EXPLOITING MOTION SYMMETRY IN CONTROL OF EXOSKELETON LIMBS

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ABSTRACT
In this paper we present a method to control a one-legged lower extremities orthosis by analyzing the current trajectory performed with the healthy leg and feeding a proper - if necessary phase-shifted - trajectory to the disabled leg encased in the orthosis.

For this, a fast and simple modified version of the cross correlation is used. The algorithm works on multiple reference curves by minimizing the error between the reference and the current data by adaptively walking forward through the reference of the healthy leg and reporting back the reference values for the disabled leg. The proposed method will be part of a control system for an exoskeleton robot that should aid the wearer in everyday-life situations like walking, standing up and sitting down.

The performance of the presented method was investigated on the leg movement in sagittal plane without contact to unknown obstacles.

KEY WORDS
Robotics, Correlation, Exoskeleton, Orthosis Control, Disabilities

1 Introduction

Natural locomotion of humans and animals is mostly a periodic movement of the limbs. Depending on the motion, the lower extremities perform the same possible phase shifted movement, as e.g. in walking or rising from a chair. So it is a reasonable idea to derive the motion of one leg from the motion of the other leg.

When considering an exoskeleton robot for a disabled person (Fig. 3) there are two main aspects that have to be regarded: First, the motion intention of the subject must be detected. This can be done in various ways, for example with force sensors or electromyographical signals (e.g. [1–4]). On the other hand, it must be guaranteed that the system is stable during the motion because the disabled person might not be able to maintain stability. Most studies in the field of biped robots are without any human interaction [5–8] or without integrating the subject directly into the control loop which is desirable for an exoskeleton robot.

1.1 Idea

In this paper we are presenting a new method of combined intention detection and calculation of a proper motion trajectory for the legs: The idea is to get the intended motion from the healthy leg, and compute an appropriate trajectory for the disabled leg.

The advantage of this approach is obvious: There is no need for complicated calibration of EMG-signals or force-sensors and the simplicity of the sensors utilized promises an easy-to-use interface for everyday life. For paralyzed people it is especially useful, since there is no possibility to record muscle signals from the disabled leg. In contrast to other input interfaces using gestures or speech, the proposed algorithm can be used very intuitively.

Of course there are some drawbacks: All movements have to be initiated with the healthy leg so that the intention can be derived, and predefined trajectories are always lacking certain flexibility of other approaches. But in Sec. 6 some ideas are presented to deal with those problems.

1.2 Goal

With recorded reference patterns for the different motions it should be possible to identify the currently performed one and the current position within the trajectory. The retrieved control vectors can be brought directly into the control loop of the exoskeleton motion controller to allow the user to have a normal movement with a very small time delay, even if the subject cannot perform the motion on its own.

The paper is organized as follows: Sec. 2 gives an overview of the whole system with the orthosis, actuator and the motion capturing system including filtering of the sensor data. In sec. 3 the correlation algorithm is explained in detail and in sec. 3.3 the properties of the suggested approach are summarized. The experimental setup is described in sec. 4. Results demonstrating the performance of the algorithm are presented in sec. 4 and discussed in sec. 5.

2 Environment

In this section, the software and hardware environment is described in which the correlation algorithm is embedded. Please refer to Fig. 1 for an initial overview of the whole software system and to Fig. 3 for the hardware of the exoskeleton.

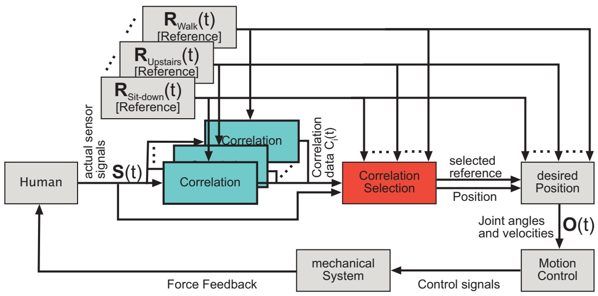

Figure 1. General control scheme for a mechanical system attached to the human body. The sensor data $\mathbf{S}(t)$ from the *Human* are given into each *Correlation* instance. In there the correlation C_i were calculated. The *Correlation Selection* block take those results and determine, with some more information, a sensible position and trajectory of the references. Afterwards the block *Desired Position* selects with this *Position* and *Selected Reference* the control vector $\mathbf{O}(t)$ for the *Motion Controller*. This block computes the control signals for the *Mechanical System*. Because of the coupling between the user and the mechanical system, the user will experience a *Force Feedback*.

As described in the introduction, the basic idea is to let the *Human* interact with the *Mechanical System*. To achieve this, the *current sensor signals* $\mathbf{S}(t)$ are read with $1kHz$ and down sampled to $100Hz$ from the sensors attached to the orthosis giving the current pose of the subject.

The blocks *Correlation* take the previously recorded reference data of the individual motions $\{\mathbf{R}_{Walk}(t), \mathbf{R}_{Upstairs}(t), \ldots, \mathbf{R}_{Sit-down}(t)\}$ and correlate them with the current pose data:

$$C_i(\tau) = \mathbf{R}_i \circ \mathbf{S} \tag{1}$$

with $\tau \in \{\text{domain of } \mathbf{R}_i\}$. The resulting *Correlation Data* C_i are then fed into the *Correlation Selection* box. With additional information of the motion and the reference trajectories one reference $\mathbf{R}_{current}$ will be chosen and the current position will be determined in a way that only possible and reachable positions remain. The resulting *Position* and *Selected Reference* is fed into the block *Desired Position* in which the suitable *Kinematic Data* (joint angles and velocities) $\mathbf{O}(t)$ of the reference data will be picked out. The *Motion Controller* takes this desired movement and computes the control signals for the *Mechanical System*. Because of the connection between the human body and the mechanical system, the motions of the actuators of the mechanical system affect the human body (*Force Feedback*).

The block *Correlation* and *Correlation Selection* is the main contribution of this paper.

In this paper only the movement of the legs in sagittal plane without unexpected collision with the environment is considered (refer to Sec. 4 for the experimental setup).

2.1 Measurement System

The measurement system is needed to capture the current and the reference data of the motion from the limbs and the torso. Two different systems are used for measuring the angles: The angles for the torso and the thighs are measured using two axes accelerometers ADXL210 from AnalogDevices Inc [9]. As shown in Fig. 2 the orientation in sagittal plane can be calculated by projecting the earth gravity field into the x- and y-axes of the sensor:

$$q_i = \arctan 2\left(\frac{G_{y\,i}}{G_{x\,i}}\right)$$

The hip angles (q_1, q_4 see Fig. 4) are calculated by $q_{Hip} = q_{Torso} - q_{Thigh}$. To reduce additional accelerations from thigh and trunk movement, the sensors are attached as close as possible to the axes of rotation of the joints. The error is small enough below an angular acceleration of $45\frac{deg}{s^2}$. The sensors unfortunately have a full-range of $\pm 10g$, so only 10% can be utilized.

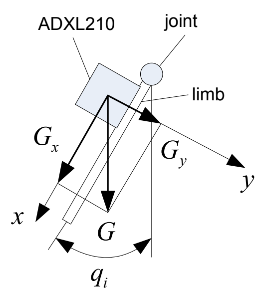

Figure 2. e.g. Capturing the thigh angle to ground with two axes accelerometer ADXL210.

For the angles in the knees (q_2, q_5) and ankles (q_3, q_6, see Fig. 4) hallsensors are used, giving analog output proportional to the angles of the joints. These sensors are mounted on the orthosis (see Fig. 3) and on a small additional exoskeleton for the left leg.

2.2 Filtering

For reasons of improved processing of the sensor signals, noise reduction for the accelerometers is necessary. All sensor signals will be measured with $1kHz$. From this input signal the mean value over the last 50 samples is calculated and down sampled to $100Hz$. The averaged and down sampled sensor data are recent enough to represent the current situation and show only little noise, so that the correlation can work properly.

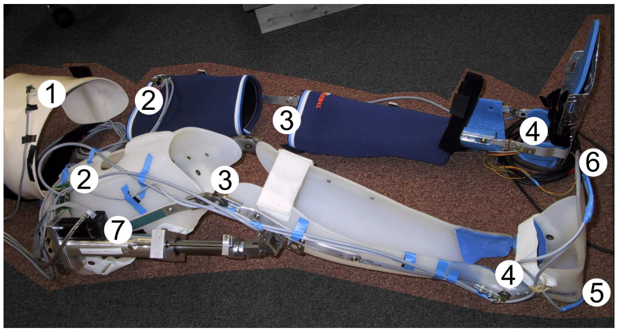

Figure 3. Orthosis with the mounted sensor system and actuator. [7 degrees of freedom measured, a single one is actuated] (1) plate with sensor for the trunk [angle relative to the horizontal line]; (2) sensor for thigh angle to the horizontal line; (3) knee angle sensor; (4) ankle angle senor; (5)(6) pressure plate to detect the toe and heel contact to the floor; (7) actuator

2.3 Coordinate System

To understand the diagrams later in this paper this section describes the coordinate systems of the model. Refer to Fig. 4 for an overview of the model.

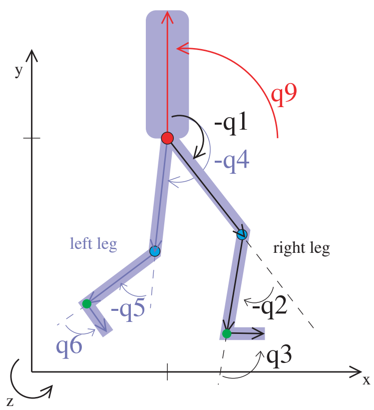

Figure 4. Definition of coordinate systems and angles between the body parts: All coordinate systems are "right handed systems", x-axes of all body-parts point along the bone from the hip, y-axes lie in the sagittal plane, possible movements are rotations around the z-axes of the coordinate systems, angles order is (hip, knee, ankle), right leg (q_1, q_2, q_3) and left leg (q_4, q_5, q_6).

For all body-parts the x-axes point along the bone of the limb away from the hip. The y-axes lie within the sagittal plane and together with the z-axes they form right handed systems. All possible movements in the model are rotations around the z-axes of the coordinate systems. The angles in the order of hip, knee and ankle are for the right leg (q_1, q_2, q_3) and for the left leg (q_4, q_5, q_6).

An upright standing human has therefore $q_1 = q_4 = -180°$ (hip angles), $q_2 = q_5 = 0°$ (knee angles) and $q_3 = q_6 = 90°$ (ankle angles). The orientation of the torso is measured between the x-axis of the reference system and the torso: $q_9 = 90°$.

3 The Algorithm

The overall goal is to search in the selection of reference movements $\mathbf{R}_j(t)$ with $j \in${Walk, Upstairs, ..., Sit-down} the closest match to the input signal vector $\mathbf{S}(t)$ recorded from the healthy leg and return the associated control vector $\mathbf{O}(t)$ for the motion of the orthosis-leg.

$$\mathbf{S}(t) \oplus \mathbf{R}_j \Rightarrow \mathbf{O}(t) \text{ with}$$

$$\mathbf{S}(t) = \begin{pmatrix} S_{leftHip}(t) \\ S_{leftKnee}(t) \\ S_{leftAnlke}(t) \end{pmatrix}, \mathbf{O}(t) = \begin{pmatrix} O_{rightHip}(t) \\ O_{rightKnee}(t) \\ O_{rightAnlke}(t) \end{pmatrix}$$

For this the *algorithm* is divided in three parts (refer to sec. 2):

1. Calculate for each reference trajectory the correlation $[C_i(t)]$,
2. selects the best correlation and determine the best position representing the current state in the given motion,
3. generate the control vector $[\mathbf{O}(t)]$ for the actuator controller.

To get better results during the correlation the angles of the reference curves (especially for the hip) are lowpass filtered with a cutoff frequency of $f_c = 5Hz$. This is possible without a time delay, because the complete reference trajectory is available before the system starts and can be computed by using acausal filter methods.

3.1 Correlation

The correlation function for finding the current position of the pose as recorded from the sensors within a given reference trajectory is defined as follows:

$$C_l(i,t) = \sum_j [g_j * \sum_{k=0}^{m} (S_j(t-k) - R_{l,j}(i-k))^2] \quad (2)$$

where

- $C_l(i,t)$: correlation value for the i-th sample resp. position of the reference trajectory l at time t
- l: selected reference from the whole set of available references: {Walk, Upstairs, ..., Sit-down}
- j: all input sensors (angle curves) that should be used in the correlation function
- g_j: the weight value for a specific sensor, to give it an adjustable contribution to the correlation
- m: length of the correlation windows, the period of comparing the reference to the actual data

- $S_j(t-k)$ current sensor output with a sensor-specific history for sensor j
- $R_{l,j}(i-k)$ reference data of the trajectory l for the sensor j at position $(i-k)$.

The correlation has some interesting features: The function works on the difference of the sensor $S_j(t-k)$ and the reference data $R_{l,j}(i-k)$, so the DC-offset in the signals is eliminated [10]. This is necessary because the DC-offset for the normal cross-correlation term $\sum_{k=0}^{m}[S_j(t-k) * R_{l,j}(i-k)]$ would wrongly result in better values for bigger DC-offsets.

Furthermore new trajectories can simply be added without additional adaption.

Through the offset elimination, comparable correlation results are computed for each sensor. This makes it possible to fine-tune the correlation through the weights g_j. On the one hand, it is possible to give the individual angle a higher priority if it is very important for the trajectory, on the other hand this is useful if the sensor has a great variance in the reference or to reduce the effect from noisy sensor values.

The choice of the correct correlation window lengths is a compromise between a good matching in the position and disregarding the motion in the joints (derivation of the angles), longer correlation windows put more weight on the path of the motion, but makes recognition more difficulty if the current motion differs too much from the reference. Currently window lengths of $0.25s$ (25 samples) are used.

The correlation is defined as a function which is always positive, returning a minimum for the best matching and has an evaluation factor for each sensor.

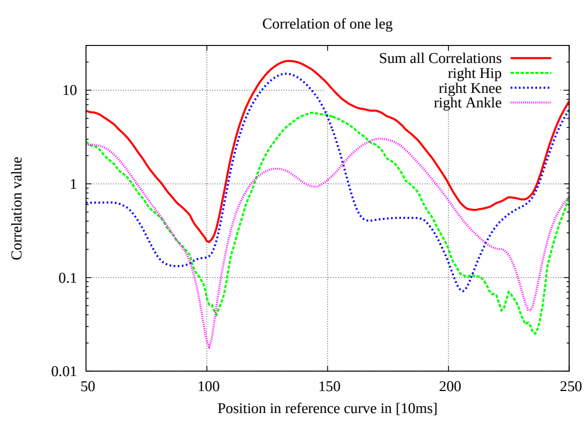

Figure 5. Correlation of the single signals from the right hip, right knee and right ankle angle as well as the final correlation signal. Motion: walk on flat ground, the right leg swings past the left in this moment. The separate correlations of the joints have no definite minimum, just the sum gives an unambiguous result.

By using the weighted sum of the correlations for every single joint angle in eq. 2 the performance of the correlation algorithm was significantly improved. In fig. 5 one can see the calculated correlations for the single joint and the sum of the correlations from the trajectory "walk straight on" in the moment of the left leg swinging past the right leg, means both thighs are parallel.

Looking at typical trajectories using the sum of the separate correlations is not only an improvement, but a vital property because many correlations have more than one local minimum. The correlation of the right hip for example would have two possible solutions at $1s$ and at $2.4s$. Other correlations give diverse results partly with multiple solutions between $2.0s$ and $2.5s$. Generally a single correlation will give ambiguous results, and only the evaluation of the sum of the correlations gives a good result, like at $t = 1.0s$.

3.2 Trajectory Handling

This part of the algorithm implements the general management of the correlation data $C_l(i,t)$ (eq. 2) and the reference trajectories.

Depending on the quality of the signals from the angle sensors, noisy signals might lead to unwanted jumps while correlating along the reference trajectory. While jumps forward might be normal and indicate that, the subject is moving (maybe faster as usual) along the predefined trajectory, backward jumps are to be avoided in any case to omit vibrations in the signals of the *Motion Control Unit* that would result in strain on the subject and the mechanical construction.

To avoid moving backwards along the trajectory, only a small region in the near future of the position calculated during the last cycle (of the currently selected motion) will be regarded. This means that the calculated position within the data can never go back for reasons like measurement errors or sensor inaccuracy.

Since one reference trajectory only contains a single period of motion it is possible to loop through trajectories for a continuous motion.

To change from one trajectory to another, special regions in the reference trajectories are defined to indicate compatibility with other trajectories. This compatibility means that it is safe to switch from one trajectory to another and will not result in unwanted jerks. To avoid repeatedly quick switches between trajectories in transition regions, a hysteresis-function will be introduced to keep track of the correct behaviour. This will be realized using a small state-machine.

Outside the transition regions the correlation function for the other trajectories can be switch off.

3.3 Summary of the Important Properties

The method has the following properties:

- Multiple motion/trajectories are correlated.
- Only valid transitions between the different motions are allowed.

- Quick response time to intended motion, accurate.
- No unpredictable or undefined behaviour for the orthosis-leg.
- Possibility to have a short "look" into the future by using $\mathbf{O}(t + \Delta t)$ instead of $\mathbf{O}(t)$

4 Experiments

The experiments were divided in two parts:

In the first part the reference trajectories for the right and left leg were recorded (refer to fig. 6 for an example). Several measurements for stand up, sit down on a chair, walk, walk slowly and go up and down stairs were recorded. The movement was always not hindered by any obstacles or other external forces beside the ground reaction forces.

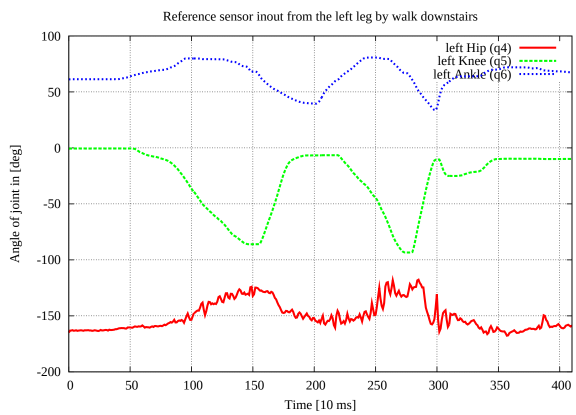

Figure 6. Sensor values for the left leg while going downstairs. The diagram is splitted in three phases: standing in front of a staircase until $0.5s$, going two stairs down until $3.5s$ and stop there. The curves show the movement in the joint angles (hip q_4, knee q_5 and ankle q_6).

During the second part of the experiments new movements of the left leg were integrated into the system. The output of the correlation for the disabled leg is compared with the measured sensor data from the right leg during normal gait.

In fig. 7 (walk upstairs) and fig. 8 (walk straight) the movement of the measured angles q_1 (hip), q_2 (knee) and q_3 (ankle) of the right leg are shown with the corresponding counterpart from the correlation algorithm. The transfer from the movement of the left leg to the right works in both cases.

When looking at fig. 7 (going upstairs) and fig. 8 (walking straight on) it can be seen that going upstairs has two times larger changes in the angle values as walking on flat ground, so it could be easier to track. But the results show that the correlations work equally good for both experiments.

As can be seen in Fig. 7 and 8 the correlation produces a sufficiently good relationship between the reference movement of the right leg and the transferred motion for the right leg.

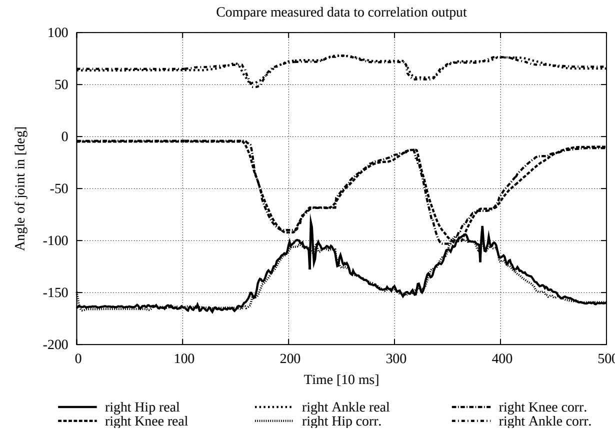

Figure 7. The diagram shows the motion of standing in front of a staircase until 1.5s and going two stairs up. The curves show the measured movement in the joint angles (hip q_1, knee q_2 and ankle q_3) and the counterpart from the correlation algorithm. The spikes in the hip angle data are caused by the contact of the foot with the stair.

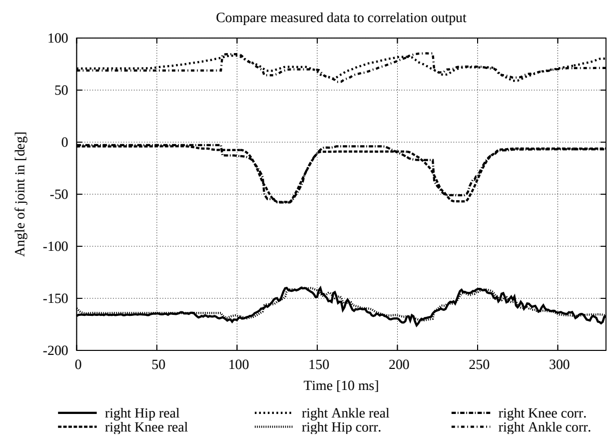

Figure 8. The diagram shows a short standing position phase from $0.5s$ followed by a two step walk straight on. The curves are the measured movement of the joint angles (hip q_1, knee q_2 and ankle q_3) and the counterpart from the correlation algorithm.

Fig. 9 shows a correlation run with an input trajectory which has no counterpart in the references. It is walking with half speed on flat ground. Still the correlation recognizes it as walking and the output is acceptable. The progress through the reference trajectory is automatically adapted through the correlation to match the pace dictated by the left leg. There are some phase shifts up to $0.2s$ in the movement of a single joint, but the overall motion is preserved. It has to be examined what the consequences of this phase shift are and if the gait is still stable.

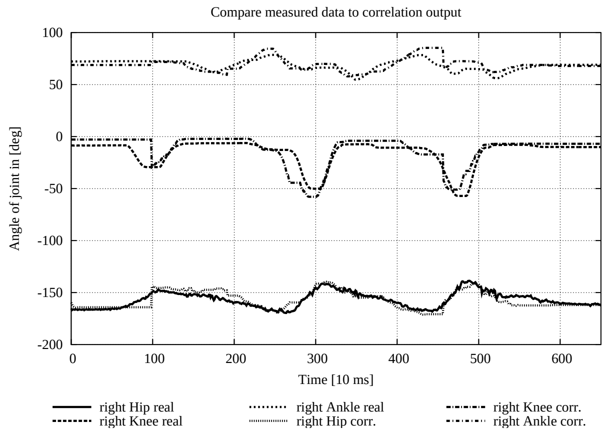

Figure 9. The diagram shows a correlation for a movement with half velocity of the reference data. After the standing phase at the beginning, at $1.0s$ a short start step followed by two steps at $3.0s$ and $5.0s$ walked very slowly straight on. The curves are the measured movement of the joint angles (hip q_1, knee q_2 and ankle q_3) and the counterpart of the correlation algorithm. The phase shift an angle errors are obviously larger.

5 Discussion

In section 4 we have seen that the correlation method with the following *Correlation Selection*-algorithm produces output that leads to quite a good recognition of the subjects movement and thus to a well synchronized output for the disabled leg. But what does *quite good* mean? As stated in the introduction, our main focus is to allow interaction of a human with an exoskeleton robot resulting in a stable gait and other movements by transferring the movement of one leg to the other as good as possible. That means, the delay between signal acquisition and delivering of the output has to be minimized. If it appears that the whole algorithm has a phase shift too large to allow a stable movement then the shift can be eliminated by retrieving values from the reference trajectory from a point originating slightly in the future.

6 Conclusion and Future Work

A method for prediction of motion was presented. The proposed algorithm was designed as part of the control system for an exoskeleton. In this context the main attention was paid to the capability of the system to identify the intended movement of the human.

It was shown that with the presented version of the algorithm calculation of the intended movement of the leg is possible (see Fig. 7 in sec. 4). At the moment, the results of the calculated movement are achieved almost at the same time with the performed movement.

One of the next steps will be to extend the *Correlation Selection*-block with a state-machine based on Markow chains and processes for a better state-model.

Another very interesting point is the possibility to feed the trajectory from the healthy leg to the disabled leg and omitting pre-defined trajectories except for initial and transition regions. This would allow adapting the stride length, step height and other parameters easily and intuitively. Also the environment would not need to be similar to the place where the trajectories have been recorded. A lot of experiments have to be performed here to check if this is a reasonable approach.

All experiments have been performed with healthy persons and without activating the exoskeleton. So it is a further step to validate the described intuitive human-to-robot interface with handicapped persons.

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