Individual Patient Support on Lower Leg Orthoses by Continuous Control over the Whole Gait Cycle

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Abstract: Patients employ orthoses for the lower limbs to gain support for movements they themselves could not perform at all, or only with difficulties. The combination of patient-abilities and a chosen controller determines suitable devices. We present a model based controller, which can be individualised with gait samples. It allows continuous control over the whole gait cycle based on the tracking of gait progress and makes no assumption on the patient's abilities. We conclude that the smoothness and linearity of the gait progress tracking allows continuous control which enhances the patient group.

Keywords: Lower Extremities Orthosis; Gait-Progress Estimation; Internal Model

1. INTRODUCTION

Lower limb orthoses (as in Fig. 1) range from passive splints to micro controller driven devices with active components, like joint locks. These devices support the patient during rehabilitation, or every day use, for example after stroke, nerve/muscle tissue damage, or other forms of paraplegia. Current devices with finite state controllers support few gaits. To extend the set of supported motions, the controller has to be able to differentiate and act according to the situation. While finite state based controllers can be extended, for example to include stair descending and ascending [1], they grow in complexity by means of states & transitions including parameters for their description. Therefore, attempts have been made to switch between sets of finite state controllers [2, 3].

Still, the design by states and transitions make assumptions about the gait dynamics, which might not fit all patients. Tuning can be done with parameters covering control output and transitions, but not all patients have the abilities to trigger all state transitions. Often, the patients are required to adapt their gait to the device.

To overcome restrictions imposed by the state-transition-design, the presented controller strives to (a) continuously apply control over the whole gait cycle and (b) learn individual gait features by observation. To this end, we train gait models for continuous, linear gait progress tracking on top of which one can define arbitrary control output; we make no assumptions about the gait dynamics and may support arbitrary gaits. We conducted tests with a healthy walker on a Knee-Ankle-Foot-Orthosis with a semi-active C-Leg knee joint from Otto Bock.

Without assumptions about when the control decisions are needed, their ability to change control output should be distributed equally over the gait cycle with as many control points as possible. In other words: to support arbitrary gaits, the controller should be able to apply control decisions at any time. We show, that our approach handles trained gaits with almost sampling resolution. The training to specific gaits requires gait model switching to maintain a high quality of control over different environments.

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2. METHODS

The presented controller is based on: (1) *Continuous tracking* of the patient's gait allows to support at any segment of the step cycle. (2) *Training to individual patient's gait* samples allows to optimise the tracking of the patient's gait. (3) An appropriate *gait selection* mechanism: The training process leads to overspecialisation of the gait tracking. This narrowing of scope can be overcome by support of several specific gaits.

Previous publications focused on item (2) in [4] and item (3) in [5]. Here, we evaluate the interaction of gait selection and gait tracking, focusing on how the combination ensures smooth gait tracking for all supported gaits.

2.1. The Device & Sensor Configuration

Development and experiments have been conducted with a healthy subject on a semi-active knee-ankle-foot-orthosis by Otto Bock with a C-Leg hydraulic damper, which allows to dampen knee flexion.

We instrumented the orthosis with a thigh- and knee-angle sensor and a ground contact switch at the heel.

2.2. Controller Overview

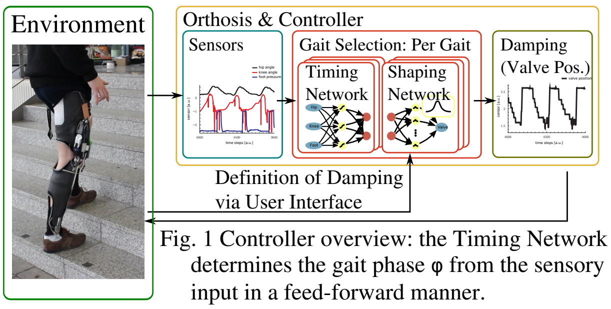


Fig. 1 Controller overview: the Timing Network determines the gait phase φ from the sensory input in a feed-forward manner.

The controller is composed of two components: **1.** A gait specific controller, which generates the desired knee damping as feed-forward output of the sensory input vector. The desired knee damping can be tuned in a closed

loop fashion with a user interface. **2.** A gait selection unit, which uses predictive models for each available gait. Using the prediction error, it decides which gait specific controller will execute its knee damping (see [5]).
In Fig. 1, the gait selection unit is represented by the outer red box in the middle, whereas the gait specific controller is depicted as two processing steps inside: for each gait, the gait phase φ is determined by the timing network, which implements continuous gait tracking. On top of this gait phase, the shaping network will apply the desired damping d as a function $d(\varphi)$. A user interface allows to manipulate the damping function $d(\varphi)$ on-line. For predictable manipulation of d, φ should map the gait progress linearly.

2.3. Gait Tracking

The timing unit implements gait progress tracking and was designed for: **(1)** *Abstraction:* transform sensory input $\vec{s}$ to a generic gait progress φ. **(2)** *Individualisation:* adapt the transformation to individual gait. **(3)** *Reaction:* react fast to cope with perturbations. **(4)** *Time-Independence:* no dependence on gait speed or length. **(5)** *Detailed control:* provide smooth gait progress representation for continuous damping control.

Further processing is independent of the implementation details because of requirements (1) and (2); (3) ensures save operation. Requirement (4) gives the flexibility to handle minor deviations in a gait and with (5) allows to change damping output accurately over the whole gait cycle: The presented controller is not event based, i.e., *changes in the controller's output are a reaction to gait progress. The quality of gait progress resolution determines the detail of applicable damping control.*

To support training and later retraining with observed samples, gait tracking was implemented with a perceptron [6], having 3 input, 3 hidden and 2 output neurons. To get best results, the gait-typical sensory input is scaled to $[-1, 1]$, and we choose the network's output to be a circular (i.e. periodic) motion in the plain, similar to the input. In a post-processing step, we derive the gait phase $\varphi \in [0, 1)$ from the 2D circular representation:

$$\vec{s} \mapsto \begin{pmatrix} x_\varphi \\ y_\varphi \end{pmatrix} = \begin{pmatrix} \cos(2\pi\varphi) \\ \sin(2\pi\varphi) \end{pmatrix} \quad ,$$

$$\varphi = \begin{cases} \frac{1}{4} & x_\varphi = 0, y_\varphi \geq 0 \\ \frac{1}{2\pi} tan^{-1}(y_\varphi / x_\varphi) & x_\varphi \neq 0 \\ \frac{3}{4} & x_\varphi = 0, y_\varphi < 0 \end{cases} \quad .$$

2.4. Experimental Evaluation of Control Detail

The quality of gait progress resolution determines the detail of control: As the control architecture applies damping based on the gait phase, only changes in gait phase can result in changes of the applied damping. We therefore want the gait phase φ to change continuously and evenly over the step. Ideally, it produces a linear mapping from 0 to 1 over the gait cycle, whereas high or near zero slopes indicate sub-optimal resolution.

Thus, we evaluate the quality of the on-line gait phases φ via the smoothness and accuracy in comparison to the ideal gait phases φ' computed off-line. Therefore, we **1.** split the recording into steps at heel strike and **2.** resample all steps to 200 samples to achieve numerical comparability; for sample i: $\varphi'_i = \frac{i}{200}$.

3. RESULTS

For experimental evaluation of gait progress accuracy, the gait phases from models for flat walking and stair climbing were evaluated on the corresponding and opposite terrains. We analysed 30 steps along a floor with 38 steps of stair climbing of a healthy subject wearing the orthosis. None of these steps covered transitions between the models to circumvent problems in the interpretation due to ambiguities [5].

The gait phases φ in Fig. 2 were evaluated online and plotted against the offline computed gait phase φ'. In Figs. 2(a) and 2(d), no model reproduces the ideal gait progress representation, but the representation is mostly monotonous with $\varphi \approx \varphi'$, except at heel-off, where fast heel pressure changes induce fast increases in φ.

For the mixed cases in Figs. 2(b) and 2(c), we observe a phase shift of the heel strike of the model representation to the real heel strike event ($\varphi' = 0$). Furthermore, the model for flat ground on stairs in Fig. 2(b) shows 4 steep increases with almost constant values in between, while the model for stair climbing on flat ground shows a decrease in gait progress for almost 20 % of the gait cycle.

The increments $\Delta\varphi$ of the gait phases are shown in Fig. 3, where the native gait model is plotted in red and the unfitting model is plotted in blue.

The histogram of increments on flat ground in Fig. 3(a) shows a tendency to more small and negative changes for the unfitting stair climbing model, for which increments $\Delta\varphi < 0$ are more frequent. For the fitting model it is reversed, the distribution has a smaller deviation from the ideal increase of $\nu_{opt} = \frac{1}{200} = 0.005$, which means fewer negative changes and fewer increments of large value. For the flat walking model, 69 % of all increments were in the interval $\left[\frac{1}{2}\nu_{opt}, 2\nu_{opt}\right]$, whereas for the stair climbing model, only 31 % were inside this interval.

The distributions for stair climbing (Fig. 3(b)) have a pronounced peak around the ideal increment ν_{opt} for the native model. Conversely, the model for flat walking has a peak for increments $|\Delta\varphi| \ll \nu_{opt}$ and more increments of large value. For the stair climbing model, 65 % of all increments were in the interval $\left[\frac{1}{2}\nu_{opt}, 2\nu_{opt}\right]$, whereas for the flat walking model 40 % were inside this interval.

The evaluated phase shifts of Fig. 2 are shown in Table 1. In case of the missing steps in the statistics of the stair climbing model on stairs, the phase reset to 0 was immediately at the end of the preceding transition steps

		Environment	
		Flat Ground [°]	Stairs [°]
Model	Flat	1.8	34.2 ± 3.7
	Stair Climbing	-18.0 ± 1.2	2.5 ± 5.5

Table 1 Phase shifts of the models for 30 steps on flat ground and while stair climbing (38 steps for flat model and 31 steps for stair climbing model).

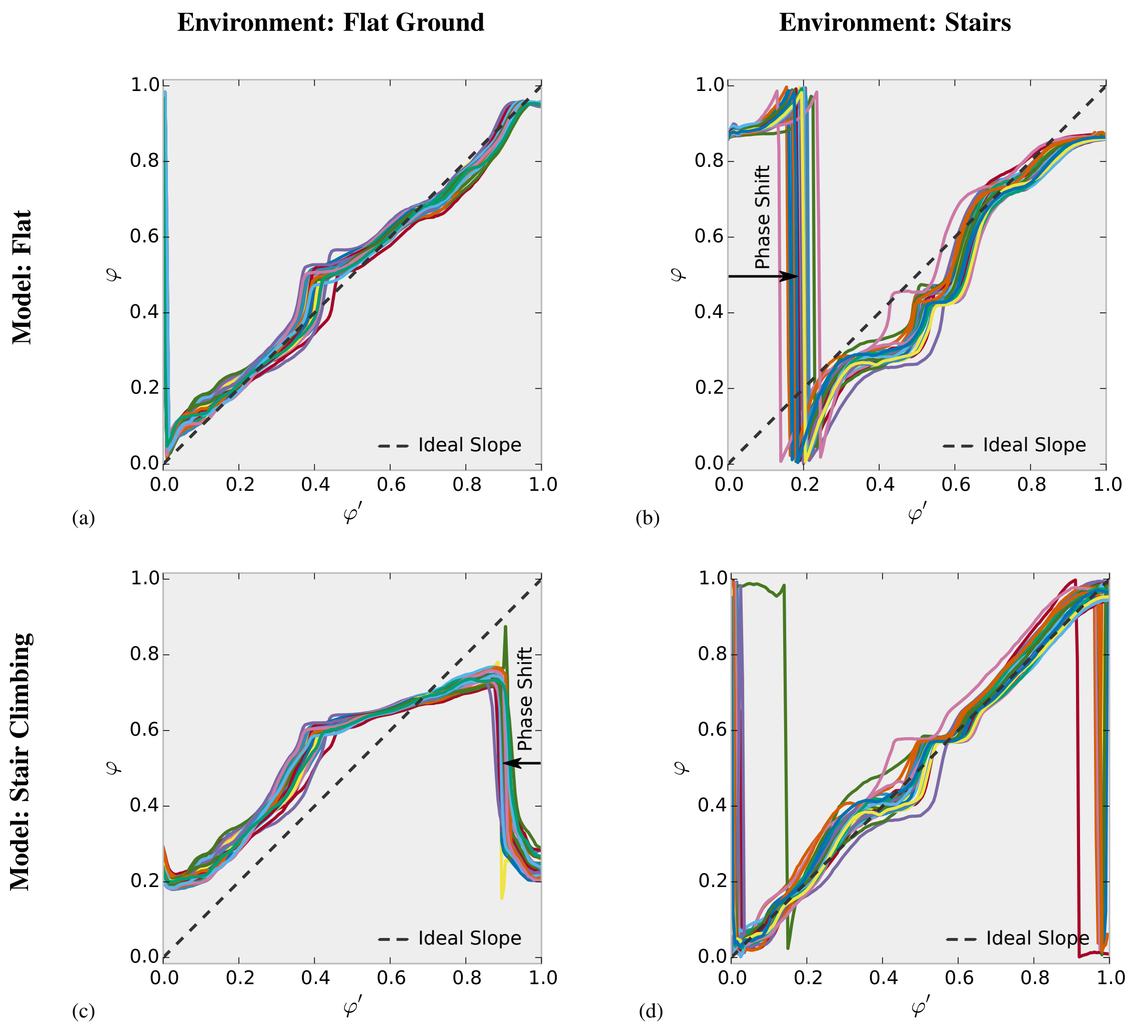
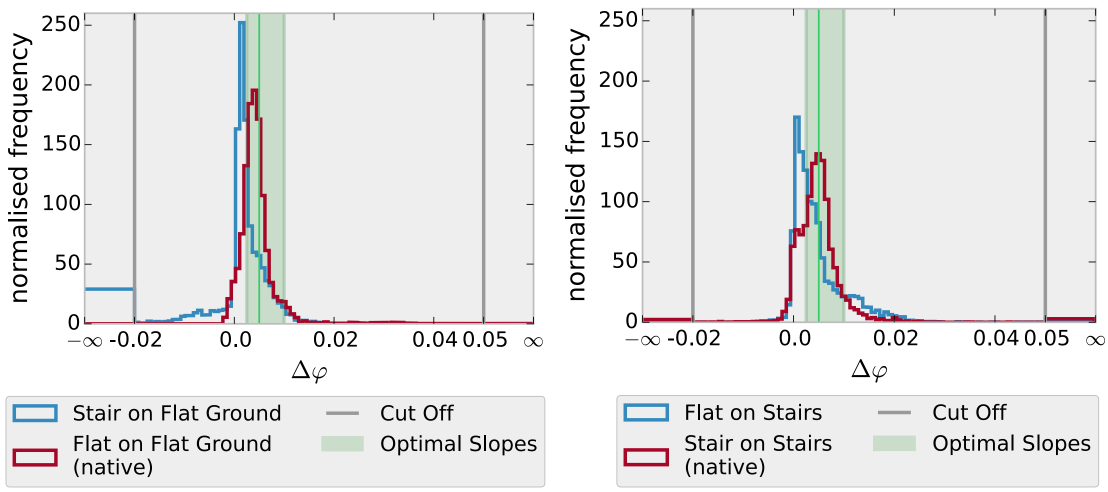


Fig. 2 Each coloured line indicates gait phases for one of 25 steps on flat ground and 8 on stairs. They are smoother for the native model in Figs. 2(a) and 2(d), while the unfitting models in Figs. 2(b) and 2(c) show phase shifts and strong deviations from the desired smooth, linear behaviour of the ideal gait phase φ' indicated by the dashed line.



(a) Increments on Flat Ground

(b) Increments while Stair Climbing

Fig. 3 Comparison of increments $\Delta\varphi$ for data from Fig. 2: the fitting model (in red) shows fewer negative or almost zero increments. For a constant function, all increments would be 0.005. The opposing model has more increments of higher magnitude (collected in one bin) while it is shifted to the left at the same time. All increments $|\Delta\varphi|$ outside the cut off were counted in the bins to the sides; the height is according to the normalisation of a bin with identical width to all other bins.

and therefore excluded, although φ was at the same order of magnitude as for other steps after heel-off, i.e., close to 0. It can be seen, that the fitting model not only offers a more linear increase in the gait phase representation, but the unfitting model is suffering a huge phase shift.

4. CONCLUSIONS

At $100\,\mathrm{Hz}$ sampling frequency, average steps have $150-200$ samples, resulting in $\frac{360}{200}^\circ - \frac{360}{150}^\circ = 1.8^\circ - 2.4^\circ$ per sample, which is comparable to the average precision shown in Table 1. We conclude, that the presented gait models are able to resolve the learned gait with a distribution of slopes, which is centred around the slope of the ideal model (cmp. Fig. 3) and a phase reset which is matching the heel-strike (cmp. the diagonal cells in Table 1). This means, they offer smooth and continuous gait progress tracking, on which model-free, individualised control can be founded.

Models trained for different gaits, on the other hand, show worse performance. We observe sub-optimal increments in Fig. 3 and significant phase shifts of the heel-strike event as in the off-diagonal cells of Table 1.

As changes in the control output are bound to changes of the gait phase φ, an even resolution of φ, or in other words a narrow distribution of increments $\Delta\varphi$, is crucial for detailed and continuous control. Fig. 2(b) shows a controller, that would only have 4 events with drastic changes of its output, whereas a good phase resolution allows fine grained control which is theoretically only limited by the sampling frequency of the underlying hardware.

The phase shift is a consequence of the sensory input's inherent phase relation, which changes with gaits, like on flat ground or stairs. This phase difference between, e.g., thigh and knee angle, makes one model for all possible gaits difficult. Nonetheless, the combination of a well chosen set of specialised gait models with appropriate gait switching [5] implements good gait progress resolution for all gaits.

This raises the important question, how many independent motions have to be supported to gain good results for a specific use case? The application of a fall-back controller to provide simple control in unknown environments is a necessary precaution.

The advantage of this approach lies in the simplicity of the used models with the ability to train all components with live data, i.e., to let the system learn by observation of its user. The absence of device- and motion-models allow manifold applications, even in active devices.

The transfer to patients should pose no problems. While gaits of patients wearing orthoses have a simpler structure in thigh-knee-angle space, when compared to healthy walkers, the only necessity is the existence of a characteristic phase relation, which every gait provides.

The ground contact sensors lead to steps in the gait phase representation, which might be solved with additional sensors or pre-processing. But they provide a safety measure by enabling immediate reactions to stumbling. The restriction to ipsilateral sensors makes the approach suitable for real world prosthetic applications.

This is in contrast to approaches which try to achieve a similar result with gait phase tracking on the healthy leg, like [7], assuming a constant phase shift between the legs. A consequence is additional effort for donning the device. But when stumbling or for other critical events, the assumed phase relation may be lost, while the presented approach faithfully reflects the device's state.

In comparison to state based controllers, the enhanced resolution of gait cycle tracking allows not only detailed control and individual patient fitting, but also prevents the controller to rely on critical points for state transitions, like specific moments or angles, whose accessibility might reduce the target group, or worse, might be depending on the patients fatigue. It handles gaits in a generic manner.

The timing unit provides good resolution for learned gaits. With gait switching it ensures reasonable resolution for all supported gaits. As all components are adaptive, they form the basis for orthoses which adapt to the patients. Whereas up to now, the patient had to adapt.

Acknowledgements: The research leading to these results has received funding from the BMBF-funded BFNT & BCCN Göttingen with grant numbers 01GQ0810 (project 3A) and 01GQ1005A (project D1), respectively.

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