Linear Time-Varying Identification of Ankle Mechanical Impedance During Human Walking

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LINEAR TIME-VARYING IDENTIFICATION OF ANKLE MECHANICAL IMPEDANCE DURING HUMAN WALKING

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ABSTRACT

This paper presents a new method to investigate the multi-variable time-varying behavior of the ankle during human walking, and provides the first experimental results from treadmill walking. A wearable ankle robot with an ensemble-based linear time-varying system identification method enabled identification of transient ankle mechanical impedance in 2 degrees of freedom, both in the sagittal and frontal planes. Several important issues of the ensemble-based identification method in practical measurements are discussed, especially a strategy to solve the limitation of the method which assumes that the system undergoes the same time-varying behavior on every stride. The suggested method was successfully applied to 15 minutes of human walking on a treadmill. Experiments with 10 young healthy subjects showed clear time-varying behavior of ankle impedance across the gait cycle, except the mid-stance phase. Interestingly, most subjects increased ankle impedance just before heel strike in both degrees of freedom. Interpretation of impedance changes was consistent with analysis of electromyographic signals from major muscles related to ankle movements.

INTRODUCTION

Human locomotion has been the subject of intense research for a long time, and both normal and pathological gaits under various walking conditions have been studied [1, 2]. Spatiotemporal parameters (step length, stride length, speed, etc.), kinematics (joint angle and velocity, trunk and foot trajectories, etc.), kinetics (reaction force, mechanical power, etc.), and electromyography are well documented in a traditional gait lab setting. However, we may better understand human locomotion by investigating the mechanical impedance of lower-limb joints, which enable natural and stable interaction with the environment. In fact, given the importance of the ankle in lower extremity function [3], ankle mechanical impedance has been studied by several research groups.

Steady-state or time-invariant ankle mechanical impedance and how it varies with muscle activation has been studied extensively both for healthy subjects [4, 5] and neurologically impaired patients [6, 7]. While most studies focused on a single degree-of-freedom (DOF), especially in the sagittal plane, recent work by the authors [8-10] investigated multi-variable ankle mechanical impedance in two coupled DOFs: dorsiflexion-plantarflexion (DP) in the sagittal plane and inversion-eversion (IE) in the frontal plane, and combinations of those two movement directions. Although steady-state static and dynamic ankle mechanical impedance may provide valuable information, it cannot be directly applicable to normal locomotion since ankle impedance varies continuously as muscle activities and lower limb configuration change.

Several different time-varying system identification methods, such as a regressive technique [11, 12], temporal expansion method [13, 14], time-frequency method [15, 16], and ensemble-based method [17-20], have been developed to investigate transient behavior of biological systems. Among them, the ensemble-based identification method outperforms others for the following reasons: It requires no a priori assumption on the structure of the system to identify, can capture very fast time-varying behavior of the system, and is robust to noisy measurements. The main limitation of this
Method is that it assumes the same linear time-varying behavior in every realization.

Some work based on simulations [18, 19] verified the effectiveness and robustness of the method to identify time-varying ankle mechanical impedance. There are also a few experimental studies that identified ankle impedance changes during imposed movements in a supine posture [17, 20]. However, to the best of our knowledge, no one has previously identified ankle mechanical impedance during human walking even in a single DOF. In fact, there is an important difficulty that arises when applying the ensemble-based method to practical measurements, which is not anticipated by simulation or constrained studies. While all of the above studies assumed the same duration of realizations, this assumption does not hold in real human walking: the stance and swing length for each stride may vary significantly. This violates the fundamental assumption of the ensemble-based identification method. In this paper, we propose a strategy to solve this problem, and suggest a novel experimental procedure to identify multi-variable time-varying ankle mechanical impedance during human walking.

METHODS

Experimental Setup

Multi-variable transient ankle impedance was identified from a treadmill walking experiment. A highly backdrivable wearable ankle robot, Anklebot [21], was used to apply pseudo random torque perturbations at the ankle in 2 DOFs. The Anklebot was mounted to a knee brace, and two linear actuators were connected to a custom shoe with a mounting bracket. Almost all of the mass (3.6 kg) of the Anklebot is concentrated at the knee, not the shank or ankle. A shoulder strap, which runs up around the neck, also bears weight and minimizes slippage of the knee brace and Anklebot. This setup minimized the effect of the device on normal walking. In fact, it has been shown that the effect of unilateral loading due to the Anklebot was smaller than the difference between overground and treadmill walking [22].

Two footswitches (force sensitive resistor membrane, Delsys Inc.), one for the heel and the other for the big toe, were used to detect the timing of heel-strike defining the zero gait phase, and the moment of toe-off separating the stance and swing phases. To monitor muscle activation levels during walking experiments, surface electromyographic (EMG) sensors (Myomonitor IV, Delsys Inc.) were attached to the belly of 4 major ankle muscles: tibialis anterior (TA), soleus (SOL), gastrocnemius (GAS) and peroneus longus (PL).

The torque exerted by the Anklebot, the resulting kinematics of the ankle in 2 DOF were recorded at 500 Hz in one computer, and footswitch and EMG data were sampled at 1 kHz in another computer. To synchronize data from 2 different computers, a single triggering step signal (0 to 5 V) was recorded by both computers before running the walking experiment. The whole experimental setup is shown in Fig.1.

Experimental Protocol

First, subjects walked on a treadmill for a few minutes to familiarize themselves with the device and choose a preferred walking speed (PWS), which was comfortable enough to maintain for the duration of the experiment with the added mass of the Anklebot. The subjects alone controlled the speed of the treadmill, so as not to be influenced by the experimenter. The PWS was selected in a two-sided manner: first choose the PWS by increasing the speed from the very slow speed, and then select the PWS by decreasing the speed from the speed considerably faster than the first selected PWS. The final PWS for the data collection was calculated as the average of those 2 selected speeds.

For data collection, subjects were instructed to walk comfortably and naturally on the treadmill. For the first minute, subjects walked without any mechanical perturbation from the Anklebot. After 1 minute, pseudo random torque perturbations (bandwidth 100 Hz) were applied to the ankle for 13 minutes. The magnitude of perturbations was determined to be strong enough to perturb the ankle in both DOFs during the swing phase, but not to disturb natural walking. The last minute consisted of unperturbed walking. The 13 minutes walking data with perturbations were used for subsequent data analysis.

Subjects

Ten unimpaired young male subjects (age: 22–32 yrs, height: 1.71–1.91 m, weight: 61–90 kg) with no reported history of biomechanical or neuromuscular disorders were recruited for this study. All subjects gave informed consent to participate after receiving an explanation of the experiment as approved by MIT’s Committee on the Use of Humans as Experimental Subjects.

Fig.1. Experimental setup for a walking test on the treadmill
**Sub-Ensemble Set Construction**

First, an ensemble data set was constructed based on foot switch data. Each realization of the ensemble set consisted of one stride defined as an interval between two successive heel strikes. To minimize possible error from unexpected variations, the outermost 5% of stride durations were discarded.

However, the ensemble-based identification method is not strictly applicable, since the length of each realization was not identical. To solve this problem, sub-ensemble data sets containing the same length of realization were generated. Each stride was divided into stance and swing phases based on toe-off timing, and further divided into 7 sub-phases: early stance (EST), mid stance (MST), terminal stance (TST), pre-swing (PSW), initial swing (ISW), mid swing (MSW), and terminal swing (TSW). The length of each sub-phase was defined following gait analysis results on healthy human subjects [1], and represented as a ratio to the mean of the stance duration ($T_{ST}$) and swing duration ($T_{SW}$) of all realizations (Fig.2).

Fig.2 illustrates how to select each realization of the sub-ensemble under variation of stride duration. For each sub-phase, realizations were selected from the reference point (depicted as a red bar in Fig.2 (a)) to the direction of an arrow so as each realization has the same length. For example, each realization of the sub-ensemble set for the EST phase can be constructed by choosing data from the moment of heel strike until the total number of data becomes $1/6T_{ST}$.

Once 7 sub-ensemble data sets were obtained, the identification method explained in the following section was applied to each sub-ensemble set.

**Ensemble-based Time-Varying Identification**

The identification method used in this study was based on the correlation approach presented in [18, 20]. For each sampling time $i$, the relationship between the input ($u_r(i)$) and the corresponding noisy output ($z_r(i) = y_r(i) + n_r(i)$), where $y_r(i)$ is the true output and $n_r(i)$ is assumed as white noise) for the $r^{th}$ realization can be represented as Eq.(1).

$$z_r(i) = \Delta t \sum_{j=M1}^{M2} \hat{h}(i, j)u_r(i - j)$$  \hspace{1cm} (1)

where $\hat{h}(i, j)$ is an impulse response function (IRF) estimate with a finite lag length $L = M2 - M1 + 1$ ( $\hat{h}(i, j) = 0$ for $j < M1$ and $j > M2$). Multiplying both sides of the Eq.(1) by $u_r(i - k)$ and summing over all realizations ($R$), we get Eq.(2), and more simply it can be written as a discrete cross- and auto-covariance relation (Eq.(3)).

$$\frac{1}{R} \sum_{r=1}^{R} z_r(i)u_r(i - k) = \Delta t \sum_{j=M1}^{M2} \hat{h}(i, j) \frac{1}{R} \sum_{r=1}^{R} u_r(i - j)u_r(i - k)$$  \hspace{1cm} (2)

$$\Phi_{zu}(i, -k) = \Delta t \sum_{j=M1}^{M2} \hat{h}(i, j)\Phi_{uu}(i - k, k - j)$$  \hspace{1cm} (3)

Finally, we can get a matrix equation (Eq.(4)) by changing index $k$ from $M1$ to $M2$, where $\Phi_{uu}(i)$ is a $L \times L$ matrix and $\Phi_{zu}(i)$ and $\hat{h}(i)$ are $L \times 1$ vectors.

$$\Phi_{zu}(i) = \Delta t \Phi_{uu}(i)\hat{h}(i)$$  \hspace{1cm} (4)

$$\hat{h}(i) = \frac{1}{\Delta t} \Phi_{uu}(i)^{-1}\Phi_{zu}(i)$$  \hspace{1cm} (5)

Once $\hat{h}(i)$ is obtained from a pseudo inverse matrix operation (Eq.(5), a frequency response function (FRF) can be easily calculated by a discrete Fourier transform.

**RESULTS**

All ten subjects walked successfully for 15 minutes on the treadmill at their own PWS. Samples of recorded data of a representative subject (with perturbations) are shown in the Fig.3.
Fig. 3. Samples of recorded data of a representative subject. First 3 rows show foot switch (toe and heel) and ankle angle (DP and IE angles) data. Last 4 rows depict raw EMG (blue) signals with estimated amplitudes (red). Units of foot switch and EMG data are voltage, and ankle angles are degrees. Orange and pale green lines denote the timing of heel strike and toe-off, respectively.

The distribution of stride durations was analyzed and the outermost 5% of the data were discarded. All subjects showed a distribution close to normal (Fig. 4). The coefficient of variation (CV), the ratio of the standard deviation (SD) to the mean, was low: the mean of all subjects was 0.027 with SD 0.005.

Fig. 4. Distribution of stride durations of a representative subject.

Sub-ensemble data sets were generated from the selected stride data, following the method described above (Fig. 2). The number of realizations generated from 13 minute walking data was more than 400 for all subjects: the mean for all subjects was 489.7 with SD 49.9.

The ensemble-based time-varying identification method was applied to each sub-ensemble set separately. A causal filter ($M_1 = 0$) was used in this study, and the size of lag ($M_2$) was determined as $M_2 = 100$, based on a simple simulation study. When a 2nd order ankle model with parameter values close to the relaxed ankle properties ($I = 0.01 \text{ Nm/rad/s}^2$, $B = 0.3 \text{ Nm/rad/s}$, $K = 20 \text{ Nm/rad}$) was simulated, the IRF response settled down close to zero in 200 ms.

The IRF was estimated at every 2 ms for each sub-ensemble set. To evaluate the reliability of estimation, absolute errors between true outputs ($z_r$) and reconstructed outputs ($\hat{z}_r$), obtained from convolution of the estimated IRF ($\hat{h}$) and input ($u_r$), were calculated for every realization, and the results are summarized in Table 1. Averaging over all subjects, in the DP direction, the swing phase errors were smaller than those of the stance phase. The IE direction errors were smaller than the DP direction for all sub-phases, and the IE errors during the stance and swing phases were comparable.

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<td>0.99</td>
</tr>
<tr>
<td>MST</td>
<td>1.59</td>
<td>0.79</td>
</tr>
<tr>
<td>TST</td>
<td>2.15</td>
<td>1.05</td>
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<td>PSW</td>
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<tr>
<td>ISW</td>
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<td>0.96</td>
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<tr>
<td>MSW</td>
<td>1.48</td>
<td>0.93</td>
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<tr>
<td>TSW</td>
<td>1.52</td>
<td>1.14</td>
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The FRF was calculated by performing a Fast Fourier Transform on the estimated IRF. Assuming that ankle behaviors do not change significantly within 50 ms, responses obtained at every 2 ms were averaged with a 50 ms moving window. A representative frequency response plot for the whole stride (Bode plots vs. time) is shown in Fig. 5. Identifications were performed separately for each sub-phase, and results were adjoined from EST to TSW. In addition, note that the response is plotted in an admittance form, since we applied torques as inputs and recorded angular displacement outputs.

Fig. 5. Magnitude and phase response plots of a representative subject (red: stance, blue: swing). Left and right columns show ankle admittance in the DP and IE directions, respectively. The x-axis represents time starting from heel strike (0 sec.) to the end of the swing phase. The black line depicts the dc component of the magnitude response.

In a linear system, admittance is an inverse of impedance. However, in general this inverse relationship does not hold in a non-linear system.
In the high frequency region, over about 8~10Hz, the response was more or less consistent with inertia-dominated behavior (magnitude decreased at ~40dB/dec). In the low frequency region, stiffness was dominant with a magnitude slope close to zero although slight deviations from zero slope were observed. Furthermore, two clear trends were observed from the full gait phase identification. First, ankle impedance decreased (admittance increases) at the end of the stance phase: 8 out of 10 subjects showed this behavior for DP and all subjects for IE. Second, ankle impedance increased (admittance decreased) just before heel strike: 9 out of 10 subjects showed this trend for DP and all subjects for IE. One exceptional subject showed a significant impedance increase in the DP direction at the moment of heel strike.

Amplitude changes of EMG signals across the gait cycle were investigated. All subjects showed qualitatively similar responses for all measured muscles except PL. The TA was active around toe-off as well as at heel strike. The SOL and GAS were active in the TST phase, but silent in the PSW phase. The results of a representative subject (the same subject as in Fig.5) are presented in Fig.6.

![Fig.6. EMG amplitude changes across the gait cycle (0~100%) of a representative subject. EMG data of all realizations were normalized to 100% and averaged. The mean and SD of EMG amplitude were illustrated as a solid line and a pale band, respectively. The vertical line at about 65% of the gait cycle indicates the moment of toe-off.](image)

**DISCUSSION**

In this paper, the multi-variable time-varying behavior of the ankle during human walking was investigated for the first time. Healthy young subjects walked successfully on a treadmill while wearing the Anklebot. The variation of stride duration was low: the mean CV of all subjects was 0.027, and even the worst case was 0.037. This low variation supports our use of ensemble-based methods to identify the time-varying behavior of the ankle during human walking.

While all previous ensemble-based identification studies, either simulation or experimental, were based on the fundamental assumption that every realization has the same duration, this assumption does not hold in real human walking data. To address this issue, we constructed 7 sub-ensemble data sets, each having the same duration. This approach was selected over normalizing the duration of different data sets, because the normalization process can distort the real neuro-musculo-skeletal properties of the ankle. Before sub-ensemble data generation, outlier stride were first discarded to minimize any error from excessive variations.

To verify the validity of the suggested method and identified results, absolute errors between true outputs and reconstructed outputs from the estimated IRFs were calculated. Care is needed to interpret this result, since the nominal range of motion of the ankle is substantially different across the 7 sub phases. When the absolute error was interpreted in reference to the nominal range of motion for each sub-phase, errors during the MST and TST were significantly higher than other sub-phase results. This was expected since the input torque from the robot is unlikely to be sufficient to move the ankle during the MST and TST phases.

Across the whole gait cycle, stiffness dominant ankle behaviors were observed both in the sagittal and frontal planes. Interestingly, most subjects increased ankle impedance just before heel strike in both DOFs, and substantially decreased it at the end of stance phase. Actually, these two behaviors were well matched with an EMG burst of the TA in the TSW phase, and a decrease in EMG activity of 3 plantarflexors (SOL, GAS, and PL) in the PSW phase.

This work paves the way to understand how human ankle behaviors in multiple DOFs change during walking. There are several possibilities to improve the current time-varying identification methods. First, we may use new criteria to generate sub-ensemble data sets. Highly repeatable kinematic data such as knee angle as well as additional foot switch information such as heel-off timing may be incorporated to better identify sub-phases of the gait cycle. Second, we may get a better result with a more centered selection of stride data. For example, using the middle 50% of stride durations rather than just discarding the outermost 5% as we did in this study may improve precision. Third, finding the optimal length of the lag used for IRF estimations may afford further improvements. Finally, further investigation is needed to test whether stronger input perturbations improve the reliability of identification.

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Drs. N. Hogan and H. I. Krebs are co-inventors of the MIT patents for the robotic devices used in this study. They hold equity positions in Interactive Motion Technologies, Inc., the company that manufactures this type of technology under license to MIT.
REFERENCES