Improvement and Assessment of Motor Rehabilitation with Control Engineering Methods

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Abstract

Two medical engineering projects will be presented that are in the field of motor rehabilitation after stroke. The first project focuses on the restitution of hand and finger movements. The concept is the generation of proprioceptive afferent input by position controlled muscle stimulation. As innovative stimulation method the Repetitive Peripheral Magnetic Stimulation (RPMS) is used.
Secondly, a novel control method (Complementary Limb Motion Estimation, CLME) for automated treadmill training for hemiparetic patients is presented. CLME deduces reference motion for the impaired limbs based on the contralateral leg. This method aims to increase the patient’s involvement and dominance during rehabilitation, while the robot acts as an assistive slave.

I) System Identification Based Spasticity Quantification During Magnetically Induced Muscle Stimulation

1. Introduction

A central paresis of the arm and/or hand, e.g. after stroke, reduces the quality of life

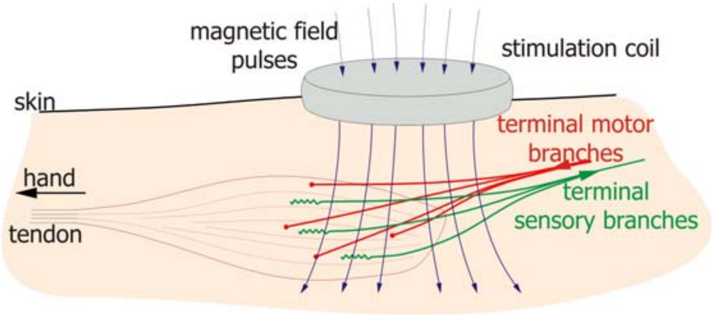

Fig 1: Principle of RPMS application

dramatically. Studies on large clinical cohorts, using standard therapeutic methods, showed that approximately 90% of stroke patients have persistent hemiparesis of the upper extremities, and in 30-40% the paresis is so severe that the affected limb can not be used any more. This data emphasizes the necessity of innovative approaches in rehabilitation of central paresis. Cortical reorganization abilities form the basis of relearning lost motor functions. In order to activate a beneficial reorganization process, the lost proprioceptive input should be reactivated. Currently, physiotherapy aims to achieve such an activation through externally applied movements. Inducing the lost movement via muscle stimulation results in a higher proprioceptive input which corresponds closer to the lost voluntary action patterns. Ultimately, this leads to an increase in the therapeutic effect [1]. In this context functional electrical stimulation (fES) is a well–known method. Though the fES activates somatosensory nerve fibers a major drawback consists of the equal activation of the cutaneous receptors. Apart from leading to pain this may also result in an additional increase in spasticity. Hence, the use of fES for therapeutic purposes appears limited, see e.g. [2]. In order to achieve a deeper penetrating, focused and painless stimulation we use the new method of repetitive peripheral magnetic stimulation (RPMS) (see fig. 1).

The repetitively applied field impulses are sinusoidal half-waves with a fixed duration of 100µs and a variable amplitude called stimulation intensity. The maximum stimulation intensity of 100% corresponds to a magnetic flux density of approximately 2.0T. The therapeutic concept of RPMS is the activation of a reorganization process by inducing a proprioceptive input to the central nervous system (CNS), physiologically corresponding to the lost input during active movements [1, e.g.]. In clinical experimental studies [3] on spasticity, cognitive functions, cerebral activation, stiffness around the elbow joint and goal-directed motor performances, it was shown, that the sensorimotor dysfunctions due to brain lesions can improve remarkably with the application of RPMS. Our current research focuses on the improvement and the assessment of RPMS-therapy. Fig. 2 summarizes our main aims:

- Optimization of the proprioceptive inflow by inducing position controlled functional ovements with multiple coils.
- Time continuous tracking of patient parameters like level of spasticity and muscle atigue based on system identification.

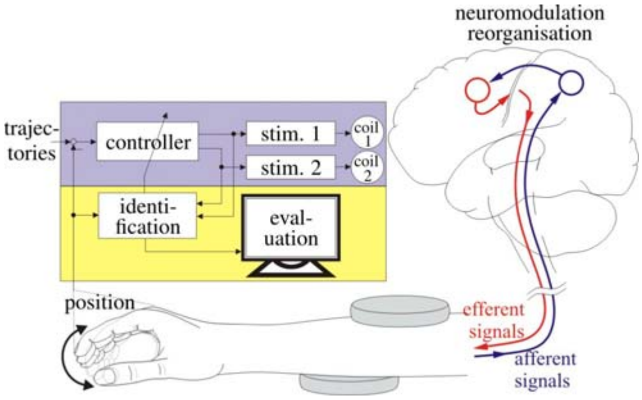

Fig 2: Overview of the main research goals

One important goal in treatment of central paresis is the reduction of spasticity. The evaluation of the spasticity level is essential for the individual therapy planning, for the evaluation of the therapy progress and most of all for the neurophysiological research to obtain a deeper understanding of the recovery processes in the CNS. Standard methods are the modified Ashworth scale [4] or EMG-measurements of the affected muscles. The modified Ashworth test is not objective and EMG measurements are time consuming and error-prone. In [5] static and dynamic spasticity components are identified by measuring the torque necessary to passively move the elbow joint, and in [6] a system identification approach is introduced which is also based on torque measurements. However, to the authors' best knowledge, a spasticity quantification during muscle stimulation without using any extra equipment like force sensors or EMG has not been introduced yet.

2. Methods

Fig 3 illustrates a simplified description of the plant. The force F generated by the stimulated muscle is transmitted via a tendon the the respective joint. The block diagram comprises the force generation and the limb dynamics. The nonlinearities N_1 and N_2 model the gravitational torque F_g elastic joint properties F_{ejp} and friction F_f, see eq. (1) and (2). In case of spasticity the tonic spasticity component S_t and the phasic component S_p have to be added. Detailed derivations can be reviewed in [7].

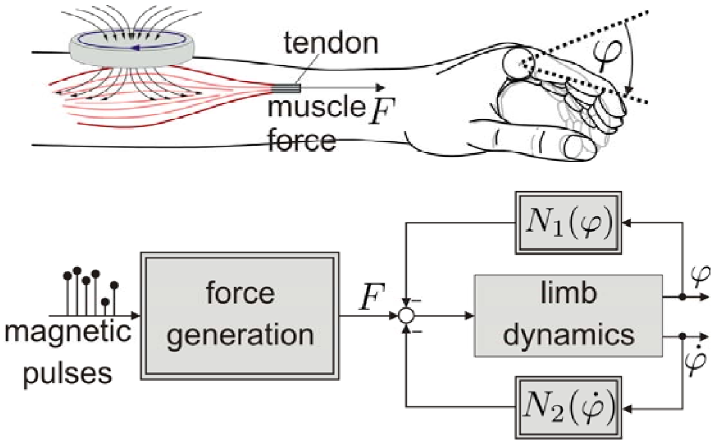

Fig 3: Simplified model of the plant

$$N_1(\varphi) = F_g(\varphi) + F_{ejp}(\varphi) + S_t(\varphi) \quad (1)$$

$$N_2(\dot{\varphi}) = F_f(\dot{\varphi}) + S_{ph}(\dot{\varphi}) \quad (2)$$

Since the only time varying components of eq. (1) and (2) are the spasticity components S_t and S_{ph} a change of spasticity can be tracked by identifying the nonlinearities N_1 and N_2.

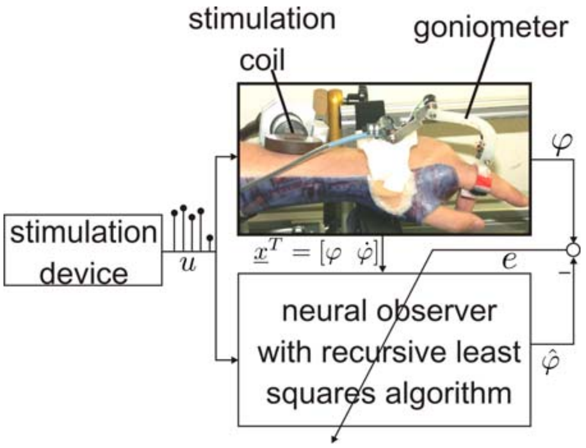

Fig 4: Output error configuration for identification of the plant parameters.

The plant parameters have been identified in output error configuration with a neural observer and a recursive least squares algorithm. Details can be reviewied in [7].

3. Results

In a pilot study the described approach has been tested with one patient (female, 71 years old, hemiplegic after stroke, spastic paretic arm and hand with neglect syndrome, time since lesion approx. 5 years): In clinical experimental studies it could be shown, that the level of spasticity decreased after the application of conditioning *RPMS* [14]. During the treatment, nonfunctional muscle contractions are applied to the flexor and extensor muscles of the forearm and the upper arm. The field pulses are applied for a period of 1.5 s followed by a break of 3 s with a total duration of approximately 15 min. In order to assess the change of flexor spasticity in the forearm due to the conditioning *RPMS*, the angle $\varphi(t)$ of the MCP joint of the index finger and the stimulation intensity $u(t)$ have been recorded during open loop stimulation of the index finger extensor immediately before (time t_1) and one hour after (time t_2) the treatment.

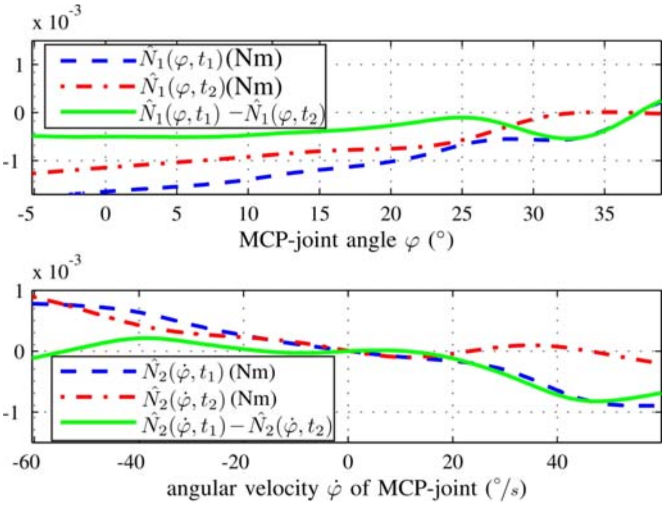

Fig 4: Output error configuration for identification of the plant parameters.

The results of the spasticity evaluation are depicted in fig. 4. The solid line describes is the difference between the nonlinear functions identified at the time t_2 and t_1. With The identification result clearly indicates a decrease of the static flexor spasticity component. The dynamic component has increased slightly for extension movements and decreased for flexion movements. These results coincide with the findings of the medical examinations.

4. Conclusion

This paper presents a novel method for rehabilitation of spastic paresis after stroke An automated system identification based spasticity evaluation has the capability to yield objective data and can be executed during the therapeutic stimulation without applying any additional equipment. Furthermore it allows a clear separation between the static and dynamic spasticity component. Hence, it can be a valuable tool for rehabilitation research to help understanding the processes of recovery after stroke. It can also help the physiotherapist to monitor the therapy process and hence, to adapt the therapy to the patient.

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II) Complementary Limb Motion Estimation (CLME)

1. 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. for 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, residual, yet insufficient muscular activity can be detected and reinforced in the paretic leg, either by observation of the generated motion [5], [6], [7], or by EMG measurements of the muscle activation [8]. However, these techniques require sufficiently coordinated activity in the motor cortex regions controlling the impaired limbs.

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

We have 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]–[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. It seems as if our brain has developed such refined control methodologies to deal with the redundancy or ”abundancy” [14], [15] of human DoFs. CLME uses the mathematical method of Principal Components Analysis (PCA) [16], [17] to extract the couplings between limbs in healthy synergistic motion. Using these physiological couplings and a patient's sound limb motion, it estimates the corresponding motion of his paretic limbs.

Simulation studies show the potential of CLME applied to gait rehabilitation of hemiparetic patients (i.e. right leg - left leg inference) in theory [10]. However, the suitability for control of gait rehabilitation robots can only be answered by practical experiments, where the human closes the loop. The first important question is whether a person can functionally walk with such a unidirectional coupling between legs. 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, another key question is whether a subject can adapt to the coupling of someone else.

To assess the questions above, we ran a series of experiments on the LOPES gait rehabilitation robot [18]. This exoskeleton-based robot [19],[20] 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 using the exoskeleton leg as a prosthesis.

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

2. Method: Complementary Limb Motion Estimation (CLME)

Principal Components Analysis (PCA) [16], [17] is frequently used as a general approach to data compression, where statistical (linear) correlation is exploited. A data set is projected onto a lower-dimensional subspace in a way that the error after re-projection into the original data space is minimized. The redundancy in the data, which is revealed by the analysis of correlations, can also be used for the reconstruction of incomplete measurements. A simple example: If only two statistical variables are involved, and they are roughly multiples of each other, then PCA will reveal the multiplication factor. Afterwards, one variable is enough to estimate the value of the other one.

For the application of motion intention estimation, PCA is used to reveal the linear correlations between both legs, i.e. it delivers a function which infers from angles and velocities of one leg to angles and velocities of the other one instantaneously. To obtain this function, joint synergies are extracted from recorded trajectories of normal human gait. Then, reference motion can be generated on-line for inoperable joints of hemiparetic patients, using the instantaneous states of the sound limbs.

The outputs of the function are angles and velocities for the impaired leg, yet both angles and velocities are subject to uncertainty. As PCA is completely static and does not account for the relationship between the time derivatives, these are not internally coherent. This means the PCA-estimated velocity is quite different from the velocity estimate obtained via differentiation of the PCA-estimated position signal. Therefore, an additional Kalman filter is used to merge the two pieces of information, and to calculate the most plausible motion of the impaired leg.

The strong inter-limb coordination during human walking allows for a very accurate reconstruction of one leg using pre-recorded trajectories, as shown in Fig. 1.

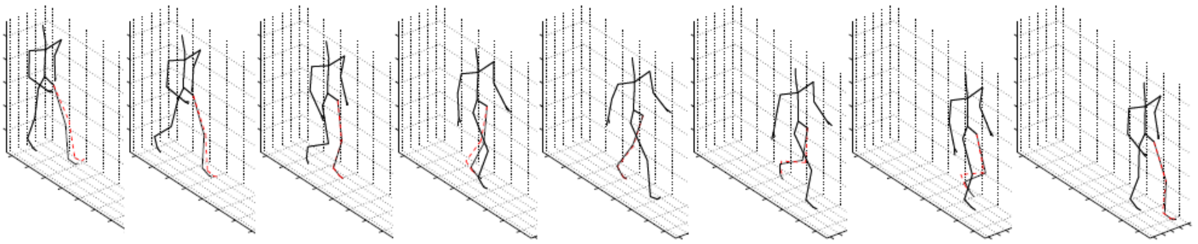

Fig 1: Estimated motion (red dashed line) of the left leg compared with the originally recorded motion (black solid line) of a healthy subject. The motion is estimated based on right leg angles and velocities. The averaged coupling information used has been extracted (separately for stance and swing phase) from the gait patterns of nine other healthy subjects.

3. Test Setup

To evaluate the feasibility of walking with unilateral coupling, we conducted a first series of experiments with healthy subjects on the LOPES robot. 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.

The LOPES 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.

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.

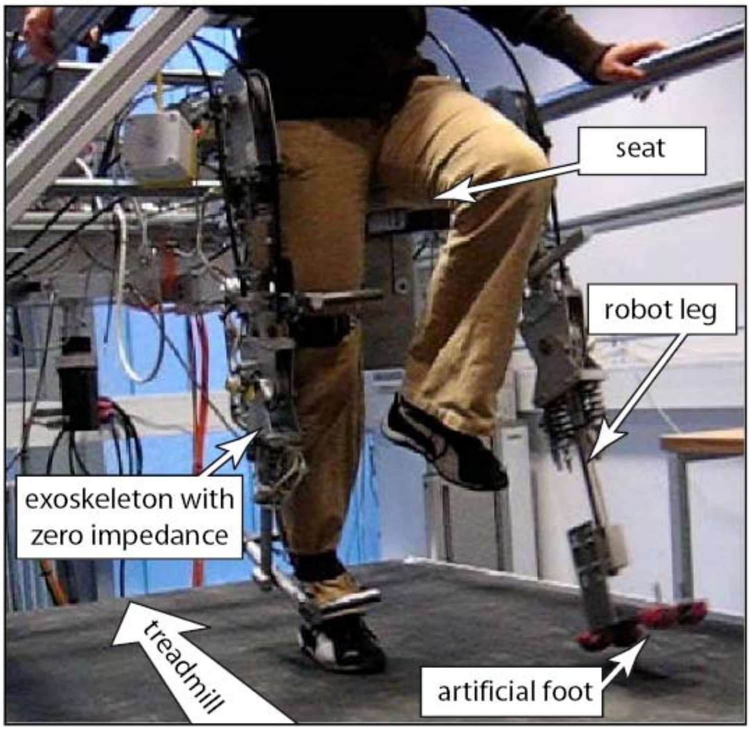

Fig. 2. The experimental setup with the LOPES rehabilitation robot. The subject rests his left buttock on a board, which is supported by a robotic leg (the LOPES exoskeleton leg with a foot attached to it). The subject’s right leg motion is measured and used as input for CLME to calculate the reference motion for the robotic leg.

Each subject then walked at 3 km/h with CLME based on the extracted coupling and norming 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. PCA was performed over 10 seconds of the reference gait without separation of swing and stance phase. Each subject was assigned a different reference subject. Subjects were allowed to hold on to the lateral bars of the LOPES frame in order to maintain balance. Only hip flexion and knee flexion angles and velocities of the right side were included to estimate the corresponding abduction, hip flexion and knee flexion of the left side, because in preliminary experiments, additional consideration of right abduction had led to insufficient robustness.

4. Results

In a professional gait analysis [21], 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 angle data (in the sagittal plane), still some important tendencies can be detected concerning spatio-temporal gait characteristics, control strategies and adaptation.

3.1 Qualitative Observations

All subjects were able to walk with the prosthetic robotic leg after a very short time of practice (15-30 sec). In the beginning, all subjects tended to do exaggerated 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 complicate the correct extension of the other leg. Several subjects hesitated to place their weight on the left side, although the foot was properly placed. This increased the step length of the right side (due to the running treadmill). Others were quite confident of their "prosthetic" foot and reached an almost normal-looking gait pattern.

3.2 Gait Symmetry

To quantify symmetry, we use a symmetry index [22] to compare joint excursions (represented by the standard deviation of the respective angle) and mean angles between legs. Although the changes in joint excursion symmetry from normal to CLME gait are not consistent among subjects (some maintain a very high level of symmetry), there is a tendency to increase the dominance of the right foot. This means, the right leg has a longer stance phase than the left leg. This is in accordance with the previously mentioned observations concerning the varying confidence the subjects had in their fake leg.

3.3 Spatio-Temporal Joint Motion

Fourier analysis reveals that 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 value mainly reflects the longer stance phase on the right. Concerning spatial joint motion, there is an interesting change above the level of significance in the mean of the right hip angle: The mean of the hip angle of the reference subject is clearly correlated with the mean 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.

3.4 Subject Control Strategies for the Right Leg

It was of particular interest in how far the subjects would 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 the recorded right leg angles and velocities. This analysis reveals a significant weakening of synergies in all subjects (indicated by a decrease in the cumulative fraction of variance explained by the first 2 principal components from an average of 88.9% to 85.2%). This might be an indication that slightly less pre-programmed control strategies are used, i.e. more voluntary or conscious control of individual joints appears. Concerning the form of synergies, there is a large variance among subjects such that no conclusions can be drawn: For some, the eigenvectors seem to approach those of the reference, for some they stay almost unaltered, for some they change in some other way.

5. Conclusion

The proposed method of Complementary Limb Motion Estimation (CLME) has been presented together with first experimental results, which affirm its suitability for patient-cooperative gait rehabilitation: Trajectories for inoperable limbs can be generated on-line using motion information of sound limbs.

Apart from an answer to the binary question of feasibility, the analysis provided some qualitative tendencies: The CLME gait pattern shows hints of adaptation to the reference gait used. Furthermore, functional walking with CLME can be asymmetric, and it seems to trigger slightly more voluntary and conscious control of the right leg.

Future investigations will now aim at an evaluation of CLME with hemiplegic patients. This way, the rehabilitative benefit of a cooperative, intention-based guidance of the impaired limbs will be investigated. For this purpose, it 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 maybe also by dynamic clustering, using methodologies such as Generalized Principal Component Analysis [23] or Correlation Clustering [24].

6. Acknowledgments

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