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Feedback Control of Foot Eversion in the Adaptive Peroneal Stimulator

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***Abstract*— The limited ability to dorsiflex the foot, known as drop foot, can be treated by functional electrical stimulation. Therein, undesired foot eversion/inversion is a common problem which is usually corrected by tedious manual repositioning of the electrodes. We address this issue by presenting a feedback-control solution featuring three major contributions: (1) an algorithm for inertial sensor-based foot-to-ground angle measurement with periodic drift correction; (2) a three-electrode setup that allows distribution of an overall stimulation intensity to the tibialis anterior muscle and to the superficial peroneal nerve that innervates the fibularis longus muscle, thus decoupling dorsiflexion and eversion control; (3) a run-to-run controller and an iterative learning controller, both of which use step-by-step learning to achieve desired eversion foot-to-ground angles. Experiments with a chronic drop foot patient demonstrate compensation of undesired eversion/inversion within at most two steps, while dorsiflexion angle trajectories are not affected.**

I. INTRODUCTION

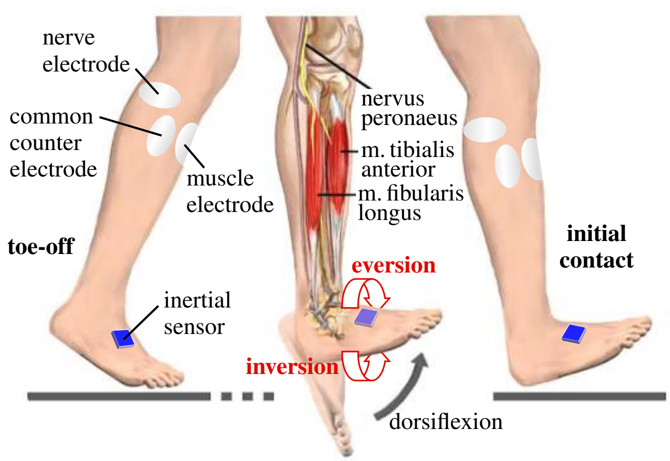

Fig. 1. Drop foot treatment by functional electrical stimulation of the nerve and the muscles that are involved in foot dorsiflexion. Unbalanced activation of the two muscles results in undesired eversion or inversion. An inertial sensor at the foot allows feedback control of the foot-to-ground angle.

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Drop foot syndrome appears in stroke patients and patients with neurological disorders. It is characterized by the limited ability to lift (more precisely to dorsiflex) the foot by voluntary muscle activation. Drop foot stimulators, also known as peroneal stimulators, are neuroprostheses [1] that represent a less passive alternative to the conventional ankle-foot orthosis treatment [2]. The stimulator supports the dorsiflexion during the swing phase of gait, i.e. between the toe-off and the initial contact of the foot, through functional electrical stimulation (FES) of the involved muscles and/or nerves. Figure 1 depicts the two muscles that pull on the inner and outer edge of the foot as well as the nerve that innervates both muscles. In this contribution we focus on FES applied via self-adhesive skin electrodes, which are most commonly used in drop foot stimulators and are also depicted in Figure 1. Via such electrodes, rectangular biphasic pulses with amplitudes of $5-50\,\mathrm{mA}$ and pulse-widths of $50-500\,\mu\mathrm{s}$ are typically applied at a frequency of $20-100\,\mathrm{Hz}$.

Most commercially available devices use heel switches to detect two gait phases: one when the heel is on the ground and the other when it is not [1], [3]. A more detailed gait phase detection can be achieved using an inertial sensor; see e.g. [4]. Furthermore, available devices only employ feed-forward control, i.e. they apply a predefined stimulation intensity profile in each step as soon as the heel is lifted. FES-activated muscles fatigue rapidly [5] and residual voluntary muscle activity as well as the muscle tone may vary. The stimulation intensity must therefore either be adapted repeatedly by the user or it must be set to a higher value from the very start, which leads to increased fatigue. Accordingly, recent research has focused on feedback approaches wherein the effect of the stimulation, i.e. the foot motion, is measured and closed-loop control is applied to adjust the stimulation intensity. This approach was demonstrated to yield improved performance, e.g. by using fuzzy control methods [6], run-to-run control [7], and predictive control [8]. Besides the sufficient foot clearance that these methods yield, the additional goal of natural and symmetric foot motion can be achieved by employing Iterative Learning Control (ILC). This method allows control of, for example, the entire dorsiflexion angle trajectory to a given reference trajectory. The effectiveness of this approach has been demonstrated in [9] by simplified experiments with a healthy subject and in [10] by experiments with stroke patients.

Generating sufficient foot clearance and physiological foot motion is an important achievement of recent research work. But it still ignores the fact that the ankle joint has two rotational degrees of freedom, i.e. dorsiflexion/plantarflexion and eversion/inversion, see Figure 1. Therefore, unbalanced activation of m. tibialis anterior and m. fibularis longus leads to undesired eversion/inversion of the foot and increases the risk of falling and ankle injuries. In [11], an automatic tuning approach has been proposed for an implanted stimulator. When using surface electrodes, however, this problem is typically addressed by repeatedly repositioning the stimulation electrodes until a position is found which yields a balanced activation. This process can be tedious, and a position that yields balanced activation may only do so for a short time, e.g. until the muscles fatigue or move underneath the skin. Recent research has therefore focused on the use of array electrodes which allow for quick manipulations of the stimulation site without the need for repositioning the array. In particular, it was demonstrated recently that both the dorsiflexion angle trajectory and the eversion angle trajectory of a healthy seated subject can be controlled by FES via array electrodes using ILC methods [12].

In the present contribution, we address the issue of undesired eversion/inversion in the particular setup of the Adaptive Peroneal Stimulator [10]. Therein, ILC is used to control the dorsiflexion foot-to-ground angle trajectory (foot pitch) by adjusting a stimulation intensity profile. As an extension of the existing system, we propose a setup with three single electrodes as well as two control methods for controlling the eversion foot-to-ground angle (foot roll). The remainder of the paper is organized as follows. In Section II we introduce the hardware setup, before we briefly explain how the angles are derived from the measurement data of an inertial sensor in Section III. The controllers are designed in Section IV, and experimental results are presented in Section V.

II. HARDWARE SETUP

We use the hardware setup of the Adaptive Peroneal Stimulator [10]. Three self-adhesive surface electrodes are attached to the lower leg of a drop foot patient, see Figure 1. One active electrode is placed above the superficial peroneal nerve and one above the tibialis anterior muscle: the former can be used to induce dorsiflexion with eversion of the foot and the latter to induce dorsiflexion with inversion. Each of these electrodes is connected to a separate output channel of a functional electrical stimulator that applies biphasic stimulation pulses [5] at a frequency of $f_{\text{FES}} = 50\,\text{Hz}$. The common counter electrode for the counter pulses of both channels is attached about $2\,\text{cm}$ lateral of the tibialis anterior electrode. At this position it was found to either have no contributing effect on foot motion or, depending on the individual subject, to slightly support eversion. The stimulator is connected to a laptop that is used to set stimulation intensities for both channels in real time. The same laptop receives measurement signals from an inertial measurement unit that is attached to the patient's paretic-side shoe and delivers three-dimensional accelerometer and gyroscope readings at $f_{\text{IMU}} = 100\,\text{Hz}$.

III. ASSESSING FOOT EVERSION/INVERSION WITH INERTIAL SENSORS

The measured angular rates and accelerations of the paretic foot are used to detect the gait events *toe-off* and *initial contact*, which mark the beginning and the end of the *swing phase*, as well as *full contact* and *heel-rise*, which mark the beginning and the end of the *foot-flat phase*. In the following, t_{to}, t_{ic}, t_{fc} and t_{hr} will denote the according time instants of the considered step, respectively. As depicted in Figure 2, the period of time between heel-rise and toe-off is referred to as *pre-swing*, and the phase between initial contact and full contact is called *loading response*. This is in accordance with standard literature, see e.g. [13]. The employed gait phase detection algorithm is described in [4] and, for the sake of brevity, is not further discussed here. Instead, we assume that we have real-time information of the current gait phase and consider the task of foot-to-ground angle measurement in the following section.

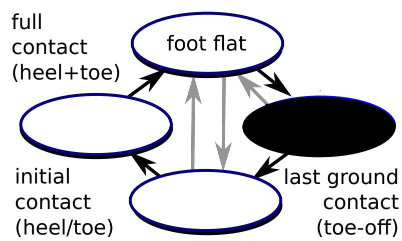

Fig. 2. Employed model (phases and transitions) of the gait cycle of one side. During foot-flat phase, the foot rests on the ground, while it has no ground contact during swing phase.

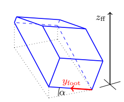

Fig. 3. Geometrical definition of the foot-to-ground angle α in eversion-direction (roll) on a left foot. The angle that the foot's mediolateral axis y_{foot} and the horizontal ground confine during swing phase is a proper measure of foot eversion/inversion. Dotted lines indicate projection into horizontal plane.

A. Measuring Foot-to-Ground Angles

Figure 3 illustrates that the foot-to-ground eversion angle is defined as the angle between the horizontal plane and the mediolateral axis y_{foot} of the foot, i.e. the axis pointing from medial to lateral. The local coordinates of y_{foot} are known if we attach the sensor such that one local coordinate axis coincides with y_{foot}. However, as discussed in our previous work on inertial sensor-based gait analysis [14], even surfaces and right angles are rarely found on the human body. We therefore present an alternative approach in which we assume that the mounting orientation and position of the sensor are both unrestricted and unknown. More precisely, the sensor may be attached to the shoe or foot (excluding the toes) in an arbitrary position and orientation. During every foot-flat phase, the accelerometer readings $a(t)$ are integrated over time and the resulting vector is normalized to unit length:

$$\hat{z}_{\text{ff}} := \sum_{t \in \text{foot-flat}} a(t), \quad z_{\text{ff}} := \hat{z}_{\text{ff}} / ||\hat{z}_{\text{ff}}||_2, \tag{1}$$

where $||\cdot||_2$ denotes the Euclidean norm. Since gravitational acceleration dominates when the foot is (almost) at rest, z_{ff} is (almost) vertical. At each heel-rise t_{hr}, a strap-down integration [15] of the angular rates is started that yields the rotation matrix $R_{\text{ff}}(t)$. This matrix transforms the local measurement vectors $a(t)$ and $g(t)$ of any time instant t between two foot-flat phases to the local coordinate system of the preceding foot-flat phase, which we will refer to as the reference coordinate system of that step. During the first step of the patient, the horizontal foot velocity $v_{xy}(\tau)$, $\tau > t_{\text{hr}}$, is estimated in reference coordinates by applying

$$a_{\text{ff}}(t) := R_{\text{ff}}(t) a(t), \tag{2}$$

$$v_{xy}(\tau) := f_{\text{IMU}}^{-1} \sum_{t=t_{\text{hr}}}^{\tau} (a_{\text{ff}}^T(t) - z_{\text{ff}} a_{\text{ff}}^T(t) z_{\text{ff}}), \tag{3}$$

We exploit the fact that the foot is resting at $t = t_{\text{fc}}$ to remove integration drift and calculate the local coordinates of the mediolateral axis y_{foot} of the foot

$$\hat{y}_{\text{foot}} := z_{\text{ff}} \times \sum_{\tau=t_{\text{to}}}^{t_{\text{ic}}} (v_{xy}(\tau) - \frac{\tau - t_{\text{hr}}}{t_{\text{fc}} - t_{\text{hr}}} v_{xy}(t_{\text{fc}})), \tag{4}$$

$$y_{\text{foot}} := +\hat{y}_{\text{foot}} / ||\hat{y}_{\text{foot}}||_2 \text{ for a left foot,}$$
$$\text{and } y_{\text{foot}} := -\hat{y}_{\text{foot}} / ||\hat{y}_{\text{foot}}||_2 \text{ for a right foot.} \tag{5}$$

Here, it is assumed that the foot travels mainly along the posterior-anterior axis during swing phase, which is a valid assumption, even in paretic gait. Furthermore, please note that the mediolateral axis y_{foot} of the foot in local coordinates does not change with time, since the sensor moves along with the foot. See Figure 3 for illustration. By transforming y_{foot} to the reference coordinate system in which the vertical axis z_{ff} is known, we calculate the time-dependent foot-to-ground angle α in eversion/inversion direction (roll):

$$\alpha(t) := \frac{\pi}{2} - \sphericalangle(z_{\text{ff}}, R_{\text{ff}}(t) y_{\text{foot}}) \tag{6}$$
$$= \arcsin(z_{\text{ff}}^T R_{\text{ff}}(t) y_{\text{foot}}) \tag{7}$$

Due to the side-dependent axis definition (5), this angle is positive when the foot is everted and negative when the foot is inverted with respect to the horizontal plane. However, it is important to note that orientation strap-down integration is always subject to drift, since, even with proper calibration, the gyroscopes have non-zero bias. Therefore, $\alpha(t)$ also drifts[1] between each two foot-flat phases. At every full contact t_{fc}, however, we can remove the drift by assuming constant bias and level ground:

$$\tilde{\alpha}(t) := \alpha(t) - \frac{t - t_{\text{hr}}}{t_{\text{fc}} - t_{\text{hr}}} (\alpha(t_{\text{fc}}) - \alpha(t_{\text{hr}})), \; t \in [t_{\text{hr}}, t_{\text{fc}}] \tag{8}$$

Figure 4 presents example trajectories of this eversion angle from experiments with healthy subjects and with stroke patients who received conventional FES-support of dorsiflexion. The common procedure of minimizing eversion/inversion by repositioning the stimulation electrodes was omitted. As demonstrated by the data, this can result in strong eversion or inversion, compared to the limited amount that is present in the gait of healthy subjects. This demonstrates that methods for automatic eversion control are required in order to avoid tedious electrode repositioning. In the following, $\tilde{\alpha}$ is used to define a scalar eversion indicator, and in Section IV-B it is used for the iterative learning control of the foot eversion/inversion.

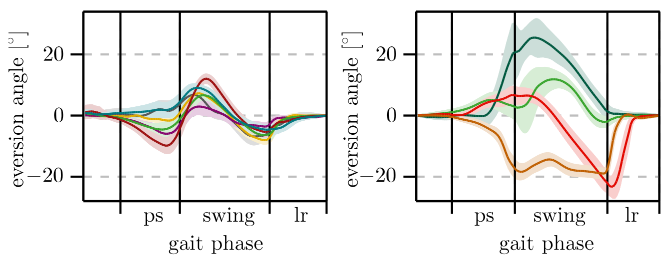

Fig. 4. Eversion angle trajectories (average lines + standard deviation bands) of healthy subjects (left) and of stroke patients who received conventional FES-support of dorsiflexion (right). Electrode positions were carefully chosen prior to stimulating but not repositioned thereafter. Eversion or inversion occurs during pre-swing (ps), swing, and loading response (lr).

B. Scalar Eversion Indicator

In order to design a run-to-run controller for foot eversion, we need a scalar indicator that quantifies the amount of eversion/inversion of an entire step. To this end, inertial data is collected from a number of treadmill experiments with stroke patients in which synchronized videos from posterior and lateral are also recorded. These videos are shown to highly experienced physicians who rate the amount of eversion/inversion in the patient's gait. Based on these examinations, it is found that eversion/inversion is most undesirable in the second half of swing phase, i.e. when the foot is closer to the ground and eversion/inversion increases the risk of touching the ground early. Therefore, we define the scalar eversion indicator as the following third-root-mean-cubed angle

$$e := \sqrt[3]{\frac{2 f_{\text{IMU}}}{t_{\text{ic}} - t_{\text{to}}} \sum_{t=\frac{t_{\text{to}}+t_{\text{ic}}}{2}}^{t_{\text{ic}}} \tilde{\alpha}(t)^3}, \tag{9}$$

where power 3 is chosen because it gives more weight to large angles while maintaining the sign information. This allows for cancellation of positive against negative values. But from careful analysis of a large data base, we find that

[1]For example, with the proposed algorithm and the employed sensor hardware, we found that $\alpha(t_{\text{fc}})$ is typically in the range of 2°.

(even in paretic gaits) it is highly uncommon that both large eversion and large inversion occur during the short amount of time of half a swing phase[2]. The scalar eversion indicator is found to correlate well with the video-based eversion ratings of experienced clinicians, as demonstrated in Figure 5. We therefore conclude that it is a proper scalar measure of the clinically relevant eversion that is present in a step.

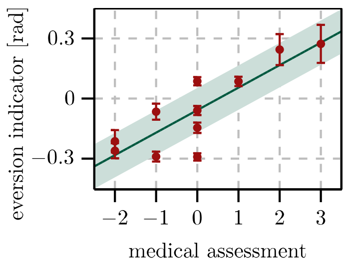

Fig. 5. Correlation of proposed scalar eversion indicator with video-based eversion ratings of experienced physicians for eleven walking sequences of stroke patients (10-20 steps each; horizontal bars show standard deviations).

IV. DESIGN OF LEARNING CONTROLLERS

We assume that the foot-to-ground angles in dorsiflexion-direction (pitch) and in eversion-direction (roll) are measured in real time using the methods from Section III. Furthermore, please recall that the hardware setup of the Adaptive Peroneal Stimulator allows us to manipulate the stimulation intensities of two distinct stimulation channels, i.e. the intensity $q_{\text{n.peron.}} \in [0, 1]$ of the nerve channel that causes dorsiflexion with eversion and the intensity $q_{\text{tib.ant.}} \in [0, 1]$ of the muscle channel that causes dorsiflexion with inversion. Both stimulation intensities are normalized by the individual maximum tolerated values that are determined during the setup of every experiment. Controlling both angles by manipulating these stimulation intensities represents a multi-input multi-output control problem with strong couplings. In order to decouple eversion control from dorsiflexion control, we employ the following strategy: the overall stimulation intensity $u_{\text{df}} := q_{\text{n.peron.}} + q_{\text{tib.ant.}}$ will be used as the manipulated variable for dorsiflexion control, while the eversion controller decides in what ratio this sum is distributed to both channels. More precisely, we assign the two stimulation channel intensities as follows:

$$q_{\text{n.peron.}} = u_{\text{df}}\,(u + 1)/2 \tag{10}$$

$$q_{\text{tib.ant.}} = u_{\text{df}}\,(1 - u)/2, \tag{11}$$

where $u_{\text{df}} \in [0, 1]$ is the manipulated variable of the dorsiflexion controller and $u \in [-1, 1]$ is the manipulated variable of the eversion controller, which we will refer to as the intensity distribution. To enhance readability, we will denote the upper bound $u = 1$ with "N" as in nerve and the lower bound $u = -1$ with "M" as in muscle.

[2]In such a case, iterative learning control of the entire eversion angle profile should be applied rather than run-to-run control of the scalar eversion indicator; see Section IV-B.

The general control task is to (first) achieve physiological dorsiflexion while (second) maintaining naturally small eversion/inversion during (at least the second half of) swing phase. We addressed the first problem in previous works [16], [17], [10] by designing an iterative learning controller, which finds the stimulation intensity trajectory that yields a desired dorsiflexion angle trajectory. For the sake of simplicity, we do not employ this approach here. Instead, we use a fixed trapezoidal stimulation intensity trajectory, the rise time and width of which are set manually to ensure sufficient dorsiflexion. This allows us to focus on the control of eversion/inversion. As pointed out in previous work, see e.g. [16], [10], the FES and muscle dynamics are too slow to apply feedback control during the short duration of a swing phase. Instead, we will follow two learning-type control approaches in the following subsections: (1) a run-to-run control that applies a constant input u_j in every step j and (2) an iterative learning control that applies a time-dependent input trajectory $u_j(t)$ in every step j. During each foot-flat phase, both controllers will use the eversion angle information of the previous step to adjust their control inputs in order to achieve a predefined desired level of eversion/inversion in the following step.

A. Run-to-Run Controller Design

At each full contact, the scalar eversion indicator e_j of the last step j is calculated from the drift-corrected eversion angle trajectory $\tilde{\alpha}(t)$. It is then compared to a given reference value r, and the deviation is used to update the intensity distribution u_{j+1} that is applied during the next step:

$$u_{j+1} = \text{sat}_{-1}^{+1}\big(\,u_j + \lambda_{\text{R2R}}(r - e_j)\,\big), \tag{12}$$

where $\lambda_{\text{R2R}} \in \mathbb{R}_{>0}$ is a positive learning gain and $\text{sat}_{-1}^{+1}(\cdot)$ saturates u_{j+1} to its meaningful range. This control law is implemented as a C-coded function in the real-time software setting described in Section II.

In order to find suitable values for the controller parameter λ_{R2R}, we evaluate the (maximum) sensitivity of the controlled variable with respect to the manipulated variable in experiments with subjects seated on a table, i.e. their shanks and feet were hanging down and they were asked to remain passive. It is found that, while results vary from subject to subject, a change of 0.2 in the intensity distribution u may lead to a change of at most $0.5\,\text{rad}$ in the eversion indicator e. Therefore, we choose $\lambda_{\text{R2R}} = 0.5$ as a starting value for further experimental tuning in Section V. While increasing the learning gain will accelerate convergence, overly high values will lead to overshoot effects, i.e. learning steps that overcompensate the setpoint deviation of the last step and lead to even larger deviations (with opposite sign) in the next step.

B. Iterative Learning Controller Design

As mentioned above, an iterative learning controller applies an internally stored input trajectory in each trial and updates this feedforward input only between the trials based on measurement information from the previous trial. Therefore, in order to carry out the ILC design, we first define the lifted signal vectors[3] $\mathbf{y}_j$ and $\mathbf{u}_j$ of the drift-corrected eversion angle and the intensity distribution, respectively:

$$\mathbf{y}_j := \begin{bmatrix} \tilde{\alpha}_j(t = T_s) \\ \tilde{\alpha}_j(t = 2T_s) \\ \vdots \\ \tilde{\alpha}_j(t = nT_s) \end{bmatrix}, \quad \mathbf{u}_j := \begin{bmatrix} u_j(t = T_s - \delta T_s) \\ u_j(t = 2T_s - \delta T_s) \\ \vdots \\ u_j(t = nT_s - \delta T_s) \end{bmatrix},$$

where j is the step index, $t = 0$ refers to the toe-off, $T_s = 0.02$ is the sample time[4], nT_s is the maximum time duration of a swing phase, and δ is a phase-lead parameter that can be used to account for delays in the plant dynamics. At each full contact and after drift-correction, the lifted vector $\mathbf{y}_j$ is determined, compared to a given reference trajectory $\mathbf{r} \in \mathbb{R}^n$, and used to update the input trajectory as follows:

$$\mathbf{u}_{j+1} = \mathrm{sat}_{-1}^{+1}(\mathbf{Q}(\mathbf{u}_j + \lambda_{\mathrm{ILC}} \mathbf{I}_{n\times n}(\mathbf{r} - \mathbf{y}_j))), \tag{13}$$

where $\lambda_{\mathrm{ILC}} \in \mathbb{R}_{>0}$ is a positive learning gain and $\mathbf{Q}$ is a symmetric Toeplitz lifted matrix containing the Markov parameters of a second-order Butterworth low pass filter, i.e. multiplying a lifted vector by $\mathbf{Q}$ low-pass filters the trajectory without introducing any time delay [18].

The above input update law is known from standard ILC literature, see e.g. [19]. However, it assumes that every trial has the same time duration (pass length) and that, for each update, a full-length measured output trajectory is available. But in FES-assisted drop foot treatment, the pass lengths are determined by the swing phase durations, which are known to vary even in healthy subjects walking at constant speed. We addressed this issue in previous publications [16], [17], in which we suggested the following strategy: set the pass length n to the maximum possible swing phase duration (in samples) and let n_j be the actual pass length of the j^{th} trial. Then, before each input update, fill the first n_j entries of the lifted output vector $\mathbf{y}_j$ with the measured values and complete $\mathbf{y}_j$ by setting its last $n - n_j$ values to zero. This approach has successfully been used for the dorsiflexion control task which faces the same problem of variable pass length. Therefore, we implement the strategy as well as the above input update law as a C-coded function in the real-time software setting described in Section II.

The learning law (13) including the outlined extension for variable pass length has previously been used for the dorsiflexion control [17], [10]. From this, we know that choosing a $\mathbf{Q}$-filter cutoff frequency of 5 Hz limits the learning to a reasonable frequency range and that a phase-lead of $\delta = 0.2$ s compensates most of the slow FES and muscle dynamics. To find suitable values for the learning gain λ_{ILC}, we recall the maximum sensitivity result of Section IV-A. Therefore, we choose $\lambda_{\mathrm{ILC}} = 0.5$ as a starting value for further experimental tuning in Section V. As before, raising the learning gain will lead to faster convergence but will eventually result in overshoot effects.

[3]Lifted signals capture finite-length trajectories of discrete-time signals, see e.g. [19].

[4]Please recall from Section II that, although measurement values are available at $f_{\mathrm{IMU}} = 100$ Hz, the stimulation intensities are only updated at $f_{\mathrm{FES}} = 50$ Hz

V. EXPERIMENTAL RESULTS

In a series of experiments with a chronic drop foot patient, we evaluate the two eversion controllers designed in Section IV. Informed consent of the patient was obtained and the trials have been approved by the ethics committee of Charité Universitätsmedizin Berlin. The patient walks on a treadmill at self-selected speed and with the hardware setup described in II. In each swing phase, the paretic foot is lifted (dorsiflexed) by applying a trapezoidal overall stimulation intensity trajectory $u_{\mathrm{df}}(t)$, which is not adapted from step to step. The ratio $u(t)$ in which this overall stimulation intensity is distributed to the nerve and muscle channel is manipulated by either of both eversion controllers.

First, the performance of the run-to-run controller is assessed by reference step tests, the results of which are given in Figure 6. Small adaptations of the intensity distribution are sufficient for large changes in foot eversion/inversion. The output follows the reference with a delay of one step, which is the fastest possible reaction for trial-to-trial feedback. The depicted eversion angle trajectories reveal that $\tilde{\alpha}$ was successfully raised, at least in the second half of swing phase. During pre-swing and early swing phase, however, the angle is alternating between eversion and inversion.

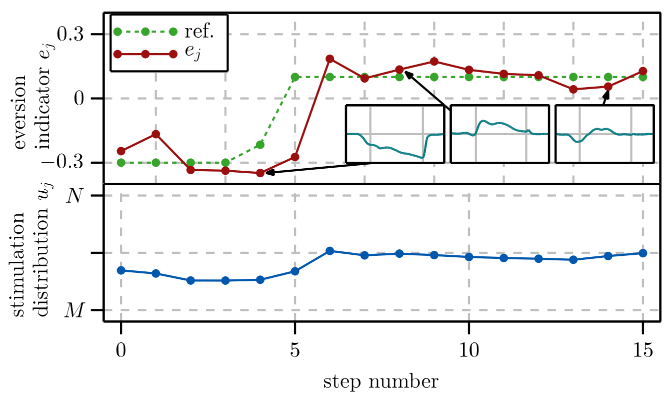

Fig. 6. Reference tracking of the run-to-run eversion controller in a chronic drop foot patient. The inversion (negative e) is compensated quickly by proper adaption of the stimulation distribution ($\lambda_{\mathrm{R2R}} = 0.5$). Small boxes sketch eversion angle trajectories of individual steps.

In a next step, we try to eliminate eversion and inversion during the entire swing phase by employing the designed iterative learning controller. Therefore, we set the reference trajectory $\mathbf{r}$ to constant zero and start with a constant intensity distribution of 50% nerve and 50% muscle, i.e. $\mathbf{u}_0 = \mathbf{0}_{n\times 1}$. Results are presented in Figure 7. Within few learning steps, the root-mean-square error between reference $\mathbf{r}$ and output $\mathbf{y}$ is reduced to less than a third of its original value. As the data show, this individual patient needs more muscle stimulation during toe-off and more nerve stimulation during mid-swing in order to avoid eversion and inversion.

Finally, it is important to note that, while the intensity distribution was manipulated by the R2R controller and by the ILC controller, observed variations in the dorsiflexion angle trajectories were only marginal; see Figure 7. This means that the controllers acted on the eversion/inversion without affecting the dorsiflexion significantly.

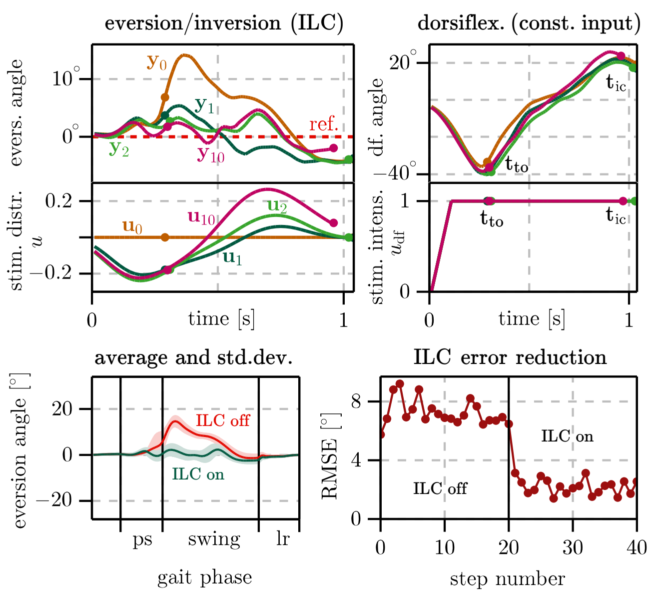

Fig. 7. Iterative Learning Control of eversion in a chronic drop foot patient. By adaption of the stimulation distribution trajectory, the ILC ($\lambda_{\mathrm{ICL}} = 0.5$) achieves constantly small eversion/inversion within few learning steps. Due to the decoupling input transformation, dorsiflexion is hardly affected.

VI. CONCLUSIONS

We presented a feedback-based approach to avoiding undesired foot eversion/inversion in drop foot stimulation. The proposed inertial sensor-based algorithm was found to provide reliable real-time measurements of the foot-to-ground angle. The three-electrode setup was found to be suitable for influencing both the eversion angle and the introduced eversion indicator. Experimental results demonstrated that the intensity distribution strategy decouples dorsiflexion and eversion control and that the two proposed learning controllers achieve desired eversion/inversion levels in one or two steps. Therefore, we conclude that both might be used in combination with the dorsiflexion ILC of the Adaptive Peroneal Stimulator. This is subject of further research as well as the integration of recent results with array electrodes [12]. Moreover, we will investigate the effect of input saturation on the controller performance and consider the case of variable gait velocity.

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