Direct Control Identification in Human Gait

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TODO

Todo list

Abstract

Write one!

Introduction

Recent research and commercial activity indicate that gait-related powered prosthetics will play an important role in both assisting humans with disabilities and enhancing the abilities of the able bodied. These devices include a variety of sensors and actuators than can be coupled to a control system to provide assisted gait. There are currently commercial version of powered trasnfemoral leg prostheses [?] and lower extremity exoskeleton [?] and many products still in the research phase [?, ?, ?, ?] that hope to increase the mobility of the disabled. As promising as these devices are the available lightweight lower extremity exoskeletons lack gait that resembles an able-bodied human both in terms of stability and "natural" gait motions.

Due to the highly non-linear plant robust control is difficult to come by from first principles for these devices. Although work based on [1] are giving promising results in simulated musculoskeletal systems [7, ?] these controllers still only produce marginally stable simulations.

Even though constraining the controller to rudimentary models of the musculoskeleteal system is fruitful, we are curious if more generic control structures can reveal more robust controllers. To improve the gait of powered prosthetics, our intent is to identify a simple, linear controller from a large set of data collected from able-bodied subjects being perturbed by random longitudinal forces.

We pose our problem as such: given a "human-like" plant, i.e. one with similar degrees of freedom and inertial properties to a human, that is actuated with simple joint torques can we identify a feedback control mechanism for this system that causes it to walk stably and recover from perturbations in much the same way a human does?

We hypothesize that typical gait measurements taken while a person is walking under the influence of perturbations can be used to identify a generic and potentially robust feedback controller for simulated or robotic system. Other researchers are also pursing this path.

[6] proposed a finite state proportional derivative feed back controller for a powered transfemoral prosthesis. The control law that generates the desired joint torques is based on three constants and a desired angle set point for each of the four modes of a gait cycle. They found the values of the controller by fitting their controller to normative joint angle, angular rate, and torque estimates from a single gait cycle from an able bodied walker. This method is unlikely to actually identify a true controller due to the inherent errors expounded by [4] but may have merit as [5] found quasi-stiffness to be equivalent to stiffness. The authors ended up hand tuning their controller based on user feel leaving them with a controller that was less than data driven.

Add in a description of Hugh Herr's BiOM controller

Elliot Rouse's [?] work is most similar to ours. They identified the parameters of a linear mass-spring-damper model of the lumped ankle's passive and active impedance by perturbing at four points in the stance phase of the gait cycle. He does not explicitly claim that their model is a controller, opting to call it modulated impedance instead. Rouse et al. carefully isolate the change in joint angle and torque due to the perturbation and derive their model parameters to avoid the issues discussed in [4]. He shows a linear relationship for stiffness with respect to 20-70% phase.

More recently [8] uses a simpler approach and is able to predict foot placement with a simple linear model derived from kinematic data that relates the mid-stance pelvic state to the following foot location. This is questionable though, as there is no way to show that this is a control mechanism and not simply a mechanical correlation. This analyses was performed without external perturbations suggesting that the walker self-perturbs enough to glean results.

We approach this "control" identification problem in a similar fashion as [5] but by making use of a much richer data set that has the potential to expose multi-input multi-ouput control mechanisms for the entire body. We collect greater than 15,000 gait cycles from 11 subjects walking at three nominal speeds on an instrumented treadmill where we measure the kinematics of a full body marker set and a full set of ground reaction loads at each foot while perturbing the subject by varying the belt speed with Gaussian-like noise. We then identify a gait phase gain scheduled non-linear controller with the so called direct identification method [2].

Methods

Experiments

The data includes a large number of gait cycles (¿ 19000) for 11 subjects subjects walking at three nominal speeds, $0.8\,\mathrm{m\,s^{-1}}$, $1.2\,\mathrm{m\,s^{-1}}$ and $1.6\,\mathrm{m\,s^{-1}}$, on a treadmill with and without pseudo-random longitudinal perturbations in the belt speed. The data is a subset of the data reported in [3] and we refer the reader to that publication for the details about the experimental protocol and data. The subject metadata parameters are given in Table 1.

Data Preprocessing

The "raw" data provided by [3] consists of 100 Hz time series of marker and ground reaction loads in addition to event time identifiers. We make use of an open source software package, GaitAnalysisToolKit, to process the data. The processing follows these steps:

1. Identify missing markers and the corresponding time instances.
2. Replace missing markers with linearly interpolated values.

Table 1: Information about the 11 study participants. The final three columns provide the trial numbers associated with each nominal treadmill speed. The measured mass is computed from the mean total vertical ground reaction force just after the calibration pose event. Generated by `src/subject_table.py`.

Id	Gender	Age [yr]	Height [m]	Mass [kg]	0.8 m/s	1.2 m/s	1.6 m/s
3	female	32	1.62	54 ± 2	46	47	48
5	male	23	1.73	71.2 ± 0.9	32	31	33
6	male	26	1.77	86.8 ± 0.6	40	41	42
7	female	29	1.72	64.5 ± 0.8	16	17	18
8	male	20	1.57	74.9 ± 0.9	19	20	21
10	male	19	1.77	92 ± 2	61	62	63
12	male	22	1.85	74.2 ± 0.5	49	50	51
13	female	21	1.70	58 ± 2	55	56	57
15	male	22	1.83	80.5 ± 0.8	67	68	69
16	female	28	1.69	56.2 ± 0.6	76	77	78
17	male	23	1.86	88.3 ± 0.8	73	74	75

3. Filter all signals with a forward/backward 2nd order low pass Butterworth filter with a cutoff frequency of 6 Hz.

4. Section the trials into unperturbed and perturbed sections based on the event times.

5. Compute the planar inverse dynamics for the lower body: right and left ankle, knee, hip joint angles, joint angular rates, and joint torques [**?**].

6. Identify the heelstrike times based on the vertical ground reaction force.

7. Segment the time series into gait cycles based on the right foot's heel-strikes.

8. Linearly interpolate the time series in each gait cycle to a specific number of data points so all gait cycles have the same number of samples.

9. Remove any outlier gait cycles that were not properly identified due to abnormal ground reaction force measurements.

After the initial processing above, the data is stored in three dimensional arrays for each phase of the trial M x N x (q + p), where M is the number of gait cycles, N is the number of phase instances in the gait cycle, and (q + p) are the number of measurements. Figure 1 shows the mean and standard deviation of across the gait cycles for selected time series for both unperturbed and perturbed walking. Furthermore, Figure 2 compares several gait statistics of interest for unperturbed and perturbed walking. These two figures are intended to show that there is variation in the subject's motion that is a direct result of the longitudinal perturbations.

Figure 1: Right leg mean and 3σ (shaded) joint angles and torques from both unperturbed (red) and perturbed (blue) gait cycles from trial 20. We define the nominal configuration, i.e. all joint angles equal to zero, such that the vectors from the shoulder to the hip, the hip to the knee, the knee to the ankle, and the heel to the toe are all aligned. Produced by `src/unperturbed_perturbed_comparison.py`.

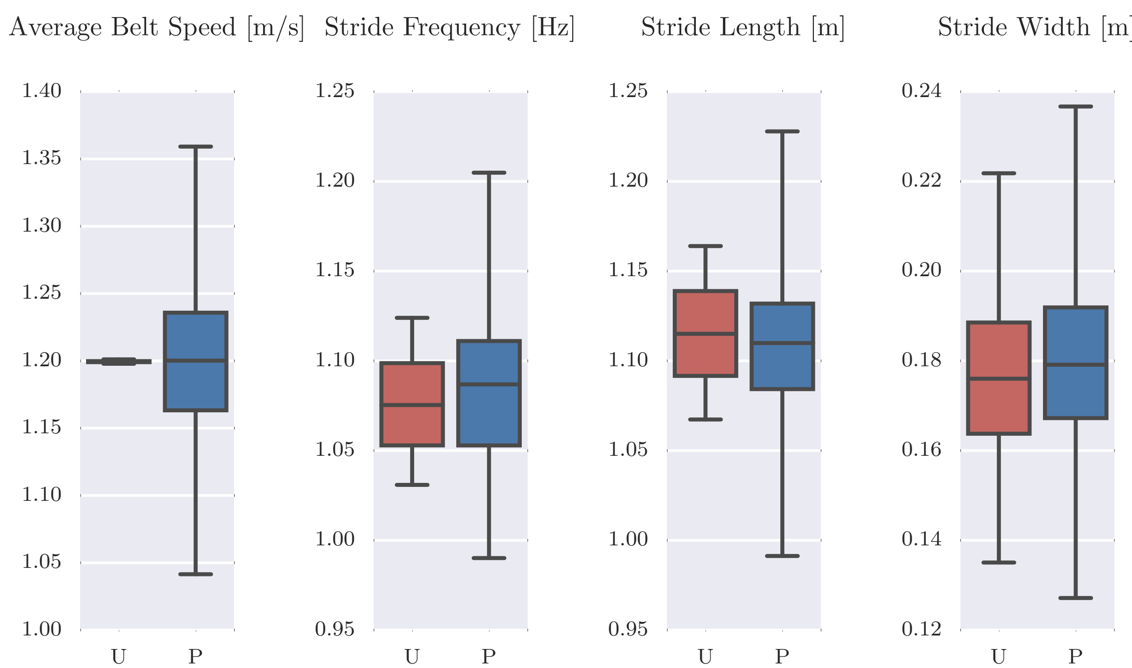

Figure 2: Box plots of the average belt speed, stride frequency, stride length, and stride width which compare 120 unperturbed (U: red) and 519 perturbed (P: blue) gait cycles. The median is given with the box bounding the first and third quartiles and the whiskers bound the range of the data. Produced by `src/unperturbed_perturbed_comparison.py`.

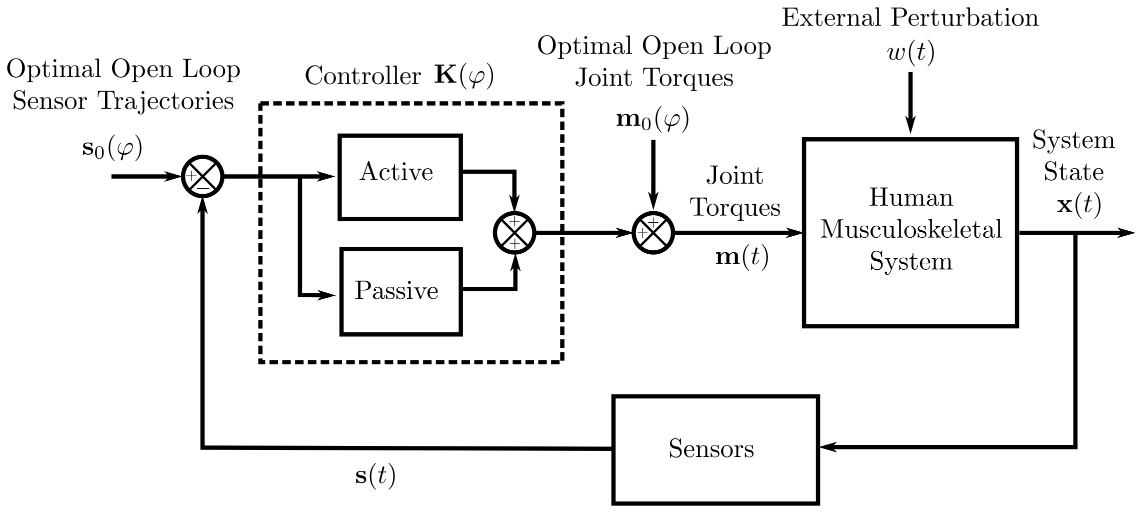

Figure 3: The controller block diagram

Controller

We assume a black box [1] control structure for the closed loop system, Figure 3. We first assume there is an unknown non-linear plant, i.e. the open loop musculoskeletal system and treadmill, that has an unknown time varying state. This plant can be perturbed by an external exogenous input $w(t)$, in our case by varying belt speed, and is also driven by joint torques $\mathbf{m}(t)$. An unknown sensor model generates feedback signals, $\mathbf{s}(t)$, that are compared to a nominal gait phase dependent reference trajectory $\mathbf{s}_0(\varphi)$ that describes the gait phase varying state for cyclic gait when no feedback is necessary. The error in these sensors are fed into the controller which generate corrective joint torques that are added to the nominal gait phase dependent joint torques $\mathbf{m}_0(\varphi)$ that correspond to the nominal trajectories, $\mathbf{s}_0(\varphi)$. We then assume that when the actual state deviates from the nominal state trajectory that the controller computes additive joint torques based on the state trajectory error to compensate for variation in gait away from the nominal.

The controller is designated as a gait phase scheduled gain matrix, $\mathbf{K}(\varphi)$, that relates the error in the state trajectories to the additive joint torques. The controller structure bounded by the box in Figure 3 can be described by the following algebraic equation.

$$\mathbf{m}(t) = \mathbf{m}_0(\varphi) + \mathbf{K}(\varphi)[\mathbf{s}_0(\varphi) - \mathbf{s}(t)] \quad (1)$$

It is important to note that this control structure will effectively lump the passive control gains with the active ones in addition to any other unmodeled

[1] black box in the system identification sense, i.e. there are parameters in the model

effects. Other authors refer to these gains as the impedance stiffness and damping. This is desirable for our intentions, as we are only concerned with mapping this identified controller to that of powered prosthetic device and it is thus unnecessary to distinguish between these.

Direct Identification

We employ a direct identification approach to find the optimal parameters for the control structure described in Section . We are aware that direct identifcation has its drawbacks. It is well known that process noise due to unmodeled affects in the identification model will bias the results towards the inverse of the plant if the external perturbations are not sufficiently large enough [2, **?**, **?**]. Determining if the perturbations are of large enough size is difficult because the process noise is generally unknown.

I need to explain why we think our perturbations may be large enough in magnitude. The problem is that we get similiar identification results from both unpertrubed and perturbed data. THis can mean one of two things: (1) the person perturbs themselves enough and the identification is correct either way or (2) our perturbations are not enough, i.e. we'd get different results by perturbing more. The only thing that I can think of here is to show the necessary perturbation level for the quiet standing case and then say that we have similar magnitudes.

We reformulate Equation 1 to make it amenable to linear identifaction. The equation can be rewritten so that is linear in the gains and a new term $\mathbf{m}^*$.

$$\mathbf{m}(t) = \mathbf{m}^*(\varphi) - \mathbf{K}(\varphi)\mathbf{s}(t) \tag{2}$$

where

$$\mathbf{m}^*(\varphi) = \mathbf{m}_0(\varphi) + \mathbf{K}(\varphi)\mathbf{s}_0(\varphi) \tag{3}$$

Assuming that we can collect noisy measurements of $\mathbf{m}(t)$ and $\mathbf{s}(t)$, $\mathbf{m}^*(\varphi)$ and $\mathbf{K}(\varphi)$ are identified simply by using linear least squares to regress the data. Given m gait cycles with n time steps in each gait cycle with q controls and p sensors there are $nq(p+1)$ unknowns and mnq equations so we need at least $p+1$ gait cycles to solve for the unknowns.

Details of coercing Equation 2 into the canonical form, $\mathbf{A}\mathbf{x} = \mathbf{b}$ can be found in the supplementary IPython notebook `form_linear_system.ipynb`.

We compute the scheduled gains and $\mathbf{m}^*$ for both the unperturbed and perturbed gait cycles for each trial. Three quarters of the data from each series of gait cycles are used to compute the unknowns and the model is validated against the remaining one quarter of the data. We compute the percentatge of variance accounted for by the model with respect to the validation data set to gauage how well the model predicts.

$$\text{VAF} = 1 - \frac{||\mathbf{m}_p - \mathbf{m}_m||}{||\mathbf{m}_m - \bar{\mathbf{m}}_m||} \tag{4}$$

Results

The formulation above allows one to choose a variety of combinations of potential sensor, $\mathbf{s}(t)$, and actuator, $\mathbf{m}(t)$, signals to generate a controller. For this analyses, we assume we are constructing a controller for a planar plant that only involves the hip, knee, and ankle joints of each leg. We choose the angle and angular rate of each joint as sensors and a torque at each joint are as the actuators.

The most general case for the controller, $\mathbf{K}(\varphi)$, has $q \times p$ unknown entries per phase point but the formulation allows for different types of control that isolate actuators from sensors. We explore four possibilities:

Full Control The acutation at a joint is affected by all of the available sensors.

Side Isolated Control The actuation at a joint is only affected by the sensors on the same side of the body.

Joint Isolated Control The actuation at a joint is only affected by the sensors at that joint.

No Feedback Control The motion is only governed by $\mathbf{m}^*(\varphi)$.

Isn't the "no feedback" equivalent to $\mathbf{m}^*(\varphi)$ being equivalent to the mean torques?

Example Result

Once a controller is identified from a selection of gait cycles from a trial the primary results of interest are the gait phase dependent gain values and how well the model can predict the acutation of indepedent validation data. The actual gain values may give some insight to the physiological nature of the feedback mechanism. Here we present a typical result from a join isolated controller structure. Figure 4 shows the estimates of the mass normalized scheduled gains with respect to the percent gait cycle in each leg as a function of the phase of the gait cycle.

The mismatch from positive feedback to negative K values is potetnially confusing, as Ton has pointed out before, but to me this is the standard way to describe a feedback system in control literature.

Figure 5 shows an example prediction of the joint torques in the right and left legs by the identified control model based on independent data from the same trial.

This plot technically shows the VAF based on the 20 samples per cycle comparison, yet I plot all of the measured values, i.e. more like 100-120 samples per cycle.

Inter subject mean

We compute the body mass normalized gains, $\frac{\mathbf{K}(\varphi)}{m}$ for each subject at each nominal speed and examine the mean and standard deviation across subjects for the inter-subject differences. Figure 6 shows the mean and standard deviation of the gains identified from a joint isolated control structure at the 1.2 $\mathrm{m\,s^{-1}}$ nominal speed.

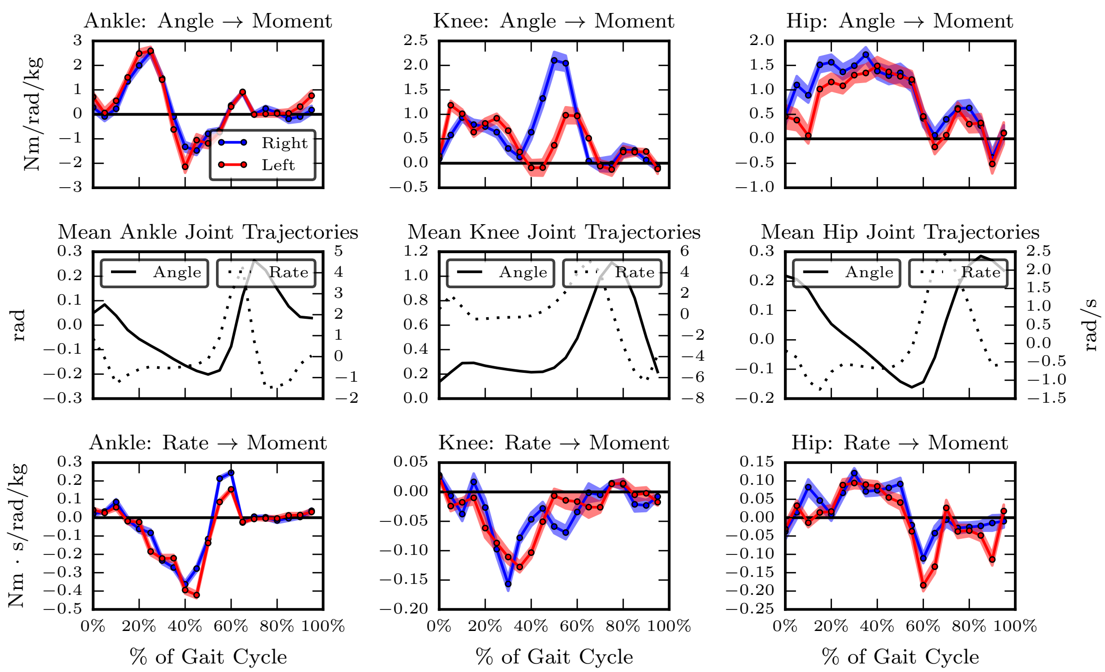

Figure 4: Example identified body mass normalized gait phase scheduled gains for the right (blue) and left (red) legs identified from a selection of gait cycles from a single trial. The top row shows the proportional gains, the middle row provides reference mean trajectories of the sensor measurements, and the final row shows the derivative gains. The columns correspond to the three joints for each leg. The shaded area bounding the gains gives the standard deviation of the parameters with respect to the fit variance. Gain values greater than zero indicate negative feedback and gains below zero indicate positive feedback.

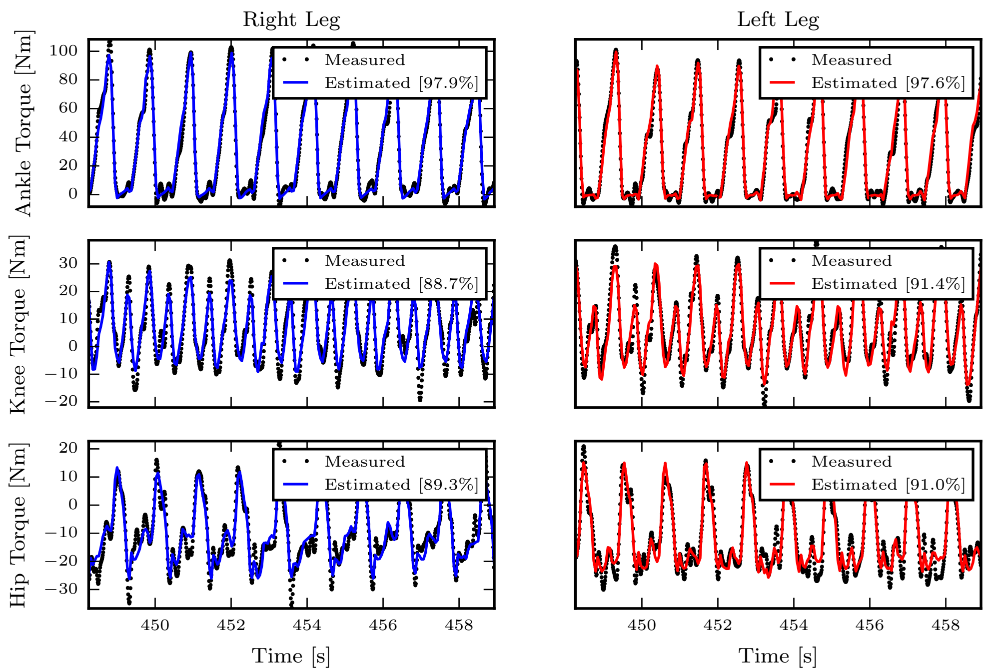

Figure 5: Predicted joint torques using the identified model shown in Figure 4 compared to those computed from inverse dynamics. The sensor and actuator estimations are taken from independent gait cycles from the same trial. The variance accounted for, VAF, is reported for all of the validation gait cycles period whereas only a select number of gait cycles are shown.

Figure 6: Mean and standard deviation (shaded) body mass normalized gains across all subjects walking at a nomimnal speed of 1.2 $\mathrm{m\,s^{-1}}$.

0.1 Speed variation

Discussion

Figure 4 shows that there are patterns that are significantly different than zero in portions of the gait phase for each gain.

How do I show that the gains are significantly different than zero?

Gains are consistent across subjects

Figure **??** indicates that the gains exhibit similar patterns across subjects. There is substantial variability at some points in the gait cycle. The variability is higher in 40% to 50%. [5] found high intersubject variability in the ankle model parameters during the stance phase.

Should I somehow check whether the subjects are significantly different from one another? i.e. check whether each subject is significantly different than the mean. Would it be useful to compute the coefficien to of variation (std/mean)? This could blow up for values around zero.

No feedback in the swing phase

During the swing phase of each leg the gains are not significantly different than zero for the ankle and knee gains. This indicates that swing leg ankle and knee may not be utilized in a feedback fashion to react from the perturbations orginating in the stance leg.

It would be nice to plot the mean toe off time on the gain plots to delineate the stance and swing phase. In addition I could add the gait man to the plots.

Gains exhibit anatomical symmetry

The gait data was split into gait cycles with respect to the right leg's heelstrikes. The gains identified from the right delineated gait cycles exhibit anatomical symmetry with respect to the right and left legs.

It is probably possible to compute whethter the right is significantly different than the left.

Directly Identified Gait Phase Scheduled Feedback Gains Exhibit Positive and Negative Feedback

The derivative gains exhibit a combination of negative and positive feedback. For example, in the middle of the stance phase the ankle derivative gain indicates a large positive feedback. This implies that if the foot deviates from the nominal angular rate, the controller will push it

If the ankle angle deviates from the nominal angle the torque is such that you will be pushed back toward the nominal position, yet at the same time if the angular rate deviates from the nominal

This is really hard for me to think about what happens.

Random variations predict random gains

If the variation in the sensor and actuator measurements is purely random, the identified gains should be random. To verify this we follow this procedure:

- Select the necessary marker coordinates and ground reaction load measurments for a single gait cycle from normal walking.
- Compute the inverse dynamics from sensor and actuator measurements.
- Fit a Fourier series to each time series so that the cycle can be perfectly cyclic.
- Form a time series of 500 gait cycles based on the fitted data.
- Add normal Gaussian noise to each sensor and actuator measurement.
- Identify a joint isolated controller from this artificially created data.

The identified gains show no apparent correlation.

Add a gain plot here showing this

Correlations due to inverse dynamics bias gains

The measurement noise present in the marker coordinates is propogated into both the sensor values (joint angles and angular rates) and the actuator values (joint torques) through the inverse kinematic and inverse dynamic computations, thus the sensors and actuator measurement estimates are correlated simply by this. We exposed this correlation by the following procedure:

- Select the necessary marker coordinates and ground reaction load measurments for a single gait cycle from normal walking.
- Fit a Fourier series to each time series so that the cycle can be perfectly cyclic.
- Form a time series of 500 gait cycles based on the fitted data.
- Add normal Gaussian noise to each measurement.
- Compute the inverse dynamics from the noisy data to produce the sensor and actuator measurements.
- Identify a joint isolated controller from this artificially created data.

The correlation based entirely on the random noise is shown in the example gain plot in Figure 7.

The proportional gains show a clear bias that is strikingly similar to a proportionally scaled vertical ground reaction force.

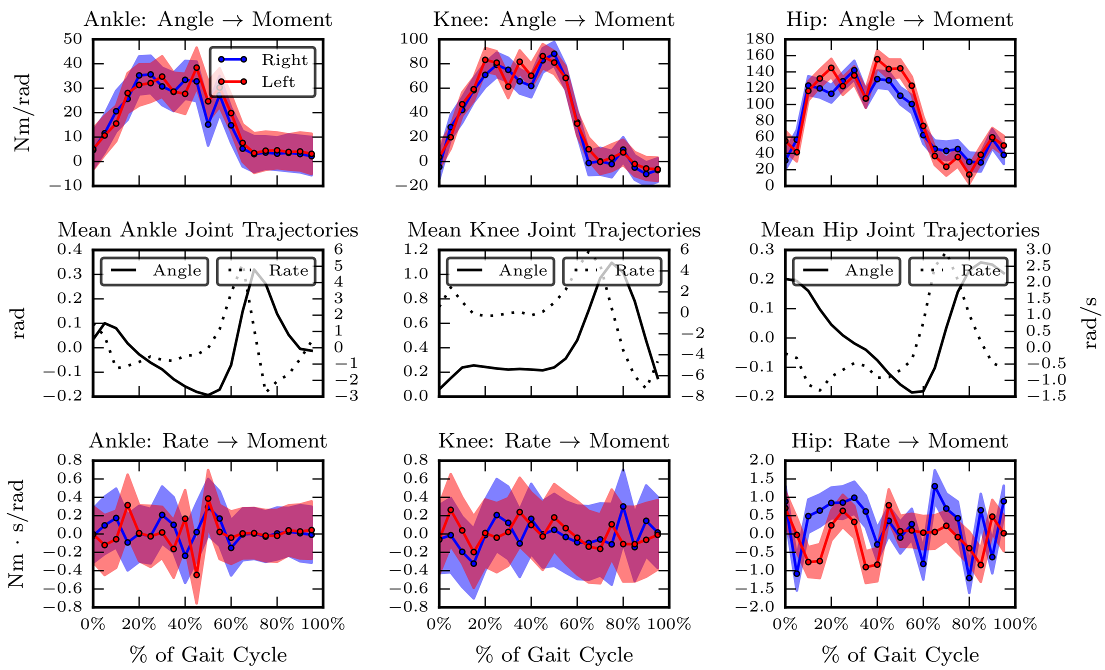

Figure 7: Gait phase percent scheduled gains for right (blue) and left (red) legs.

Table 2: Generated by `src/table_no_control_vaf_comparison.py`.

	No Control	Joint Isolated Control	Full Control
Left.Ankle.PlantarFlexion.Moment	0.930155	0.965969	0.974489
Left.Hip.Flexion.Moment	0.930070	0.942240	0.968361
Left.Knee.Flexion.Moment	0.841471	0.888560	0.935461
Right.Ankle.PlantarFlexion.Moment	0.943745	0.971717	0.979205
Right.Hip.Flexion.Moment	0.965763	0.973759	0.984328
Right.Knee.Flexion.Moment	0.810439	0.854908	0.901859

$\mathbf{m}^*$ accounts for most of the variation

Ideally the variation in the gait cycles is sufficient to identify the acutation due to feedback encapsulated by the gait matrix. If the feedback contribution is assumed to be zero, then $\mathbf{m}^*$ can be identified alone. If the VAF decreases significantly with $\mathbf{K}\phi = 0$ then one can assume that the feedback terms are not just contributing to overfitting the data.

Table 2 shows that $\mathbf{m}^*$ alone is sufficient to explain a large portion of the variance in the data. Adding the feedback terms pushes the VAF closer to 100%.

Similar gains are predicted from both unperturbed and perturbed

This means that either that there is enough feedback variation in normal walking to identify the controller or that are not identifying anything that is significant.

Conclusion

We are able to identify a simple linear controller that exhibits larger gains in the stance phase than in the swing phase. Additionally, similar gain patterns in the right and left legs are observed that use both positive and negative feedback. The controller is capable of predicting the measured joint torques with greater than 65% VAF in all joints. Results and conclusions from a larger sample of subjects and conditions will be presented at the conference.

Acknowledgments

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