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

Sun-Jong Na[a], Jin-Woo Shin, Su-Hong Eom[b] and Eung-Hyuk Lee
Department of Electronic Engineering, Korea Polytechnic University, Siheung, Gyeonggi-do, Korea

Keywords: Prothesis, Knee Angle, Decision Tree, Random Forest.

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

[a] https://orcid.org/0000-0002-0601-9058
[b] https://orcid.org/0000-0001-8493-1432

Na, S., Shin, J., Eom, S. and Lee, E.
A Study on the Activation of Femoral Prostheses: Focused on the Development of a Decision Tree based Gait Phase Identification Algorithm.
DOI: 10.5220/0007950707750780
In *Proceedings of the 16th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2019)*, pages 775-780
ISBN: 978-989-758-380-3
Copyright © 2019 by SCITEPRESS – Science and Technology Publications, Lda. All rights reserved

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

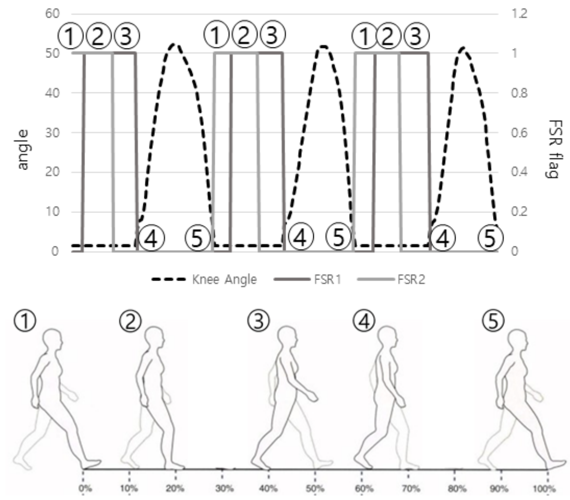

Figure 1: Gait phases according to changes in the knee angles, separated by a pressure sensor, of a passive type prosthesis wearer.

As shown in Figure 1, the knee joint a typical passive type prosthesis wearer will fold the knee from the point (④) 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).

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.

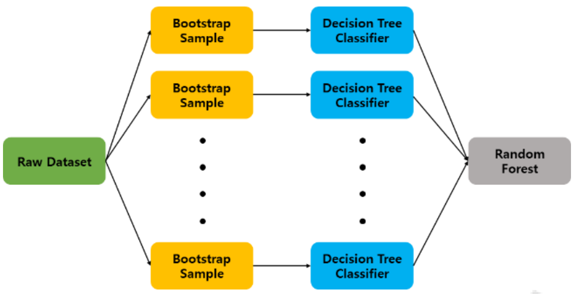

Figure 2: Structure of the random forest algorithm.

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).

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

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

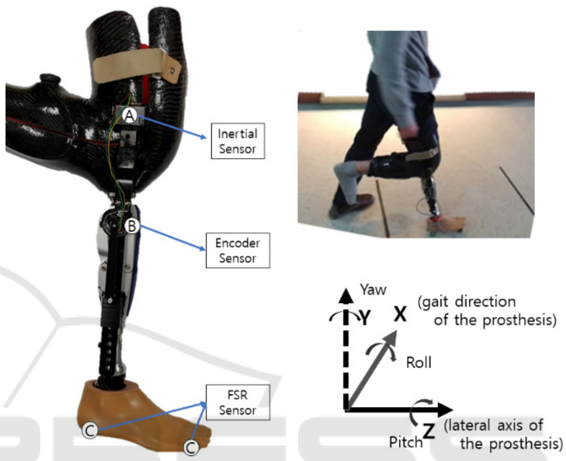

Figure 3: Passive type prosthesis adaptor and sensor attachment locations, experimental setting image and coordinate system used in this experiment.

In this study, an inertial sensor is described in relation to the coordinate system shown in Figure 3 by rotating it 90° clockwise by x-axis. A total of five men in their 20s, two 70kg and three 80kg, walked by wearing a mechanical prosthesis adapter with a 5 steps at 30cm intervals, and a total 500 steps from 20 times on the ground. The characteristics of the dataset for training consisted of knee angles, three axis of acceleration generated during walking, three axis of gyro, and three axis angles of the hip joint. The gait phases for each gait were labelled according to the gait phases using the ground reaction force and FSR. In the sampling of the obtained dataset, 80% of the total data was used as training data and 20% of the data was used as verification data. The inertial sensor was attached to the point Ⓐ for measuring acceleration, angular velocity, and angle data in the hip joint while walking on the surface of the adapter. The sensor Ⓑ was a variable resistance for measuring knee angles by converting variations in the resistance value of walking into angles. The pressure sensors, Ⓒ, were used to separate the stance phase into three

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

stages. The specifications for each sensor are shown in Table 1.

Table 1: Specifications for Each Sensor.

Name	Spesification
Inertial Sensor	NGIMU (x-io) Communication speed: 50 Hz Communication method: Wifi
Variable Resistance	Max. 10 kΩ
Pressure Sensor	FSR402 (10N Sensitivity)

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.

Model / Depth	STANCE 3		STANCE 3 + SWING	
	Training	*Test*	*Training*	*Test*
0	99.8%	98.4%	100%	99.2%
1	67.9%	69.8%	61.9%	62.5%
2	92.5%	93.5%	79.3	79.3
3	94%	94.4%	92.8	92.9
4	94.3%	95%	94.1	94
5	95.2%	95.4%	95.1	94.4

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.

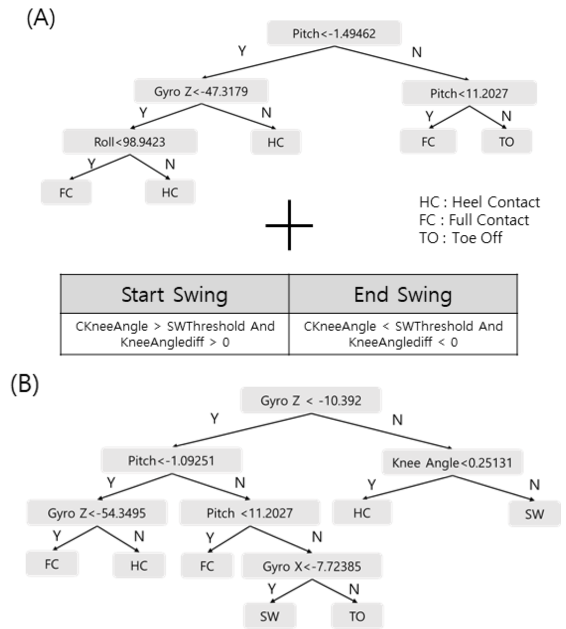

Figure 4: Developed convergence algorithm (A) and the decision tree (B) with the same 94% verification data accuracy.

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).

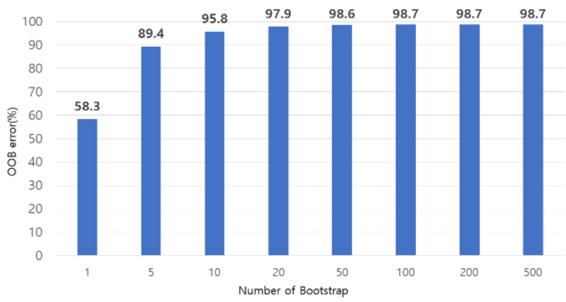

Figure 5: Changes in OOB error values according to the number of bootstrap samples.

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.

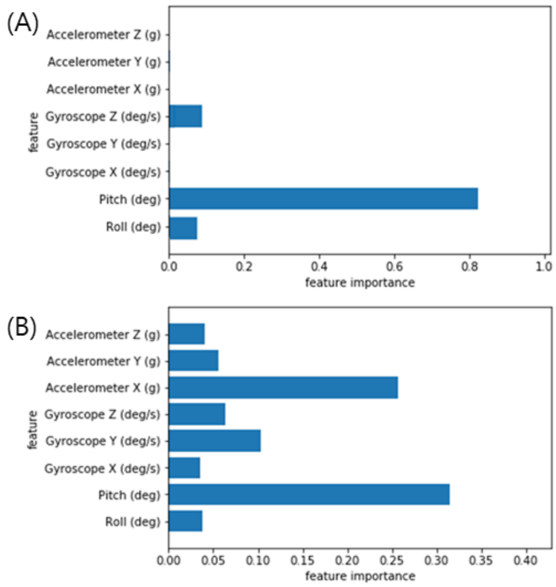

Figure 6: Feature importance of the single decision tree (A) and random forest (B).

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.

ACKNOWLEDGEMENTS

This research was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF2017R1A2B2006958).

This research was supported by the Bio & Medical Technology Development Program of the NRF funded by the Korean government, MSIP (NRF-2017M3A9E2063260).

This research was supported by the Technology Innovation Program (NO.10082455, Service Development of Spo-Edutainment School Indoor Thema park) funded By the Ministry of Trade, Industry & Energy (MOTIE, Korea).

REFERENCES

K. Ziegler-Graham. (2008). Estimating the prevalence of limb loss in the United States: 2005 to 2050, *Arch. Phys. Med. Rehabil., vol. 89, no. 3, pages 422 - 429*.

Shun Yoshida, Takahiro Wada, Koh Inoue. (2015). A passive transfemoral prosthesis with movable ankle for stair ascent, *IEEE International Conference on Rehabilitation Robotics (ICORR), pages 7 - 12*.

Koh Inoue, Tomohiro Tanaka, Takahiro Wada, Shin'ichi Tachiwana. (2016). Development of a passive knee mechanism that realizes level walk and stair ascent functions for transfemoral prosthesis, *IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob), pages 522 – 527*.

Guzhñay Cordero Andrés, Calle Arévalo Luis, Zambrano Abad Julio. (2015). Walking cycle control for an active ankle prosthesis with one degree of freedom monitored from a personal computer, *International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pages 3651 – 3654*.

Ahmet Doğukan Keles, Can Yücesoy. (2017). Development of Artificial Neural Network Based Active Ankle Prosthesis Algorithm Using Gait Analysis Data, *National Biomedical Engineering Meeting (BIYOMUT), pages 1 – 4*.

Muhammad Faraz Shaikh, Zoran Salcic, Kevin Wang. (2015). Analysis and selection of the Force Sensitive Resistors for gait characterization, *International Conference on Automation, Robotics and Applications (ICARA), pages 370 - 375*.

Yuta Karasawa and Yuta Teruyama. (2013). A Trial of Making Reference Gait Data for Simple Gait Evaluation System with Wireless Inertial Sensors, *International Conference of the IEEE EMBS, pages 3427-3430*.

YoungGwang lim, SeongBong Yoo, SuHong Eom, EungHyuk Lee. (2016). A Study On Estimation of Gait Phase Using Peak Point Detector and Finite State Machine, *ICS′, pages 109 - 111*.

Sun-Jong Na, Su-Hong Eom, Chol-U Lee, Mun-Seok Jang, Eung-Hyuk Lee. (2019). A study on the Application of Decision Tree Algorithm to Differentiate Gait Phases in the Users of Transfemoral Prostheses, *International Conference on Electronics, Information and Communication (ICEIC), pages 997 - 1001*.

A. Rezaei, A. Ejupi, M. Gholami, A. Ferrone, C. Menon. (2018). Preliminary Investigation of Textile-Based Strain Sensors for the Detection of Human Gait Phases Using Machine Learning, *IEEE International Conference on Biomedical Robotics and Biomechatronics (Biorob) pages 563 – 568*.

L. Breiman, (2001). "Random Forests," *Machine Learning, vol. 45, pages 5 - 32*.

SCITEPRESS
SCIENCE AND TECHNOLOGY PUBLICATIONS