Least Mean Squares Regression with Stochastic Gradient Descent for Gait Phase Estimation in Exoskeleton Hip Assistance

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***Abstract*—Exoskeletons have the ability to augment the strength of the user. This can have industrial and military applications, to increase the users strength to a level above an able bodied individual, or for medical applications to supplement the users strength to regain a level of mobility or strength that was lost. To achieve this augmentation, one method is to use motors at the joint to assist the movement. While this can provide significant assistance to the user, the current research question is how to time the assistance with the user's motion during tasks such as walking. We propose using the information from the on board sensors to apply machine learning techniques offline to build a hypothesis to predict the gait phase in real time. Specifically, we will be using a least mean squares regression with stochastic gradient decent to create a function for phase estimation.**

***Index Terms*—Machine Learning, Gait Estimation, Stochastic Gradient, Least Mean Squares Regression**

INTRODUCTION

Powered exoskeletons have the potential to improve the mobility of individuals with varying levels of functional mobility. There are two main applications for this super human behavior. The first is for industrial and military applications, where the human strength is being augmented by the exoskeleton to achieve a level of mobility or strength that is beyond the level of an able bodied human [1]. The second application of augmentation is for individuals with a physical disability, to augment their current mobility level to one that matches an able bodied individual. Specifically, exoskeletons have successfully assisted individuals with lower limb paralysis or spinal cord injuries in moving out of a wheelchair and being able to walk across the room [2]. This augmentation that the exoskeleton provides is achieved through assistance of each joint's movement.

The joint movements can be assisted in various methods. Some exoskeletons use a series of pulleys or boden cables to assist individuals with a soft user interface, thus these are considered soft-exosuits [3], [4]. Often, this method results in a light assistance of each joint to improve joint movement efficiency but not able to provide significant levels of augmentation. An alternative method for assisting joint movement is through the use of motors [1], [2], [5]. This method has the highest level of assistance, but also requires a high level of accuracy for when the assistance is provided. In order to protect the human joint attached to the exoskeleton, mechanical end stops and control architecture is implemented to limit the range of motion of the exoskeleton. However, the predicted level of torque or assistance is correlated either with time or with with the gait pattern of the user.

The Bionic Engineering Lab here at the University of Utah has a fully powered bilateral hip exoskeleton that assists in both flexion and extension. The hip-exo is also equipped with an IMU, which allows the device to measure the orientation of the user's thigh [5]. The user's thigh and hip kinematics along with hip kinetics are recorded online at 100 Hz. Currently the assistance provided from the hip-exo is time-based. This type of assistance suffices for cases in which the user is walking continuously at the same speed. However, if the user delays or increases their walking speed, the torque assistance does not adjust accordingly. Ideally we would

This is the final report for Machine Learning, CS 6350, for Fall 2019. The team name is **Cheddar Maple Bacon Biscuit Scone**, named after the best scone served at Red Moose Coffee Company. **The project was discussed with Dr. Lenzi and Dr. Srikumar**.

like this algorithm to work at a minimum of 500 Hz which is the speed at which the controller operates at.

An alternative to time-based assistance is “percentage of stride” or gait assistance. Gait refers to the cyclical pattern performed during a movement. Specifically during walking, gait pattern refers to the joint behavior of the lower limbs from heel strike to heel strike [6]. Because human movement during walking is a cyclical pattern, the level of torque assistance can best be approximated using the gait pattern as a reference and to gain a better understand of the level of assistance needed from the exoskeleton [7]. This is advantageous, as it will allow for continuous walking at variable speeds.

This project seeks to develop an online algorithm that accurately predicts where the user is in the gait cycle. This will allow for real time adaptation of the torque assistance needed for variable speed walking. Given the large number of features and samples, it seems appropriate to apply machine learning techniques to develop our desired algorithm. Machine learning techniques have been previously suggested for prosthesis and exoskeleton control [8], [9], [10]. We can use the large amount of collected data to train the algorithm from the kinetics and kinematics of the user that occur at each part of the gait cycle. The learned algorithm can then be implemented in the controller for real time prediction.

METHODS

A. Data Collection

The data was collected using the University of Utah bilateral hip exoskeleton [5]. The output variables are collected using on board encoders, IMUs, and gyroscopes. These variables are then used in real time using the adaptive frequency oscillator (AdOsc) and the accelerations from the gyroscope, Fig. 1, to estimate the gait cadence of the exoskeleton and the phase evolution within the gait stride [5]. The AdOsc is a mathematical tool that enables the exoskeleton to synchronize with cyclical human motion to provide a estimate of the gait cadence. Then cadence is combined with information about the start of the gait cycle (i.e., heel strike) to provide a continuous phase estimate, which is then used to synchronize the desired assistive torque with the user at any gait cadence.

While this AdOsc is able to estimate the phase variable, it is reliant on the accuracy of the heel strike detection to be able to predict the phase correctly. The phase prediction is key in being able to provide the appropriate level of assistance to the user. With the phase predicted correctly, user interface allows for modification

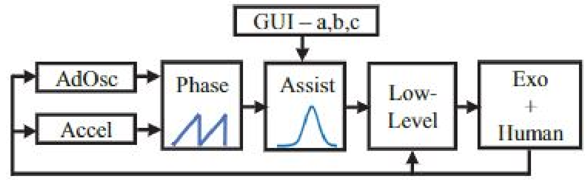

Fig. 1. High and low-level control strategy implemented on the exoskeleton, shown with experimenter input through the GUI. Note that the phase or percent of gait is an input in the level of assistance.

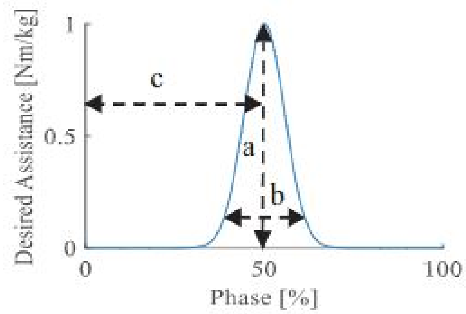

Fig. 2. Gaussian distribution assistance profile with online adaptive parameters: (a) amplitude, (b) density, and (c) offset.

of the torque assistance by modulating the amplitude, density and offset of the torque profile. As shown in Fig. 2 [5], these parameters can change the strength and duration of the assistance.

Previous testing of the hip exoskeleton has provided this project with the data needed to build a learner for real time approximation of the phase, to replace the prediction that is heavily reliant on heel strike detection. Data collection specifically records hip position, thigh position, hip desired torque, motor current, 3 axis acceleration from an IMU on the thigh, spring deflection, and slider position. These parameters are specific to the joint and require minimal processing in real time, thus they will be used for the learning algorithm.

B. Problem Definition

Our project was set up as a least mean squares regression problem. Each data point along the stride served as an individual sample. Previous testing of the hip exoskeleton has provided us with a large amount of data with which to train and test our learning algorithm. Currently, an offline analytical solution is applied during post-processing to determine the gait phase. The “labels” resulting from this offline solution will be used as our “ground truth.”

C. Least Mean Squares Regression

Least mean squares regression was used to determine our gait phase classifier. The loss function for this type of regression is given in Eq.1, where y_i corresponds to the true value we are trying to match and x_i corresponds to the different examples [11].

$$J(x) = \frac{1}{2}\sum(y_i - w^T x_i)^2 \quad (1)$$

The objective of our regression problem is to minimize this loss function as denoted in Eq.2,

$$\min_{w}\frac{1}{2}\sum(y_i - w^T x_i)^2 \quad (2)$$

In relation to our project, this objective is the equivalent of minimizing the error between our predicted gait phase value and the true gait phase value provided by our dataset.

D. Stochastic Gradient Descent

Stochastic gradient descent was our strategy for minimization. Using this method our weight vector, ω, was updated in accordance to Eq.3, where η corresponds to our learning rate.

$$w^{t+1} = w^t - \eta\nabla J(w^t) \quad (3)$$

As shown in [11], the gradient of the loss function can be simplified, and the update rule can be rewritten as Eq.4.

$$w^{t+1} = w^t + \eta(y_i - w^T x_i) \quad (4)$$

A regularization term Eq.5 was also added to address any overfitting that might occur with the training set. The resulting update equation, (Eq.6), with the gradient of this regularization term includes a loss-tradeoff coefficient, C, that determines the effect that the regularization term has on the update.

$$R(w) = \frac{1}{2}\sum(w_i^2) \quad (5)$$

$$w^{t+1} = w^t + \eta(y_i - w^T x_i) + \eta C w^T \quad (6)$$

E. Machine Learning Setup

For learning, 70% of the data was allocated for training, 10% for validation, and 20% for testing. 5-fold cross validation was carried out to determine the optimal learning rate, η, and loss-tradeoff coefficient, C, for training. The learning rate was chosen from $\eta = [.00001, .0001, .001]$, and the loss-tradeoff coefficient was chosen from $C = [.0001, .001, .01]$. We found that the inclusion of higher learning rates and loss trade-off values did not allow the weight vector to converge, which resulted in an overflow error.

Once the best hyper-parameters were determined through cross-validation, our least mean squares regression problem was solved via stochastic gradient descent. Our learner was set to iterate over our training set up to 10 epochs, or up to the point where the overall error fell below 5%. Samples were iterated over at a random order for each epoch. The weight vector was initialized as W = 0 for all features. The bias was included in the examples and its corresponding weight was included as the last element of the weight vector. The predicted value for our gait phase was bounded between 0 and 1, with 0 corresponding to the start of a stride and 1 corresponding to the end of a stride at heel strike. Once training was finished, the resulting weight vector was applied to our test dataset to measure the accuracy of our gait phase prediction. The number of training epochs was determined through early validation of our learner. When comparing the training and testing error resulting from different epochs, we found that after about 10 epochs the training error remained constant while the testing error increased with the number of epochs, as seen in Fig. 3. Taking this as a sign of overfitting, 10 epochs was set as the limit for our learner.

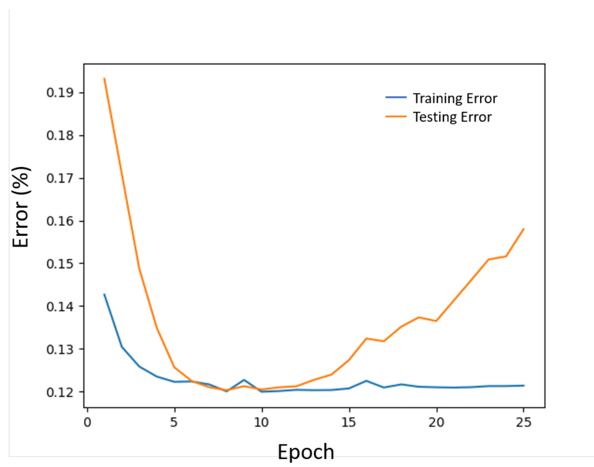

Fig. 3. Training error and test error trend with increasing level of epoch.

Feature size was determined throughout the inital setup of our learner. At first, all of the features from the original dataset were included for our learning. However, after failing to converge to a weight vector, certain features, such as acceleration, were removed due to their amount of noise. The decision to reduce the number of features was also chosen to reduce overfitting with the training set. The features hip position, thigh position, slider position, and spring deflection were the only features taken from the original dataset. Combinations of these original features were then treated as additional features. Such combinations included conjunction of different features, or the square of individual features.

$$F_{norm}(i) = \frac{Max(F) - F(i)}{Max(F) - Min(F)} \tag{7}$$

For all features and feature combinations, a normalization was performed using Eq.7. The Maximum of each feature and the minimum of each feature were found and used to scale each value of the feature such that each value is in the range of 0 to 1. This is crucial in allowing for each feature to have an equal weight in the prediction.

RESULTS

We found that the error threshold of 5% was not reached during the cross-validation or training. Therefore, stochastic gradient descent always ran up to the 10 epoch limit. Through cross-validation we found that the optimal hyper-parameters for training were $\eta = .001$ and $C = .001$. For a training run with these hyper-parameters, the resulting weight vector from the training set was W = [0.73, -0.86, 0.25, -0.05, -0.16, 0.47, -0.77, 0.49, 0.64]. The average error of this weight vector when applied to the training set was .120, but .121 for the testing set, meaning that overfitting was not an issue in our learner.

DISCUSSION

While stochastic gradient descent managed to converge on a weight vector, the resulting error is too high to practically use online. Adjustments to our learner, or applications of other learning methods may reduce the error. For example, variables such as acceleration were not included to the level of noise in the signal. However, once filtered, they might provide significant information on the gait phase. Future variables that are relevant biomechanically can be calculated from saved variables and added into the learning algorithm. Furthermore, the fact that the data points within a single stride are not independent from another was not taken into consideration. Therefore, alternate learning strategies that address this issue, such as structured regression might be more appropriate.

Additional preparation of our training data could have improved the performance of our learner. The original dataset could have been checked for segments in which the subject might have stopped walking (i.e. low joint velocity). These segments could have then been removed as they are not representative to the gait phase that we were trying to predict for walking. Different feature spaces and feature scales could be explored similar to how different hyper-parameters were explored. Finding an “optimal” set of feature could have improved the accuracy of our gait phase prediction.

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