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Internal Models Support Specific Gaits in Orthotic Devices

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Patients use orthoses and prosthesis for the lower limbs to support and enable movements, they can not or only with difficulties perform themselves. Because traditional devices support only a limited set of movements, patients are restricted in their mobility. A possible approach to overcome such limitations is to supply the patient—via the orthosis—with situation-dependent gait models.

To achieve this, we present a method for gait recognition using model invalidation. We show that these models are capable to predict the individual patient's movements and supply the correct gait. We investigate the system's accuracy and robustness on a Knee-Ankle-Foot-Orthosis, introducing behaviour changes depending on the patient's current walking situation. We conclude that the here presented model-based support of different gaits has the power to enhance the patient's mobility.

Keywords: Orthosis; Gait-Classification; Internal Model; Model Invalidation

1. Introduction

Orthoses are supportive devices, which range from splints over passive, mechanical automatons to active components, which are equipped with their own controller. This controller has to work in accordance with the user's movements. Current whole leg orthoses often control the device without instructions from their user. The here presented Knee-Ankle-Foot-Orthosis (KAFO) strives to support movements their user can not (or only with difficulties) perform on his/her own. These orthoses are applied for a variety of medical indications, ranging from stroke, and nerve/muscle tissue damages to many other forms of paraplegia. They are worn in rehabilitation for a limited time or, in many cases, constantly supporting the patient.

Because of size and weight constraints, current orthoses have limited capacities, including computational power, pushing sophisticated control strategies out of reach. The existing controllers are manually tuned to fit the patient, enabling him/her to achieve a basic set of gaits such as walking, sitting down and stair climbing.

To support a wider range of actions, the controller needs knowledge of the corresponding movements and the ability to differentiate between those gaits. Methods for machine driven gait analysis and gait detection were developed in laboratories with an observer[1] or with motion tracking systems.[2] Many different approaches have been employed, including different model based approaches on a variety of extracted features.[3–5] Recently, gait analysis has moved into devices in the vicinity of the body, like mobile phones[6] or sensors embedded in clothes, like shoes.[7] These systems depend on external information or the sampling of a complete stream of sensory data—at least for a complete step—for post-hoc analysis. But application in an orthosis requires immediate gait analysis.

Therefore, we focus on the use of internal models classifying the ongoing movement to estimate the support needed at the moment. In this way, different movements are differentiated early and supported in time.

For standing and walking,[8] and walking on flat ground and slopes[9] a similar on-line approach was applied. Another investigation tested stair descending and ascending in a finite state based controller.[10]

The presented approach is developed and tested on semi-active C-Leg hardware from Otto Bock,[11] which modulates the knee's damping, and thus allows a wide range of behaviours while maintaining low power consumption, as only valves in a hydraulic system need to be actuated. Tests on a real device ensure real world applicability of the method.

2. Methods

2.1. *The device*

The study has been conducted with a KAFO by Otto Bock. The device is spanning from thigh to foot. At the knee joint, a C-Leg$^{\mathrm{TM}}$-element controls the joint's damping properties for knee flexion with a hydraulic system. We employed a prototype with a flexible ankle joint for the experiments in this study. Nevertheless, the controller has been verified to work with a fixed ankle joint, too. The orthosis was equipped with a thigh-angle, a knee-angle and a foot pressure sensor. The latter is so sensitive that it acts as a contact switch.

2.2. *Controller overview*

Here we assume a general controller, which handles the appropriate damping for the 3D input vector of thigh-, knee-angle and foot contact. This controller allows pursuing different gaits, like walking on flat ground or stair climbing, for which it employs individual support. The choice of the appropriate gait is subject to gait classification with the here presented method (see below).

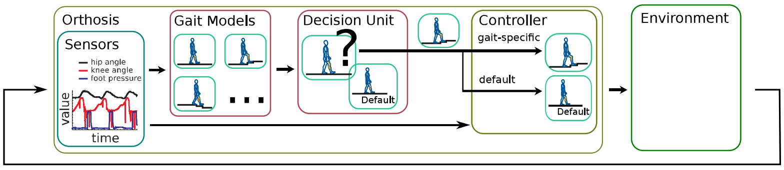

Figure 1. Control flow: Gait models predict the sensory input, i.e., thigh-, knee-angle, and foot contact. The decision unit chooses the model which minimises the error between sensory input and prediction. The actual controller can act according to the specific gait or according to a default mode, if no model fits the current gait. (The human figures are based on a brochure by Otto Bock.)

For each of the supported gaits, an internal model predicts future motion. A decision unit tracks the likelihood, that the current sensory input represents this gait. The decision unit acts on the internal models' output to grant control to the controller which fits the current movement best.

2.2.1. *Internal gait models*

Internal gait models are the basis of the gait classification system. For each supported gait, an internal gait model is trained to predict at every moment in time the next sensory input for the thigh- and knee-angle

$$p^{t+1} = \begin{pmatrix} thigh^{t+1} \\ knee^{t+1} \end{pmatrix} = \text{prediction}(\vec{s}_t, \vec{s}_{t-1}, \ldots)$$

from a history of sensory input vectors s_t, as is shown in Fig. 2 (a). These internal gait models are implemented with multi-layered perceptrons.[12] In our experiments a history of elements up to 20 time steps was used, accounting for $\frac{1}{5}$ s at 100 Hz sampling frequency.

Based on recorded gait data, these gait models were trained to track the individual gait of the user and then applied to additional data sets and tested in the running system.

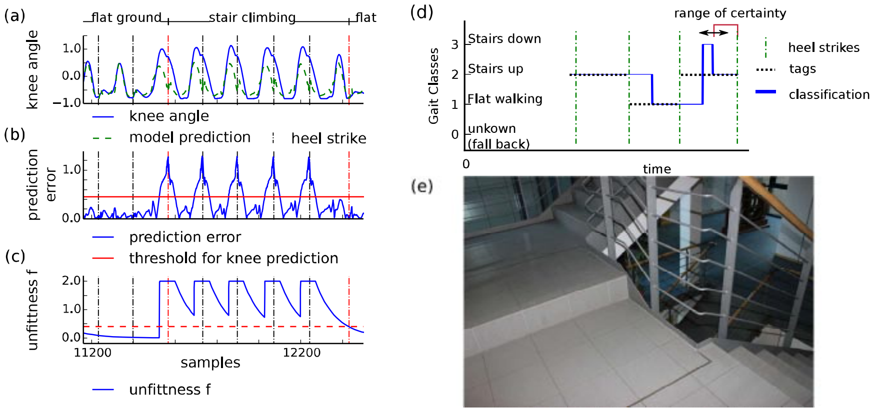

Figure 2. Left column: Gait prediction schematics in open loop condition: a flat walking model in transitions to and from stair climbing. (a) The knee angle sensor and the model's prediction. (b) The low pass filtered prediction error and the threshold θ_i. (c) The processed error count f on which the decision unit chooses the appropriate model. Right column: (d) Gaits are denoted vertically; a sequence of three steps is shown along the horizontal axis. The user's annotations were extended to the beginning of a step and plotted as horizontal lines of black dots. In solid blue, the trained system's output is shown. On the top right the red interval marks the range of certainty, which is the part of the step with correct classification decision which precedes the heel strike. It is normalised on the heel-off-to-heel-strike interval to gain a comparable measure. (e) Picture of the staircase, which was used for open- and closed-loop runs.

2.2.2. *Decision unit*

The decision unit evaluates all model prediction errors for the thigh and knee angles

$$e^t = \left| p^t - \begin{pmatrix} s_t^{thigh} \\ s_t^{knee} \end{pmatrix} \right|$$

for the current time step. To reduce the influence of noise, the low pass filtered errors $\tilde{e}^t$ are checked against a model- and angle-specific threshold. They are ignored if they are below the threshold. Errors greater or equal to the threshold θ_i are counted (see Fig. 2 (b))

$$f_i^t = \alpha \begin{cases} f_i^t, & \text{if } \tilde{e}_i^t < \theta_i \\ (\max(f_i^t + 1, 2)), & \text{else} \end{cases} , \alpha \in \mathbb{R}, 0 < \alpha < 1.$$

f describes how unfit the model is to capture the current sensory input. To obtain a value which can be interpreted on the time scale of a step, the capped error count f is decaying with factor α (compare Fig. 2 (c)). The decision unit chooses from all models with unfitness values below a certain threshold the one with the best, i.e., lowest unfitness value. This process is indicated with a dashed line in Fig. 2 (c). If all models produce too high unfitness values f, the decision unit labels the current gait as unknown. Then the existing default controller will ensure basic orthosis operation.

2.3. *Walking experiments*

Walking experiments were conducted by a healthy subject equipped with the prototype. As a ground truth for evaluation of the classification accuracy, the user annotated his/her current gait, such as walking on flat ground or climbing stairs. Figure 2 (d) shows three steps of a recording. Also recorded were the sensory input, and the decision unit's gait classification. Walking experiments took place indoors, along long floor passages and stair cases over five stories.

2.4. *Quantification of prediction quality*

To quantify the quality of gait classification, we measured success rate and timing, i.e., how early the correct classification occurred. Here we put a focus on the correct classification before the heel strike, to make sure, that in an on-line scenario the classification is available in time. We define the *range of certainty*, which constitutes the consistent last fraction between heel-off and heel strike, where the correct gait is continuously detected up to the heel strike, as illustrated in Fig. 2 (d). A range of certainty of 100 % therefore means, that the gait is known on heel-off. A range of certainty of 0 %, in contrast, means that the gait is not classified correctly before heel strike.

The achieved range of certainty is depending on the individual step and the specific gait. Thus, to explore the reliability of gait recognition we investigate (a) the average success rates for all gaits, and (b) the classification accuracy if *minimal ranges of certainty* of 20 % and 3 % are *required.*

3. Results

The predicting models have been created with training sets sized 146 steps for flat walking, 35 steps for stair climbing and 32 steps for descending stairs. These training sets contained selected steps from four recordings and included no gait transitions. For evaluation, three independent recordings including gait transitions have been used, totalling 215 steps (81 steps on flat ground, 64 steps mixing flat ground and stair climbing, and 70 steps mixing flat ground and stair descending).

Figure 3 (c) shows the dependence of the averaged classification success rate on the chosen minimal range of certainty averaging all gait models. While over 83 % of all steps are correctly classified at the beginning of the step, naturally, for all other steps the success rate increases, when the range of certainty is reduced. In this experiment, the average success rate was slightly above 94 % at heel strike.

The distribution of the classification results can be seen in the confusion matrices for required minimal ranges of certainty of at least 20 % in Fig. 3 (a), and 3 % in Fig. 3 (b). In these matrices the annotated gait is contrasted with the model based predictions.

In general, the classification performance is quite good for walking on flat ground with over 94 % accuracy and 100 % for stair climbing, whereas the performance for steps descending a stair is lower with at least 84 %. Noticeable are comparably low frequencies of false positives classifying flat walking as descending stairs (1 %), descending stairs as flat walking (5 %), and flat walking as stair climbing with 5 % in the case of a 20 % range of certainty. The success rates increase, when the range of certainty is reduced, as detailed in Fig. 3.

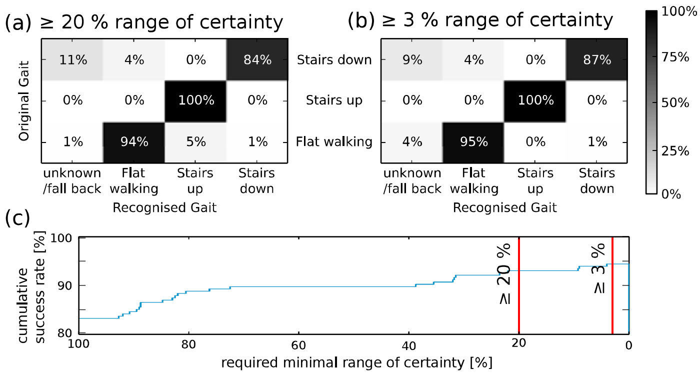

Figure 3. For 215 steps (c) is showing the success rate depending on the required minimal range of certainty, which goes slightly above 94 %. Earlier success or sequences of consecutive steps provide the high offset. For the ranges marked by the vertical red lines, at 20 % and 3 %, the detailed comparison is shown in (a) and (b), respectively. There the manual annotation in the rows is compared with the method's results in the columns. The field on the intersection show the frequency of steps with a tag which end up in the corresponding class. The class "unknown/fall back" catches all steps which no model could reliably predict, ensuring basic operation of the device. The number of false positives and unknown gaits decreases with the required minimal range of certainty.

The false positives are associated with transition steps, i.e., the gait often changes in a step. For the user annotating his/her gait this poses the problem, that pinning down the moment of transition to a specific point is difficult. Therefore, the ground truth created with this method is debatable. After inspection, the effected steps seem ambiguous and the method's output reasonable. For the same reason, a range of certainty of 100 % is not achievable.

The required minimal range of certainty should be short enough, to react in the same step, while being long enough for the controller to react. For our setup, which is sampling its sensors with 100 Hz, and typical step lengths between 130 and 180 steps for flat walking and stair climbing, respectively, this means that a required minimal range of certainty of $\gtrsim 3\,\%$ is sufficient. For this value, the average success rate for all gaits is above 94 %.

The second important result shown in Fig. 3 is that there is a diminishing rate of false positives, even if a specific model provides lower accuracy. The proposed method classifies unrecognised steps as "unkown gait", thus preventing the controller to treat the coming heel strike in a wrong and possibly dangerous way. This allows the system to apply a fallback control method, which always ensures the patient's safety, although most probably sacrificing comfort.

4. Conclusions

The advantages of our approach are the general applicability and flexibility of the internal models with respect to applied sensors, hardware configuration, and classification intervals, demonstrated with gaits for flat walking, stair descending and ascending with comparably few (3) sensors and a low sampling frequency of 100 Hz. It makes no assumption on specific transitions between states or other dynamic properties, like a finite state based controller, and is able to switch any time in the gait and as often, as the user changes his intent.

The here presented method classifies gaits in an on-line scenario with reaction times fast enough for in step adaptation, high recognition rates and a diminishing rate of false positives approaching heel strike.

Many approaches apply model invalidation on many sorts of models.[3–5] In the here presented case, as long as a model is predicting the sensory input with a sufficiently small error, the assumption is, that the controller can apply a control scheme fitting for this model. The important elements for successful application are (a) a set of suitable sensors, to resolve the different dynamics; (b) thresholds, which define if the prediction error is still acceptable and (c) a set of gaits, the controller can actually handle. As long, as these factors are well chosen, the presented method is independent of the set of sensors and the actual geometry of the device, to which it is applied. In the case of lower extremities, the method allows specialised support of multiple gaits or movements, increasing the patient's comfort and safety.

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