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Iterative Learning Control and System Identification of the Antagonistic Knee Muscle Complex During Gait Using Functional Electrical Stimulation

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Abstract: Functional Electrical Stimulation (FES) can be used to support the gait of stroke patients. By measuring joint angles and adjusting the stimulation intensities automatically to the current need of the patient, setup times can be reduced and time-variant effects like muscle fatigue can be compensated. This was achieved in recent publications by using Iterative Learning Control (ILC) on the ankle complex. In this paper we consider FES of the antagonistic knee muscle complex (quadriceps and hamstring muscles) that controls knee flexion/extension. We used a coactivation strategy in order to map the two stimulation channels to a single control input. A large class of dynamic models was obtained by system identification based on data from two experiments: one with standing subjects and one with subjects walking on a treadmill while being stimulated during different time segments of the gait cycle. Time delays, system poles, and in particular the system gains were found to vary largely. Furthermore, large differences were observed between muscle dynamics in standing pose and during walking. We designed an iterative learning controller that is stable for almost all models. In experiments with eight healthy subjects walking on a treadmill, the ILC was found to reduce deviations from a reference trajectory to about five degrees within two strides.

Keywords: iterative learning control (ILC), functional electrical stimulation (FES), stroke rehabilitation, gait, neuroprosthesis, system identification, multichannel, adaptive, knee angle

1. INTRODUCTION

One of the symptoms of stroke is an impairment of gait originating from a partial paralysis of one side of the body. In milder cases, the patients can be actively supported in their movements by using gait-triggered Functional Electrical Stimulation (FES). The first FES-based neuroprosthesis by Liberson et al. (1961) used a foot switch to trigger a stimulation of the tibialis anterior muscle during the swing phase, successfully supporting foot drop patients. Many more foot drop stimulators have been developed since. A review can be found in Lyons et al. (2002). In the 1970s, the single channel stimulation was extended to multichannel stimulation of different muscle groups of the entire gait muscle complex, e.g. gastrocnemius, hamstrings, quadriceps, gluteus maximus, gluteus medius and even shoulder muscles. Each muscle group was then triggered with an individual timing, duration and stimulation intensity. Bogataj et al. (1997) could show that multichannel stimulation had a better effect on rehabilitation than single channel stimulation.

While many studies could show the positive effects of the FES neuroprosthesis, a lot of practical problems still remain. With fixed, triggered stimulation patterns, the clinician or user has to choose the timing, duration and the stimulation intensity of every stimulation channel. From stroke patient to stroke patient there are vast differences in gait due to compensation movements and different severity of paralysis. Hence, highly individualized parameters for the stimulation of each muscle group are needed. Finding a satisfying parametrization is a nontrivial and time-consuming task for the clinician, especially in the often short rehabilitation training sessions. The optimal parameters can also vary within the same individual due to variation of electrode placement, muscle fatigue and bodily changes.

A way to solve this problem is to measure an important parameter of the gait, e.g. the joint angle, and use an automatic algorithm to adapt the stimulation patterns according to the measurement. Since the interaction between stimulation, gait and the human being controlling the gait is a highly nonlinear and time-varying process, robust methods are crucial. One very natural and robust approach is a cyclic adaptation of the stimulation parameters. This means learning from the previous steps to tune the parameters of the current step. Franken et al. (1995) used a cycle-to-cycle control strategy to tune the stimulation duration of the hip flexor muscle at every step by measuring the hip angle range. A more powerful approach is the use of Iterative Learning Control (ILC),

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which is able to not only tune a single parameter but learn an entire input trajectory. ILC was first used together with FES by Dou et al. (1999) to control the elbow angle. Nahrstaedt et al. (2008) were the first to apply ILC during gait on the tibialis anterior muscle. Hughes et al. (2009), Freeman et al. (2009) and Meadmore et al. (2012) further investigated into ILC strategies for the upper limbs. Seel et al. (2016) used ILC to control the tibialis anterior and fibularis longus muscle achieving physiological dorsiflexion and eversion of the foot in walking stroke patients without the need of manual parameter tuning.

So far, ILC was only used in connection with a one or two channel foot drop neuroprosthesis. The tuning and the stability analysis was done by either identifying the dynamics of a sitting subject or by using heuristic tuning methods. During gait the system dynamics are expected to differ from sitting or standing due to the voluntary muscle contractions, the reaction of the subject's movements to the FES and the general complexity of the gait.

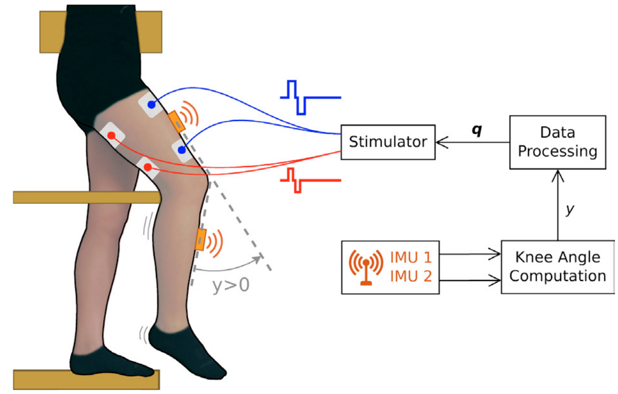
In this paper we want to move closer towards an ILC-based multichannel neuroprosthesis. In order to achieve this, we designed an ILC for the antagonistic knee muscle complex. This ILC could be later used together with an ILC of the ankle complex. One of our main goals was to investigate into the dynamics of stimulation and knee angle during gait. We used a coactivation strategy in order to map the two stimulation channels to a single control input. 5 healthy subjects were asked to walk on a treadmill while being stimulated at different times of gait. From this data we identified simple dynamic models and compared them to models that we identified on standing subjects. In a second experiment 8 healthy subjects were asked to walk on a treadmill while the ILC was tested.

2. METHODS

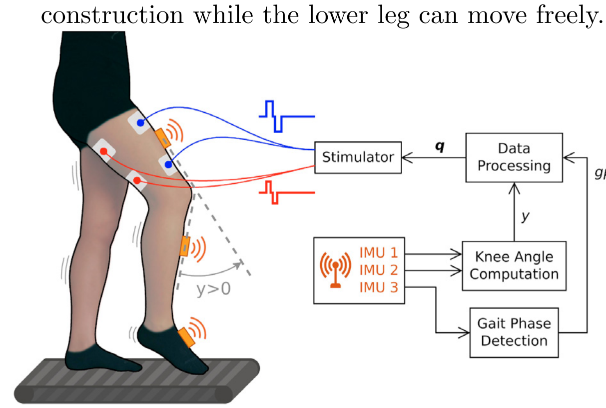
2.1 Experimental Setup

In order to measure the joint angles and detect gait phase events, we used three wireless Inertial Measurement Units (IMUs) sampling at 100 Hz (MTw wireless units, Xsens Technologies B.V., Netherlands). An eight-channel stimulator was used for the electrical stimulation with a frequency of 50 Hz (Rehastim, Hasomed GmbH, Germany). The placement of the electrodes and the IMUs is depicted in Fig. 1. The stimulation intensity of each channel was controlled by a parameter q proportinal to the stimulation charge. A $q = 0$ would mean a pulse width of 0 and a current of 0, both were linearly increased so that a $q = 1$ corresponds to a pulse width of 500 μs and a current of 50 mA.

For the IMUs on the upper and lower leg, an orientation estimation algorithm was used to estimate the absolute orientation from the gyroscope, accelerometer and magnetometer data. The real-time knee angle was then calculated using Euler decomposition and downsampled to 50 Hz. The IMU mounted to the foot was used to detect real-time gait events, using a threshold-based approach (Müller et al., 2015). Four distinct events could be detected: initial contact, full contact, heel-off and toe-off (also downsampled to 50 Hz).



(a) Static standing setup resembling the posture during the swing phase. The upper leg is fixed by the construction while the lower leg can move freely.



(b) Walking setup. The subject walks on a treadmill at a fixed speed.

Fig. 1. Experimental setup for the standing and walking experiments

For all experiments, two different setups were used. The standing pose resembling the swing phase is shown in Fig. 1a, here the upper leg was fixed by a construction. In the second and main setup, the subject were asked to walk on a treadmill at a constant speed of 1.5 km/h (Fig. 1b). The three following experiments were conducted in the scope of the paper:

- System identification while standing (5 healthy subjects)
- System identification while walking (same subject group)
- ILC while walking, preceded by a brief system identification while standing (8 healthy subjects)

2.2 Coactivation Strategy

Most simple control problems are Single-Input Single-Output (SISO) systems. In our case there are two control inputs, the stimulation intensity of the quadriceps and of the hamstring muscles. However, there is only one system output, the knee flexion angle. A straightforward way to use a standard ILC controller is by mapping the two stimulation inputs to one virtual control input, creating a SISO problem.

The basic idea of mapping both stimulation inputs to one virtual input is that a positive input leads to an increase of the knee angle, while a negative input causes a decrease. When controlling antagonistic muscle pairs, the human body often uses cocontraction in order to increase the stiffness of the joint and to avoid dead zones. Zhou et al. (1997) looked deeply into different coactivation control strategies when using FES on an antagonistic muscle pair.

We wanted to use an as simple as possible solution which could still enhance the joint stiffness and decided on a full-time cocontraction mapping. For the quadriceps and hamstrings stimulation intensity q_q and q_h that means

$$q_q = \begin{cases} q_{q0} & \text{if } u > 0 \\ q_{q0} + k_q u & \text{otherwise} \end{cases} \quad q_h = \begin{cases} q_{h0} + k_h u & \text{if } u < 0 \\ q_{h0} & \text{otherwise} \end{cases}$$

where q_{q0} and q_{h0} are the minimum cocontraction values, k_q and k_h the stimulation gain and u the new system input. Due to the full-time cocontraction, a certain stiffness and therefore controllability is always given. At the crossing point $u = 0$, a smooth transition from one muscle to the other is ensured by choosing q_{q0} and q_{h0} above motor threshold.

2.3 System Identification

One of the main reasons we chose ILC as control strategy is, that we do not need a precise model of the system dynamics. ILC is capable to handle nonlinearities and disturbances as long as they are repetitive from step to step.

That being said, the ILC still has to be tuned and any implementation of ILC is only performing well within a certain range of system properties. If we know approximately what the system dynamics look like during gait, we can systematically find ILC parameters and analyze the stability and performance.

There are a lot of disturbances due to movements and voluntary contractions during gait which can compromise the quality of the system identification results. This is why we decided to first do experiments in a static pose and then relate those results to the results of the dynamic walking process.

For the static standing experiments (see Fig. 1b) we applied a Pseudo Random Binary Signal (PRBS) as system input of the coactivation strategy. We used both positive and negative steps to separately account for quadriceps and hamstrings dynamics.

FES muscle contraction can be modeled using complex high-order physiological models. However, when using a finite number of experimental data a trade-off has to be found between model complexity and not overfitting the limited data. We decided to choose a simple first-order model with an additional input-output delay

$$G(s) = \frac{e^{-T_d s} K_p}{T_{p1} s + 1} \quad (1)$$

where s is the Laplace parameter, T_d the time delay, K_p the gain, T_{p1} the time constant.

The procedure was the following: after equipping the subjects, we first tuned the parameters q_{q0} and q_{h0} for the coactivation strategy, then we applied the positive and negative PRBS input sequences. We divided the data in two sets, one for positive and one for negative input u. For each set we fitted the model (1) in an optimal way by using the Matlab command `procest`.

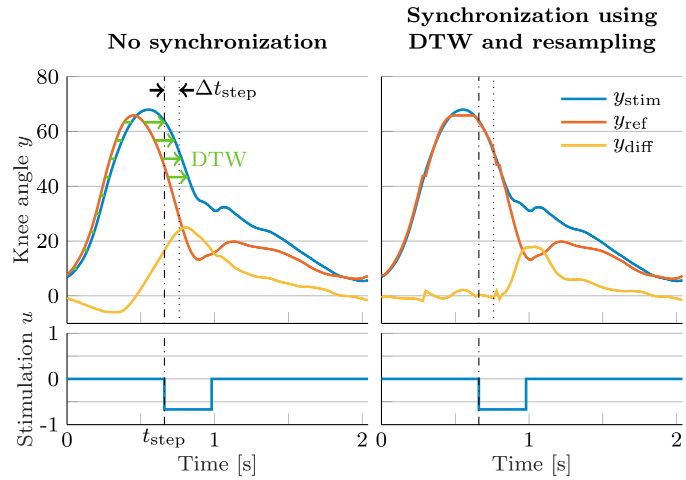


Fig. 2. The knee angle of a step without stimulation is plotted together with the knee angle of a step with stimulation. Additionally the difference of the two trajectories as well as the stimulation input are shown. On the right side, both angle curves are aligned to fit until the onset point of stimulation.

For the system identification while walking, single pulse inputs were triggered at different times of the swing and preswing phase. The subjects were asked to walk on a treadmill which was set to a speed of 1.5 km/h. During the experiments, the coactivation module was used, which means that both hamstrings and quadriceps were continuously stimulated at the low values q_{q0} and q_{h0}. The pulses were triggered at nine different times, starting at −45% of the swing phase equally spaced to +75% of the swing phase. The pulse timings where estimated by using the average gait phase durations of the previous steps. The duration of the pulses was fixed to 0.3 s. The subjects walked four steps with no stimulation ($u = 0$) and four steps with stimulation with one constant pulse timing. This was repeated until all 9 timings were recorded for both positive and negative pulses. Hence each subject was asked to walk 72 steps in total.

When the stimulation input is kept zero, naturally during gait the measured output (knee angle) is not zero due to the voluntary muscle contractions. If we assume a linear model, with the model input $U(s)$ being the stimulation plus the voluntary contraction $V(s)$,

$$Y(s) = G(s)(U(s) + V(s)), \quad (2)$$

we can get the pure system reaction to the stimulation input by subtracting $G(s)V(s)$ from the measured output. This can be approximated by measuring the output of a step without stimulation and subtracting it from a step with stimulation. In our case, we used the average knee angle of the respective preceding set without stimulation.

Unfortunately, due to inaccuracy of the gait phase detection, due to natural variations but also due to the effects of stimulation the knee angle trajectory can vary even before the point of stimulation. If the knee angle would be for example shifted in time due to an imprecision of the gait phase detection, the trajectory of the subtraction would be far from zero. In order to account for problems arising from shifting, we attempted to synchronize the two trajectories such that the knee angle is identical at the point of stimulation. To find the delay at the onset point of stimulation, we firstly used a dynamic time warping algorithm to synchronize the entire trajectory. Subsequently, we then extracted the time delay at the onset point of stimulation and shifted the unaltered trajectory using this value. Fig. 2 shows an example of this process, on the left is the unaltered measurement of the knee angle with and without stimulation, on the right the new synchronization.

For each single stimulation pulse we identified the parameters of (1) using the output trajectory of the above method.

2.4 Iterative Learning Control

In this paper we chose to use a very simple proportional (P-type) ILC as described in (Bristow et al., 2006) and which was also used by Seel et al. (2016) and Nahrstaedt et al. (2008). Using the P-type ILC, we expected more robustness and predictability compared to a complex model-based ILC approach, due to the many uncertainties and the simple identified models. The P-type ILC has three parameters that need to be tuned, the scalar learning gain λ, the assumed plant delay $T_d = mT_s$ (where T_s is the sampling time and m the number of delay steps) and the dynamic Q-filter. In the lifted system framework, the learning equation results in

$$\begin{aligned} \mathbf{u}_{j+1} &= \mathbf{Q}(\mathbf{u}_j + \lambda \mathbf{I}\hat{\mathbf{e}}_\mathbf{j}) \\ \hat{e}_j(k) &= e_j(k+m)\ \forall\ k = 1 \ldots N, \end{aligned} \tag{3}$$

where $\mathbf{u}_j$ is the input trajectory of cycle j, $\mathbf{Q}$ is the Q-filter matrix, $\hat{\mathbf{e}}_\mathbf{j}$ is the error trajectory shifted forward by the assumed plant delay and N is the number of samples in one cycle.

In order to account for variations in the step length, we chose N bigger than the expected maximum pre-swing plus swing time. When less samples then N were recorded, the remaining values of the error were set to zero, such that the ILC could not directly affect the input after the end of the swing phase (analogous to Seel et al. 2016).

Since there are upper limits to the stimulation, measures have to be taken against a windup of the ILC. The maximum and minimum inputs were calculated out of the maximum stimulation values of quadriceps and hamstrings and the rules of the cocontraction strategy. The new input $\mathbf{u}_{j+1}$ is then saturated to the calculated values at each cycle.

For the Q-Filter, a noncausal zero-phase filter was chosen in order to avoid delays introduced by the filter. This was achieved by using a 2nd-order Butterworth filter and filtering in both directions.

Before starting the walking experiment with a certain subject, first the system identification while standing experiment was conducted. From the identified model gains K_p for hamstrings and quadriceps, the gains k_q and k_h of the coactivation strategy were tuned, such that the resulting static gain equals one.

The purpose of this paper is to promote the development of an adaptive neuroprosthesis for stroke patients. In this case, the desired goal is to come as close as possible to a healthy gait, which means that the ILC reference trajectory has to reflect that. Here, however, we are planning to conduct experiments with healthy subjects, which do already have a healthy gait. To test the performance of the ILC we had to introduce reference trajectories that differ from healthy gait but are still possible to walk without falling or stumbling. For this we modified the average knee angle trajectory of the respective subject to either require more or less knee flexion.

Table 1. Identified parameters from the standing experiment.

	Quadriceps			Hamstrings		
Subject	K_p	T_{p1}[s]	T_d[s]	K_p	T_{p1}[s]	T_d[s]
1	54.38	0.093	0.188	37.11	0.151	0.295
2	37.25	0.115	0.244	21.28	0.116	0.316
3	36.33	0.099	0.212	58.41	0.123	0.270
4	23.72	0.140	0.154	33.88	0.346	0.249
5	9.77	0.054	0.167	10.42	0.053	0.207

After conducting the standing system identification, we used the identified system gains to tune the coactivation strategy. With the tuned coactivation strategy, a static system gain of one can be assumed. Consequently, the ILC was tuned to a constant learning gain of $\lambda = 0.5$. The Q-filter was set to a constant cutoff frequency of $f_Q = 5\,\mathrm{Hz}$ and the delay m was tuned according to the identified model delay. For the number of samples calculated by the ILC we chose $N = 75$. Subsequently, the subjects were asked to walk on a treadmill set to a speed of $1.5\,\mathrm{km/h}$. As with the system identification the coactivation strategy was active during the entirety of the experiment. For each subject, 5 ILC experiments were conducted for each of the two reference trajectories. During the first five steps, the knee angle was recorded, averaged and the two references were calculated. For the next 10 steps the ILC was turned on for the first experiment. After the ILC experiment followed a break of five steps, then the next ten-steps experiment was started.

3. RESULTS AND DISCUSSION

The results of the system identification experiments underline how crucial robustness is in this area. Much variation and little consistency can be observed between subjects, even if they are healthy. Table 1 shows the model parameters that were identified during the standing experiments. Especially the model gains show big variations between subjects and the muscle groups. The model poles show less variations and the identified model delays are the most consistent. This means that assuming a universal model pole and delay is much less problematic than assuming a universal gain.

In order to visualize how the dynamics change during gait compared to when standing, the identified parameters of each subject were normalized with the parameters of the respective standing experiment. The parameters were then plotted over the gait cycle time, see Fig. 3. A linear and a second order polynomial fitting was used to visualize the tendencies of the parameters. The fitting was done on a reduced data set, where outliers had been removed.

When identifying system parameters during gait, we can expect to encounter many disturbances and unwanted dynamics. This gets clearly reflected by the results. Many times, the model could not be fitted in a satisfying way. Fig. 3 shows how much the parameters vary. The identi-

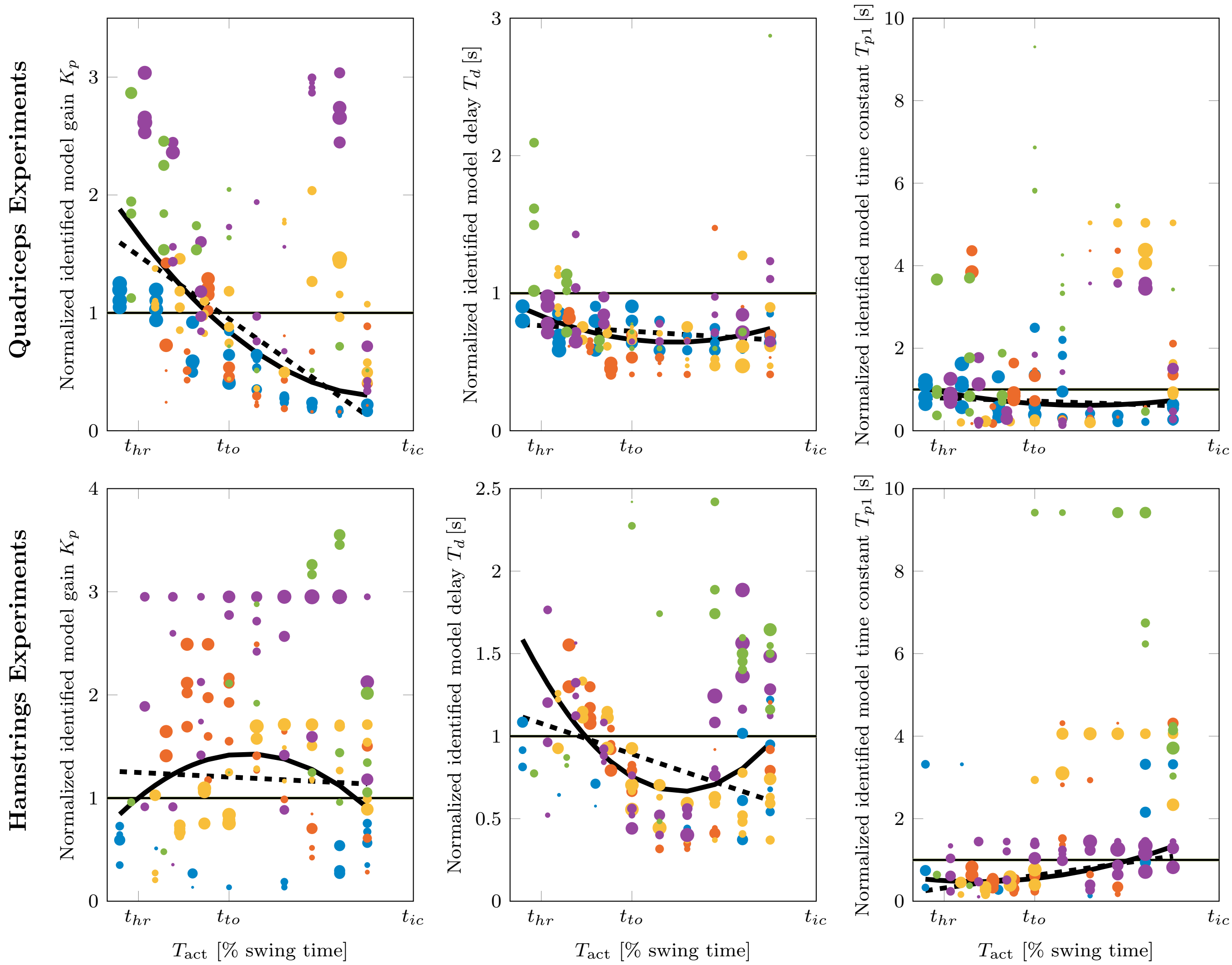


Fig. 3. Identified system parameters from the walking experiment. Each of the 5 subjects is represented by a different color. The parameters were normalized using the parameters identified in the standing experiment of the respective subject. The size of the radii represent the quality of the model fit. The x-axes are presented in % of the swing time with the gait events heel rise (t_{hr}), toe off (t_{to}) and initial contact (t_{ic}) indicated.

fication when stimulating the hamstrings was the most problematic, getting a good electrode placement and a strong motor response turned out to be difficult with most of the subjects. Another problem that arose during the experiments was that people tended to almost stumble when the quadriceps was activated close to heel rise. This corrective response also explains the higher system gain of the quadriceps close to heel rise. However, despite of all the noise in the results, clear tendencies can be observed especially for the quadriceps muscle. The system delays and poles were spread fairly narrow whereas the gains varied the most.

Using the knowledge that we gain from the system identification experiments, we can now analyze the stability of the ILC. Here, we assumed an ILC tuned with $\lambda = 0.5, T_d = 0.25\,\mathrm{s}, f_Q = 5\,\mathrm{Hz}$. The decoupling is assumed to be tuned, hence, the system system gain is expected to be 1. From the results of the system identification while walking, we chose extreme values for all parameters in both positive and negative directions. Using all possible combination of the extreme and nominal parameters we tested the asymptotic stability as well as the monotonic convergence of the ILC. For this we used the equations provided by Bristow et al. (2006). The stability results shown in Table 2 are promising. Even with the extreme parameters which result mainly from disturbances in the

Table 2. Stability and convergence analysis of the ILC using all combinations of the extreme values that were observed during the system identification experiment. Here, "y" stands for monotonic convergence, "(y)" for asymptotic stability and "n" for unstable.

Stability and convergence analysis					Values
		K_{p-}	K_{p0}	K_{p+}	
T_{p10}	T_{d0}	y	y	y	$K_{p0} = 1$
T_{p1+}	T_{d0}	y	y	y	$K_{p+} = 3$
T_{p1-}	T_{d0}	y	y	y	$K_{p-} = 0.1$
T_{p10}	T_{d+}	y	y	y	$T_{p10} = 0.1$
T_{p10}	T_{d-}	y	y	n	$T_{p1+} = 0.5$
T_{p1+}	T_{d+}	y	y	y	$T_{p1-} = 0.02$
T_{p1+}	T_{d-}	(y)	(y)	n	$T_{d0} = 0.25$
T_{p1-}	T_{d+}	y	y	(y)	$T_{d+} = 0.4$
T_{p1-}	T_{d-}	y	y	n	$T_{d-} = 0.1$

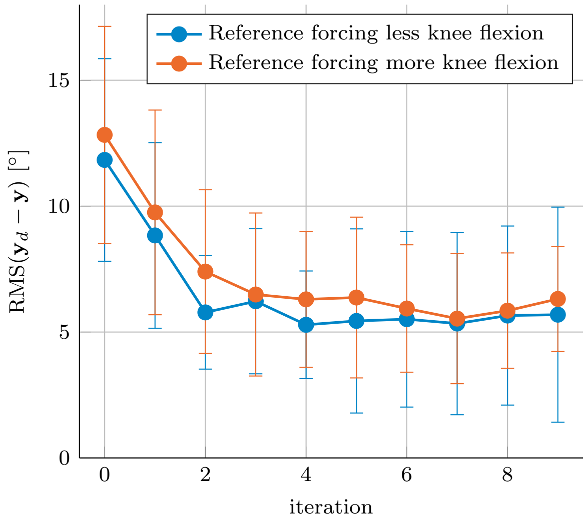


Fig. 4. RMS error values of the knee angle during the swing phase. Shown are the mean and standard deviation values for 2 times 40 experiments, conducted with 8 subjects.

system identification process, the ILC is stable for all but three combinations. All cases are for an unexpected high plant gain with an unexpected low plant delay. Hence, when tuning the ILC one should be conservative with the assumed plant delay but generous with the assumed plant gain.

The results from the system identification suggest that the ILC should be stable in all likely cases, this can be validated with the experiments where the ILC is applied. The 80 ILC experiments on 8 subjects are summarized in Fig. 4, by showing the mean and standard deviations of the RMS values of the error trajectories after each iteration. For both cases, the reference with more and with less knee flexion, the ILC error decreased almost identically. It can be observed that the optimum is reached after about 4 iterations.

4. CONCLUSION

Clearly, performing system identification during gait is non-trivial. While individual results might not be conclusive, some clear tendencies can be observed when looking at the entirety of the results. By evaluating the obtained results it is now possible to get a good insight on how the system parameters change with respect to the parameters of a static standing experiment. Using this knowledge we could tune the ILC-based on a simple standing experiment. By utilizing the ILC together with the cocontraction strategy we were capable of changing the gait of the subjects towards a desired trajectory.

Still much has to be done to obtain a working multichannel FES neuroprosthesis. First of all, studies with the ILC implementation should be done together with stroke patients. Here, the subject-to-subject variability is expected to be even higher and the motor response lower. Secondly, a simpler tuning procedure than the standing system identification should be established for an application in the clinic. This could be done by utilizing the crucial procedure where the subject has to indicate the comfort thresholds to obtain the static system gains.

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