MECHANICAL ENGINEERING
TEXAS A&M UNIVERSITY

Gait Phase Estimation of Powered Transfemoral Prosthesis using RNN

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The union of humans and robots

RESEARCH HIGHLIGHT

- Gait phase estimation for the powered prosthesis was proposed using machine learning.
- Network architecture with five LSTM layers successfully estimated gait phase

INTRODUCTION

Importance of gait phase

- Human walking can be divided into heel-strike, flat-foot, push-off, and toe-off [1].
- The gait phase is widely used to control powered assistive devices like prosthetics and exoskeletons. The controller's desired trajectories or gains are modified depending on the gait phase.

Machine learning for gait phase estimation

- Long Short-Term Memory (LSTM) has been widely used in the field of translation, text, and time series prediction with continuous properties since past events have a direct ed cycle that can affect future results.
- Since the gait phase consists of a series of data, LSTM is a suitable method.

POWERED PROSTHETIC SYSTEM

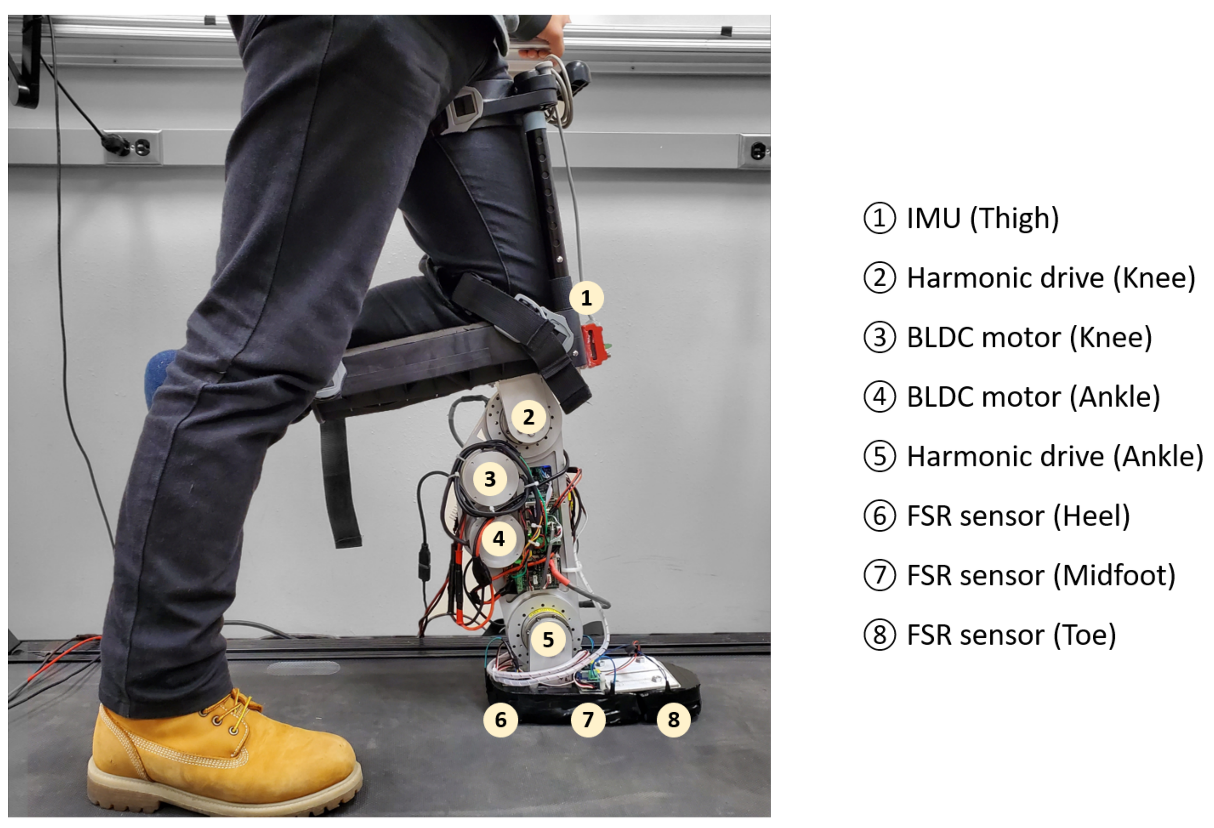

Fig. 1 Custom-built robotic transfemoral prosthesis, AMPRO II

Powered Transfemoral Prosthesis

- AMPRO II, the 2nd generation of custom-built A&M powered transfemoral prosthesis, has two actuations at ankle and knee.
- So far, the gait phase has been estimated by a phase variable calculated from a global thigh angle, which is measured from a 9-axis IMU (MPU9150, SparkFun Electronics, USA) on the L-shape simulator (for the able-bodied subject) of the prosthesis
- However, the gait phase estimation can be more robust and accurate for more reliable control. This necessitates the investigation of the gait phase estimation using machine learning techniques.

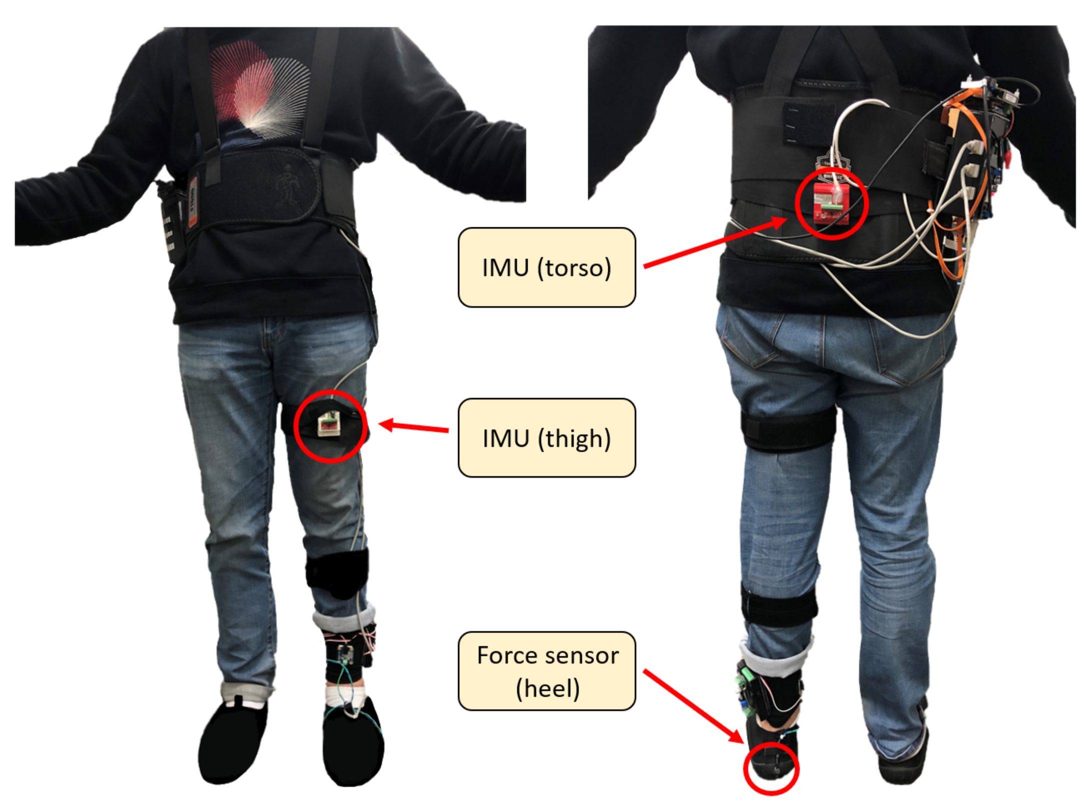

Fig. 2 Wearable sensor set for the gait phase estimation: 2 IMUs for the thigh and torso, and a force sensor for the heel

IMU Setting

- As it is shown in Figure 2, two IMUs are located at the subject's back and thigh, respectively, and a force sensor is at under the heel. During the walking experiment, each sensor data was recorded in the micro-processor in 200 Hz.

CONTROL FRAMEWORK

Gait phase definition and data setup

- In order to train the neural network, it is required to label the ground truth as a reference. We used linear interpolation method.
- The linear interpolation method used a threshold of the heel sensor data to obtain HS points. All points between HS points were then linearly interpolated. Therefore, one gait cycle increases linearly from 0 to 1, resets to 0 at the end of one cycle.
- The refined data consisted of 200 data points per gait cycle.
- To verify the model, we collected data for 400 steps at various speeds (0.25 m/s to 1.75 m/s).

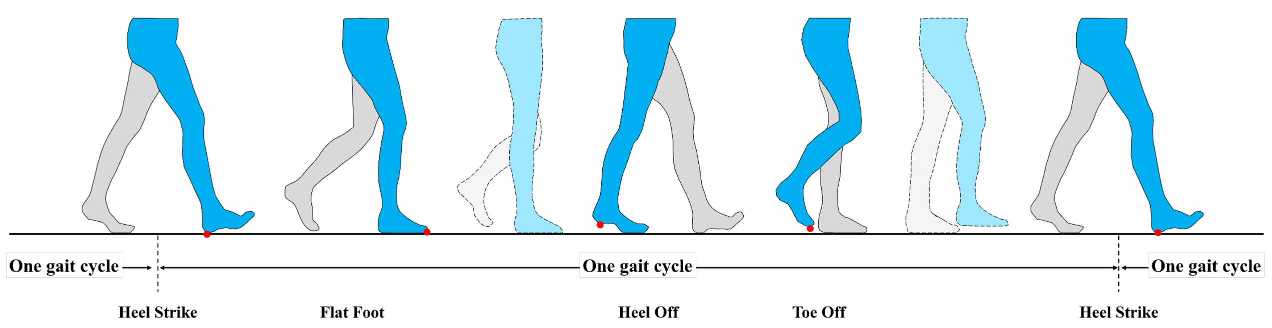

Fig. 3 Gait cycle with important kinematic changes

Networks architecture

- Our network architecture consists of five layers: LSTM (256), bidirectional LSTM (128), LSTM (128), and bidirectional LSTM (64), and fully connected layer.
- To prevent overfitting, each layer implemented a dropout rate of 0.1 and recurrent dropout rate of 0.4.
- We used the Adam optimizer with initial learning rate = 0.001, momentum = 0.9, batch size = 128, epochs = 30, and mean squared error (MSE) as the loss function [2, 3].
- To train the network's model, we prepared a dataset of 100 steps at three walking speeds (0.75 m/s, 1m/s, and 1.25 m/s).

EXPERIMENTAL SETUP

Experiment subject

- A healthy male (31 years, height 175cm, weight 75kg)
- Using equipment to track the gait phase on the left leg

Experiment environment

- On a flat-ground treadmill with four different walking speed (0.25, 0.5, 1.0, 1.25, 1.5, 1.75 m/s)

Experiment data recording

- For each trial, 20 gait cycles were recorded.
- The kinematic data (i.e., position, velocity of thigh and torso) were captured via 2 IMU.
- The kinetic data (i.e., force at the heel and toe) was measured from force sensors underneath a foot.

RESULTS

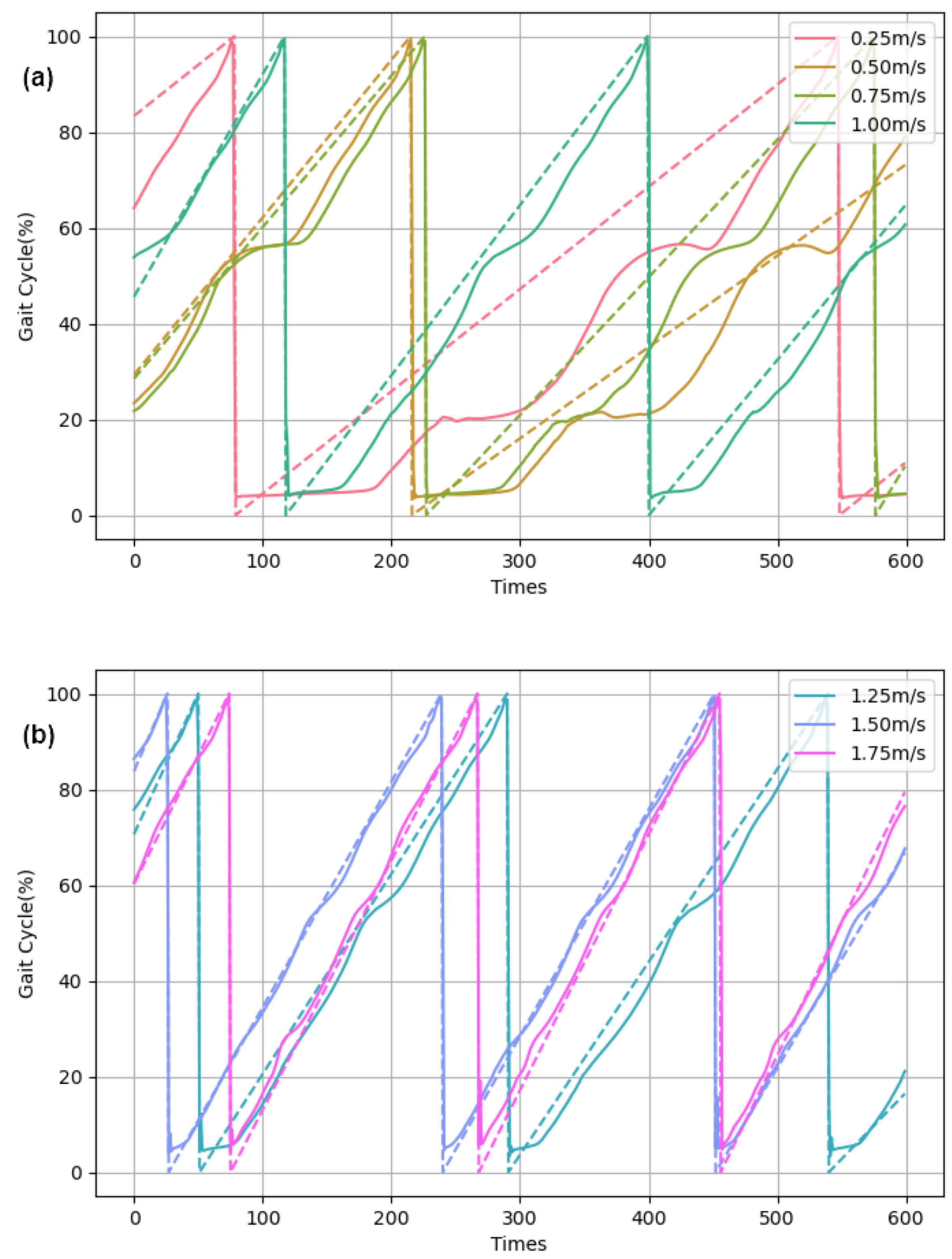

Fig. 4 Gait cycle according to low walking speed (a) and hight walking speed (b). Dotted line is ground truth and solid line is predicted cycle.

- The gait cycle was accurately predicted at 1.25 m/s.
- However, there were a few inaccuracies in predicting the gait phase during the stance phase at lower walking speeds.
- Since the model was trained by the data of walking speed ranging from 0.75 m/s to 1.25 m/s, inaccurate predictions can be expected at slow speeds such as 0.25 m/s.
- Slow walking speed can increase sensor variation, which can cause prediction errors.

CONCLUSIONS

It was observed that

- In this study, we proposed the networks using LSTM for the gait phase estimation.
- At a speed of 1.25m/s or higher, the network performed good estimation.
- However, when the speed was slow, the networks performance tended to deteriorate.

FUTURE WORKS

- We will train the network by transforming the label to polar coordinates from linear interpolation.
- Also, we will use the trained gait estimation model to control a powered transfemoral prosthesis.

References

[1] W. Hong et al., International Conference on Robotics and Automation (ICRA), 2019, pp. 2838-2844.
[2] K. Seo et al., IEEE International Conference on Rehabilitation Robotics (ICORR), 2019, pp. 809-815.
[3] I. Kang et al., IEEE Transactions on Medical Robotics and Bionics 2 (1) (2020) 28-37.