Complementary Limb Motion Estimation based on Interjoint Coordination: Experimental Evaluation

Heike Vallery, Ralf Ekkelenkamp, Martin Buss, Herman van der Kooij

Abstract— **For motor rehabilitation of hemiplegic patients by means of motorized orthoses, as well as in intelligent prosthetics, a major challenge is the coordination of healthy and robotically assisted limbs. The new method of Complementary Limb Motion Estimation (CLME) analyzes dependencies among human Degrees of Freedom (DoFs) in healthy subjects. Based on this knowledge, adequate motion for inoperable DoFs in patients is estimated on-line from sound limb motion. Thus, the intention of a partially paralyzed person or an amputee can be deduced from residual body motion, in order to coordinately actuate or supervise the impaired limbs. The aim is to increase the dominance of the patient and to reduce the robot to an assistive device. In continuity of priorly published evaluation by comuter simulations, this paper presents a first experimental proof of concept of CLME with healthy subjects. The results of these preliminary tests affirm the suitability of the algorithm for cooperative human-robot interaction.**

I. Introduction

To replace or restore lost motor functions, a growing number of robotic devices are available. Rehabilitation robots, e.g. such as surveyed in [1], facilitate early and extensive therapy, which promotes effective rehabilitation after brain injury [2]. In search of suitable control strategies for such robots, a look at the therapeutic outcome of classical motor rehabilitation methods offers general guidelines: Various evaluation studies on rehabilitation strategies, e.g. on Constraint Induced Movement Therapy [3] or Functional Electrical Therapy [4], have confirmed that therapy is more successful if it aims at a restoration of functional use of the impaired limbs, and if the patient participates actively. Controller design should therefore aim at a provocation of active cooperation of the patient, whose movements should not be just externally imposed, but rather assisted.

In some cases, existent yet insufficient muscular activity can be detected and reinforced in the paretic leg, either by observation of the generated motion [5], [6] or by EMG measurement of the muscle activation [7]. However, all these techniques require sufficiently coordinated activity in the motor cortex regions controlling the impaired limbs.

If the intended motion is not detectable at the impaired limbs themselves, one possibility is to provide a physiologically correct reference trajectory and to guide the patient's legs along it with as much impedance as necessary, depending on his abilities, whereby, ideally, a certain range of automatic adaptation to the patient is included [8].

An alternative approach lies in the observation of the patient's sound limbs, which might still reveal his movement intention. For example, [9] suggests to observe thorax acceleration in order to detect the intention of a paraplegic patient to stand up.

Recently, we presented an automated, generic method ("Complementary Limb Motion Estimation", CLME) that infers from the motion of sound limbs to the intended motion of paretic or amputated limbs [10]. The starting point of this idea are control strategies of the human brain that are employed for the execution of complex, learned motion patterns [11], [12], [13]: During functional motions such as grasping or walking, the individual Degrees of Freedom (DoFs) are strongly coupled; these linear correlations are also called "synergies". This observation indicates a reduced set of manipulated variables. Obviously, our brain has developed such refined control methodologies to deal with the redundancy or "abundancy" [14] of human DoFs (A phenomenon first referred to as "motor equivalence" by [15]). CLME uses Principal Components Analysis (PCA) [16], [17] to extract the couplings between limbs in healthy synergetic motion. Using these physiological coulings and a patient's sound limb motion, it estimates the corresponding motion of his paretic limbs. Ideally, such a controller in a rehabilitation robot would lead to a cooperative motion of healthy and robotically assisted limbs with increased active involvement and dominance of the patient, and eventually to improved therapeutic outcome.

Up to now, only simulation studies have been presented which show the potential of CLME used for right-left inference in theory [18]. Results of these theoretical investigations, however, are no guarantee for a stable walking pattern. This is due to the fact that walking is a controlled motion, where the limbs of the body interact in performance of the control task. By contrast, the simulation study simply extracts a feedforward control input (the motion of one leg), which is taken from an intact controlled system. This way, the loop is cut open, and feedback is neglected.

A first important question is whether a person can functionally walk with unidirectional coupling between legs. There is little secured knowledge on the human internal controller, which makes it hard to predict how it might interfere. Although the coupling of joint variables is known, the driving control variables themselves and the way how the brain generates them remain speculative. One hypothesis is e.g. the existence of a so-called "central pattern generator"

This work was supported by Studienstiftung des Deutschen Volkes

H. Vallery and M. Buss are with the Institute of Automatic Control Engineering, Technische Universität München, 80290 München, Germany heike.vallery@tum.de, M.Buss@ieee.org

R. Ekkelenkamp and H. van der Kooij are with the Faculty of Mechanical Engineering, University of Twente, 7500 AE Enschede, The Netherlands r.ekkelenkamp@ctw.utwente.nl, H.vanderKooij@ctw.utwente.nl

(CPG) in the human spine [19], as it can be found in animals [20], yet this theory is highly controversial.

Another question is whether patients walking with CLME might produce asymmetric, yet functional walking patterns.

Considering the fact that the patient's own original gait pattern probably remained unrecorded, a key question is whether a subject can adapt to the coupling of someone else. Optimistic expectations are drawn from the literature: Firstly, movement patterns during gait are similar for subjects with the same hip height [21]. Furthermore, the mechanisms of motion synergy generation seem to be not unalterably inborn, but adaptive, as has been shown by [14]: Their finding is that patients with partly impaired limbs still exhibit synergetic reaching, but with altered synergy patterns. This means that joint synergies have adapted to the new constraints, which have been imposed by the lesion.

To assess the questions above, we ran a series of experiments on the LOPES gait rehabilitation robot [22], [23]. This exoskeleton-based robot allows automated limb guidance and measurements during treadmill-walking. Furthermore, due to its Series Elastic design and lightweight exoskeleton, it offers very low resistance in zero-impedance mode, such that the sound leg can move almost unhindered. For this first rather qualitative proof of concept, healthy subjects were recruited, and a one-sided impairment was simulated by using the exoskeleton leg as a prosthesis.

This paper contains a brief description of Complementary Limb Motion Estimation. Then, the experimental setup on the LOPES robot and the obtained results are presented.

II. Complementary Limb Motion Estimation (CLME)

A. Step 1: Exploitation of Interjoint Couplings using PCA

Principal Components Analysis (PCA) [16], [17] is frequently used as a general approach to data compression, where statistical (linear) correlation is exploited. A high-dimensional set of variables is projected onto a lower-dimensional set in a way that the maximum amount of information (measured by variance) is preserved.

PCA thus delivers a solution to the following problem: Find an orthonormal transformation matrix $\mathbf{\Gamma}$, which maps the sample of n points $\boldsymbol{x} \in \mathbb{R}^d$ onto the new coordinates $\boldsymbol{y} \in \mathbb{R}^d$:

$$\boldsymbol{y} = \mathbf{\Gamma}^T \boldsymbol{x} \tag{1}$$

with the inverse transformation

$$\boldsymbol{x} = \mathbf{\Gamma} \boldsymbol{y} \tag{2}$$

(due to orthogonality, $\mathbf{\Gamma}^{-1} = \mathbf{\Gamma}^T$), such that if the last $d-p$ components of $\boldsymbol{y}$ are discarded and $\mathbf{\Gamma}$ is truncated accordingly to p columns, the least variance is lost during the projection (1) into the lower-dimensional subspace $\mathbb{R}^p$. This is equivalent to minimizing the squared error between the original uncompressed variables $\boldsymbol{x} \in \mathbb{R}^d$ and their reconstruction out of the compressed variables $\boldsymbol{y} \in \mathbb{R}^p$

$$||\boldsymbol{x} - \mathbf{\Gamma}\boldsymbol{y}||^2. \tag{3}$$

The solution to this problem is provided by an analysis of covariance among the variables x_i in $\boldsymbol{x}$: The (symmetric) covariance matrix $\mathbf{M}$ with entries

$$M_{ij} = \frac{\sum_{k=1}^{n}(x_{i,k} x_{j,k})}{n-1}. \tag{4}$$

includes information about the variance of each variable, as well as their correlations. It can be shown that the d eigenvectors of $\mathbf{M}$ form the orthonormal basis of the optimal coordinate transformation. If they are sorted into the matrix $\mathbf{\Gamma}$ in descending order of their corresponding eigenvalue, (1) maps $\boldsymbol{x}$ onto the new coordinates $\boldsymbol{y}$ in such a way that y_1, the first component of $\boldsymbol{y}$, has the maximum variance that can be reached by projecting $\boldsymbol{x}$ on an arbitrary unit vector. Therefore, y_1 is called the first *principal component*. Recursively, this is valid for the remaining y_i, and the last component of $\boldsymbol{y}$ has smallest variance. Neglecting the last components of $\boldsymbol{y}$, the data is reduced in a way that the least information is lost. The principal components to be included can be chosen based on their eigenvalues, i.e. on the cumulative contribution to the sum of all eigenvalues. This percentage gives an estimate of how much information will be preserved during compression.

In order to perform PCA, the variables x_i need to have zero mean, possibly requiring prior subtraction of the mean value. Frequently, it is also advisable to norm the data to a standard deviation of 1, especially when dealing with strongly varying magnitudes among variables.

The redundancy in the data, which is revealed by the analysis of correlations, can also be used for the reconstruction of incomplete measurements of $\boldsymbol{x}$. The equation system (2) with known matrix $\mathbf{\Gamma} \in \mathbb{R}^{d \times p}$ is (over-)determined, if the number q of unknown components of $\boldsymbol{x}$ is not higher than the dimensionality p of $\boldsymbol{y}$. Then, it can be solved for the unknown y_i and the partly unknown x_i. Assuming that the first components $\boldsymbol{x}_1 \in \mathbb{R}^{(d-q)}$ of $\boldsymbol{x}$ are known, and the remaining part $\boldsymbol{x}_2 \in \mathbb{R}^q$ is unknown, (2) is separated into

$$\boldsymbol{x}_1 = \mathbf{\Gamma}_1 \boldsymbol{y} \ , \quad \boldsymbol{x}_2 = \mathbf{\Gamma}_2 \boldsymbol{y} \ , \tag{5}$$

with $\mathbf{\Gamma}_1 \in \mathbb{R}^{(d-q)\times p}$ and $\mathbf{\Gamma}_2 \in \mathbb{R}^{q \times p}$ being the corresponding submatrices of $\mathbf{\Gamma}$. Thus, $\boldsymbol{x}_2$ is reconstructed from $\boldsymbol{x}_1$ by

$$\boldsymbol{x}_2 = \mathbf{\Gamma}_2 \mathbf{\Gamma}_1^{\#} \boldsymbol{x}_1 =: \mathbf{C}\boldsymbol{x}_1 \ , \tag{6}$$

with $\mathbf{\Gamma}_1^{\#}$ being the left pseudoinverse of $\mathbf{\Gamma}_1$. The matrix $\mathbf{C}$ is the estimation matrix, which allows direct inference from $\boldsymbol{x}_1$ to $\boldsymbol{x}_2$.

For the application of CLME, "known data" $\boldsymbol{x}_1$ is the motion of healthy limbs, "missing data" $\boldsymbol{x}_2$ is the motion of impaired limbs, and correlation information inclosed in $\mathbf{C}$ describes interjoint coupling (e.g. right leg to left leg during walking motion). In [18], it has been shown that best results are obtained if the vector $\boldsymbol{x}$ not only contains current joint angles $\boldsymbol{\varphi}$, but also velocities $\dot{\boldsymbol{\varphi}}$ (accelerations did not improve results):

$$\boldsymbol{x}^T = (\boldsymbol{\varphi}^T, \dot{\boldsymbol{\varphi}}^T) \ . \tag{7}$$

All variables are normed to have zero mean and standard deviation 1.

Prior to intention estimation, joint synergies need to be analyzed using recorded trajectories for all DoFs during healthy gait. The result is the coupling matrix $\mathbf{\Gamma}$, respectively the estimation matrix $\mathbf{C}$. Then, reference motion can be generated on-line for inoperable joints, using the estimation matrix $\mathbf{C}$ and the instantaneous states of the sound limbs $\boldsymbol{x}_1$, as stated in (6). The estimated values need to be augmented again by mean and standard deviation (of the reference subject) to yield the limb reference motion.

B. Step 2: Integration of Temporal Information

During the reconstruction procedure, redundant data is generated: velocities and angles are estimated. As PCA is completely static and does not account for the relationship between time derivatives, these are not internally coherent. This means the PCA-estimated velocity is quite different from the velocity estimate derived via differentiation of the PCA-estimated position signal.

The redundancy of uncertain estimates can be exploited using a Kalman filter. The filter is designed for each joint separately based on the simple dynamic model of a double integrator. During filtering, each of the values is corrected so that they become coherent and fit the model. Under the assumption that the errors in the PCA-estimated variables φ_e and $\dot{\varphi}_e$ can be modelled as Gaussian, uncorrelated noise (considering that the velocity is independently estimated, and not calculated via differentiation of the angle), better estimates $\hat{\varphi}$ and $\hat{\dot{\varphi}}$ are produced on-line. This design is displayed in Fig. 1. The "measurement noise" levels $E(v_1^2)$ and $E(v_2^2)$ are quantified by a simulated right leg/left leg inference in recorded healthy gait patterns, followed by an analysis of the errors between PCA-reconstructed angles and velocities and original angles and velocities. The "process noise" level $E(w^2)$ equals the original acceleration variance.

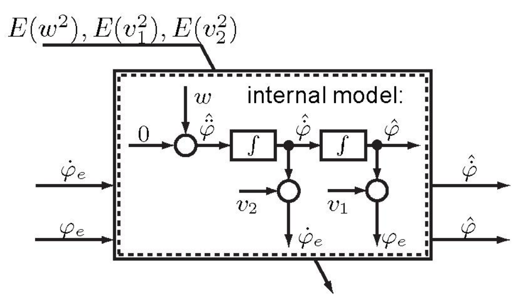

Fig. 1. Design of the Kalman Filter. The internal model regards the PCA-estimated values φ_e and $\dot{\varphi}_e$ as noisy outputs of a double integrator, and the filter produces improved values $\hat{\varphi}$ and $\hat{\dot{\varphi}}$, which fit the model, via stochastic optimization. For the optimization procedure, noise levels have to be quantified: $E(v_1^2)$ and $E(v_2^2)$ are assessed based on an error analysis of PCA-reconstructed trajectories, and $E(w^2) = E(\ddot{\varphi}^2)$.

III. Evaluation

To evaluate the feasibility of walking with unilateral coupling, we conducted a first series of experiments with healthy subjects. To simulate a one-sided impairment, subjects walked with their own right leg and a robotic left leg, the motion of which was commanded in dependance of the right leg motion.

A. Test Setup

An ideal testbed was provided in form of the gait rehabilitation robot LOPES developed at the university of Twente. This robot consists of a treadmill in combination with a light-weight exoskeleton for the lower extremities. It actuates sideways and forward motion, hip abduction, hip flexion and knee flexion using the principle of Series Elastic Actuation and bowden cable transmission.

In the study, 8 healthy subjects took part (6 male, 4 female, aged between 18 and 28, weight between 68 and 82 kg). First, they walked for 3 minutes at 3 km/h in the frame in zero-impedance mode in order to get used to the robot. Then, they were asked to "sit" left-sidedly on a small board mounted to the LOPES frame. Furthermore, a foot was attached to the exoskeleton leg on this side, such that the left LOPES leg became a prosthesis. Fig. 2 shows the setup in action.

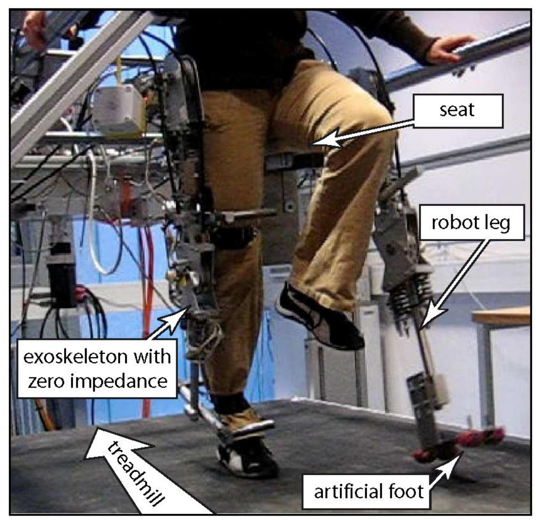

Fig. 2. The experimental setup with the LOPES rehabilitation robot (without weight support). The subject rests his left buttock on a board, which is supported by a robotic leg (the LOPES exoskeleton leg with a foot attached to it). The subject's right leg motion is measured and used as input for CLME to give the reference motion for the robotic leg.

Furthermore, a partial weight compensation system was used in order to lower the forces acting on the exoskeleton (which was being challenged far beyond its originally intended function as a joint torque source). This weight compensation was always adapted to lower the subject weight to residual 50 kg, thus the weight compensated was different for each subject.

Each subject then walked at 3 km/h with CLME based on the extracted coupling and norming parameters of a physiologically comparable person (criteria were gender, hip height and weight), whose gait pattern had previously been recorded in zero-torque mode at 3 km/h. Each subject was assigned a different reference subject, whereby the original gait pattern of most subjects in this study also provided a reference for others. The matching was not ideal due to the limited number of available subjects. The most unfavourable compromise was taken for subject 6, whose hip height is approximately 8.5 cm lower than that of his reference subject. Subjects were allowed to hold on to the lateral bars of the LOPES frame in order to maintain balance.

Prior to the experimental series, a workable input of DoFs of the right leg was tried out. First, hip abduction, hip flexion and knee flexion angles of the right leg plus the respective velocities were used to estimate the same variables for the left leg. Whereas the simulative forecast looked fine, this appeared not to be a workable approach in practice. This was due to the fact that the reconstruction algorithm (working with normed values) became very sensitive to small abduction movements, because the range of abduction is very small compared to hip and knee flexion. It was almost impossible for the subjects to dominate their abduction with sufficient exactitude. Therefore, walking with this configuration was neither robust nor intuitive and was replaced by another approach: Only hip flexion and knee flexion angles and velocities of the right side were taken to estimate the corresponding abduction, hip flexion and knee flexion of the left side. Although this showed slightly less precise results in simulation, walking now became feasible and robust.

B. Evaluation Criteria

In a professional gait analysis [24], joint angles are generally measured via a motion tracking system, and ground reaction forces are recorded using force platforms or sensor insoles. However, the test setup for this experiment did not include measurements apart from joint angle information. Neither ground reaction forces nor events like heel-strike or toe-off were detected, because the primary goal of this study was to answer the binary question of feasibility. However, using only kinematic data (exoskeleton angles), still some important tendencies can be detected concerning control strategies of the right leg, spatio-temporal gait characteristics, and gait symmetry. To assess these gait characteristics, simple criteria are defined in this section.

1) Control Strategies of the Sound Leg: It is of particular interest in how far the subjects maintain or adapt the control strategies of their right leg when walking with the robotic left leg. This question is assessed by looking at the synergies present in the right leg only, i.e. a PCA is performed on right angles and velocites. Then, a correlation is sought between the original subject's coupling, the reference subject's coupling, and the coupling during CLME-controlled walking. Features of interest are the amount of variance explained by the first principal components, i.e. the strength of correlation, and the form of correlation itself. For the qualitative analysis of the trajectories of the first two principal components, step-to-step variance is eliminated by the application of a Fourier series fit with four harmonics: First, the fundamental frequency is extracted using Fast Fourier Transformation, then, a least-squares approach is used to identify the Fourier coefficients.

2) Spatio-Temporal Joint Motion: Temporal joint motion is assessed by a quantification of the walking cadence, i.e. the frequency, which has already been extracted during the Fourier series fit. Given a fixed velocity (commanded by the treadmill), the frequency is inversely proportional to the average step length. For a further quantification of spatial joint motion, the mean values $\bar{\varphi}$ and the standard deviation $S(\varphi)$ of the individual joint angles are calculated. The standard deviation of the hip angle provides an indicator for hip excursion, and thus the step length and the duration of stance. The hip angle is defined at the exoskeleton with respect to the inertial system, because patient trunk inclination is not measured.

3) Gait Symmetry: For symmetry, a large amount of criteria and indices are available. In [25], a thorough survey on gait symmetry measures is given. Most compare the same gait parameter, e.g. step length or stance to swing ratio, between legs. A frequently used symmetry index SI, which compares left and right parameter values x_l and x_r, has been introduced by [26]. Later, it has been slightly modified such that its absolute value ranges between 0 % and 100 % for positive parameters [27]:

$$SI = \frac{x_r - x_l}{x_r + x_l} \cdot 100\% \, , \tag{8}$$

with 0% indicating perfect symmetry.

This index is used in this study, and the chosen parameter x is the standard deviation of the hip and knee angle (with the hip value representing an indirect measure of stance duration and step length).

IV. Results

All subjects were able to walk with the prosthetic robotic leg after a very short time of practice (15-30 sec). The observations made during these trials, as well as the quantitative measures will be described in this section.

A. Qualitative Observations

All subjects first exhibited exaggerated right hip flexion and too little extension. This was obviously due to the fact that their left leg was "sitting", the hip continuously being flexed. Anatomical constraints such as elastic joint moments then obstruct the correct extension of the other leg. The repercussions of this shifted hip motion (during the learning phase) on the robotic leg were the following (which accords with calculations): Excessive right hip flexion caused excessive extension of the left (robotic) hip, combined with excessive knee flexion. However, this caused much less functional problems than the lack of right hip extension, which produced a lack of left hip flexion on the other side, combined with insufficient knee extension. This led to deficient foot placement. All subjects quickly learned to control left foot placement by adjusting their right hip extension, but many maintained their functionally uncritical excessive hip flexion.

Apart from these difficulties, which were caused by the experimental setup, no major difficulties appeared. Several subjects hesitated to shift their weight onto the left leg, although the foot was properly placed. This increased the stance phase and the step length of the right side (due to the running treadmill). Others (expecially subjects 3,7, and 8) were quite confident of their "prosthetic" foot and reached an almost normal-looking walking pattern. Longer practice times might have given more confidence to all subjects, but due to the uncomfortable and exhausting posture and due to the high mechanical strain on the device, longer trials were discarded.

B. Quantitative Analysis

This section describes the outcome of the criteria defined in III-B.

1) Subject Control Strategies for the Right Leg: From the analysis, only a few observations are above the level of significance (here and in the following, $p = 0.05$): The cumulative fraction of variance explained by the first 2 principal components decreases slightly (from an average of 88.9% to 85.2%. This shows a decrease of the strength of correlations. This might be an indication that less pre-programmed control strategies are used, i.e. more voluntary or conscious control of individual joints appears. The form of synergies changes as well, indicated by a slight variation of the first 2 eigenvectors. However, no clear correlation was found (e.g. that the new eigenvectors would resemble more those of the reference subjects). Instead, there was a large variance among subjects. To illustrate these individual differences, in figure 3, the trajectories of the first 2 principal components, approximated by their Fourier series equivalents, are depicted exemplarily for four subjects. Whereas subject 5 seems to have maintained his own couplings almost entirely, subject 8 seems to have adopted the couplings of his reference gait. However, no conclusions can be drawn from these contradictory results, especially given the small sample.

2) Spatio-Temporal Joint Motion: The step frequency decreases in all subjects (from an average of 89 to 65 steps per minute), which is equivalent to an increase in average step length. This is further affirmed by a significant increase in the standard deviation of the right hip flexion by 5.6°. There is also a slight increase in the standard deviation of the left hip, but below the level of significance.

Several correlations exist between the change of statistical parameters of the subject and the statistical parameters of the reference person, but only one is above the level of statistical significance (considering the small number of subjects): The mean angle of the hip of the reference subject is clearly correlated with the mean angle of the hip in CLME-walking, whereas the mean of the original subject's hip angle is clearly uncorrelated with both. This is interpreted as an indication that the subject adapts to the reference gait to some extent when walking with the CLME-controller.

3) Gait Symmetry: To illustrate gait symmetry, the indices have been plotted in Fig. 4 for the eight subjects, showing both original values and values for CLME walking. Negative values show a prevalence of the left leg, positive values of the right leg.

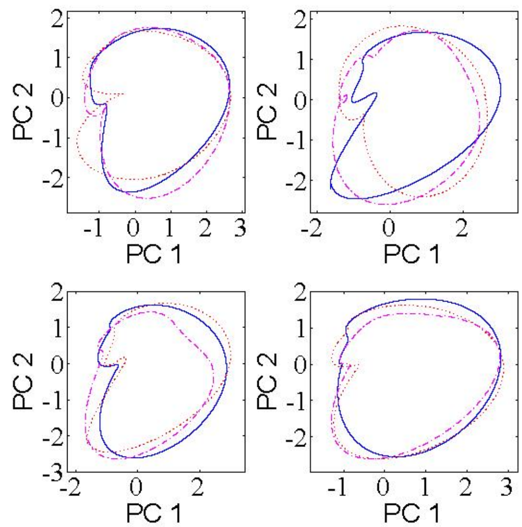

Fig. 3. Fourier-series approximations (with 4 harmonics) of the first 2 PCs (of the right leg only) plotted against each other for subjects 5-8. Solid blue line: Original gait of the subject, dotted red line: gait pattern of the reference subject, dash-dotted magenta line: gait trajectory during CLME walking. The reference gait for each subject is different and has been taken from a physiologically similar person.

The changes in joint excursion symmetry are not consistent among subjects (some maintain a very high level of symmetry), but there is a tendency to increase the dominance of the right foot. This is indicated by a larger hip standard deviation on the right, and more knee excursion on the left. This means, the right leg makes longer steps and thus has a longer stance phase and shorter swing than the left leg. This is in accordance with the previously mentioned observations in section IV-A, concerning the confidence the subjects had in their fake leg.

V. Conclusion

This study aimed at an experimental evaluation of Complementary Limb Motion Estimation (CLME) and its suitability for patient-cooperative gait rehabilitation. An important question that arose from prior theoretical studies is the capability of humans to control their leg via the other one, meaning how far a subject can cope with a unidirectional coupling scheme of sound and robotically moved DoFs. Based on the results obtained from a series of experiments with the rehabilitation robot LOPES, this question can now be answered affirmatively: Inoperable limbs can be controlled on-line using motion information of sound limbs. Functional walking was reached after a very short time by all subjects. The level of gait symmetry varies widely among subjects, probably due to a varying level of confidence in the robotic prosthesis. It has also been shown that it is possible to use synergy information from other healthy reference subjects, and indications of adaptation to the reference pattern have been found.

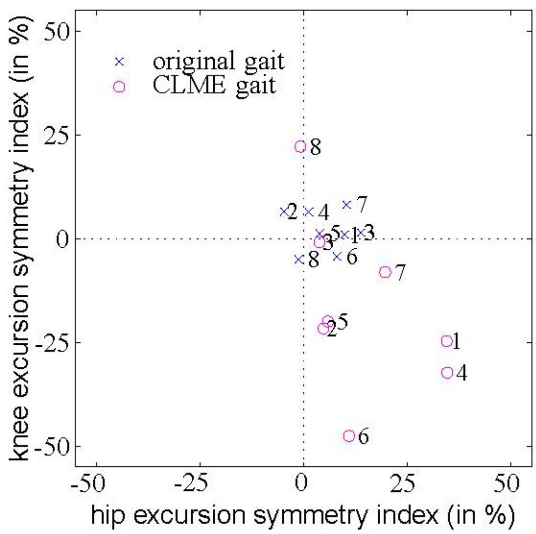

Fig. 4. Symmetry indices SI of the standard deviation of hip flexion and knee flexion. 0 % indicates perfect symmetry; the labelling refers to subject numbers. Displayed are the SI for each subject's normal gait and his gait with CLME control and the robotic prosthesis replacing his left leg. Positive values indicate a prevalence of the right leg.

Future investigations will now aim at an evaluation of CLME with hemiplegic patients. This way, the rehabilitative benefit will be investigated. For this purpose, the controller will probably be combined with a simple balance control using lateral and frontal guidance at the hip, as suggested by the LOPES frame construction.

Another future project is the application of CLME to above-knee prostheses. For this purpose, the algorithm will be made more flexible, in order to cope with different motion patterns. The required motion segmentation could be performed by hand, but possibly also by dynamic clustering, using methodologies such as Generalized Principal Component Analysis [28] or Correlation Clustering [29].

VI. Acknowledgments

The authors would like to thank Gert Jan Nevenzel, Jan Veneman, and Edwin van Asseldonk (all Laboratory of Biomechanical Engineering, University of Twente) for their valuable contribution to this project, all subjects who participated, and the Studienstiftung des Deutschen Volkes for financial support. Special thanks go to Prof. Frans van der Helm (TU Delft) and to Dr. Rainer Burgkart (Klinikum Rechts der Isar, München) for valuable advice.

References

[1] S. Hesse, H. Schmidt, C. Werner, and A. Bardeleben. Upper and lower extremity robotic devices for rehabilitation and for studying motor control. *Current Opinion in Neurology*, 16:705–710, 2003.

[2] T.Sinkjær and D. B. Popovic. Trends in the rehabilitation of hemiplegic subjects. *Journal of Automatic Control*, 15:1–10, 2005.

[3] E. Taub, G. Uswatte, and R. Pidikiti. Constraint-induced movement therapy: a new family of techniques with broad application to physical rehabilitation: a clinical review. *J Rehabil Res Dev*, 36(3):237–51, 1999.

[4] M. B. Popovic et al. Clinical evaluation of functional electrical therapy in acute hemiplegic subjects. *Journal of Rehabilitation Research and Development*, 40(5):443–454, 2003.

[5] R. Riener and T. Fuhr. Patient-driven control of fes-supported standing up: A simulation study. *IEEE Trans on Rehab Eng*, 6:113–124, 1998.

[6] H. Kazerooni, Jean-Louis Racine, Lihua Huang, and Ryan Steger. On the control of the berkeley lower extremity exoskeleton (BLEEX). In *Proceedings of the 2005 IEEE International Conference on Robotics and Automation*, pages 4364–4371, April 2005.

[7] H. Kawamoto and S. Kanbe. Power Assist Method for HAL3, Estimating Operator Intention Based on Motion Information. In *Proceedings of IEEE International Workshop on Robot and Human Interactive Communication*, pages 67–72, 2003.

[8] S. Jezernik et al. Automatic gait-pattern adaptation algorithms for rehabilitation with a 4-dof robotic orthosis. *IEEE Transaction on Robotics and Automation*, 20(3):574–582, June 2004.

[9] C. Azevedo and R. Héliot. Rehabilitation of functional posture and walking: Coordination of healthy and impaired limbs. *Journal of Automatic Control*, 15(Supplement):12–14, 2005.

[10] H. Vallery and M. Buss. Complementary limb motion estimation based on interjoint coordination using principal components analysis. In *Proceedings of the IEEE 2006 International Conference on Control Applications*, Munich, October 2006.

[11] A. Alexandrov, A. Frolov, and J. Massion. Axial synergies during human upper trunk bending. *Exp Brain Res*, 118(2):210–220, January 1998.

[12] N. St-Onge and A. G. Feldman. Interjoint coordination in lower limbs during different movements in humans. *Exp Brain Res*, 148(2):139–149, 2003.

[13] V. Dietz, K. Fouad, and C. M. Bastiaanse. Neuronal coordination of arm and leg movements during human locomotion. *European Journal of Neuroscience*, 14(11):1906–1914, December 2001.

[14] D. S. Reisman and J. P. Scholz. Aspects of joint coordination are preserved during pointing in persons with post-stroke hemiparesis. *Brain*, 126(11):2510–2527, November 2003.

[15] N. Bernstein. *The Coordination and Regulation of Movements*. Pergamon Press Ltd., London, 1967.

[16] K. Pearson. On lines and planes of closest fit to systems of points in space. *Philosophical Magazine*, 2(6):559–572., 1901.

[17] I. T. Jolliffe. *Principal Component Analysis*. Springer- Verlag, New York, 2 edition, 2002.

[18] H. Vallery and M. Buss. Bewegungsintentionserkennung mit Principal Components Analysis. In *Proceedings of Automed 2006*, 2006.

[19] J.E. Duysens and H.W. Van de Crommert. Neural control of locomotion: The central pattern generator from cats to humans. *Gait and Posture*, 7(2):131–141, 1998.

[20] K. Matsuoka. Mechanisms of frequency and pattern control in the neural rhythm generators. *Biol Cybern*, 56(5-6):345–53, 1987.

[21] M. P. Murray. Gait as a total pattern of movement. *Am J Phys Med*, 46(1):290–333, February 1967.

[22] J.F. Veneman et al. Design of a series elastic- and bowdencable-based actuation system for use as torque-actuator in exoskeleton-type training. In *Proceedings of the 2005 IEEE 9th International Conference on Rehabilitation Robotics*, 2005.

[23] R. Ekkelenkamp et al. LOPES : Selective control of gait functions during the gait rehabilitation of CVA patients. In *Proceedings of the 2005 International Conference on Rehabilitation Robotics*, 2005.

[24] J. Perry. *Gait Analysis: Normal and Pathological Function*. Slack, Inc., 1992.

[25] H. Sadeghi, P. Allard, F. Prince, and H. Labelle. Symmetry and limb dominance in able-bodied gait: a review. *Gait and Posture*, 12:34–45, 2000.

[26] R.O. Robinson, W. Herzog, and B.M. Nigg. Use of force platform variables to quantify the effects of chiropractic manipulation on gait symmetry. *J Manipulative Physiol Ther*, 10:172–6, 1987.

[27] 2 Brian L. Davis Ph.D.1 Jonathan B. Dingwell, M.S.1 and C.P.3 Dean M. Frazier. Use of an instrumented treadmill for real-time gait symmetry evaluation and feedback in normal and below-knee amputee subjects. *Prosthetics and Orthotics International*, 20:101–110, 1996.

[28] R. Vidal, Y. Ma, and S. Sastry. Generalized principal component analysis (GPCA). *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 27(12):1945–1959, december 2005.

[29] C. Böhm et al. Computing clusters of correlation connected objects. In *ACM SIGMOD Int. Conf. on Management of Data*, 2004.