Title: Optimal and Adaptive Control of a Variable Stiffness Prosthetic Ankle using Reinforcement Learning for Sit-to-Stand and Stand-to-Sit

Aim and Scope:
The aim of this thesis is to design an optimal controller for a prosthetic ankle with variable-stiffness series elastic actuation (SEA) to enhance sit-to-stand (STS) and stand-to-sit (ST) transitions. The controller seeks to reduce intact knee loading, which has been associated with significantly higher flexion moments in prosthetic users[1], and to decrease motor energy consumption. A reinforcement learning (RL) agent will be utilized to adjust the controller in real-time, enabling adaptation to individual users and environmental variations. The scope of this work encompasses developing control strategies for simultaneous torque and stiffness modulation, integrating an RL agent to dynamically tune controller parameters, and assessing performance through simulations. Key evaluation metrics include intact knee loading (e.g., peak flexion moment) and motor energy consumption, alongside secondary considerations such as transition time, loading asymmetry, and stability (e.g., center of mass trajectory). The thesis will also examine the controller's robustness to variations in user characteristics (e.g., weight and initial pose) and environmental conditions, as well as the effectiveness of the RL agent in tuning the controller across different simulated users and modified states. These objectives are feasible within the thesis timeline.

Literature Review Structure:

- Biomechanics of STS/ST Transitions
  - Outlines the mechanics of STS/ST, challenges for amputees, and why passive prosthetics struggle.
  - Purpose: Grounds the reader in the problem.
- Prosthetic Solutions: From Passive to Active Variable Stiffness
  - Covers passive, quasi-passive, and active prosthetics, focusing on variable stiffness approaches (quasi-passive vs. active SEA) and their trade-offs (energy, control, adaptability).
  - Purpose: Merges sections 2 and 3 for a concise overview, spotlighting your thesis's focus.
- Control Strategies for Variable Stiffness Prosthetics
  - Reviews control methods for active and quasi-passive devices, emphasizing challenges and opportunities for variable stiffness SEA in STS/ST.
  - Purpose: Links actuation to practical implementation.
- Reinforcement Learning for Adaptive Prosthetic Control
  - Introduces RL as a tool for optimal, adaptive control, contrasting it with traditional methods and highlighting its potential for SEA.

[1] Teater et al., "Unilateral Transtibial Prosthesis Users Load Their Intact Limb More than Their Prosthetic Limb during Sit-to-Stand, Squatting, and Lifting."

    - Purpose: Positions RL as your innovative angle.
- Research Gap and Proposed Approach
    - Identifies the gap in real-time, adaptive control for variable stiffness SEA during STS/ST and previews your RL-based solution.
    - Purpose: Ties everything together and sets up your contribution.

Pipeline:

1. Develop a Simulation Environment for the Healthy Human Model
    a. Objective: Create a baseline simulation to synthesize STS/ST transitions for a healthy human model, generating reference data for later use.
    b. Steps:
        i. Implement a synthesizer/controller from the literature (e.g., a Model Predictive Control (MPC) controller) to simulate STS/ST transitions.
        ii. Start with a simple 2D model in MATLAB, minimizing a cost function that combines metrics like transition time, effort, jerk, and stability.
        iii. Use an RL agent (e.g., adjusting weights of the cost function) to ensure the model's kinematic and kinetic outputs align with real-world data, avoiding overfitting.
        iv. Transition to a full musculoskeletal model in OpenSim and validate the controller against real-world kinematic and kinetic datasets.
    c. Output: A validated simulation of healthy STS/ST transitions with optimized trajectories and metrics.
2. Build the Human-Prosthetic Simulation and Design the Prosthetic Controller
    a. Objective: Simulate a human model with a prosthetic ankle and design a dedicated controller to achieve your research aims.
    b. Steps:
        i. Modify the OpenSim model by replacing one ankle with a Series Elastic Actuator (SEA) capable of simultaneous torque and stiffness control.
        ii. Develop a prosthetic controller (an MPC system) for the prosthetic ankle, distinct from the model controller used in Step 1. These controllers operate independently:
            - Model Controller: Simulates voluntary control of the intact limbs (e.g., muscle activations or joint torques) during STS/ST transitions, based on the healthy model or literature.
            - Prosthetic Controller: Controls the prosthetic ankle's torque and stiffness, optimizing a cost function focused on reducing intact knee loading

(e.g., peak flexion moment) and motor energy consumption.

iii. Define the prosthetic controller's inputs (e.g., joint angles, velocities, or desired states) separately from the model controller's inputs, ensuring they work "oblivion to each other."

c. Output: A simulation environment where the model controller drives the intact limbs and the prosthetic controller manages the SEA ankle, tailored to your research goals.

3. Enhance the Prosthetic Controller with RL
    a. Objective: Improve the prosthetic controller's performance and adaptability using RL.
    b. Steps:
        i. Integrate an RL agent (e.g., Deep Deterministic Policy Gradient, DDPG) to fine-tune the prosthetic MPC controller's parameters in real-time.
        ii. Train the RL agent in the simulation across diverse STS/ST scenarios (e.g., varying user weights, initial poses, or chair heights) to:
            - Optimize the MPC controller for reducing intact knee loading and energy consumption.
            - Enable self-tuning for specific users, eliminating the need for manual adjustments.
    c. Output: An RL-enhanced prosthetic controller that adapts to user-specific and environmental variations.
4. Evaluate Controller Performance
    a. Objective: Assess the prosthetic controller's effectiveness with and without RL enhancement.
    b. Steps:
        i. Run simulations of STS/ST transitions using:
            - The baseline prosthetic MPC controller (non-adaptive).
            - The RL-tuned prosthetic MPC controller.
        ii. Test across a range of conditions (e.g., user weights from 50-100 kg, different chair heights).
        iii. Measure key metrics:
            - Intact knee loading (e.g., peak moment or force).
            - Motor energy consumption.
            - Transition time and stability (e.g., center-of-mass trajectory).
        iv. Compare results against real-world data (e.g., from healthy or amputee subjects) to validate performance.
    c. Output: Quantitative comparison showing the RL-tuned controller's improvements over the baseline.
5. Assess Robustness and Self-Tuning Capability
    a. Objective: Validate the RL-enhanced controller's reliability and adaptability.

b. Steps:
    i. Robustness: Introduce errors or variations (e.g., modeling inaccuracies, noise in sensor inputs) and evaluate the controller's performance on the same metrics.
    ii. Self-Tuning: Test the RL agent's ability to adapt the controller for a new user with limited data (e.g., only height and weight), measuring convergence time and metric improvements.
    iii. Use statistical analysis (e.g., paired t-tests) to confirm significance of results.
c. Output: Evidence of the controller's robustness and its ability to self-tune, supporting your thesis's practical applicability.