A Study on the Activation of Femoral Prostheses: Focused on the Development of a Decision Tree based Gait Phase Identification Algorithm

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Abstract: This paper aims to classify the phase of gait for passive transfemoral prostheses as a preliminary study for the development of a knee flexion angle control device in prosthetics by attaching it to the knee joint in order to produce a walk trajectory like a normal person, while walking on a flat. However, it is not possible to determine a gait stage according to the inflection point of a knee, since there are few angular changes in the knee joint in the form of a seat that will support the body. Thus, in previous studies, algorithms were developed to distinguish between three stages of the stance in the swing phase using a decision tree learning method. However, the decision-making tree is prone to overfitting. This can be a high level of accuracy for training data, but it is difficult to generalize when verification data or new data are entered. Therefore, in this paper, we want to develop an algorithm for preventing the overfitting step-by-step using two different methods.

1 INTRODUCTION

Based on the 2017 report of the WHO (World Health Organization), an estimated 30 million people with lower limb amputees are expected to double by 2050 (Ziegler-Graham, 2008). Based on this basis, the research on prostheses that help to compensate lower limb amputees is being studied in a variety of ways for the convenience of the disabled.

The prostheses are divided into passive and active types according to the way they operate. Passive type prostheses are able to walk on a level surface through storing and using the force of the wearer without power, but it is difficult to implement power for activities such as stair climbing and running (Yoshida et al., 2015; Inoue et al., 2016). However, active type prostheses are able to make their own strength by using actuators such as cylinders or motors, so they can perform various motions. However, they are expensive (Andrés et al., 2016; Keles et al., 2017).

The active type prostheses can create gait trajectories similar to normal people through actuator control even on level walking. However, the passive type prostheses work only as a supporting stand of the body for the next step because they do not have the power to create gait trajectories like normal people.

Thus, the objective of this study is to classify gait phases in passive type prostheses as a pilot study for the development of devices that adjust the flexion angle of knee joints according to the gait phase by attaching them to the knee joint of the passive type prostheses.

Studies to distinguish gait phases have now been conducted in two different ways. The first method is to use ground reaction force to separate the point at which the feet do not touch the ground (Shaikh et al., 2015). The second method is to distinguish gait phases according to changes in the knee angle (Karasawa et al., 2013). Estimates of the gait phase according to changes in the knee angle are divided by using the maximum flexion of the knee angle and the inflection point in the extension trajectory (Lim et al., 2016).

The passive prostheses, however, have little changes in the knee angle of the knee joint, and the gait trajectory varies depending on the length of the affected area. Also, it is not easy to apply the inflection point based estimation method of gait...
phases as a result of the change in the knee angle of these passive prosthesis users because the new practice of gait habits after amputation varies from person to person.

Therefore, in the previous study, an algorithm was developed to classify the swing phase through dividing the stance phase into three stages and separate the gait phase by using the decision tree learning method in the form of ‘IF ~ THEN’ to distinguish the gait phase of the passive type prosthesis users (Na et al., 2019).

However, the decision tree learning method becomes more complex as models become more complex and may represent overfitting. Although this may be a high accuracy for training data, it is a disadvantage that it is difficult to generalize as verification data or new data are entered.

There are two ways to prevent this overfitting. The first method is to simplify the decision tree and control the depth of the tree. The second method is to use a random forest model which is one of the machine learning ensemble techniques that results in more predictive ability and less overfitting in training data than a single decision tree by categorizing it through means of multiple independent decision trees (Rezaei et al., 2018).

In this study, two methods are used to prevent the overfitting. The first method is to simplify decision trees, and the second method is the application of a random forest model. Then, this study compares the differences between decision trees based on previous studies.

2 METHOD

In this study, changes in the knee angle are measured during walking of passive type prosthesis wearers and identify the limit of the classification of the gait phase in the stance phase. To solve this issue, the changes in the hip angles obtained using the acceleration of an inertia sensor attached to the surface of the prosthetic adapter and a three-axis gyro are divided into three stages based on the ground reaction force in order to produce training data entered as labels. The training data develop a convergence algorithm by adding both the decision tree that divides the stance phase into three stages using the decision tree learning method and an algorithm that identifies the swing phase using the inflection point of the knee joint. Also, this study applies algorithms using the random forest technique to compensate for the shortcomings of the decision tree method and compare them with previous research methods.

2.1 Characteristics of Knee Angle Changes in Passive Type Prosthesis Wearers

As shown in Figure 1, the knee joint of a typical passive type prosthesis wearer will fold the knee from the point (①) at which one steps off the ground. Then, the knee, which had been folded from the point where it passed through the intermediate swing phase (⑤), will be stretched out again for the next step. Therefore, the swing phase (④ ~ ⑤) can be identified by the change of the knee angles.

In the stance phase, however, it is difficult to distinguish between the initial landing on the ground (①), the intermediate stance phase (②), and the final stance phase (③) as there is little change in the knee angle because the prosthesis acts as a stand to support the wearer.

In order for the wearers to avoid feeling awkward in their gaits, it is necessary to create a gait trajectory of about 18 degrees like the gait by a normal person at the intermediate stance phase (②). Thus, it was possible to identify the stance phase as three different stages using the measured values at each FSR section through the FSR attached to the toe end and heel and the ground reaction force. It allows for the creation of gait trajectories through the device at the point of the intermediate stance phase (②).

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2.2 Random Forest Method

The random forest technique is one of the ensemble techniques among the various machine learning techniques that increases the accuracy of classification by aggregating the results from several classification models. It is possible to maintain biased data and to reduce overfitting by decreasing variance because the ensemble techniques apply the average value of the results of multiple classification models.

![Figure 2: Structure of the random forest algorithm.](image)

A bootstrap sample must be created to use the random forest technique. The bootstrap sample can be created by dividing the original dataset by attributes and then randomly selecting the attributes for the original dataset size. As the attributes are extracted using an iterative extraction method, they can overlap within a bootstrap and cause missing attributes. Thus, it can reliably output classification values even when new data is entered for classification because the decision tree generated by each bootstrap is independent of each other.

The equation for determining the probability that one attribute will be excluded from the sample due to iterative extraction from one bootstrap sample is as shown in (1).

\[
\lim_{n \to \infty} \left(1 - \frac{1}{n}\right)^n = e^{-1} = 0.3678
\]

The random forest method evaluates the accuracy of the model using an OOB (Out-Of-Bag) error, which collects 36.78% of excluded samples and evaluates performance with verification data (Breiman, 2001).

3 EXPERIMENT AND RESULTS

3.1 Experimental Procedures

In this study, we intend to simplify decision trees as the first way of reducing overfitting. The previous research method was a decision tree that classifies the total of four categories, three stages in the stance phase and one swing phase. In this study, however, we intend to develop a convergence algorithm that divides only the three stages in the stance phase by using the decision tree learning method for simplifying the model, and using the inflection point of the knee joint in order to identify the swing phase. In the second option, we intend to verify that this method reduces overfitting but increases accuracy over the previous research method by using a random forest technique, a set of independent trees.

![Figure 3: Passive type prosthesis adaptor and sensor attachment locations, experimental setting image and coordinate system used in this experiment.](image)
stages. The specifications for each sensor are shown in Table 1.

Table 1: Specifications for Each Sensor.

<table>
<thead>
<tr>
<th>Name</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inertial Sensor</td>
<td>NGIMU (x-io)                          Communication speed: 50 Hz</td>
</tr>
<tr>
<td></td>
<td>Communication method: Wifi</td>
</tr>
<tr>
<td>Variable Resistance</td>
<td>Max. 10 kΩ</td>
</tr>
<tr>
<td>Pressure Sensor</td>
<td>FSR402 (10N Sensitivity)</td>
</tr>
</tbody>
</table>

3.2 Results

As the depth of the decision tree was adjusted with the pre-pruning of the decision tree generated by the previous research method and the convergence algorithm developed in this study, the results were obtained as follows.

Table 2: Difference in Accuracy according to the Depth of Each Algorithm.

<table>
<thead>
<tr>
<th>Model</th>
<th>STANCE 3</th>
<th>STANCE 3 + SWING</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Training</td>
<td>Test</td>
</tr>
<tr>
<td>0</td>
<td>99.8%</td>
<td>98.4%</td>
</tr>
<tr>
<td>1</td>
<td>67.9%</td>
<td>69.8%</td>
</tr>
<tr>
<td>2</td>
<td>92.5%</td>
<td>93.5%</td>
</tr>
<tr>
<td>3</td>
<td>94%</td>
<td>94.4%</td>
</tr>
<tr>
<td>4</td>
<td>94.3%</td>
<td>95%</td>
</tr>
<tr>
<td>5</td>
<td>95.2%</td>
<td>95.4%</td>
</tr>
</tbody>
</table>

As the pre-pruning was not applied, the previous research models represented overfitting. It was possible to verify that the accuracy of the tree increased as it became more complex. Both the developed convergence algorithm and the decision tree generated by the previous research method with the same 94% verification data accuracy are as follows.

Figure 4: Developed convergence algorithm (A) and the decision tree (B) with the same 94% verification data accuracy.

In the equation for identifying the swing phase presented in Figure 4 (A), CKneeAngle is the knee angle currently being measured, and KneeAnglediff represents increases or decreases in the knee angle. SWThreshold is the boundary value for identifying the swing phase, in this study, the accuracy of 96.87% was set at about 0.4° considering the amount of variation in the knee angle generated by the swing phase. The depths of the decision tree of (A) and (B) represent 3 and 4 respectively with the same accuracy, but the decision tree in converged (A) was found to be simpler than (B).

Figure 5: Changes in OOB error values according to the number of bootstrap samples.

As shown in Figure 5, 50 bootstrap samples were 98.6% and 50 or more were 98.7%, and the accuracy of the bootstrap was not significantly different even if the number of bootstrap increases.
Figure 6: Feature importance of the single decision tree (A) and random forest (B).

The feature importance is an indicator of which properties are used most importantly as a decision tree is generated. It is determined as a value between 0 and 1, which means that 0 is not used at all, and 1 has all the information for classification. Figure 6 (A) represents the feature importance of the decision tree shown in Figure 4 (A) and uses only three features: Pitch, Roll, and Gyro Z. Figure 6 (B), however, (B) is the feature importance graph of the random forest that uses all the attributes in training data. Thus, it reduces the overfitting and shows easy generalization compared to (A).

4 CONCLUSIONS

In this study, as the first step in developing a device for the activation of passive prostheses, the objective was to identify the gait phase in the walking of passive prosthesis wearers. Two methods were used to reduce overfitting. First, a decision tree that identifies the three stages of the stance phase and a convergence algorithm that calculates threshold values for determining the swing phase from the changes in knee angles were developed. It showed that it becomes a simple model even though it has the same accuracy as the previous research method.

Second, it was verified that the accuracy was improved to 98.6% while reducing the risk of overfitting in the decision tree through applying the random forest method.

Future plans will be to develop a machine running algorithm to identify the gait environment on a level, slope, and stairs and to automatically change the gait mode for each environment.

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