Identification of Time-Varying Ankle Joint Impedance During Periodic Torque Experiments Using Kernel-Based Regression

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Abstract Joint impedance is a common way of representing human joint dynamics. Since ankle joint impedance varies within the gait cycle, time-varying system identification techniques can be used to estimate it. Commonly, time-varying system identification techniques assume repeatably of joint impedance over cyclic motions, without taking into consideration the inherent variability of human behavior. In this paper, a method that assumes smooth, cyclic joint impedance, yet allows for cycle-to-cycle variability, is proposed. The method was tested on isometric, cyclic experimental data from the ankle under conditions with a time variation comparable to the expected one during the gait cycle. The estimated model could describe the data with high accuracy (VAF of 94.96%) and retrieve realistic inertia, damping and stiffness parameters. The results provide motivation to further apply the method on experiments under dynamic conditions and to employ the proposed method as a tool for investigating the human joint dynamics during cyclic movements.

1 Introduction

The dynamical behavior of a human joint can be described by joint impedance. Joint impedance characterizes how much resistance a joint opposes to an angular perturbation. During locomotion, the joint impedance of the lower limbs' joints is

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regulated over time by the neuromuscular system. For example, the joint impedance of the ankle is low during the swing phase, and increases during the stance phase to allow for the generation of a net torque for push-off [1]. Knowing how the ankle joint impedance is regulated during locomotion provides important information to design biomimetic wearable devices that can reproduce the function of a healthy ankle joint [1].

Joint impedance can be estimated using system identification techniques, starting from the measurements of an angular perturbation applied to the joint and the resulting joint torque. Since joint impedance changes within the gait cycle, time-varying system identification techniques are required. In literature, system identification techniques that assume repeatably of the joint impedance over cyclic motions have been proposed [2]. This assumption is not in accordance with the inherent variability of human behavior and therefore the identification techniques might lead to biased estimates when applied to human data.

In this article, a kernel-based regression (KBR) method is proposed. A smooth, cyclic behavior of the joint impedance is assumed, yet a cycle-to-cycle variability is allowed. The method is applied to the analysis of isometric experimental data, in which the ankle torque tracks a periodic trajectory, designed to induce a time variation of joint impedance comparable to the expected one during the gait cycle.

2 Method

2.1 Experiment

The experimental data were acquired from one healthy subject. Prior to the experiment, the subject gave written informed consent. The protocol was approved by the ethics board of the University of Twente. The right foot of the subject was attached to the Achilles Rehabilitation Device (MOOG, Nieuw-Vennep, The Netherlands). The apparatus is a one degree of freedom ankle manipulator which can apply angular perturbations to the ankle joint in the sagittal plane [3]. The foot of the subject was firmly attached to the footplate of the manipulator, such that the angle of the manipulator corresponded to the angle of the ankle joint. The angle of the manipulator was controlled. The angular displacement was designed as a 90 s multisine signal (sum of sinusoidal waves) with RMS amplitude 0.015 rad, random phase and excitation frequencies from 0.6 to 20 Hz.

The device measured both the angular displacement and the torque applied by the subject with a sampling frequency of 2048 Hz. The subject was instructed to change the ankle torque to track a predefined desired trajectory, shown in black in Fig. 1a. The desired torque trajectory was periodic within the frequency range of normal human walking and the amplitude was adjusted to be comfortable for the subject and limit muscular fatigue. The subject received visual feedback on the desired torque trajectory and on a low-passed representation the exerted ankle torque. Three trials were measured, each composed of 45 cycles of the torque trajectory. The signals are considered positive in the dorsiflexion direction.

2.2 System Identification

It is assumed that the measured torque $\tau_{\mathrm{m}}(t)$ is the superposition of voluntary torque $\tau_{\mathrm{ext}}(t)$, i.e. the desired trajectory and uncorrelated with the perturbations, and perturbation-induced torque $\tau_{\mathrm{Œ}}(t)$, which can be described by an inertia-spring-damper model:

$$
\begin{aligned}
\tau_{\mathrm{m}}(t) &= \tau_{\mathrm{ext}}(t) + \tau_{\mathrm{Œ}}(t) \\
&= \tau_{\mathrm{ext}}(t) + I\ddot{\phi}_{\mathrm{m}}(t) + B(t)\dot{\phi}_{\mathrm{m}}(t) + K(t)\phi_{\mathrm{m}}(t)
\end{aligned}
\tag{1}
$$

where $\phi_{\mathrm{m}}(t)$, $\dot{\phi}_{\mathrm{m}}(t)$and $\ddot{\phi}_{\mathrm{m}}(t)$ are the angular position and its first- and second-order derivatives, respectively, I is the constant (time-invariant) inertia, and $B(t)$ and $K(t)$ the time-varying damping and stiffness. $B(t)$, $K(t)$ and $\tau_{\mathrm{ext}}(t)$ are considered Gaussian processes, whose statistical properties are characterized by a covariance function, called the kernel function. A locally periodic kernel function is selected, which imposes that the variations of the parameters are smooth and have a periodicity of 2 s, with a cycle-to-cycle variability of 20% [5]. The unknown inertia, stiffness, damping and external torque $\hat{\tau}_{\mathrm{ext}}(t)$ are retrieved simultaneously by means of KBR [4, 5], considering the angular position as input and the measured torque as output. The estimate of the measured torque $\hat{\tau}_{\mathrm{m}}(t)$ is consequently computed. The identification is performed in the frequency domain, at bins up to 20 Hz. The accuracy of the estimate is expressed in terms of the variance accounted for (VAF) [5] between $\tau_{\mathrm{m}}(t) - \hat{\tau}_{\mathrm{ext}}(t)$ and $\hat{\tau}_{\mathrm{m}}(t) - \hat{\tau}_{\mathrm{ext}}(t)$.

3 Results

The measured torque is plotted in Fig. 1b, where the abscissa was normalized to represent the measurements with respect to the cycle percentage. The measurements for 15 randomly selected cycles are shown. The estimated external torque $\hat{\tau}_{\mathrm{ext}}(t)$ component is represented in Fig. 1a, where each colored line represents the estimate for one cycle. The estimate resembles the desired torque trajectory and the resulting VAF is of 94.96%. The estimated damping and stiffness are represented in Fig. 1c, d, respectively. For each cycle, the estimated stiffness has a peak value in correspondence to the maximum plantarflexion (around 45% of the cycle), whilst the estimated damping has a peak around 50% of the cycle. The inertia estimate is 0.019 Nms^2/rad.

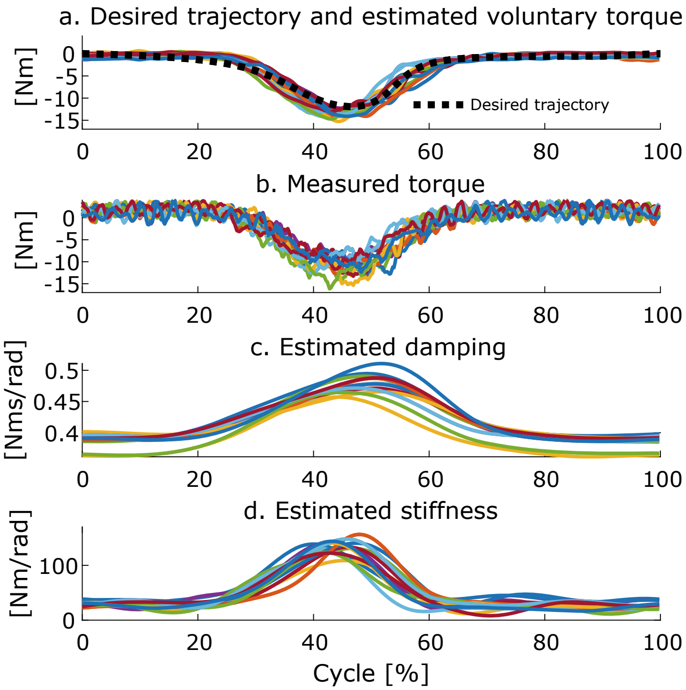

Fig. 1 **a** Desired torque trajectory (dotted black line) and estimated voluntary torque. **b** Measured torque. **c**, **d** Estimated damping and stiffness. For all the plots, the abscissa is normalized to represent the quantities with respect to the percentage of the cycle (length 2 s), and the quantities are represented for 15 randomly selected cycles of the torque trajectory

4 Discussion

4.1 Estimated parameters

The variability of the subject behavior is observable in Fig. 1b, in which there are cycle-to-cycle differences in the maximum amplitude of the measured torque and the timing of the amplitude peaks. The estimated damping and stiffness parameters present a plausible time-varying behavior in accordance with the measured torque, with peak values in correspondence to the maximum plantarflexion torque for each cycle. The estimated stiffness resembles the estimate obtained in [6]. Future work should be done to provide a physiological interpretation of the parameters, potentially comparing the results with physiological-based models [3].

Accordingly to the experimental conditions, the inertia was set time-invariant. However, the identification method can deal with time-varying inertia.

4.2 Experimental Condition

With the given experimental condition, we wanted to test the proposed identification method on human experiments with a time variation comparable to the expected one during the gait cycle. The high VAF supports the validity of the estimated model. Furthermore, the estimator was previously validated on a simulation study with a comparable time variation [5].

The experiment was performed during isometric conditions, where the time variation of the joint impedance was an artifact of the experimental task. However, the good performance of the method on the presented data provides motivation to continue testing the method on more realistic experimental conditions. Future work should include adjusting the method to be applicable to closed-loop conditions, in order to identify joint impedance during experiments under dynamic conditions, and provide a human-inspired guideline for the design of actuated wearable devices [1].

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