Reference Trajectory Generation for Rehabilitation Robots: Complementary Limb Motion Estimation

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***Abstract*—For gait rehabilitation robots, an important question is how to ensure stable gait, while avoiding any interaction forces between robot and human in case the patient walks correctly. To achieve this, the definition of "correct" gait needs to adapted both to the individual patient and to the situation. Recently, we proposed a method for online trajectory generation that can be applied for hemiparetic subjects. Desired states for one (disabled) leg are generated online based on the movements of the other (sound) leg. An instantaneous mapping between legs is performed by exploiting physiological interjoint couplings. This way, the patient generates the reference motion for the affected leg autonomously. The approach, called Complementary Limb Motion Estimation (CLME), is implemented on the LOPES gait rehabilitation robot and evaluated with healthy subjects in two different experiments. In a previously described study, subjects walk only with one leg, while the robot's other leg acts as a fake prosthesis, to simulate complete loss of function in one leg. This study showed that CLME ensures stable gait. In a second study, to be presented in this paper, healthy subjects walk with both their own legs to assess the interference with self-determined walking. Evaluation criteria are: Power delivered to the joints by the robot, electromyography (EMG) distortions, and kinematic distortions, all compared to zero torque control, which is the baseline of minimum achievable interference. Results indicate that interference of the robot is lower with CLME than with a fixed reference trajectory, mainly in terms of lowered exchanged power and less alteration of EMG. This implies that subjects can walk more naturally with CLME, and they are assisted less by the robot when it is not needed. Future studies with patients are yet to show whether these properties of CLME transfer to the clinical domain.**

***Index Terms*—Assist-as-needed, exoskeletons, gait therapy, intention estimation, legged locomotion, shared control, stroke, synergies.**

I. Introduction

TO PROMOTE effective rehabilitation after brain injury, a key element is intensive training [1]–[3], which is facilitated by gait rehabilitation robots such as the commercial devices Lokomat [4], Gait Trainer 1 [5], or AutoAmbulator [6]. The first exemplars used position control and a fixed reference gait pattern, which has been proven to be as effective as manual therapy for severely affected patients [7], [8]. However, new results indicate that this is not the full potential of rehabilitation robots: therapy is more successful if the patient participates actively [9]. Evaluation of diverse rehabilitation methods such as constraint induced movement therapy [10], functional electrical therapy [11], and "Assist-as-Needed" [12] confirms this finding. The patient's movements should thus not be externally imposed, but rather assisted to match the correct pattern. The important question remains what the "correct" motion is. Although it is possible to generate trajectories for a given task that resemble the average pattern of a healthy subject, e.g., using optimization [13], such a reference is not tailored to the individual patient and situation. Furthermore, any reference trajectory that is fixed in space and/or time constrains the natural variability of gait.

Generally, there are three solutions (and combinations) to the problem of reference generation. The first tolerates deviations from a given fixed reference trajectory, e.g., by use of a compliant device [14], [15] or compliant control [16]. The allowed deviations can also be temporal. For example, the pneumatic assistive robot presented by [15] uses a reference pattern that is variable in time and constantly synchronizes with the patient's gait. Another strategy that allows both spatial and temporal deviation is Path Control [17]. This controller tolerates all joint motion within a virtual "tunnel." The second solution to the reference generation problem is to adapt an initially suboptimal reference to the individual patient. This has been realized by Jezernik *et al.*, who used cycle-to-cycle adaptation to minimize interaction torques [18]. The third approach abandons the constraints of a fixed reference trajectory. For example, [19] presented a gravity-compensating assistance, which does not introduce any power, but relieves the patient from body weight support, thus lowering the threshold of muscle force needed to walk. More guidance is offered by Virtual Model Control (VMC), which has been implemented on the LOPES [20], [21]. VMC assists subtasks of walking for specific training foci (e.g., foot clearance).

Whether deviations are tolerated, the reference is adapted, or no reference is used at all, all listed strategies rely on voluntary, sufficiently coordinated activity in the impaired limbs. This implies that severely affected patients have little influence on the reference, and they are led along a fixed pattern.

To enable self-dominated gait also for patients with severe unilateral impairment (e.g., resulting from stroke), we recently proposed a generic method [22] to generate reference motion online. The idea is based on a particularity of human motor control: during complex motions such as grasping or walking, the individual degrees of freedom (DoFs) are strongly coupled; these linear correlations are also called *synergies*, and they are

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often analyzed using principal components analysis (PCA) [23], [24]. This observation indicates a reduced set of manipulated variables. Possibly, our brain has developed such control strategies to deal with the redundancy or "abundance" [25] of human DoFs (a phenomenon first referred to as *motor equivalence* by Bernstein [26]). Although the coupling of joint variables can be quantified, the driving control variables themselves and the way how the brain generates them remain speculative. One hypothesis is the existence of a *central pattern generator* (CPG) in the human spinal cord [27], [28], yet this theory is controversial.

Whatever the origin of couplings may be, the effect itself can be exploited for the simplified generation of motion patterns with a reduced set of control variables [29], and it has been used for animation [30], [31] and biped robots [32]. Extending the idea beyond the autonomous *generation* of full motion patterns, we proposed to exploit joint couplings also for the *completion* of partially preserved human motor capabilities, as needed for rehabilitation and intelligent prostheses. We call this *Complementary Limb Motion Estimation* (CLME). CLME uses statistical regression [here, either PCA or best linear unbiased estimation (BLUE)] to extract couplings between limbs in healthy synergetic motion. Using these physiological couplings and a patient's sound limb motion, CLME estimates the corresponding motion of the patient's affected limbs. The estimate can e.g., be used as reference for impedance control. This inference does not cause any delay like "echo-control" [33], where the reference is a time-shifted replay of the sound leg's motion; instead states are mapped instantaneously. In the context of gait rehabilitation, CLME can be categorized in the third group mentioned above, as it does not define a full template pattern. By defining "correct" walking only on the level of interjoint couplings, the algorithm allows a wide range of movements. Other advantages are that sound limbs are not directly influenced, and that the reference for the affected leg is intrinsically synchronized.

Simulations show that the strong interlimb coordination during gait allows a very accurate right leg–left leg inference in prerecorded trajectories [22]. However, the suitability for control of rehabilitation robots can only be answered by practical experiments, where the human closes the loop. The evaluation proceeds along two questions. The first question is related to "functionality," denoting the requirement that even in the case of no voluntary control in the paretic leg, the patient can walk without tripping nor falling. The second question is whether in the case of coordinated voluntary activity in the assisted leg, the controller allows self-determined gait with minimum interference by the robot. We use the term "interference," referring to the form and amount of actuator power introduced to the human body, and to the repercussions in terms of altered electromyography (EMG) activity and kinematic trajectories. This question concerns whether CLME is useful in a later therapy stage, to supervise gait with minor corrections.

We conducted two studies on the LOPES gait rehabilitation robot addressing these requirements. These experiments were done with healthy subjects, thus, they do not suffice to prove the suitability of CLME for stroke patients, who might not dispose of one perfectly "sound" or "unaffected" leg to control their paretic leg. Optimistic expectations can be drawn from the fact that stroke patients mostly exhibit only mild impairments on the "unaffected" side (which seem to be due to cognitive deficits) [34] and fast recovery thereof, at least for right hemispheric stroke [35]. Clinical studies with CLME will have to show whether these expectations are justified. The first study addresses the question whether subjects with no control of one leg can walk with robotic assistance based on CLME. Results have been presented in [36] and will only briefly be summarized here. Eight healthy subjects were recruited, and a one-sided impairment was simulated by using the exoskeleton leg as a prosthesis: Subjects were asked to "sit" with their left buttock on a board mounted to the LOPES frame, and a foot was attached to the left exoskeleton leg. Subjects then walked with their own right leg (in zero torque mode) and the robotic left leg, the motion of which was commanded by PCA-based CLME in dependence of the right leg. Each subject walked based on the extracted coupling of another person. Mechanical constraints of the LOPES robot required certain precautions: the stiffness is limited to the stiffness of the actuator's elastic element (then 155 Nm/rad), as explained in [37]. For persons of up to 50 kg, the stiffness was sufficient, but for heavier subjects, the robotic leg could not bear the body weight during stance. Furthermore, the mechanical construction is designed to transmit joint torques, not forces. Therefore, a weight support was used to lower the residual weight of each participant to 50 kg. All subjects were able to walk after a very short time of practice despite the anatomically awkward "sitting" position. Some walked asymmetrically, showing that CLME does not restrict the subject to symmetric gait. This first study thus demonstrates that CLME can generate functional reference motion.

The focus of this paper is on the second study. The goal is to see whether CLME interferes less with self-determined gait of healthy subjects than impedance control with a fixed trajectory. Thereby, the two alternative regression methods are compared (PCA and BLUE). Criteria to evaluate "interference" are: interaction torques or introduced power, distortion of EMG patterns with respect to undisturbed gait, and distortion of the kinematic gait pattern. The optimum would be to match the robot's behavior in zero torque control for both legs, where desired interaction torques are zero, and this condition is included as the baseline for comparison.

II. CLME

The goal of CLME is a mapping function that outputs reference states (angles and velocities) for impaired limbs directly in dependence of the current states of sound limbs. To obtain this function, interjoint coordination patterns are extracted from recorded physiological gait trajectories. Numerous approaches in statistical regression exist to tackle this problem. We have investigated two simple linear ones among them: PCA [38], [39], which is frequently used to analyze joint synergies, e.g., in [24], and BLUE from standard linear regression [40].

Assuming that the left leg is affected, the states of the right leg are known, and they are subsumed in the vector $\boldsymbol{x}_r$

$$\boldsymbol{x}_r^T = \left(\boldsymbol{\varphi}_r^T, \dot{\boldsymbol{\varphi}}_r^T\right). \tag{1}$$

The states $\boldsymbol{x}_l$ of the left leg with

$$\boldsymbol{x}_l^T = \left(\boldsymbol{\varphi}_l^T, \dot{\boldsymbol{\varphi}}_l^T\right) \tag{2}$$

now need to be estimated. Prior to regression, variables are normalized. Previously [22], [41], we suggested to use PCA to provide an estimate of $\boldsymbol{x}_l$ by minimizing the quadratic error

$$\left\| \begin{pmatrix} \boldsymbol{x}_r \\ \boldsymbol{x}_l \end{pmatrix} - \begin{pmatrix} \boldsymbol{\Gamma}_1 \\ \boldsymbol{\Gamma}_2 \end{pmatrix} \boldsymbol{y} \right\|^2 \rightarrow \min \tag{3}$$

with unknown matrix $\boldsymbol{\Gamma} = [\boldsymbol{\Gamma}_1^T \boldsymbol{\Gamma}_2^T]^T \in \mathbb{R}^{d \times p}$, $p < d$, and orthogonal column vectors, such that the vector $\boldsymbol{y} \in \mathbb{R}^p$ is of lower dimensionality than $\boldsymbol{x} = [\boldsymbol{x}_r^T, \boldsymbol{x}_l^T]^T \in \mathbb{R}^d$. The basis of this approach is the assumption that the commands sent to the limbs have a common source in a lower-dimensional subspace, i.e., that there is a subset of control variables $\boldsymbol{y}$ that can be reconstructed and used to estimate the remaining joint variables. Solution of the optimization provides the estimator

$$\hat{\boldsymbol{x}}_{l,\mathrm{PCA}} = \boldsymbol{\Gamma}_2 \boldsymbol{\Gamma}_1^{\#} \boldsymbol{x}_r =: \mathbf{C}_{\mathrm{PCA}} \boldsymbol{x}_r \tag{4}$$

with the superscript $^{\#}$ denoting the left pseudoinverse. The matrix $\boldsymbol{\Gamma}$ contains the first eigenvectors (the so-called principal components) of the covariance matrix $\mathbf{M}$ of $\boldsymbol{x}$.

Another approach is to search for the best mapping directly by solving the optimization problem

$$\|\boldsymbol{x}_l - \mathbf{C}\boldsymbol{x}_r\|^2 \rightarrow \min \tag{5}$$

with unknown matrix $\mathbf{C}$. The solution is provided by the BLUE. Using the respective covariance matrixes $\mathbf{M}_{rr}$ and $\mathbf{M}_{rl}$, this estimator is given by

$$\hat{\boldsymbol{x}}_{l,\mathrm{BLUE}} = \left(\mathbf{M}_{rr}^{-1}\mathbf{M}_{rl}\right)^T \boldsymbol{x}_r =: \mathbf{C}_{\mathrm{BLUE}} \boldsymbol{x}_r. \tag{6}$$

The difference between the two regression methods is that PCA-based CLME departs from the hypothesis of a "common controller" for both legs, and it reconstructs the common variables in an intermediate step; BLUE-based CLME, in contrast, simply exploits the phenomenological coupling between legs, and infers directly from right to left without consideration of underlying reasons. The outputs of both regression approaches are augmented again by mean and standard deviation of the reference gait pattern, yielding reference angles and velocities for the impaired joints. Due to imperfections in the regression model, both angles and velocities are subject to uncertainty. Thus, the estimated velocity differs from the differentiated estimated position. A Kalman filter (one for each joint) is used to merge the two pieces of information, yielding the most plausible motion intention. The internal model of the Kalman filter interprets the estimated values angle $\hat{\varphi}_l$ and angular velocity $\hat{\dot{\varphi}}_l$ of the joint as noise-corrupted measurements. Via stochastic optimization, the filter produces improved values, based on the model of a simple integrator between velocity and angle. To derive the Kalman Filter gains for angle and velocity, noise levels are quantified by simulations with the reference gait pattern: First, the left leg is reconstructed from the recorded trajectory of the right leg using the mapping function extracted from the same pattern. Then, the reconstruction is compared to the original left leg's trajectory, yielding the error expectations $\mathrm{E}((\hat{\varphi}_l - \varphi_l)^2)$ and $\mathrm{E}((\hat{\dot{\varphi}}_l - \dot{\varphi}_l)^2)$. In summary, a recorded physiological gait pattern is reduced to the regression matrix, the Kalman gains, and mean values and standard deviations of the states. These parameters are then used to drive the online reference generation algorithm. In our practical realization, best results were obtained when the predicting variables of the right leg in $\boldsymbol{x}_r$ are only hip flexion and knee flexion in the sagittal plane, although the estimated joint vector $\boldsymbol{x}_l$ additionally contains hip abduction [36].

III. Experimental Design

To study interference with self-determined gait, healthy subjects walk in LOPES (on both their own legs) with CLME, with conventional fixed-reference impedance control of both legs, and with zero torque control of both legs. To rate the relative performance of CLME concerning undesired interaction compared to the two other control modes, evaluation criteria are formulated in terms of interaction torques, distortion of EMG patterns, and distortion of joint trajectories.

A. Setup and Protocol

Nine healthy subjects took part (aged 19–37, weight 51–100 kg, two female, seven male). Some subjects already had experience walking in the device with other controllers, and most had at least some knowledge of the purpose of the study. Each subject walked with four different controllers: impedance control of both legs along a fixed reference trajectory, PCA-based CLME control (with the right leg in zero torque mode), BLUE-based CLME control in the same configuration, and zero torque control of both legs. The block diagrams for these three controllers are displayed in Fig. 1. The impedance in fixed-reference mode, and of the left leg in CLME mode was identically set to the maximum value of 155 Nm/rad (the maximum stiffness of the robot was limited then due to the compliant actuation, as outlined in [37]). Sideways and forward DoF of the robot were controlled in zero torque, the vertical DoF is passively weight compensated. The four control modes directly followed each other, whereby each controller was active for 2 min, with a gradual blending of 5 s between controllers. Subjects were not informed which controller was active, and they were instructed to walk actively the way they wanted to, yet to avoid walking out of phase with the robot (which was possible due to the limited stiffness). The reference gait pattern used for each subject stemmed from a randomly chosen preceding participant in zero torque mode, who was not necessarily of comparable physique. This alien reference was used both for the fixed reference mode (by simple replay), and for the CLME controllers (by extraction of the mapping function). The experiment was repeated with the subject's own recorded gait pattern in zero torque mode as reference, in order to assess also the potential benefit of an individually tailored reference. Recorded signals were: hip and knee joint torques and angle trajectories in the sagittal plane, and EMG signals from four major muscle groups of each leg: Rectus Femoris,

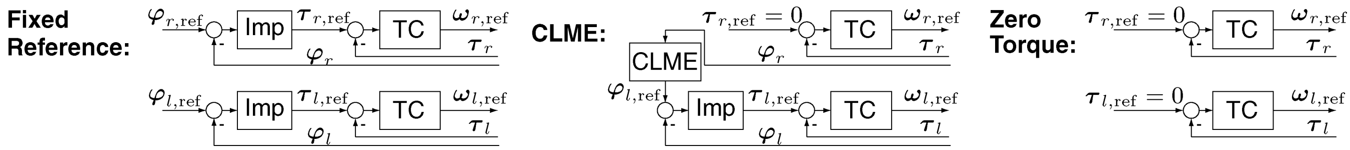

Fig. 1. Block diagrams of the three controllers. Fixed-reference control guides right (r) and left (l) leg along given reference joint angle vectors $\boldsymbol{\varphi}_{\mathrm{ref}}$. CLME control only uses the extracted joint coupling of the same reference trajectory and complements the current right leg's motion $\boldsymbol{\varphi}_r$ online via regression to generate the reference $\boldsymbol{\varphi}_{l,\mathrm{ref}}$ for the left leg. CLME and fixed-reference control use identical settings for the joint impedance control (IMP), and all controllers use the same settings for the Series Elastic Actuator torque control (TC), which controls the joint torque vectors $\boldsymbol{\tau}$ via the motor velocities $\boldsymbol{\omega}$.

Biceps Femoris, Tibialis Anterior, and Gastrocnemius. We also documented subjective feedback of the subjects.

B. Evaluation Criteria and Data Analysis

For the evaluation, the results of zero torque are defined as the baseline, i.e., the best achievable result, with the following rationale: both with the fixed reference and in CLME mode, a joint-space impedance controller calculates the desired interaction torques as a reference for the low-level force controller (see Fig. 1). If the reference joint trajectory matched the subject's actual motion flawlessly, the *desired* interaction torques would be zero, and the resulting behavior would be identical to zero torque mode. This behavior does not imply zero *actual* interaction forces, because the underlying force controller cannot be ideal, and there is still some resistance generated (mainly due to uncompensated friction). Thus, zero torque mode represents the best possible outcome given a perfectly matched reference trajectory.

A first and very direct criterion of interference is given by the robot's joint torques. In order to distinguish between torques that assist and those that resist, the torques are not compared directly, but instead the power delivered to the left leg is calculated by a multiplication with the joint velocity (The power introduced to the right leg does not provide any additional knowledge, because this leg is in zero torque mode in both CLME controllers.). To obtain a single number for statistical analysis, accumulated power is calculated via integration. In order to exclude adaptation effects, only the last 60 s of each mode are used.

A second criterion is derived from muscle activity, as measured by the EMG. Highpass filters ($n = 2, \omega_e = 5\,\mathrm{Hz}$) are used to extract movement artifacts and drift. Afterward, the EMG is rectified and then smoothed by spline approximation. The criterion used is the distortion with respect to the "normal," minimally perturbed muscle activity pattern in zero torque mode. In order to assess this distortion of muscle activity quantitatively in a systematic way, EMG of each muscle and each single step is compared to the respective subject's mean EMG activity in zero torque mode. This comparison is performed using the algorithm of *spatio-temporal correspondence* developed by Giese and Poggio [42], which has already been used for various tasks in motion analysis, e.g., to assess cerebellar dysfunction [43]. This algorithm minimizes a quadratic cost functional by dynamically warping a (possibly multidimensional) template trajectory onto a trial trajectory. It is based on dynamic programming and outputs a temporal and spatial, nonuniform distortion of the template. Therefore, it can adaptively cope with varying combinations of spatial and temporal distortions. For one step, average absolute temporal and spatial distortions are calculated, as suggested by [43]. Fig. 2 shows the principle of the spatio-temporal correspondence. It also illustrates a characteristic of the algorithm that has to be taken into account when applying it to periodic patterns: The outcome highly depends on the chosen begin and end of the trajectory, because any distortion there is interpreted as spatial distortion. To obtain distortion values of the same order of magnitude for all muscles, we define the start- and endpoint of each muscle's EMG trajectory at a different constant offset from the heel strike, in such a way that the major burst of the muscle's zero torque EMG pattern is in the middle (this process is robustly automated for each subject and muscle using a sinusoidal approximation of the EMG). In order to exclude adaptation effects, only the last 30 steps with each controller are used to calculate a mean distortion value for each subject, muscle, and controller. Furthermore, all trajectories are scaled by the standard deviation of the zero torque activity.

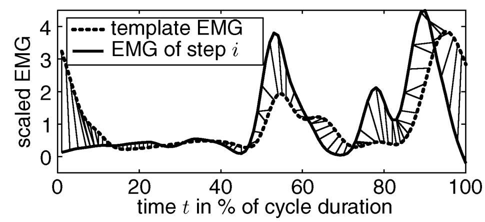

Fig. 2. Spatio-temporal correspondence: EMG of the Rectus Femoris in step i is compared to the template, which is the average EMG in zero torque mode. EMG signals are scaled to have a standard deviation of 1 in zero torque mode. Dynamic optimization separates temporal and spatial distortion of each sample: Horizontal connection lines represent purely temporal distortion; vertical lines represent purely spatial distortion. The incorrect matching observable here at beginning and end (heel strike) is due to endpoint constraints of the algorithm; this problem is avoided in the further analysis by a varying definition of the gait cycle begin for each muscle.

A third criterion is obtained by an analysis of kinematic trajectories. In order to asses distortions of hip and knee trajectory with respect to zero torque gait quantitatively, the spatio-temporal algorithm is used again. Here, it is applied to compare the 2-D hip-knee trajectories of each of the last 30 steps in each condition to the zero torque mean.

Statistical analysis of all three criteria is performed independently, but in a similar fashion. A two-factor ANOVA (factor 1: controller, factor 2: own or alien gait) is performed for both legs separately and for each of the criteria: Accumulated joint power, EMG distortion, and kinematic distortion. The chosen level of significance is $\alpha = 0.05$, and a Bonferroni adjustment compensates for multiple comparisons. This statistical analysis of all criteria, especially of EMG and kinematic distortions, can only be performed after a transformation of the data, because the distributions are skewed, and standard deviations differ heavily between conditions. Transformations are applied to obtain normally distributed data between steps for each condition and to

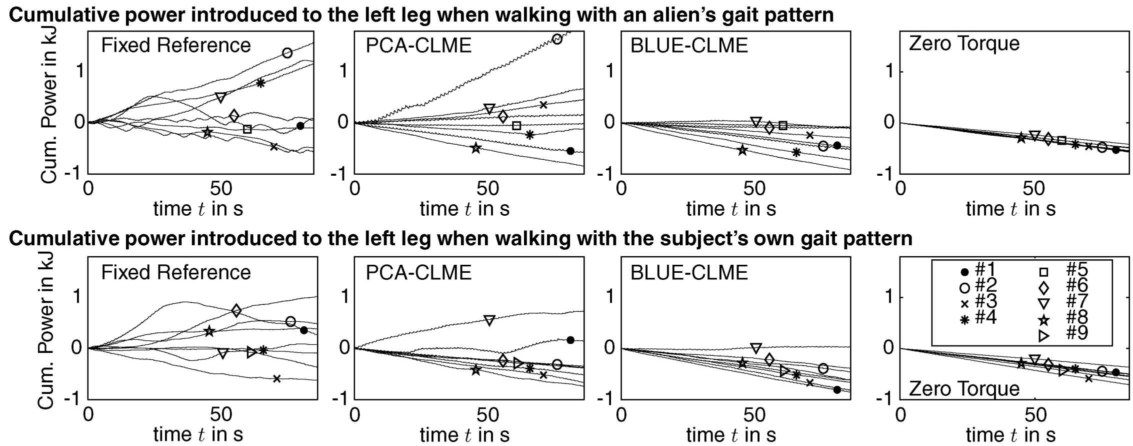

Fig. 3. Cumulative power supplied to the left leg (excluding initial adaptation), when walking with an alien and the own gait pattern as reference for the three assistive controllers and zero torque mode. Positive slopes indicate that the robot assists, negative mean that it resists the subject's motion.

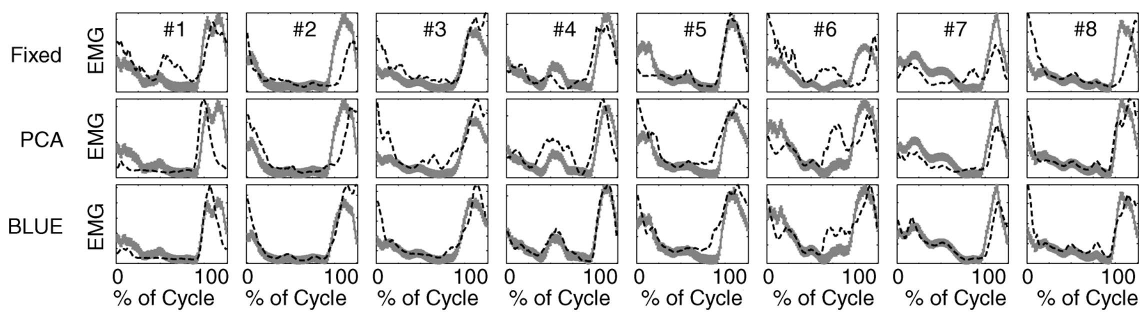

Fig. 4. EMG of the Biceps Femoris of all subjects. Displayed are the median EMG of the last 30 steps with each controller (dashed black line), as well as the mean EMG in zero torque mode with standard error (gray), when walking with an alien reference.

fulfill the requirement of sphericity between conditions. Accumulated power is transformed by offsetting and taking the square root. To EMG and kinematic distortions, the log-transform is applied twice. As a scalar parameter for the statistical analysis, the mean of the transformed EMG of all muscles is used.

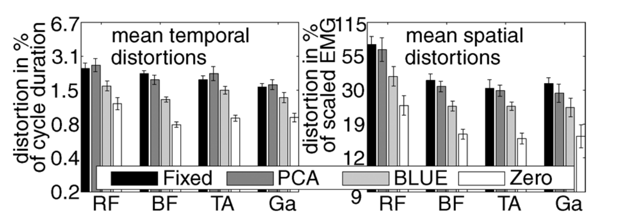

Fig. 5. Mean absolute spatial and temporal distortions of the left leg's EMG (with respect to zero torque mean EMG) and standard error among the eight subjects. Note the double logarithmic scale. Mean values for each subject are drawn from the last 30 steps for each controller, when walking with an alien reference gait. Muscles: Rectus Femoris (RF), Biceps Femoris (BF), Tibialis Anterior (TA), Gastrocnemius (Ga).

IV. Results

Due to technical problems, two subjects completed only one of the two conditions: one (#9) walked only with his own, the other (#5) with an alien gait. These unmatched trials are included in the plots (such that the number of subjects there is eight in each case), but they are not included in the multivariate statistical analysis (such that the sample size is seven). All subjects noticed a transition between fixed-reference control and CLME, as well as between CLME and zero torque, although the latter often not at once. Four of the subjects did not notice any difference between PCA and BLUE mode, four preferred the BLUE controller, one the PCA controller. For both CLME conditions, most reported that they had to do more active foot clearance than usual, or they mentioned a general impression of increased resistance in comparison to zero torque. One subject (#2) could not cope well with PCA-based CLME and walked in a strange manner.

For a first look at robot–human interaction, Fig. 3 displays the cumulative power, i.e., energy introduced over time. Impedance control with a fixed reference exhibits considerable inter- and intrasubject variances. For several subjects, the interaction oscillates. This phenomenon is especially strong and also visible in the figure when walking with an alien's gait (top). When walking with the own gait, the phenomenon also occurs, yet less pronounced. Apart from these oscillations, there are several abrupt changes in slope with the fixed reference. With the CLME controllers, the slope is rather constant. Furthermore, introduced power tends to be higher in fixed-reference mode compared to BLUE. For PCA-based CLME, systematic differences to the other two controllers are less obvious. These observations hold both for the own and the alien reference gait. The two-factor ANOVA for the left leg confirms the difference between BLUE and fixed-reference mode: BLUE does indeed introduce significantly less energy than fixed-reference control, and it does not even differ significantly from zero torque. PCA

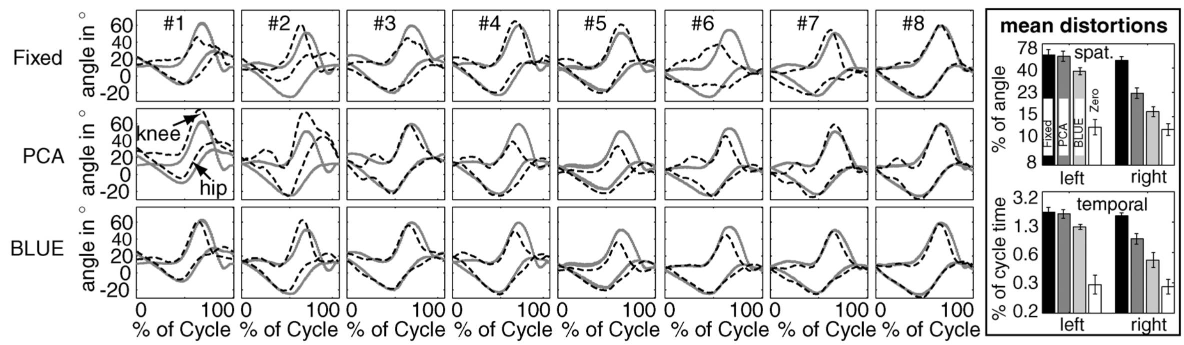

Fig. 6. Median hip and knee trajectories (dashed black lines) of the 30 last steps for each controller and each subject when walking with an alien reference gait pattern, each compared to the mean zero torque trajectory with standard error (gray, the standard error is quite small). In the box on the right, mean and standard error among subjects of spatial and temporal distortions of the hip–knee trajectory are shown for the left and for the right leg, analogous to EMG.

does not differ significantly from any other condition. A significant influence of the second factor (own or alien gait) cannot be shown, and the interaction between factors is not significant either.

As an example for muscle activity, Fig. 4 shows the EMG of the Biceps Femoris for the last 30 steps. The median is taken instead of the mean in order to reduce the effects of variation in timing of the EMG bursts present in fixed-reference mode, which lower the mean EMG amplitude there and give the other controllers an unfair advantage in visual impression. Fig. 5 shows the distribution of the transformed (double logarithmic, as stated earlier) mean EMG distortions among the eight subjects. Between fixed reference mode and PCA, there is no clear tendency for one or the other. In contrast, BLUE seems to lower the distortion compared to a fixed reference. The two-factor ANOVA for spatial distortions shows no significant differences between PCA-CLME and the fixed reference, but it confirms the difference between BLUE-CLME and fixed-reference mode for both legs. Only in the left leg, distortions with BLUE are also significantly lower than with PCA. For temporal distortions, neither BLUE nor PCA cause significantly less distortions than the fixed reference. The analysis also shows that all assistive controllers distort the EMG of left and right leg both temporally and spatially significantly more than explained by normal variation in zero torque. The second factor (own or alien gait) reaches a level of significance for the left leg's spatial EMG distortions only. The interaction of both factors is not significant.

To assess kinematics, knee and hip joint motion is analyzed. Fig. 6 illustrates temporal and spatial distortions of the subject's median gait pattern for the last 30 steps at the end of each controller condition. The results of the two-factor ANOVA with respect to the first factor (controller) show no clear advantage of CLME on the left leg. The right leg's path, however, is disturbed significantly less by both CLME algorithms. For both sides and both criteria, all assistive controllers differ from zero torque, and PCA and BLUE do not differ significantly from each other. For the left leg, the second factor, i.e., whether own or alien reference is used, reaches significance only for spatial distortions. For the right leg, the factor is significant both in temporal and spatial distortions. For all controllers, distortions are lower when the subject's own gait pattern is used, interaction of both factors is not significant.

V. Discussion

The oscillations in joint power can be explained by the compliance of the device: subjects can walk out-of-phase with respect to a fixed reference pattern. Oscillations with a frequency of about 0.05–0.1 Hz have previously been observed and described as "beat phenomenon" in [15] for a pneumatic gait training robot. CLME control inherently avoids out-of-phase walking, and thus no beat phenomenon occurs. However, the phenomenon could also be avoided by a constant synchronization between a fixed reference pattern and the subject's gait, as suggested by [15].

The differences in introduced power suggest that fixed-reference control tends to assist the subjects, although they could walk on their own. Concerning this criterion, BLUE-based CLME hardly differs from the results of zero torque mode (the best achievable result with the robot), both moderately resist the subject's motions. Furthermore, the fixed reference provokes changes in slope, which might stem from adaptation of the subject. In BLUE mode, on the contrary, each subject is influenced almost invariably over time, leading to the deduction that there is hardly any adaptation needed to walk with this controller.

With respect to timing of EMG and kinematics, the improvement of BLUE compared to a fixed reference is less pronounced than with respect to spatial distortion. This suggests that deficient synchronization of reference patterns might not be the only cause of undesired interaction torques.

In Fig. 6, the distortion introduced by BLUE seems systematic and always concerns the late swing phase. This is in congruence with subject commentaries and with simulated reconstructions of one leg based on the other. An explanation is the weakness of the linear estimator used for BLUE, which cannot capture all details of the gait cycle and systematically underestimates knee flexion amplitudes. It is probable that better results could be obtained by using a nonlinear estimator. In contrast, PCA and fixed-reference control show rather unsystematic distortions among subjects. Furthermore, their intersubject variation is also higher.

It would be expected that subjects are less perturbed when their own gait pattern is used as a reference, because then the reference is tailored to them. However, this effect seems to be quite small compared to the controller type used, as it is only significant for a few criteria (given the small sample).

An interesting result is that CLME also influences the right leg. This might be an indication that disturbances on one side show repercussions on the other due to mechanical coupling, but it could also be due to the subjects' adaptation.

The fact that all observed effects are rather small is attributed to the high level of compliance of the robot. Even in the stiffest possible configuration, subjects can enforce their normal pattern (depending somewhat on their physical strength), and they exhibit quite natural EMG activity.

VI. Conclusion

This paper presented an experimental evaluation of CLME as a method to generate reference trajectories for gait rehabilitation robots online. The study assessed interference with self-determined gait, and it is complementary to a previous one, which confirmed that CLME is capable of generating functional gait for subjects with no voluntary control of the assisted leg. Now, two CLME algorithms (BLUE and PCA) were used to generate the reference for an impedance controller online, and they were compared to two extreme other controllers: impedance control along a fixed gait pattern on the one hand, and zero torque control (as the best possible controller in this context) on the other hand. Results indicate that fixed-reference control tends to introduce energy, thus it assists more than needed. In BLUE-based CLME, the introduced energy is significantly lower, i.e., the robot assists less and subjects walk more on their own. Furthermore, the fixed reference trajectory caused out-of-phase walking, which would demand for additional synchronization. This problem is inherently solved by both CLME algorithms. EMG patterns with BLUE-based CLME are more similar to unperturbed gait in comparison to the fixed reference. However, significantly reduced kinematic distortions could only be shown for the right, unassisted leg. Subject reaction to guidance along a fixed reference varies strongly, both within and between subjects. BLUE-based CLME reduces intersubject and intrasubject variability; all subjects react more or less similar. They exhibit a small systematic distortion of their natural gait concerning a specific gait feature, which is foot clearance. This makes further fine-tuning easier, e.g., using superposed Virtual Model Control. For all criteria, BLUE-based CLME outperforms the original PCA method, which did not show any significant improvement compared to a fixed reference, except for the solution of the synchronization problem. The fact that the specific method of regression has such a big influence on the performance motivates further investigations in this direction, possibly by an extension into the nonlinear domain. Future investigations will also aim at a clinical evaluation of CLME with hemiplegic patients, and at an application of the algorithms to above-knee prostheses.

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