8. Workshop Automatisierungstechnische Verfahren für die Medizin vom 20.-21. März 2009 in Berlin

„Iterative learning support for robot-aided gait rehabilitation"

Alexander Duschau-Wicke, Simon Felsenstein, Robert Riener
Sensory-Motor Systems Lab, Institute of Robotics and Intelligent Systems (IRIS), ETH Zurich, Switzerland
E-Mail: duschau@mavt.ethz.ch

Alexander Duschau-Wicke, Robert Riener
Spinal Cord Injury Center, University Hospital Balgrist, Zurich, Switzerland

Thomas Brunsch
Hocoma AG, Volketswil, Switzerland

Thomas Brunsch
Control Systems Group, Technical University Berlin, Germany

Band: Fortschritt-Bericht VDI Reihe 17 Nr. 274 „Automatisierungstechnische Verfahren für die Medizin, 8. Workshop, Tagungsband"
Editors: Thomas Schauer, Henning Schmidt, Marc Kraft
ISBN: 978-3-18-327417-8
Pages: 1-2

Iterative learning support for robot-aided gait rehabilitation

Alexander Duschau-Wicke[1,2,3], Thomas Brunsch,[3,4] Simon Felsenstein[1] and Robert Riener[1,2]

[1]Sensory-Motor Systems Lab, Institute of Robotics and Intelligent Systems (IRIS), ETH Zurich, Switzerland
[2]Spinal Cord Injury Center, University Hospital Balgrist, Zurich, Switzerland
[3]Hocoma AG, Volketswil, Switzerland
[4]Control Systems Group, Technical University Berlin, Germany
Contact: duschau@mavt.ethz.ch

Introduction

Walking disabilities are a common consequence of neurological conditions such as stroke and spinal cord injury. Body weight supported treadmill training (BWSTT) is successfully applied to the rehabilitation of patients suffering from these conditions [1, 2].

Robotic rehabilition devices such as the Lokomat (Hocoma AG, Switzerland) [3], the ReoAmbulator (Motorika, USA), and the Gait Trainer (Reha-Stim, Germany) automate BWSTT by moving patients repetitively along predefined walking trajectories. However, neuroscience research [4] implicates that movements have to be trained not only with a large number of repetitions but also with a certain amount of variance to optimize retraining of motor abilities. Therefore, patient-cooperative control strategies [5], which increases variance in the spatial pattern of movement, are being developed for these devices. In these cooperative approaches, the robots need to behave in a compliant way to allow patients to influence their movements. However, patients also require support during certain gait phases to walk successfully.

We propose an adaptive algorithm based on iterative learning control that adjusts the support to the amount needed to maintain walking, but keeps the patient constantly challenged to participate as much as possible in the training. We will demonstrate the use of the algorithm in two different applications for the rehabilitation robot LOKOMAT: first, to shape an assistive force field applied at the knee joint to assist weight bearing during stance phase, and second, to automatically adjust the amount of body weight support provided to the patient.

Methods

Gait rehabiliation robot: The rehabilitation robot LOKOMAT automates body weight supported treadmill training of patients with locomotor dysfunctions in the lower extremities such as spinal cord injury and hemiplegia after stroke [3]. It comprises two actuated leg orthoses that are attached to the patient's legs. Each orthosis has one drive in the hip joint and one drive in the knee joint to induce flexion and extension movements of hip and knee. A closed-loop controlled body weight support (BWS) system relieves patients from a definable amount of their body weight via a harness which is attached to the patient's trunk (Fig. 1).

Iterative Learning Support: An adaptation algorithm based on iterative learning control (ILC) [6] is used to adjust the amount of support provided to the patient. The basic idea of ILC is the iterative improvement of an input function for a cyclic process. The input function for the $(k+1)^{\text{th}}$ cycle $\underline{u}^{(k+1)}(t)$ is determined by adding a correction term to the input function of the k^{th} cycle

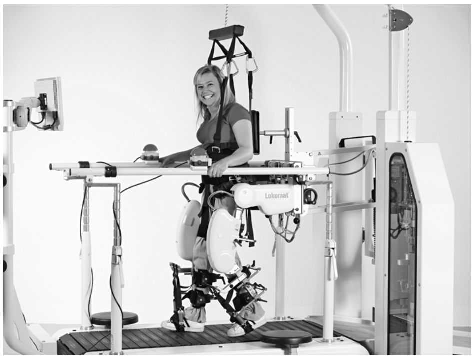

Figure 1: The rehabilitation robot LOKOMAT (photo courtesy of Hocoma AG)

$$\underline{u}^{(k+1)}(t) = \underline{u}^{(k)}(t) + \underline{\Gamma}(t)\underline{e}^{(k)}(t) \tag{1}$$

where $\underline{e}^{(k)}(t)$ represents the control error during the k^{th} cycle, and $\underline{\Gamma}(t)$ is the "learning gain" of the process.

Emken et al. [7] showed that an adaptive controller which is supposed to assist only as much as needed must incorporate a forgetting factor in order to keep patients continuously challenged. Introducing such a factor $k_{\text{f}} \in [0,1]$ in eq. (1) yields

$$\underline{u}^{(k+1)}(t) = (1-k_{\text{f}})\underline{u}^{(k)}(t) + \underline{\Gamma}(t)\underline{e}^{(k)}(t). \tag{2}$$

Adaptive stance support: When the compliance of the LOKOMAT is increased to let patients move more freely, many patients are not capable of keeping their knee joints extended. Therefore, we applied additional supportive torques during stance phase to prevent knee buckling. For this particular case, the control error $e^{(k)}(t)$ during the k^{th} cycle is a scalar function of the control deviation in the knee joint during stance phase. Based on this error, a scalar supportive torque for the knee joint is calculated.

$$\tau_{\text{sup}}^{(k+1)}(t) = (1-k_{\text{f}})\tau_{\text{sup}}^{(k)}(t) + k_{\text{l}}e^{(k)}(t) \tag{3}$$

This supportive torque is added to the output of the closed-loop impedance controller [5] as a feed forward term.

Adaptive BWS: Assistive knee torques are well suited for smaller amounts of support up to 20 Nm. If more support is needed, the links between exoskeleton leg and patient leg are not sufficiently rigid to transfer the forces. In such cases, the body weight support via the harness at the patient's trunk can assist more effectively. We applied an iterative learning law analog to eq. (3) to adjust the level of body weight support during LOKOMAT training. The error function $\underline{e}^{(k)}(t)$ was defined such that the subject in the LOKOMAT would reach a defined level of physical activity.

Results

Adaptive stance support: The adaptive stance support reduced unwanted knee flexion during stance phase when subjects (healthy, $n = 3$) walked passively. The amount of support was adjusted according to the individual needs of the subjects. The BWS system was used to simulate a subject-dependent need for more or less support (Fig. 2).

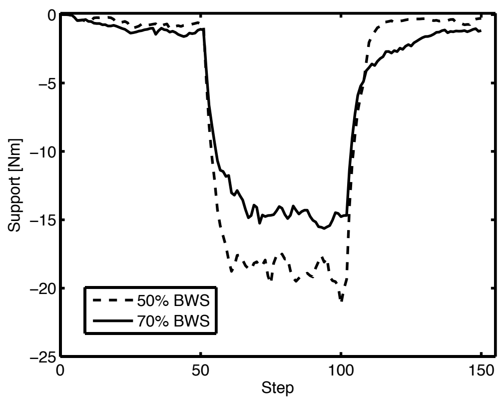

Figure 2: Adaptive stance support for a test subject during walking with different levels of BWS. The graph shows the average knee support during stance phase for each step. The subject was active during the first 50 steps, passive during the next 50 steps, and active again during the last 50 steps.

Adaptive BWS: The iterative learning algorithm for adapting the body weight support successfully tracked desired levels of physical activity in healthy test subjects (Fig. 3).

Conclusion

Cooperative control approaches for gait rehabilitation that rely on increased compliance can be improved by adding supportive forces/torques. Furthermore, the level of activity of a patient during gait training is strongly influenced by the amount of body weight support. Iterative learning control algorithms are well suited to adapt these means of support to the individual capabilities of a patient. Thus, patients can be trained at a constantly challenging level.

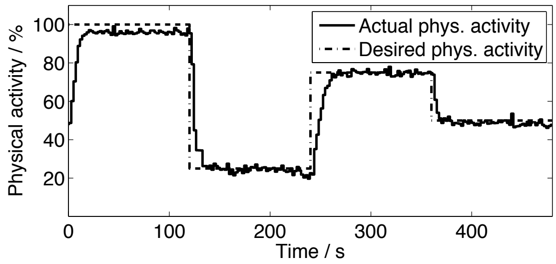

Figure 3: Desired physical activity tracked by iterative learning algorithm for adaptive body weight support in an experiment with a healthy test subject

References

[1] SULLIVAN, K. J. ; BROWN, D. A. ; KLASSEN, T. ; MULROY, S. ; GE, T. ; AZEN, S. P. ; WINSTEIN, C. J.: Effects of Task-Specific Locomotor and Strength Training in Adults Who Were Ambulatory After Stroke: Results of the STEPS Randomized Clinical Trial. In: *Phys. Therapy* 87 (2007), Nr. 12, S. 1580–1602

[2] DOBKIN, B. ; BARBEAU, H. ; DEFORGE, D. ; DITUNNO, J. ; ELASHOFF, R. ; APPLE, D. ; BASSO, M. ; BEHRMAN, A. ; HARKEMA, S. ; SAULINO, M. ; SCOTT, M.: The evolution of walking-related outcomes over the first 12 weeks of rehabilitation for incomplete traumatic spinal cord injury: the multicenter randomized Spinal Cord Injury Locomotor Trial. In: *Neurorehabil. Neural Repair* 21 (2007), Nr. 1, S. 25–35

[3] COLOMBO, G. ; WIRZ, M. ; DIETZ, V.: Driven gait orthosis for improvement of locomotor training in paraplegic patients. In: *Spinal Cord* 39 (2001), Nr. 5, S. 252–255

[4] GRAU, James W. ; CROWN, Eric D. ; FERGUSON, Adam R. ; WASHBURN, Stephanie N. ; HOOK, Michelle A. ; MIRANDA, Rajesh C.: Instrumental Learning Within the Spinal Cord: Underlying Mechanisms and Implications for Recovery After Injury. In: *Behav Cogn Neurosci Rev* 5 (2006), Nr. 4, S. 191–239

[5] RIENER, R. ; LÜNENBURGER, L. ; JEZERNIK, S. ; ANDERSCHITZ, M. ; COLOMBO, G. ; DIETZ, V.: Patient-cooperative strategies for robot-aided treadmill training: first experimental results. In: *IEEE Trans. Neural Syst. Rehabil. Eng.* 13 (2005), Nr. 3, S. 380–394

[6] ARIMOTO, Suguru ; KAWAMURA, Sadao ; MIYAZAKI, Fumio: Bettering operation of Robots by learning. In: *Journal of Robotic Systems* 1 (1984), Nr. 2, S. 123–140

[7] EMKEN, J. L. ; BOBROW, J. E. ; REINKENSMEYER, D. J.: Robotic movement training as an optimization problem: designing a controller that assists only as needed. In: *Proc. IEEE 9th Int. Conf. Rehabil. Robot.* Chicago, 2005, S. 307–312

Acknowledgment

The contents of this publication were developed in part with support of the National Center of Competence in Research (NCCR) on Neural Plasticity and Repair of the Swiss National Science Foundation and in part under a grant from the US Department of Education, NIDRR grant number H133E070013.