AI for Engineering Systems: Prosthetics

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AI for Robotics
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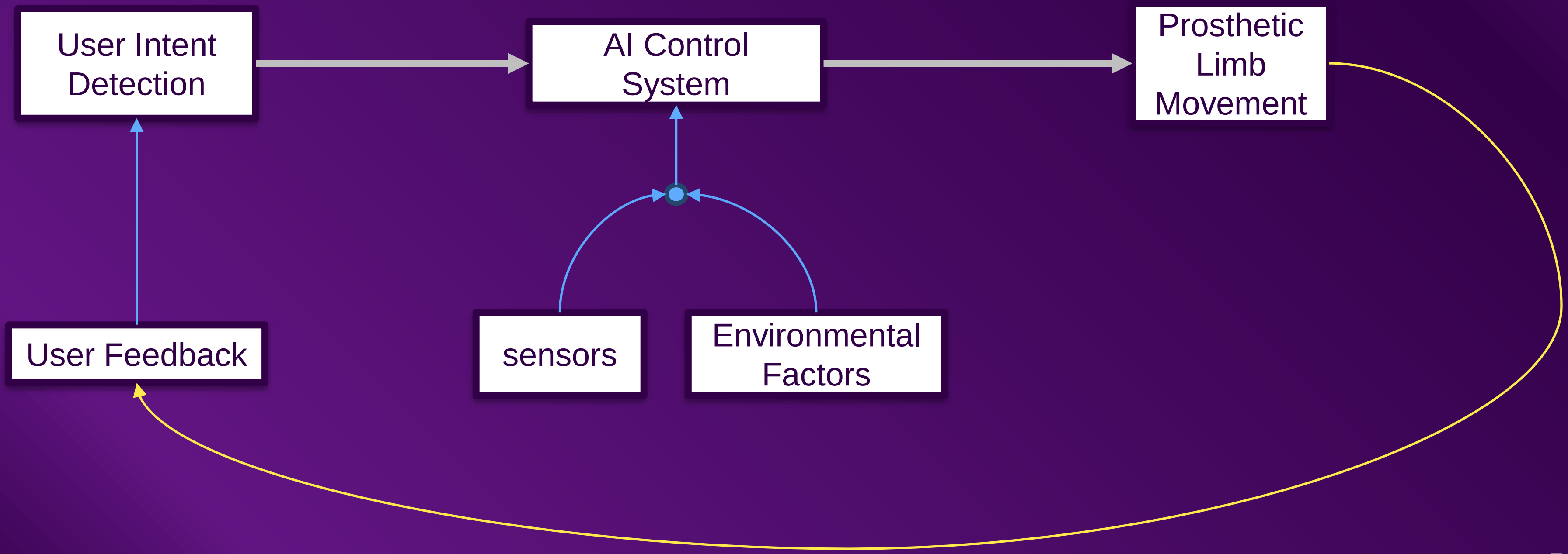
01 Introduction

Overview

Prosthetics are artificial limbs that integrate sensors, mechanical structures, and actuators to replace missing body parts. They may incorporate control systems that use AI to interpret complex inputs, enabling natural, intuitive control that improves mobility and quality of life for amputees.

AI prosthetic system



02

Research

Ways in which AI is improving Prosthetics

Reading Environments

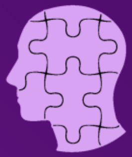
AI uses sensors to detect surfaces like tile or grass and adjusts prosthetic gait in real-time for better function.

Reading Body Signals

Sensors track changes in residual limbs over time and AI automatically tunes socket fit based on individual activity patterns and preferences.

Ways in which AI is improving Prosthetics

Reading Intent



AI learns to precisely interpret EMG and nerve signals from the body and brain to enable natural prosthetic control.

Self-Calibration

Implanted prosthetics require periodic retuning as muscle and nerve tissues change. AI enables devices to detect these changes and self-recalibrate for sustained performance.

Decoding Intent from Muscle Signals

- EMG involves placing electrodes on the skin to detect electrical signals generated when muscles contract.

- Accurately reading EMG signals is challenging due to noise sources like layers of tissue, sweat, and physiological changes in the residual limb over time.

- Bayesian inference and SVMs are proposed approaches to deal with the uncertainty in EMG signals. They allow updating probabilities or classifications of intended movements as new EMG data comes in.

Bayesian inference example

"What is the probability that the patient intends to open their hand, given that a certain signal is detected?"

- Bayes' rule updates prior probabilities of intended hand movements with each new EMG data sample. This calculates posterior probabilities of the patient wanting to open their hand.

$$P(A|B)=\frac{P(B|A)P(A)}{P(B)}$$

$$\begin{aligned}&P(\text{Open}|\text{High})\\&=\frac{P(\text{High}|\text{Open})P(\text{Open})}{P(\text{High}|\text{Open})P(\text{Open})+P(\text{High}|\text{Closed})P(\text{Closed})}\\&=\frac{0.70\times0.20}{(0.70\times0.20)+(0.10\times0.80)}\\&=0.636\end{aligned}$$

next interval if signal is still in the high range

$$\begin{aligned}&=\frac{0.70\times0.636}{(0.70\times0.636)+(0.10\times0.364)}\\&=0.925\end{aligned}$$

Wininger & Johnson (2018) - "Prosthetic Hand Signals"

EMG Strengths and Weaknesses

Pros

- Has a long history of research and commercial use
- Noninvasive method to extract control signals
- Relatively easy to obtain signals
- Contains useful information about intended movements

Cons

- Offline performance doesn't directly translate to real-time control
- Signal variability
- Sensitive to factors like sweat and physiological changes
- Unintuitive, requiring unnatural contracted motions and extensive user training.

Peripheral Nerve Interface

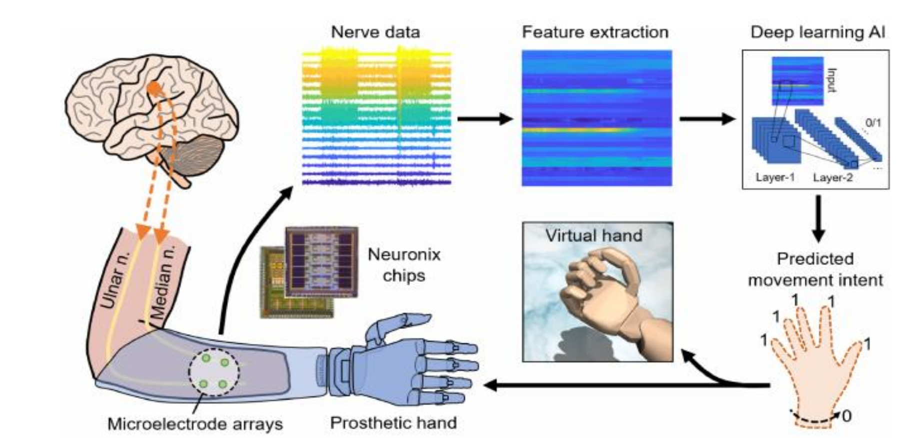
- Aims to enable intuitive and real-time prosthesis control purely by thoughts, allowing to achieve a natural user experience.

- Involves connecting the artificial limb directly to peripheral nerves, providing precise control signals.

- Allows the system to be used by a larger population of amputees with various amputation levels.

- Major challenge is the generation a large amount of high-dimensional data. However, deep learning approaches help leverage this challenge.

Deep Learning-Based AI Neural Decoder



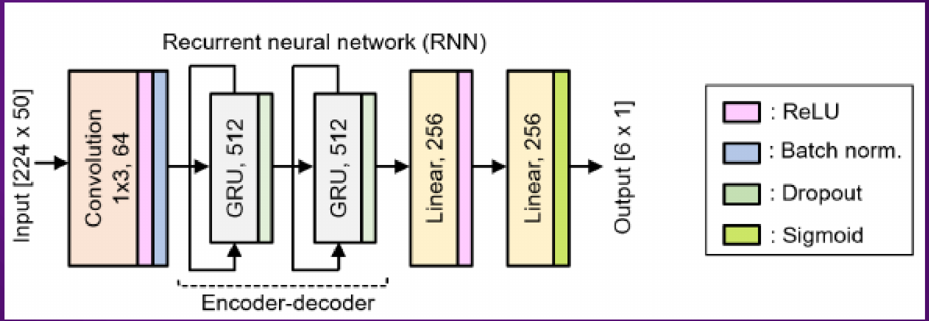
- Nerve data acquired with neuromodulation system
- 16 Channels which belong to a subset of the active sites are recorded.
- Sites that have high SNR and strong vCAP during voluntary movement are selected.

$P_{dB} = 10\log_{10}(1/n\Sigma_{i=1}^{n} V[i]^2)$ $[SNR] = P_{dB,\ flex}/P_{dB,\ rest}$

- 14 Features extracted from filtered signals using sliding window.
- 2D data with [16 channels] × [14 features] × [50 time-series] = [224 x 50] is compiled as the input to AI Agent
- AI agent classifies the movement of 6 DOF: 5 for individual finger flexing and 1 for wrist pronation.
- prediction output is mapped to the movement of prosthetic hand

Luu et al. (2022) - "Artificial Intelligence Enables Real-Time and Intuitive Control of Prostheses via Nerve Interface"

Deep Learning-Based AI Neural Decoder



- The model consists of 1.6 million trainable parameters
- Relatively shallow since the model must be able to be deployed in a portable edge computing device
- Parameters are as follows:
  Adam optimizer with the default parameters β1 = 0.99, β2 = 0.999, weight decay L2 = 10^{-5} , mini-batch of 64, initial learning rate of 10^{-4}, and maximum number of epoch of 5.
- The final activation function is sigmoid, so predicted probabilities for each DOF range from 0 to 1.

Luu et al. (2022) - "Artificial Intelligence Enables Real-Time and Intuitive Control of Prostheses via Nerve Interface"

Conclusion

- Peripheral nerve interfaces show potential for intuitive prosthesis control without the need for direct brain interfaces.
- Benefits include controlling prosthetics without muscles and potentially restoring sensory feedback.
- Further research is still required to overcome difficulties like long-term compatibility and prevention of nerve damage from implants.

03 Discussion

Topics

- How do you feel about prosthetics that connect nerves or the brain directly? Is it an exciting advancement or concerning?
- If attaching devices gave new abilities, is retaining "natural" bodies limiting?
- What responsibilities do engineers and regulators share regarding oversight, and long-term implications of advances linking human neurobiology with AI/robotics?
- Should prosthetic enhancements beyond natural human abilities be allowed in professional sports? Why or why not?

04

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Thanks for your attention!