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Human Lower Leg Parameter Estimation using a Passive Exoskeleton Structure

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Abstract: This paper introduces a framework for estimation of lower-leg biomechanical parameters (inertia, damping, stiffness) using a passive exoskeleton with embedded IMUs and position encoders. By combining Kalman filtering with sequential least squares optimization, we achieve subject-specific identification during natural movement without motion capture systems.

Keywords: Exoskeleton, Lower Leg, Parameter Estimation, Optimization, Kalman filter

1 Introduction

Assistive exoskeletons show increasing potential in healthcare applications, particularly for mobility support in aging populations. While active exoskeletons can provide personalized gait assistance through torque-controlled actuators, their effectiveness fundamentally depends on accurate biomechanical parameters of the user's limbs - including joint inertia, damping coefficients, and segmental stiffness. Current parameter identification methods face critical limitations in practical deployment scenarios. In multi-user environments like retirement homes, where exoskeleton operators frequently change, traditional approaches requiring elaborate measurement scenarios are not feasible. If the exoskeleton is an actively powered exoskeleton, it is advantageous to have precise knowledge of the mechanical properties in order to optimize the support provided by the exoskeleton. Such parameters can be the inertia and stiffness of the joints of the person wearing the exoskeleton. If the user of the exoskeleton is constantly changing, it is not possible to perform complex and expensive measurements to calibrate the exoskeleton to the user. Therefore, this paper presents a simple and fast method for estimating various human limb parameters using an exoskeleton. To make a first evaluation of the method, a Parameter estimation is done for the lower leg. In this study, the movement is imposed only through rotation of the knee joint.

1.1 Related Work

In the literature the estimation of human lower limb parameters is achieved in several ways. One prominent way to determine parameters of the knee, such as stiffness and damping, is by using an optical tracking system in combination with sensors such as electromyography (EMG) or force sensors [1]. The optical system is used to measure the position of the human limb, while the EMG or force sensors can be used to estimate the torque applied to the observed joint. Therefore a model of the muscles and the joint as in [2, 4] is needed. Otherwise, an inverse dynamics approach can be used, where the relationship between ground reaction forces and joint accelerations is used to determine the exerted inertia. Another way to determine the applied torque on the joint is to use functional electrostimulation (FES) to control the muscles [4]. In an active exoskeleton, the joint torque can also be applied by the actuators when the leg muscles are relaxed. Due to the lack of methods that include only an exoskeleton frame with sensors, we present a novel approach where several parameters of the human lower leg, such as mass and stiffness, can be estimated using only the sensors on the exoskeleton and prior knowledge from human anatomy.

2 Methods

The following section describes the overall applied workflow. This includes accquisition of the motion data, data postprocessing and the usage of an optimization algorithm to find a parameter set that can reprdoduce the recorded motion. First, the measurement of the angle ϕ, angular velocity $\dot{\phi}$ and angular acceleration $\ddot{\phi}$ is done on a *Arduino Nano 33 IoT* in combination with the onboard Inertia Measurement Unit (IMU) *LSM6DS3* and an angle encoder of type *AS5600*. The used exoskeleton segment is part of a newly built exoskeleton at the Institute for Medical Information Technology (MEDIT). The exoskeleton together with the used sensory components is shown in **Figure 1**.

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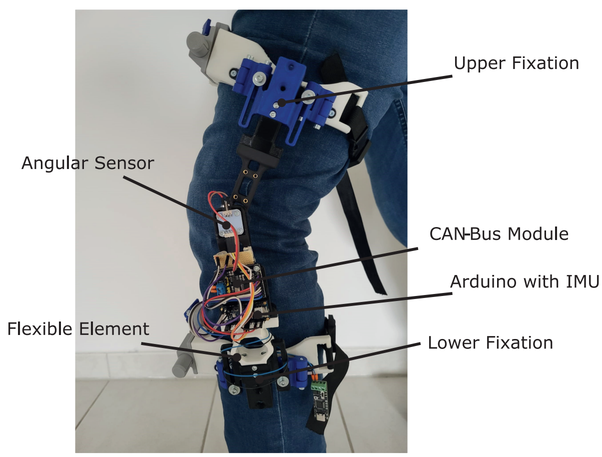

Fig. 1: Exoskeleton with components for data aquisition

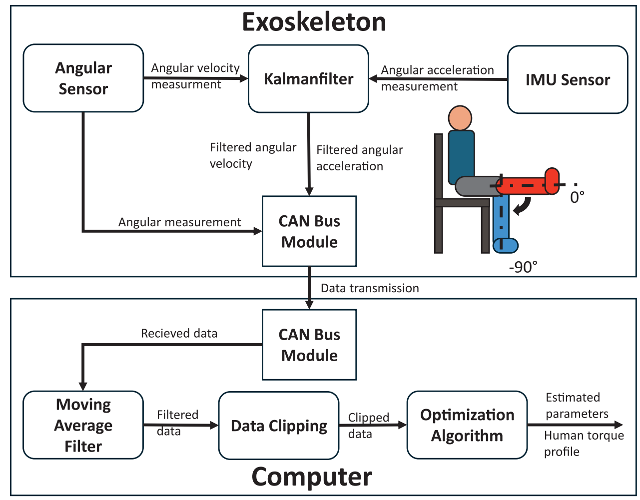

Fig. 2: Workflow Diagramm

In addition to the used sensors, the exoskeleton consists mainly of an additive manufactured PETG structure that connects the thight and shin. Moreover, a flexible element made of TPU is used to compensate for deviations of the knee joint in relation to the hinge joint of the exoskeleton. It can also compensate for misalignment between the exoskeleton and the human to still be comfortable. In addition to the main structure, two adjustable cuffs connect the exoskeleton to the human at the thigh and shin. Using the Arduino and a Kalman filter, ϕ, $\dot{\phi}$, $\ddot{\phi}$ are acquired. Then the data is sent to a stationary computer using a CAN bus network. On the computer, the recorded data is filtered using a moving average filter and then clipped to extract only the useful part of the graph. It is then fed to an optimization algorithm to obtain the mass (m) and inertia (J) of the lower leg. Additionally, the distance from the joint to the center of mass of the shin (l), the joint stiffness (c), and the damping (d) are calculated. The complete workflow is shown in **Figure 2**.

2.1 Data Aquisition

To reduce noise in the measurement, a Kalman filter on the Arduino is applied based on [5]. The filter uses finite differences to relate angle ϕ, angular velocity $\dot{\phi}$ and acceleration $\ddot{\phi}$, with the system matrix $\mathbf{A}$ defining their correlation:

$$\mathbf{A} = \begin{pmatrix} 1 & \Delta t & 0.5\Delta t^2 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{pmatrix} \tag{1}$$

$$\mathbf{x} = \begin{pmatrix} \phi \\ \dot{\phi} \\ \ddot{\phi} \end{pmatrix} \tag{2}$$

Here, Δt represents the sample time on the embedded system, which is set to 0.01sec. The filter corrects predicted states using both measured states and diagonal weighting matrices $\mathbf{Q}$ and $\mathbf{R}$ to suppress noise. The Kalman filter serves, as a noise-rejecting integrator, enabling parameter estimation for subsequent physical modeling.

2.2 Data Postprocessing

The motion, we want to record, is a simple up and down motion. The movement starts with the lower leg being up at $0°$, going down to about $-90°$ and back up again, as shown in **Figure 2**. The recorded profiles are then filtered with a moving average filter to obtain only the characteristic trajectory of the motion [6]. This is especially necessary for the acceleration because the leg muscles tend to twitch when moving slowly and concentrating on a constant speed.

$$\hat{\mathbf{T}}_\phi(i) = \frac{1}{h} \cdot \sum_{j=0}^{N-1} \phi(i+j) \tag{3}$$

The variable $\hat{\mathbf{T}}_\phi$ is the filtered trajectory of ϕ in the window of size h. This procedure is applied successively for all recorded values N of ϕ and corresponding $\dot{\phi}$, $\ddot{\phi}$. In addition, the regions, where no significant motion is recorded, are clipped using the motion criterion $\dot{\phi} > 20\ {}^\circ\,\mathrm{s}^{-1}$. The frequency f of the driving torque can also be estimated by half the time (T) that the leg needs to return to its initial position.

$$f = 2 \cdot \frac{1}{T} \tag{4}$$

2.3 Prior Knowledge from Human Anatomy

To obtain feasable starting values for the optimization and for comparison, values from literature are used. To get the expected mass for the lower leg, the mass distribution data based on the analysis from [3] is used. The distribution is relative to the total body weight m_{total}:

$$m_{shin} = 0.05 \cdot m_{total} \tag{5}$$

$$m_{feet} = 0.02 \cdot m_{total} \tag{6}$$

Based on the relative mass and the position of the center of mass (COM) of feet and shin ($\mathbf{d_F}, \mathbf{d_S}$) in the knee joint coordinate frame, the distance (l) between the knee joint and the combined COM of shin and feet can be calculated [7].

$$l = \|\mathbf{d_{COM}}\|_2 = \left\| \frac{\mathbf{d_F} \cdot 0.02 + \mathbf{d_S} \cdot 0.05}{0.02 + 0.05} \right\|_2 \tag{7}$$

To estimate the inertia (θ) of the lower leg, a simplification of the shin as a capsule is performed, where the effect of the foot is considered negligible. With the capsule oriented so that the z-axis of the moving knee joint coordinate system points along the capsules central axis, the corresponding inertia (θ) can be calculated as follows:

$$\begin{aligned}\theta = &\rho \cdot V_{cylinder} \cdot \left(\frac{l_{shin}^2}{12} + \frac{r_{shin}^2}{4} \right) \\ &+ \rho \cdot V_{sphere} \cdot \left(\frac{2r_{shin}^2}{5} + \frac{l_{shin}^2}{2} + \frac{3l_{shin} \cdot r_{shin}}{8} \right)\end{aligned} \tag{8}$$

With the shin radius (r_{shin}) based on [8], the capsule can be separated into a cylindrical and a spherical part [9]. The density ρ can be calculated from the shin mass and the volume of the capsule. The length l_{shin} is the length of the cylindrical part of the capsule, which is the difference of the shin length and the shin diameter. For the stiffness and damping, as well as for the torque applied to the knee joint, reference values from the literature are used. Based on Lyu et al. the stiffness (c) and damping (d) of the knee joint are about $1.6\mathrm{N\,m\,rad^{-1}}$ and $28.8\mathrm{N\,m\,rad^{-1}\,s^{-1}}$ for a healthy young male [4]. According to [9], the human torque on the knee joint can reach up to $300\mathrm{N\,m}$ for isometric knee extension.

2.4 Optimization Algorithm

In order to estimate parameters for the human shin, using a Sequential Least Squares Quadratic Programming (SLSQP) algorithm, a cost function must be formulated. Therefore, we derive the dynamic model of the lower leg using a pendulum model. The dynamic of the exoskeleton made completly out plastic, is considered neglectable.

$$\ddot{\phi} = \frac{1}{J} \left(\tau_{human} - mlg \cdot \cos(\phi) - c \cdot \phi - d \cdot \dot{\phi} \right) \tag{9}$$

$$\tau_{human} = \left\{ \begin{array}{ll} -\tau \cdot \sin(2\pi f \cdot t), & \text{if } t \leq \frac{T}{2}, \\ \tau \cdot \sin(2\pi f \cdot t), & \text{if } t > \frac{T}{2} \end{array} \right) \tag{10}$$

A sinusoidal torque (τ_{human}) is assumed, which changes its sign after half of the measured period. The signs and the passive forces can be derived from **Figure 2**, where g is the gravitational acceleration with $9.81\mathrm{m\,s^{-2}}$. Based on the equation **9** we can formulate the cost function to minimize the error between the measured angle $\hat{\mathbf{T}}_\phi$ and the computed angle $\widetilde{\mathbf{T}}_\phi$. We get the simulated angle from the simulated acceleration via forth order Runge-Kutta integration.

$$\min_{\mathbf{P}} \left(\left\| \hat{\mathbf{T}}_\phi - \widetilde{\mathbf{T}}_\phi(\mathbf{P}) \right\|_2^2 + \lambda \cdot \|\mathbf{P}_{exp} - \mathbf{P}\|_2^2 \right) \tag{11}$$

The variable $\mathbf{P}$ is the parameter vector, containing $\mathbf{P} = (m, J, l, d, c, \tau)$. We can also push the optimization towards the expected values from anatomy, by using a regularisation that punishes the deviation between the expected parameter vector $\mathbf{P}_{exp}$ and the computed $\mathbf{P}$. The influence on the optimization can be regulated by use of the parameter λ. In addition we can formulate the inequality constraint:

$$J - ml^2 \geq 0 \text{ with } J = ml^2 + \theta \tag{12}$$

Additionaly, we get the boundary conditions for $\mathbf{P}$ based on the findings from section **2.3**.

$$\mathbf{P} \in \Big([2; 6], [0.15; 1], [0.15; 0.6], [0; 60], [0; 4], [-250; 250] \Big) \tag{13}$$

3 Experiment

To validate the proposed procedure, the exoskeleton is worn by a young male with a body weight of $77\mathrm{kg}$. To record the data, the subject sits on a chair with the leg fully extended. The leg is moved as described in chapter **2.2**. Based on body weight, shin radius and length for an average male with a height of $1.8\mathrm{m}$ the expected parameter vector is as follows, where τ is unknown.

$$\begin{aligned}\mathbf{P}_{exp} = (&5.39\mathrm{kg}, 0.35\mathrm{kg\,m^2}, 0.2461\mathrm{m}, \\ &30\mathrm{N\,m\,rad^{-1}\,s^{-1}}, 2\mathrm{N\,m\,rad^{-1}}, \tau)\end{aligned} \tag{14}$$

The estimated average parameter vector from two movement cycles is:

$$\begin{aligned}\mathbf{P} = (&4.929\mathrm{kg}, 0.736\mathrm{kg\,m^2}, 0.221\mathrm{m}, \\ &0.162\mathrm{N\,m\,rad^{-1}\,s^{-1}}, 2.127\mathrm{N\,m\,rad^{-1}}, -5.39\mathrm{N\,m})\end{aligned} \tag{15}$$

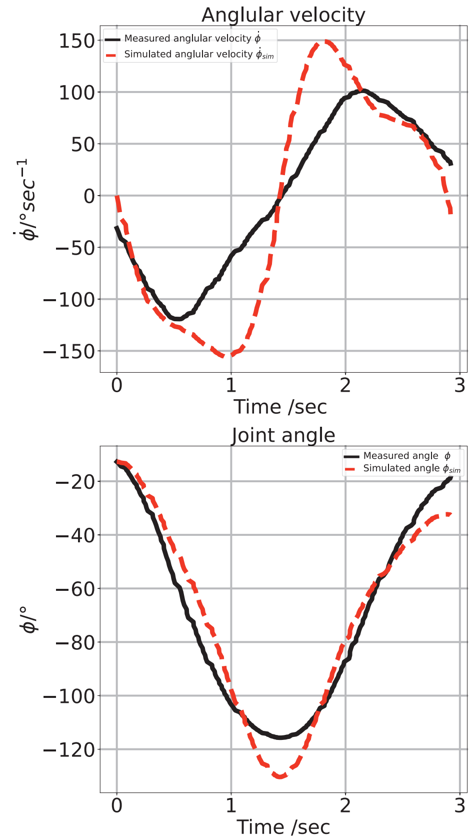

Fig. 3: Comparison of measured and simulated (dashed line) angle and angular velocity

The trajectorie for the measured angle and angular velocity of the first movement is shown in **Figure 3**. The simulation exhibits a significant convergence between the computed angular trajectory and the measured data, although the angular velocity is approximated with lower accuracy. The negative amplitude of the estimated joint torque indicates that the human generated damping counteracts gravity induced movement. Furthermore, the estimates for mass, stiffness, and knee joint distance closely align with literature benchmarks, whereas the value for inertia is higher than expected and the damping value is nearly neglectable. This discrepancy can be attributed to the existence of multiple parameter sets that reproduce the measured movement, thereby allowing for parameter variability within a certain range.

4 Conclusion and Outlook

This study presents a method for estimating human inertia, mass, damping, stiffness and peak amplitude using a sensor-equipped passive exoskeleton combined with an optimization algorithm that uses literature and anatomical reference values. Although the measured joint angle is accurately tracked, deviations in its derivatives and the occurrence of multiple parameter sets indicate that the current optimization requires further refinement. Additionally, misalignment between the exoskeleton and the human leg causes the measured angle to be slightly below zero at full extension, which should be incorporated in future studies. Further developments include integrating actuators and an onboard computing unit to enable real-time optimization and optimized control.

Author Statement

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References

[1] Mallat, Randa, Vincent Bonnet, Weiguang Huo, Patrick Karasinski, Yacine Amirat, Mohamad Khalil, und Samer Mohammed. „Human-Exoskeleton System Dynamics Identification Using Affordable Sensors“. In 2018 IEEE International Conference on Robotics and Automation (ICRA), 6759–65. Brisbane, QLD: IEEE, 2018.

[2] Pfeifer, Serge, Heike Vallery, Michael Hardegger, Robert Riener, und Eric J. Perreault. „Model-Based Estimation of Knee Stiffness“. IEEE Transactions on Biomedical Engineering 59, Nr. 9 (September 2012): 2604–12.

[3] Misgeld, Berno J. E., Markus Luken, Robert Riener, und Steffen Leonhardt. „Observer-Based Human Knee Stiffness Estimation“. IEEE Transactions on Biomedical Engineering 64, Nr. 5 (Mai 2017): 1033–44.

[4] Lyu, Chenglin, Marlon Nievenheim, L. Cornelius Bollheimer, Steffen Leonhardt, und Philip Von Platen. „FES- and Camera Sensor- Based Estimation of Knee and Ankle Stiffness“. IFAC-PapersOnLine 58, Nr. 24 (2024): 350–55.

[5] Ma, Hongbin, Liping Yan, Yuanqing Xia, und Mengyin Fu. Kalman Filtering and Information Fusion. Singapore: Springer, 2020.

[6] Smith, Steven W. The Scientist & Engineer’s Guide to Digital Signal Processing. First Edition. San Diego, Calif: California Technical Pub, 1997.

[7] WANK, Veit: Biomechanik der Sportarten: Grundlagen der Sportmechanik und Messtechnik - Fokus Leichtathletik. Berlin : Springer, 2021 (Lehrbuch).

[8] DEUTSCHES INSTITUT FÜR NORMUNG E. V.: DIN 33402-2:2020-12, Ergonomie- Körpermaße des Menschen- Teil 2: Werte

[9] LOVROVIC, Bojan: Capsule Inertia Tensor. In: GameDev.net (12.01.2015). https://www.gamedev.net/tutorials/programming/math-and-physics/ capsule-inertia-tensor-r3856/

[10] Pincivero, Danny, Yuliya Salfetnikov, Robert Campy, und Alan Coelho. „Angle- and gender-specific quadriceps femoris muscle recruitment and knee extensor torque“. Journal of biomechanics 37 (1. Dezember 2004): 1689–97.