Time-Varying Ankle Mechanical Impedance During Human Locomotion

Sameer Arjun
Department of Maryland Applied Graduate Engineering
University of Maryland, College Park
MD, USA
ssarjun@umd.edu

Yashas Shetty
Department of Maryland Applied Graduate Engineering
University of Maryland, College Park
MD, USA
yshetty@umd.edu

***Abstract*—This study uses data from the Anklebot wearable ankle robot to investigate ankle impedance during locomotion. Departing from traditional linear time-invariant models, we employ modified linear time-varying (LTV) ensemble-based system identification. Our focus extends beyond the steady state to capture time-varying characteristics throughout the gait cycle, specifically pre-swing through early stance.**

The model, mathematical equations, and results of this novel approach are discussed. The study contributes insights into ankle rehabilitation by offering a dynamic understanding of ankle mechanics. The findings have implications for tailoring rehabilitation programs to specific gait phases. Future directions for research in biomechanics and rehabilitation are outlined.

***Index Terms*—Anklebot, linear time-varying system, ensemble-based system**

I. Introduction

The ankle joint plays a crucial role in various aspects of human movement, particularly during locomotion. It acts as a critical link between the foot and the rest of the body, contributing to stability, propulsion, and shock absorption. Understanding the mechanical behavior of the ankle during locomotion is crucial for rehabilitation and physical therapy. Understanding how ankle impedance changes due to injuries or neurological conditions can guide therapists in developing more effective rehabilitation programs. Human walking is often modelled as a function of the ankle joint angle. It is seen that any defects at the ankle of a person reflect an improper gait cycle. There is a lot of study in the rehabilitation field regarding techniques for measuring ankle impedance.

There have been studies on measuring ankle impedance in a steady state before. In these studies, the system is considered a linear time-invariant system. There have been few studies where ankle impedance is measured as a time-varying system [1]. However, identification was limited to the period when the foot was flat to the ground and to a single degree of freedom. The paper we implement uses data gathered from a wearable ankle robot, Anklebot and modified linear time-varying (LTV) ensemble-based system identification methods to characterize ankle impedance from pre-swing through swing to early stance, complementing the previous work [3]. In the following sections we describe the model we use, mathematical equations of standard LTV ensemble-based system identification methods, [2] [4] , the novel approach tried in this project our results and the future scope of this work.

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II. Literature survey

Understanding the biomechanics of human locomotion is crucial for the development of assistive devices, rehabilitation strategies, and a deeper comprehension of motor control. One key aspect of this biomechanics is the time-varying mechanical impedance at the ankle joint, which plays a pivotal role in regulating stability and adaptability during walking and other forms of locomotion. Initial investigations into ankle mechanical impedance date back to early studies in the 20th century, where researchers focused on static measures. Classic works by Winter et al. (1998) [**?**] and Hof (2008) [6] laid the foundation for understanding ankle biomechanics, but they primarily examined average properties rather than the dynamic nature of impedance. Recent advancements in experimental techniques, such as wearable sensors, force plates, and electromyography, have allowed researchers to delve deeper into the time-varying aspects of ankle impedance. Research by Mancini et al. (2015)) [7] introduced wearable inertial sensors to quantify dynamic ankle stiffness during walking, providing insights into the adaptive nature of ankle impedance. Investigating the neuromuscular control mechanisms contributing to time-varying ankle impedance has been a growing area of interest. Studies by Ivanenko et al. (2013)) and Sawers et al. (2015) [8] highlighted the role of muscle activation patterns in modulating ankle stiffness and damping during various phases of gait. Clinical Applications and Rehabilitation: Researchers have explored the implications of time-varying ankle impedance in clinical settings and rehabilitation. A study by Piazza and Steele (2018)) [9] investigated how altering ankle impedance through training could enhance stability in individuals with gait disorders, providing potential avenues for therapeutic interventions. The development of robotic exoskeletons and prosthetic devices has spurred interest in replicating and enhancing natural ankle impedance. Studies by Malcolm et al. (2017) and Zhang et al. (2020) [10] demonstrated the importance of mimicking physiological ankle impedance to improve the naturalness and efficiency of human-machine interfaces. Despite significant progress, challenges remain, including the need for standardized measurement protocols and a deeper understanding of the interaction between ankle impedance and other joints. Future research directions could involve exploring the impact of age, pathology, and diverse locomotor tasks on time-varying ankle impedance. In conclusion, the literature on time-varying ankle mechanical impedance during human locomotion reflects a dynamic field with implications for biomechanics, rehabilitation, and assistive technology. Advancements in technology and a growing understanding of neuromuscular control have opened new avenues for research, offering promising insights into the intricacies of ankle impedance in diverse contexts.

III. Experimental conditions

As mentioned earlier, the data we use has been measured by the Anklebot. The data will be measured for a complete gait cycle(s). Mild random torque perturbations applied at the ankle joint and these are the inputs for our system and they are assumed to be noise free. Angular displacements at the ankle (about the axis of ankle rotation) were measured as the output of the system. The inputs are given during the inversion-eversion (IE) and dorsi-plantar flexion (DP) directions movements and the measurements are taken in the same duration.

Fig. 1. Ankle bot

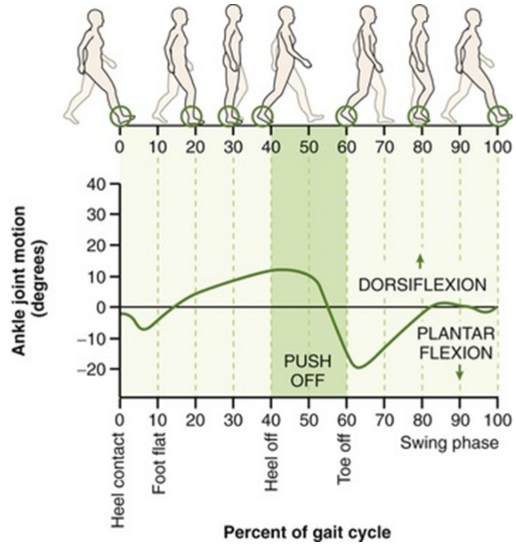

Fig. 2. Human gait cycle

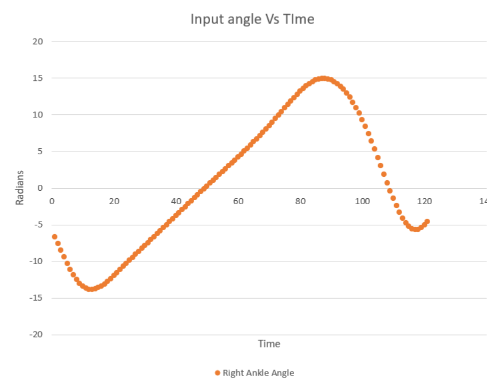

Fig. 3. Ankle angle Vs Time

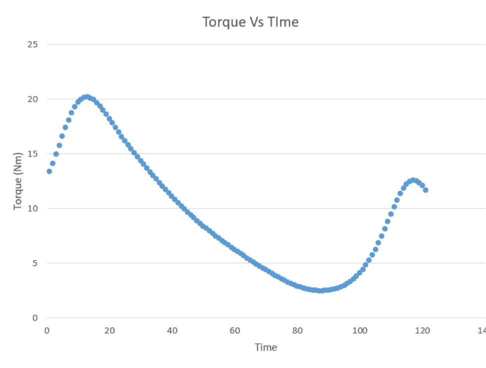

Fig. 4. Ankle torque Vs Time

IV. METHODOLOGY

The human walking is a repetitive and periodic event that can be described as a gait cycle. To investigate changes in ankle impedance at each stage of the gait cycle, a time-varying system identification method is required. The ensemble-based method is well-suited for this study because it can capture the fast time-varying behaviour of the system and is efficient when multiple ensembles of input-output realizations are available. This method is based on the correlation approach, which assumes that every realization experiences the same underlying time-varying behaviour. By evaluating the input-output relation using data across realizations and time, the system dynamics can be identified at a specific time t.

A. Discrete convolution equation

For each discrete time step i, the relationship between noise-free inputs $(u_r(i))$ and the corresponding noisy outputs $(z_r(i))$ is represented as a discrete convolution equation given by:

$$z_r(i) = \Delta t \sum_{j=0}^{M} \hat{h}(i,j) u_r(i-j)$$

where,

- $\hat{h}(i,j)$ is the Impulse Response Function (IRF) with a finite lag length $L = M+1$ and M denotes the time.
- Lag length L is selected long enough such that the IRF estimate can settle down close to zero.
- $u_r(i)$ noise-free torque inputs
- $z_r(i)$ corresponding noisy outputs of angular displacements at the joint

B. Wiener-Hopf equation

Multiplying both sides of the equation with $u_r(i-k)$ and summing over all realizations and dividing them by the number of realizations R, the Wiener-Hopf equation is obtained as follows:

$$\frac{1}{R}\sum_{r=1}^{R} z_r(i) u_r(i-k) = \Delta t \sum_{j=0}^{M} \hat{h}(i,j) \frac{1}{R}\sum_{r=1}^{R} u_r(i-j) u_r(i-k)$$

where,

- R is the number of realizations in the ensemble
- Δt is the sampling interval
- j, k are the lag indices
- $\hat{}$ indicates that it is an estimated value

1) Input-output cross-correlation function estimate: The above equation can be rewritten as:

$$\hat{\phi}_{zu}(i,-k) = \Delta t \sum_{j=0}^{M} \hat{h}(i,j) \hat{\phi}_{uu}(i-k, k-j)$$

Where,

- $\hat{\phi}_{zu}$ is the input-output cross-correlation function estimate at the time i and $i-k$
- $(\hat{\phi}_{uu})$ is the input auto-correlation function estimate at $i-k$ and $i-j$

By changing the lag index k of the above equation from 0 to M, the following matrix can be obtained:

$$\hat{\mathbf{\Phi}}_{zu}(i) = \Delta t \hat{\mathbf{\Phi}}_{uu}(i) \hat{\mathbf{h}}(i)$$

Where,

- $\Phi_{zu}(i)$ is a Lx1 vector
- $\Phi_{uu}(i)$ is a LxL matrix

Which can also written as:

$$\hat{\phi}_{zu}(i) \\ = [\hat{\phi}_{zu}(i,-M1)\hat{\phi}_{zu}(i,-M1-1)\cdots\hat{\phi}_{zu}(i,-M2)]^{\mathrm{T}}$$

2) Input auto-correlation function estimate: $\hat{\phi}_{uu}(i-k,k-j)$ Is given by:

$$\hat{\phi}_{uu}(i-k,k-j) = \frac{1}{R}\sum_{r=1}^{R} u_r(i-j) u_r(i-k)$$

And $\Phi_{uu}(i)$ is a LxL matrix given by:

$$\hat{\Phi}_{uu}(i) =$$

$$\begin{bmatrix} \hat{\phi}_{uu}(i-M1,0) & \hat{\phi}_{uu}(i-M1,-1) \\ \hat{\phi}_{uu}(i-M1-1,1) & \hat{\phi}_{uu}(i-M1-1,0) \\ \vdots & \vdots \\ \hat{\phi}_{uu}(i-M2,M2-M1) & \hat{\phi}_{uu}(i-M2,M2-M1-1) \\ \cdots & \hat{\phi}_{uu}(i-M1,M1-M2) \\ \cdots & \hat{\phi}(i-M1-1,M1-M2+1)] \\ & \vdots \\ \cdots & \hat{\phi}_{uu}(i-M2,0) \end{bmatrix}$$

$\hat{\phi}_{yu}(i,-k)$ Is given by:

$$\hat{\phi}_{yu}(i,-k) = \frac{1}{R}\sum_{r=1}^{R} y_r(i) u_r(i-k)$$

And $\hat{\phi}_{yu}(i)$ is given by:

$$\hat{\phi}_{yu}(i) = [\hat{\phi}_{yu}(i,-M1)\hat{\phi}_{yu}(i,-M1-1)\cdots\hat{\phi}_{yu}(i,-M2)]^{\mathrm{T}}$$

Then,

$$\mathbf{h}(i) = [h(i,M1)\ldots h(i,0)\ldots h(i,M2)]^{\mathrm{T}}$$

Then the IRF estimate can be obtained from the below equation

$$\hat{\mathbf{h}}(i) = \frac{1}{\Delta t}\hat{\mathbf{\Phi}}_{uu}(i)^{-1}\hat{\mathbf{\Phi}}_{zu}(i).$$

In our calculations, we have considered R to be 1 implying that we have only 2 realisations considered.

C. Smoothed IRF Estimation

The smoothed IRF estimate can be calculated by:

$$\hat{\mathbf{h}_s}(i) = \frac{1}{N_w} \sum_{j=i-w/2}^{i+w/2} \hat{\mathbf{h}}(j)$$

Where,

- $\hat{\mathbf{h}_s}(i)$ is the smoothed IRF estimate
- N_w is the number of $\hat{\mathbf{h}}(i)$ inside the window between i-$w/2$ and i+$w/2$
- The window size w for the moving average function was considered as 40 ms based on experimental data

The smoothed IRF estimates $\hat{\mathbf{h}_s}(i)$ were approximated by a second-order model consisting of inertia $I(i)$, viscosity $B(i)$, and stiffness $K(i)$, and its goodness-of-fit was calculated.

D. Calculation of best-fit parameters

For each time step i, the best-fit parameters $(I^*(i), B^*(i), K^*(i))$ were estimated by minimizing the mean squared error between the IRF of the model $(\mathbf{h_{model}}(i))$ constructed by $I(i), B(i), K(i)$ and $\hat{\mathbf{h}}_\mathbf{s}(i)$.

The optimal parameters $(I^*(i), B^*(i), K^*(i))$ include contributions from the robot dynamics as well as ankle dynamics, ankle parameters $(I^*_{\text{Ankle}}(i), B^*_{\text{Ankle}}(i), K^*_{\text{Ankle}}(i))$ can be obtained after compensating for Anklebot dynamics in ankle joint coordinates, which also were accurately approximated by a second order system $(I_{\text{Abot}}, B_{\text{Abot}}, K_{\text{Abot}})$. The Ankle parameters are calculated using the formula:

$$I^*_{\text{Ankle}}(i) = I^*(i) - I_{\text{Abot}}$$
$$B^*_{\text{Ankle}}(i) = B^*(i) - B_{\text{Abot}}$$
$$K^*_{\text{Ankle}}(i) = K^*(i) - K_{\text{Abot}}$$

As per [4] we get the I_Abot = 0.035, B_Abot = 0.25, K_Abot = 20. As compared to the the I^*, B^*, K^* which were 0.04, 0.9 and 35, they are very significant and hence cannot be ignored.

E. Reliability of IRF estimation

The reliability of IRF estimation was evaluated by calculating the percentage variance accounted for VAF between $z_r(i)$ and $\hat{z}_r(i)$ for each realization r and averaged over the entire selected realizations R, where $\hat{z}_r(i)$ was the output predicted by the convolution of $u_r(i)$ and $h_s(i)$.

$$\%VAF\_\text{output}(r) = 100 \times \left(1 - \frac{\text{var}\,(z_r(i) - \hat{z}_r(i))}{\text{var}\,(z_r(i))}\right)$$

$$\%\text{VAF\_IRF(i)} = 100 \left(1 - \frac{\text{var}\left(\hat{\mathbf{h}}_s(i) - \mathbf{h}^*_{\text{model}}(i)\right)}{\text{var}\left(\hat{\mathbf{h}}_s(i)\right)}\right)$$

V. Improvement efforts in the paper

As an attempt to add novelty to the existing work, we studied the effect Anklebot dynamics on the estimations based on measurements. As we can see in the above equations, we correct the measured estimations by subtracting the dynamics (i,e, inertia, viscosity and stiffness of Anklebot from each estimation). We evaluate the error if this correction is not done.

Another thing tried out in this project is that this method has been tried out for only 1 realisation. The ensemble method relies on the fact that we take an average of a certain number of realisations. Thus we have evaluated the effect of decreasing the number of realisations as well.

VI. Results

The mechanical impedance of an ankle was estimated using the ensemble technique. Inertia, viscosity, and stiffness were estimated for each time step. The plots for the same are shown below.

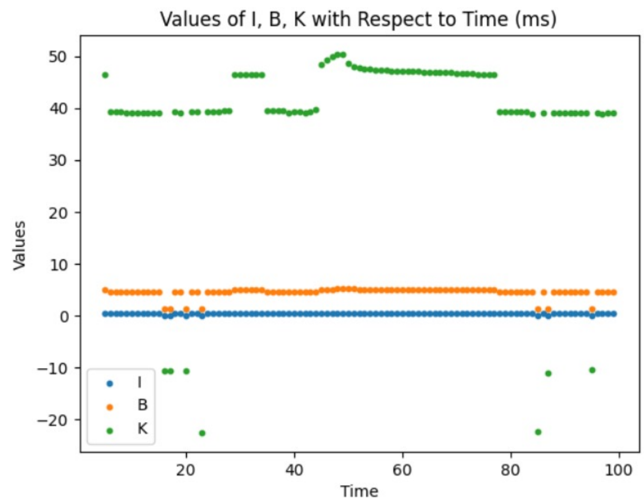

Fig. 5. I_ankle, B_ankle,K_ankle

As we can see we were able to replicate the results shown in the paper. As per observation, the Anklebot dynamics are a quite significant part of the estimated dynamics and it is necessary to compensate them if we want to accurately calculate the ankle dynamics.

Also there is a significant error in the output plots, we can see the outliers in the above plots . Thus we can confirm that taking only 1 realisations is not robust enough.

The average results for VAF were as follows,

$$VAF\_output = 24\%$$

VAF_model = 23 %

The code implementation for our work is on github. Below is the link for the same.

VII. Conclusion

We have replicated the ensemble method of estimating the human ankle impedance when input torque and measured ankle angle are present. We were able to compute the impulse response function and estimate the ankle dynamics from it. As part of modifications, we evaluated the significance of the

Anklebot dynamics in the dynamics of the entire system which is obtained from the inputs and outputs. We also checked the effect reducing the number of realisations had on the accuracy of the algorithm.

VIII. Future Work

As mentioned in the paper we can slightly modify the current system identification method, such as by using the multi-segment algorithm , to significantly shorten the measurement time. Additionally, implementing this technique on a paretic ankle would be valuable to better understand how paretic ankles move during walking, we can create more favourable conditions for studying patients. One way is to use a weight support system to reduce the burden of their added body mass on the treadmill.

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[6] Hof (2008) contributed to the understanding of balance mechanisms in standing humans through equations of motion2.

[7] Mancini et al. (2015) introduced wearable inertial sensors to quantify dynamic ankle stiffness during walking, providing insights into the adaptive nature of ankle impedance3.

[8] Ivanenko et al. (2013) and Sawers et al. (2015) conducted studies highlighting the role of muscle activation patterns in modulating ankle stiffness and damping during various phases of gait45.

[9] Piazza and Steele (2018) investigated how altering ankle impedance through training could enhance stability in individuals with gait disorders6.

[10] Malcolm et al. (2017) and Zhang et al. (2020) demonstrated the importance of mimicking physiological ankle impedance for the development of robotic exoskeletons and prosthetic devices78.