)$ and $\tilde{H}$ is a non-casual along the trial mapping.

Due to stroke impairment, $\tilde{K}_R$, $\tilde{K}_H$ are difficult to identify. It must therefore be assumed that system $P: \tilde{y} = \tilde{G}(\tilde{H} \tilde{r} + \tilde{u})$ is unknown but belongs to a specified uncertainty set $\tilde{U}$. The objective is to control $\tilde{u}$ such that the closed-loop system is stable, and the output matches the intention of the CNS, i.e. the output achieves $\tilde{y} = \tilde{B} \tilde{r}$, where $\tilde{B} \tilde{r}$ is the reference trajectory. Since motion kernel operators can be reliably generated, e.g. by applying the minimum jerk computation of [5] to a suitable set of times at which each joint position/velocity is reasonably achieved. For simplicity it is assumed that $o = m$ and $\tilde{G}$ is invertible.

A. Equivalent System Representation

We now reformulate the system in order to apply the EMMILC framework of [8]. First denote $\tilde{u}_{i,1,1} = \tilde{u}, \tilde{y}_{i,1,1} = \tilde{y}$ and replace $\tilde{r}$ by $\tilde{y}_{i,2,1}$. Then augment the plant and controller with additional outputs, $y_{i,2,2}$, $\tilde{u}_{i,2,2}$ respectively, and introduce external disturbances on all signals. Due to the repeated nature of the task, we can then express all signals as single samples in a ‘lifted’ space by defining repetition index superscript $k \in \mathbb{N}_+$ and $u_{i,j}(k) = \tilde{u}_{i,j}^k, y_{i,j}(k) = \tilde{y}_{i,j}^k, r(k) = \tilde{r}$. The corresponding operators

\[ G: l_2^m [0, T] \times \mathbb{N} \rightarrow l_2^m [0, T] \times \mathbb{N} \]

\[ H: \mathbb{R}^{n_1} \times \cdots \times \mathbb{R}^{n_o} \times \mathbb{N} \rightarrow l_2^m [0, T] \times \mathbb{N} \]

\[ : u_{i,1,2} \mapsto v \mapsto v(k) = \tilde{H} u_{i,1,2}(k) \]

are the lifted representations of along-the-trial dynamics $\tilde{G}$ and $\tilde{H}$. These definitions mean system Fig. 1b) can be equivalently represented as in Fig. 2, where $\tilde{u}_0 = (0, r)^T \in U_e, \tilde{y}_0 = (0, r)^T \in Y, u_i = (u_{i,1,1}, u_{i,2,1})^T \in U_e, y_i = (y_{i,1,1}, y_{i,2,1})^T \in Y_e, i \in \{0, 1, 2\}$ in which the lifted spaces

\[ U := l_2^m [0, T] \times \mathbb{R}^{n_1} \times \cdots \times \mathbb{R}^{n_o} \times \mathbb{N}, \]

\[ Y := l_2^m [0, T] \times \mathbb{R}^{n_1} \times \cdots \times \mathbb{R}^{n_o} \times \mathbb{N}, \]

\[ \tilde{P} := \begin{pmatrix} G & \tilde{G} \\ 0 & 0 \end{pmatrix} \begin{pmatrix} u_{i,1,2} \\ u_{i,2,1} \end{pmatrix} \in P \]

where $P$ is the set of all LTI operators of appropriate dimension. The distance between system models will be measured using the well-established gap metric, $\delta(P, \tilde{P}_1), \tilde{P}, \tilde{P}_1 \in \tilde{U}$, introduced in [9]. Note that it can be shown that unlifted and lifted gaps are equal, i.e. $\delta(P, \tilde{P}_1) = \delta(P, \tilde{P}_1)$ [7].

![Augmented lifted ILC system fitting within EMMILC framework.](image)

III. CONTROLLER FORMULATION

In this section it is assumed that plant model $P = P_i$, with components $H_i, G_i$, is known. We must design controller $C_j \in C$, with components $N_j, L_j, B_j$, to stabilise the system and satisfy tracking requirement $y_{i,1} = B_j r$. Here $C$ is the set of all LTI operators of consistent dimension.

**Proposition 1:** Let $H_i$ be given and $G_i$ have state space form $(A_G, B_G, C_G)$. The along-the-trial ILC objective

\[
\min_{u_{i,1,2}(k) \in l_2 [0, T]} \left\{ \| \tilde{B}_i \tilde{r} - y_{i,1,1}(k) \|_Q^2 + \| u_{i,1,1}(k) - u_{i,1,1}(k-1) \|_1 \right\}
\]

is solved in the absence of disturbances by the control input

\[
\tilde{u}_{2,1}(k, t) = \tilde{u}_{2,1}(k-1, t) + \Phi(t) (\tilde{x}(k, t) - \tilde{x}(k-1, t)) - B_G \tilde{G} \tilde{x}(k, t) + O(C_G \tilde{x}(k, t) + \tilde{y}_{2,1}(k, t)),
\]

with $\Phi(t) = (I + B_G \tilde{G} K(t) B_G)^{-1} B_G \tilde{G} K(t) A_G$, estimated state $\tilde{x}(k, t + 1) = A_G \tilde{x}(k, t) + B_G ((\tilde{H}_i \tilde{r})(t) - \tilde{u}_{2,1}(k, t)) + O(C_G \tilde{x}(k, t) + \tilde{y}_{2,1}(k, t))$, and the feedforward term $\tilde{\xi}(k, t) = (I + K(t) B_G \tilde{G} \tilde{H}_i \tilde{r})(t + 1) + \tilde{y}_{2,1}(k, t) - 1)$.

**Proof:** Embeds $H_i, \tilde{B}_i$ within the structure of [18]. To apply the multiple model switching framework it is necessary to express (6) - (9) in the lifted form as follows. Define the lifted integrator block which embeds ILC action

\[
M : l_2^m [0, T] \times \mathbb{N} \rightarrow l_2^m [0, T] \times \mathbb{N} : z \mapsto x
\]

\[
x(k + 1) = x(k) + z(k)
\]

and $N_j : a \mapsto b : a(k) = \tilde{N}_j b(k), B_j : a \mapsto b : a(k) = B_j b(k), L_j : a \mapsto b : a(k) = L_j b(k)$.

**Proposition 2:** Control action (6) - (9) is realised by

\[
\tilde{N}_j = \Xi_j \tilde{B}_j \tilde{B}_j \tilde{B}_j = (\Xi_j \tilde{G}_i - I) (I + \tilde{G}_j R \tilde{G}_i)^{-1} \tilde{G}_j R \tilde{G}_i
\]
with \( A_2(t) = A_G - B_G \Phi(t) + OC_G = (I + B_G B_G^T K(t))^{-1} A_G + OC_G \). The tracking error monotonically converges as

\[
\| \bar{B}_r - y_{1,1}(k+1) \| \leq (I + \sum (\hat{G}_i \hat{G}_i^T))^{-1} \| \bar{B}_r - y_{1,1}(k) \|
\]

with \( \lim_{k \to \infty} y_{1,1}(k) = \bar{B}_r \). The control action converges to the ideal input \( w_2^{P_1} = (-G_i^{-1} B_j - H_i)^r, 0, -B_r \bar{r}, \bar{r})^T \).

Proof: Involves extensive manipulations to give \( I + \hat{Z}_{ij} \hat{L}_j = I + \hat{G}_i \hat{G}_i^T \) where \( \hat{Z}_{ij} = (I - \hat{G}_i \hat{N}_j)^{-1} \hat{G}_i \).

The next result establishes stability bounds with disturbance and model mismatch. We consider a plant \( P_i \) comprising \( G_i, H_i \) that is switched into closed loop with an arbitrary controller \( C_j \) (comprising \( N_j, L_j, B_j \)).

Proposition 3: 1) (Linear growth of \( |P_i, C_j| \)): Let \( P = P_i \) and \( C = C_j \) be given by (11) with the signal connections of Fig. 2. Let \( l_1, l_2, l_3, l_4 \in \mathbb{N}, l_1 < l_2 < l_3 < l_4 \) and \( I_1 = [l_1, l_2], I_2 = [l_2, l_3], I_3 = [l_3, l_4] \). Then the control signal \( w_2 \) is bounded with respect to the ideal solution for plant \( P_1 \) of \( \hat{w}_2 = ( -G_i^{-1} \hat{B}_j - \hat{H}_i )^r, 0, -B_r \bar{r}, \bar{r})^T \) by

\[
\| w_2 \|_{w_2^{P_i}} \leq \sum_k \| I + \hat{Z}_{ij} \hat{L}_j \|_{|I|+|I_2|+1} \| I - \hat{N}_j \hat{G}_i \| (I - \hat{N}_j \hat{G}_i)^{-1} \| w_2 \|_{r_1} \| w_2 \|_{w_2^{P_i}}
\]

\[
\alpha(P_i, C_j, |I_2|, |I_3|) + \left[ (\hat{A}_{ij} |I_2|+1 + \hat{X}_{ij}^{l_1+1}) \hat{X}_{ij}^{l_1} \cdots \hat{X}_{ij}^{l_1} \Gamma_{ij} \right]
\]

\[
\cdot \| w_0 \|_{I_1 \cup I_2 \cup I_3}
\]

where \( \hat{A}_{ij} = -(I - \hat{N}_j \hat{G}_i)^{-1} (I + \hat{L}_j \hat{Z}_{ij} \hat{G}_i) \) and \( \hat{X}_{ij} = (I - \hat{N}_j \hat{G}_i)^{-1} (I + \hat{L}_j \hat{Z}_{ij} \hat{G}_i) \). Here \( \alpha(P_i, C_j, \hat{A}, \hat{X}) \) is the monotonic function of \( \alpha(\hat{P}_i, \hat{C}_j, a, x) \) to \( a \to \infty \).

Proof: Follows after extensive manipulations and the identity \( \| x \|, \| y \| = \| (x, y) \|, x, y \in I_2 \).

IV. EMMILC TRACKING STRUCTURE

EMMILC was introduced in [8] and comprises the switching algorithm illustrated in Fig. 3. The corresponding structural requirements are shown in Table I. The control design procedure \( \Psi \) assigns a stabilizing controller \( C_i \) to each plant \( P_i \), such that \( [P_i, C_j] \) is gain stable. The powerset of \( P \) is denoted \( P^* \) and \( G \subset P \) is a constant set of candidate plant models thought to represent the true plant. For each \( P_i \in G \) we implement an estimator \( X \) which uses observations \( w_2 \) to generate a residual \( r_i[k] \) at sample \( k \). These are fed to the minimization operator \( M \), which returns the index, \( q_f \), of the plant with minimal residual. The purpose of operator \( D \) is to delay the free switching signal \( \alpha(k) \) long enough to prevent instability effects caused by rapid switching, and to ensure overall convergence of the closed-loop signals. For this purpose we associate with every plant a minimum delay \( \Delta(i) \) which must elapse before another is permitted. The signal \( q_f \) then determines the atomic controller choice \( \Psi(q_f) \) corresponding to the selected plant. Together these components comprise the switching operator \( S \) shown in Fig. 3, where \( P_s \) denotes the true plant.

A. Estimation Problem

Estimator \( X \) is selected as the biased infinite horizon operator, defined for each \( P_i \) as

\[
r_i[k] = X(w_2(k))(P_i) = \inf \{ \| v \|, v \in \mathbb{N}^{L_0, k}(w_2) \}
\]
where the set of weakly consistent disturbance signals for
plant $P_i$ and observation $w_2 = (u_2, y_2)^\top$ with bias $\tilde{w}_0 = (\tilde{u}_0, \tilde{y}_0)^\top$ over trials $k = a, \ldots, b$ is
\[
N_{i, \tilde{w}_0}^{[a,b]}(w_2) := \{ v \in \mathcal{W}_[a,b] \mid \exists (u_0, y_0)^\top \in \mathcal{W}_e \text{ s.t.} \}
\] \[
R_{b-a,b}P_i(u_0 + \tilde{u}_0 - u_2) = R_{b-a,b}(y_0 + \tilde{y}_0 - y_2),
\]
\[
v = (R_{b-a,b}u_0, R_{b-a,b}y_0)
\] (28)

This is computed as follows.

**Theorem 1**: Residual (27) is given by
\[
r_i[k] = \sum_{b=0}^k \left\| \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & I & 0 & 0 \\ \tilde{G}_i & \tilde{G}_i & \tilde{H}_i & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \tilde{G}_i & \tilde{G}_i & \tilde{H}_i & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \right\| (\tilde{G}_i u_2,1(b) - \tilde{H}_i \tilde{r}) - y_2,1(b) \right\|
\] (29)

**Proof**: Since the plant dynamics along each pass are independent of the previous pass, we can write
\[
N_{i, \tilde{w}_0}^{(0,k)}(w_2) = N_{i, \tilde{w}_0}^{(0,0)}(w_2) \times N_{i, \tilde{w}_0}^{(1,1)}(w_2) \times \cdots \times N_{i, \tilde{w}_0}^{(k,k)}(w_2).
\]

This means residual (27) can be obtained recursively as
\[
r_i[k] = \sum_{b=0}^k i_b \text{ with } i_b := \inf\{\|v\| \in N_{i, \tilde{w}_0}^{[b,b]}(w_2)\}
\]

Within (28), the restriction becomes $R_{0,b}v = v(b)$, and since $P_i$ is a static mapping
\[
R_{0,b}P_i(u_0 + \tilde{u}_0 - u_2) = \tilde{P}_i(u_0(b) + \tilde{u}_0(b) - u_2(b))
\]
so that
\[
N_{i, \tilde{w}_0}^{[b,b]}(w_2) := \{ v \in \mathcal{W}_[b,b] \mid \exists (u_0, y_0)^\top \in \mathcal{W}_e \text{ s.t.} \}
\] \[
\tilde{P}_i(u_0(b) + \tilde{u}_0(b) - u_2(b)) = y_0(b) + \tilde{y}_0(b) - y_2(b),
\]
\[
v = (u_0(b), y_0(b)) \}.
\] (30)
Since
\[
y_0(b) = \tilde{P}_i(u_0(b) + \tilde{u}_0(b) - u_2(b)) - \tilde{y}_0(b) + y_2(b) \] (31)
we obtain $i_{b,\tilde{w}_0}[b] = \inf_{u_0(b) \in [0,T]} \{ \| \tilde{P}_i(u_0(b) + \tilde{u}_0(b) - u_2(b)) - \tilde{y}_0(b) + y_2(b) \| \}$
whose solution yields (29).

**Theorem 2**: Residual (29) can be efficiently computed by
\[
r_i[k] = \sum_{b=0}^k \sum_{t=0}^T \| y_2,1(b,t) + CG \tilde{x}(b,t) \|_{C_G \Sigma(t) C_G^\top + I}^{-1} \frac{1}{2}.
\] (32)

where the Kalman filter is implemented on trial $b$ by
\[
\tilde{x}(b,t+1/2) = \tilde{x}(t) - \Sigma(t) C_G^\top C_G \Sigma(t) C_G^\top + I \]
\[
\tilde{y}_2,1(b,t) + CG \tilde{x}(b,t) \]
\[
\Sigma(t+1/2) = \Sigma(t) - \Sigma(t) C_G^\top C_G \Sigma(t) C_G^\top + I \]
\[
\tilde{x}(b,t+1) = A_G \tilde{x}(t+1/2) + B_G((H \tilde{r})(t) - \tilde{w}_2,1(b,t)) \]
\[
\Sigma(t+1) = A_G \Sigma(t+1/2) A_G^\top + B_G B_G^\top \]
(33)
with $\tilde{x}(b,0) = 0, \Sigma(0) = 0.$

**Proof**: Follows from the deterministic interpretation of the Kalman Filter, see e.g. [21].

V. NOMINAL STABILITY AND GAIN BOUNDS

The gain bounds that follow depend on the size and geometry of a ‘cover’ of the plant uncertainty set $U$, rather than on the plant uncertainty set itself. This enables the bounds to avoid scaling with the number of candidate models, unlike most multiple model frameworks. The notion of the cover is as follows. Let $A \in \mathcal{P}$ be a plant set and let $\nu := map(\mathcal{P}, \mathbb{R}^+) \text{ be given.}$ Now define for $P \in \mathcal{P}$
\[
B_\delta(P, \nu(\tilde{p})):={P} \cup \{P \in \mathcal{P} \mid \delta(P, P_1) < \nu(P) \} \rightleftharpoons U,
\]
to be the set of plants that reside within a neighbourhood of radius $\nu(P)$, as measured by gap $\delta$, around $P$. For an appropriate choice of $(A, \nu)$, the union of the corresponding neighbourhoods in $U$ then leads to a cover for $U$, so that

**Definition 1**: $(A, \nu)$ is a cover for uncertainty set $U$ if
\[ U \subseteq \{ \cup_{P \in A} B_\delta(P, \nu(\nu(P))) \} \]
We next give gain bounds for the interconnection of the controller with ‘true’ plant $P_*$, with components $G_*, H_*$.

**Theorem 3**: Let control design $\Psi$ be such that given $P_*$, and $C_i = \Psi(P_i)$ is defined by (11). Let $P_e \in U$ where $U$ is an LTI uncertainty set of appropriate dimensions we seek to control. Suppose $(A, \nu)$ is a finite cover for $U$. Let $G \subset \mathcal{P}$ be a suitable sampling of $U$ specifying the available candidate plant set. Suppose
\[
\exists P \in G, \delta(P, P_*) < \varepsilon \chi_\nu(A, \nu) \] (34)
The true plant response is shown in Fig. 4 and illustrates the number of 'point-to-point' movement of a single joint, hence assisted via FES applied to the triceps. The task is a single rehabilitation platform of [11], in which elbow extension is a rapid onset of fatigue, associated with each candidate P, i.e. ω, ε, P, δ. This represents a maximum value of ρ = εχν(A, ν), which is used in (34) to specify a maximum distance between the models in G. This distance is measured by the gap metric in either lifted or unlocked plant space. Hence G is designed by constructing a covering of U by neighbourhoods of radius ρ with centre Pi ∈ G.

VI. SIMULATION EXAMPLE

The control scheme is now applied to the upper limb stroke rehabilitation platform of [11], in which elbow extension is assisted via FES applied to the triceps. The task is a single ‘point-to-point’ movement of a single joint, hence m = o = 1, p = 1, o1 = 1 with r = 2 rads. The maximum sample number T is fixed at 400 in all tests, with padding applied for attempts finishing earlier. The candidate plants P, i.e. Kii, Kiii, Kiiii: proportional gain, ki; for simplicity. Pii; critically damped muscle dynamics (s) = ω2/(s2 + 2ζωi s + ω2), as shown to accurately capture muscle dynamics [6]. The sampling period is 0.01 s. Together these yield G, H, i via (1), (2), and are therefore each candidate P, i.e. 1, 2, 3, 4, 5, 6, 7, 8, are parametrised by the set (T, ki, ωi, γi). We define the true plant P, analogously, with ζ = 1, ω = 5, k1 = 0.5, T1 = 320 on trials 1 to 14, and then subsequently with ζ = 0.7, ω = 8, k1 = 0.3, T1 = 200. This represents a rapid onset of fatigue, associated with faster dynamics and weaker voluntary effort. The candidate plant set G is designed via Theorem 3 and comprises all combinations of the following elements:

ζ = {0.4, 0.7, 1.0, 1.3, 1.6}, ω1 = {2, 5, 8, 11}, k1 = {1, 2, 3, 4, 5, 6, 7, 8}, T1 = {220, 260, 300, 340, 380}

The true plant response is shown in Fig. 4 and illustrates the level of voluntary input. The control design Ci = Ψ(Pi) is defined by (11) with Q = 10. The results are shown in Fig. 5 and Fig. 6. These confirm that the EMMILC framework is able to accurately assist voluntary effort while adapting to the plant dynamics, the level of voluntary effort, and the required task.

VII. CONCLUSION

A multiple model ILC framework has been developed which is capable of assisting human motor control. This is the first approach to combine ILC and models of human motor control, and is motivated by the need of stroke rehabilitation to precisely assist patient’s voluntary completion of functional tasks. A key feature of the framework is its potential to remove the need for model identification and controller tuning. Future work will focus on applying the framework to stroke patients within clinical feasibility trials.

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Fig. 4. Voluntary signals $G_{x,r}, G_{y,H_{x,r}}$ of true plant $P_s$ (i.e. no FES).

Fig. 5. Tracking results (top), estimated voluntary effort (middle) and applied FES (bottom) for $Q = 10$.


