Gait Phase Estimation of Powered Transfemoral Prosthesis using RNN

Jinwon Lee, Woolim Hong, and Pilwon Hur
Department of Mechanical Engineering, Texas A&M University, College Station, TX, USA
Email: {jinwon, ulim8819, pilwonhur}@tamu.edu Web: http://hurgroup.net

Introduction

The gait phase informs us of the human's progress in the gait cycle. It 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. Human walking can be divided into heel-strike, flat-foot, push-off, and toe-off [1]. Human gait is considered to consist of two walking phases: i) stance phase when the foot is in contact with the ground and ii) swing phase when the foot is not in contact with the ground. The first 60% of the gait cycle belongs to the stance phase and the next 40% of the gait cycle belongs to the swing phase.

Recently, there were studies using long short-term memory (LSTM) machine learning to estimate the gait phase. LSTM introduced cell state to solve the long-term dependency problem found in Recurrent Neural Networks (RNN). The concept of the cell state is three gates; forget gate, input gate, output gate. Forget gate is to erase unnecessary past information using the sigmoid function. In the input gate, a sigmoid function decides whether to reflect the new information in the cell state. If new information needs to be reflected, the current cell state is updated through the *tanh* function. The output gate determines which part of the information is sent to the cell's output using a sigmoid function. Finally, the output is fed to the input of the next cell state.

Methods

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].

The data collection experiment had one healthy participant (age:31 years, height:175 cm, weight: 75 kg) who walked on a flat-ground treadmill. The treadmill speed varied from 0.25 m/s to 1.75 m/s. To gather kinematic and force data, we attached two IMU sensor (at the thigh and torso) and one force sensor (at the heel). 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). The data was suitably labelled. The refined data consisted of 200 data points per gait cycle. Training on this dataset took 30 minutes to converge with Tensorflow and two RTX 4000 GPU. To verify the model, we collected data for 400 steps at various speeds (0.25 m/s to 1.75 m/s).

Results and Discussion

Figure 1 shows gait phase estimation. Regardless of the speed, the point where the heel strike occurred was accurately predicted. In particular, 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 training data used only data 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 speeds can increase sensor variation, which can cause data noise.

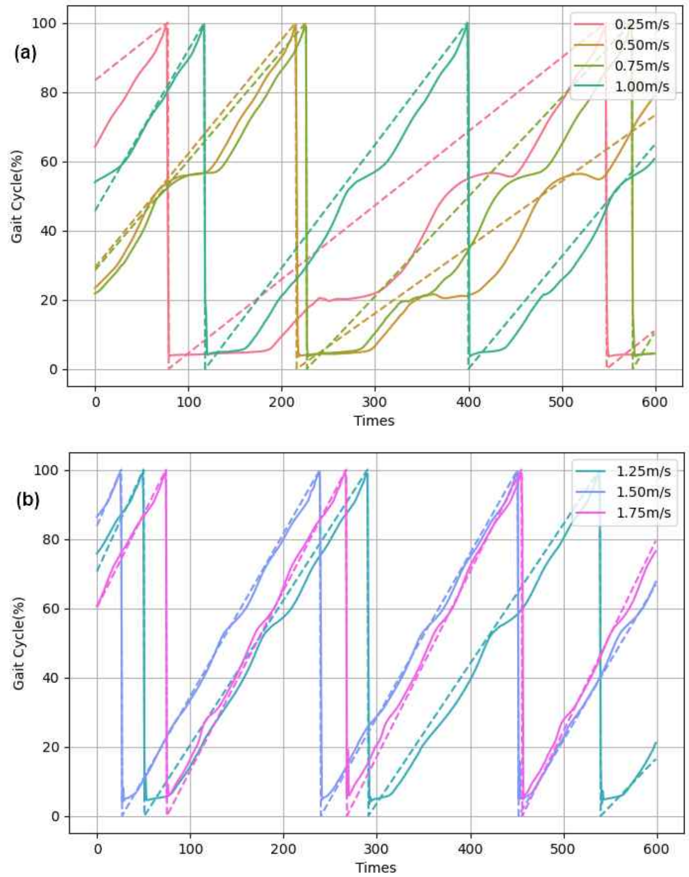

Figure 1: Gait cycle according to low walking speed (a) and hight walking speed (b). Dotted line is ground truth and solid line is predicted cycle.

Significance

Powered lower limb assistive devices rely on the gait phase parameter to determine suitable control inputs. Previously, the gait phase was predicted using multiple sensors and complex calculations. To reduce the prosthetic's weight and battery power efficiency, we must reduce the number of required sensors. In this study, we generated a gait phase estimation model using LSTM. The model requires only two IMUs and one force sensor. Future studies 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.