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„Variable Pass Length ILC in FES-based Drop Foot Rehabilitation“

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Variable Pass Length ILC in FES-based Drop Foot Rehabilitation

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Introduction

Iterative learning control (ILC) is based on the notion that the performance of a system that executes the same task multiple times can be improved by learning from previous executions (trials, iterations, passes) [1]. Since rehabilitation typically includes numerous iterations of predefined movements, both robotic and FES-based assistance systems have been equipped with ILC algorithms in the past, see e.g. [2–4]. However, unlike robotic applications, most biomedical engineering systems do not meet the assumptions that ILC theory requires to hold. In many cases, the system dynamics and the disturbances vary from pass to pass. Input signals, such as electrical stimulation intensity, are subject to saturation. And often the time length of the iterations, known as pass length, is not constant. Therefore, ILC theory needs to be extended to allow for proper controller design and convergence proofs.

In this contribution we outline a new ILC theory extension for variable pass length systems. Subsequently, we explain how the aforementioned challenge of variable pass length arises in the stimulation control problem of a drop foot neuroprosthesis. And finally, we demonstrate how the recent results on variable pass length learning can be used to design an iterative learning controller that accomplishes monotonic convergence in a novel error concept.

ILC for Variable Pass Length Systems

Consider a discrete-time linear single-input single-output process with relative degree m that is repeated over a number of trials indicated by the index j. Unlike traditional ILC, we allow the length n_j of the trials to vary arbitrarily within certain bounds: $n_j \in [\underline{n}, \overline{n}] \forall j$. For the j^{th} trial we define the following lifted signal vectors (i.e. vectors of a finite number of sequent sample values):

$$\begin{aligned} u_j &= [u_j(1-m), u_j(2-m), \ldots, u_j(\overline{n}-m)]^T \in \mathbb{R}^{\overline{n}}, \\ \hat{y}_j &= [y_j(1), y_j(2), \ldots, y_j(n_j)]^T \in \mathbb{R}^{n_j}, \\ v &= [v(1), v(2), \ldots, v(\overline{n})]^T \in \mathbb{R}^{\overline{n}}. \end{aligned}$$

Here u_j and $\hat{y}_j$ are the system's input and output signals, respectively, and v is an unknown, but iteration-invariant, disturbance signal. Then the system dynamics are given by

$$\hat{y}_j = [P u_j + v]_{n_j} , \tag{1}$$

where $P \in \mathbb{R}^{n \times n}$ is the lifted system matrix of the process (for a short example, please see Appendix A of [5]) and $[\cdot]_{n_j}$ extracts the first n_j entries of a vector. Furthermore, define the tracking error $\hat{e}_j = [y_d]_{n_j} - \hat{y}_j$ as the deviation from a desired output $y_d \in \mathbb{R}^{\overline{n}}$. In traditional ILC the control task is to successively, i.e. from pass to pass, reduce that error (in some norm) to a small number. However, both the values and the norm of $\hat{e}_j$ strongly depend on the current pass length n_j and thus the classic notions of both stability and monotonic convergence loose their practical meaning in the case of variable pass length processes. Instead, we define e_j as the error that would be observed if n_j was equal to $\overline{n}$, i.e. the maximum pass length (MPL) error, and find that

$$e_j = y_d - (P u_j + v) . \tag{2}$$

Apparently, the MPL error e_j is only a theoretical concept and not a measurable signal. In practice, the j-th pass actually terminates after n_j samples. Thus, only the first n_j samples of e_j can be measured and used for learning. A fairly general input update law is

$$u_{j+1} = u_j + L H_{n_j} e_j , \tag{3}$$

where the last $(\overline{n} - n_j)$ samples of e_j are set to zero by the block-diagonal matrix $H_{n_j} = \text{blockdiag}\{I_{n_j}, 0_{\overline{n}-n_j}\}$, with I_{n_j} and $0_{\overline{n}-n_j}$ being identity and zero matrices, respectively.

Although e_j is only accessible in simulation, its convergence properties well describe whether the controller performance actually improves from trial to trial. Therefore, the concept of the MPL error is crucial for convergence analysis. In a recent publication we presented first criteria for monotonic convergence in variable pass length systems [5]. The following was found to be the most practical criterion for controller design:

Theorem 1 *Consider system (2) with arbitrary pass lengths $n_j \in [\underline{n}, \overline{n}] \forall j$ and disturbance v. Apply control law (3), then $||e_j||_1$ decreases monotonically, if and only if*

$$\gamma := ||I_{\overline{n}} - PL||_1 \leq 1 \tag{4}$$

For the proof, the interested reader is referred to [5].

ILC for FES in drop foot correction

Stroke patients who suffer from the drop foot syndrome can be supported, for example, by controlling the ankle joint angle during the swing phase of gait via electrical stimulation of the peroneal nerve or the tibialis anterior muscle. Due to the repetitive nature of gait, ILC seems to be a promising tool for this application. But in human gait

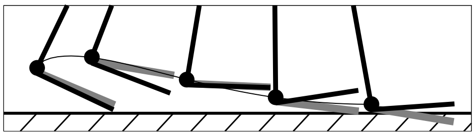

Figure 1: Foot movement with optimal (black foot lines) and insufficient (grey foot lines) stimulation profile: If the stimulation intensity is too low at the end of swing phase, then the foot touches ground early.

the duration of swing phase, i.e. the pass length in the ILC setting, varies with walking speed. One possible approach is to rescale the input, reference and output signals in time-direction, but in practice the length of a step is usually not known until shortly before the heel strike. If we consider humans walking at constant speed, e.g. on a treadmill, then the pass length is almost constant and ILC has been successfully applied to that case [2]. However, it was found that a stroke patient's steps are often cut short by putting the foot down when balance or strength is lost. Assuming that up to this point the movement was hardly different from the movement in a full-length step, we should use the data gathered in these aborted steps for learning. Even more important, if the initial stimulation profile is insufficient, then the toes touch ground early, as depicted in Figure 1. In that case we *must* use the data from the unfinished trial for learning since otherwise the next step will be the same. Typically, these issues are either ignored completely, or a heuristic approach is used hoping for convergence to be maintained. But using the outlined recent results it is possible to design controllers and guarantee monotonic convergence of the maximum pass length error for such variable pass length systems.

Simulation Results

A linear model of the electrical stimulation dynamics in a drop foot neuroprosthesis sampled at 50 Hz is employed, cf. [2]. Therein, the stimulation intensity and the ankle joint angle are the input variable and the output variable, respectively. The lifted system matrix P is calculated and a two-parameter learning gain matrix L is designed by minimizing γ from equation (4), resulting in $\gamma \approx 0.4$. We assume the ankle trajectory, i.e. the thin line in Figure 1, to be iteration-invariant in order to calculate, for each instant in time, the ankle joint angle that corresponds to the toes touching ground. Apparently, this is only an approximation, since the ankle trajectory as well as the voluntary muscle activation vary slightly from pass to pass. To account for such iteration variance we add a random low-frequency disturbance to the output. The resulting closed loop system is simulated for ten passes. Whenever the output falls below the ground-touch line, the trial is terminated. Results are presented in Figure 2. The controller performance improves from trial to trial despite the foot touching ground early on the first trials. As the angle trajectory converges

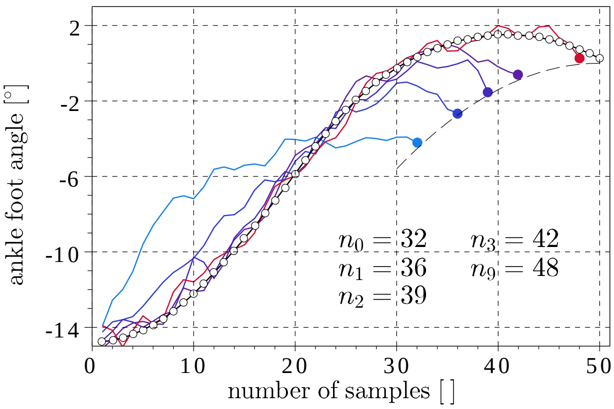

Figure 2: Simulation results for variable pass length learning of a drop foot neuroprosthesis: Angle trajectories of ten passes, reference trajectory (circles), and ground-touch line (dashed). The controller learns from unfinished trials and as the foot movement gets better, the steps get longer.

to the reference, the foot touches ground later, and the pass length increases. Since the distance between reference trajectory and ground-touch line decreases near $\overline{n}$, the trial-to-trial increase in n_j decreases as well. From a large number of simulation runs it was found that the pass length reaches its upper bound $\overline{n}$ in about ten to twelve trials.

Conclusions

The use of ILC in biomedical engineering applications calls for ILC theory extensions. A first step was taken by developing a mathematical framework for variable pass length ILC and applying the results to the control of a drop foot neuroprosthesis. Herein, trials were terminated based on output constraint violations. Simulation results revealed that the controller learns from unfinished trials, and that the pass length approaches its maximum value within a few trials. Experimental validation and implementation in FES-based assistance systems will follow. Also, practical solutions for varying walking speed need to be found and the issue of input saturation needs to addressed.

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