A MACHINE-LEARNING-BASED GAIT ESTIMATION FROM THE FOOT ARCH PARAMETERS MEASURED BY A FOOT SCANNING SYSTEM

Kyung-Ryoul Mun[1], Hwansu Jeong[1], Hyungan Oh[1], Junngi Hong[2], Jae Yeong Cho[3], and Jinwook Kim[1]

Image Media Research Center, Korea Institute of Science and Technology, Seoul, Korea[1]
College of Medicine, Cha University, Seoul, Korea[2]
Young Chang Eco Co., Ltd[3]

The purpose of this study is to develop a machine-learning-based regressor to estimate the gait-related parameters from the foot characteristics extracted by a foot scanning system. A fully-connected feed-forward neural network model was used to predict the gait parameters. The inputs of the model were the foot arch features and body anthropometric data, while the outputs of the model were the spatiotemporal gait parameters of the regular walking. The performance of the model was verified showing the accuracy of 95% or higher confirming the facts that foot features are dominant factors to estimate personalized gait patterns. In conclusion, the gait pattern can be easily assessed by measuring the foot depth-image from the foot scanner without using complex and expensive traditional methods if the data pools are significantly increased.

KEYWORDS: gait spatiotemporal parameters, foot scanner, foot arch parameters, a machine-learning-based regressor

INTRODUCTION: Gait contains substantial clues in diagnosing and monitoring muscular skeletal diseases and neurological disorders, and can be measured from one's spatiotemporal gait parameters. Conventional approaches for gait assessment require a laboratory environment, expensive equipment, and complicated experimental settings which can restrict the natural gait pattern. In addition, these approaches are very susceptible to noise and other unexpected movements (Filippeschi et al., 2017). To overcome these limitations, there have been many attempts to predict the kinematics of the lower limbs and gait parameters using unconventional approaches. Artificial intelligence has emerged as an area to quantitatively predict human gait due to its high accuracy, robustness in interferences with noisy, and ability to classify motion signals (Ardestani et al., 2014). Many researchers have tried to develop a generic wavelet neural network model, a statistical and stochastic model, convolutional neural network, and a recurrent neural network model to predict human joint moments, joint angles, gait spatiotemporal parameters, and to recognize various motion intentions based on human movements (Ardestani et al., 2014; Rampp et al., 2015; Yun et al., 2014). These studies have led to excellent results with high level of accuracy compared to conventional methods and showed that a variety of human factors such as joint kinematics, electromyography, and body anthropometric data can be used as an input of neural network models to predict human gait. Our previous work which observed the correlation between the features of foot arch and gait spatiotemporal parameters showed that the medial-longitudinal-arch (MLA) parameters are related to gait temporal parameters, while the lateral-longitudinal-arch (LLA) features are correlated to gait spatial parameters (Mun, Choi, Chun, Hong, & Kim, 2017). This is because each arch can move independently despite their physical constraint and contribute to the different perspectives of the gait. This study showed a clear indication that the foot can serve as a predictor to estimate the personalized gait pattern, thus there will be a high possibility of estimating the gait parameters from extracted foot features. Gathering traditional gait-related parameters is considerably more expensive and difficult compared to collecting foot features. The aim of this study is to develop a machine-learning based regressor to estimate and quantify gait spatiotemporal parameters from the foot characteristics extracted by a foot scanning system.

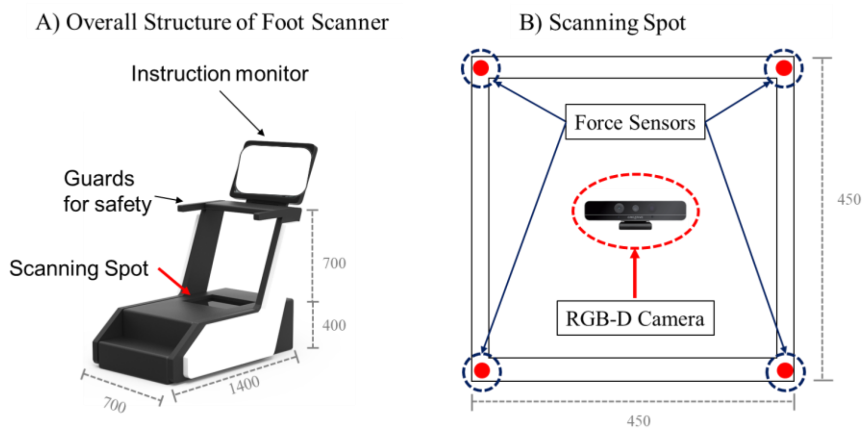

Figure 1: An overview of the foot scanner and scanning spot

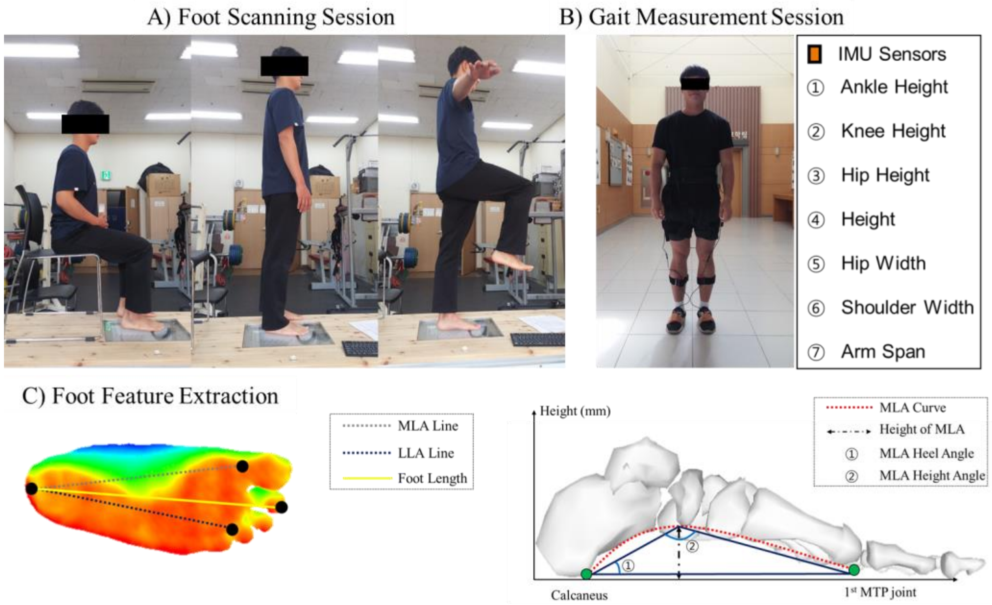

Figure 2: Experimental protocols of (A) foot scanning session, and (B) gait measurement session. The foot feature parameters measured by the foot scanner are shown in (C).

METHODS: The foot scanner was fabricated as a standing type structure which comprised an instruction monitor, guard handles, and scanning spot (Figure 1). The scanning spot comprised four uniaxial force sensors at the corners of a colourless acrylic panel (450 mm (length) × 450 mm (width) × 400 mm (height)) to measure centre of pressure (CoP) of the body and a single RGB-depth (RGBD) camera (Intel Realsense F200) underneath the panel to obtain foot structural information. While subjects were on the spot, it was able to measure the various foot parameters shown in Figure 2C. A total of 42 subjects with 17 healthy young subjects and 25 semi-professional marathoners participated in this study. Experimental protocols consisted of two sessions; i) foot scanning session, and ii) gait measurement session (Figures 2A and B). During the foot scanning session, all subjects were instructed to keep a sedentary position with their ankle and knee joint angle at 90° in a sitting condition and then quietly stand for 5 seconds for the standing condition. Subsequently, the subjects were asked to maintain their body balance as stable as possible on one leg for 10 seconds (Figure 1). During the scanning session, foot length, height and curve area of the MLA and LLA and the arch angles (heel angles and height angles) were obtained (Figure 2C).
Before the gait session, all subjects' body anthropometric data were manually measured. During the gait session, a commercialized IMU sensor-based motion-capture system (Xsens MVN, Enschede, Netherland) was used to obtain gait-related information (Figure 2B). The subjects walked along a 30-meter straight floor at their preferred walking speed.

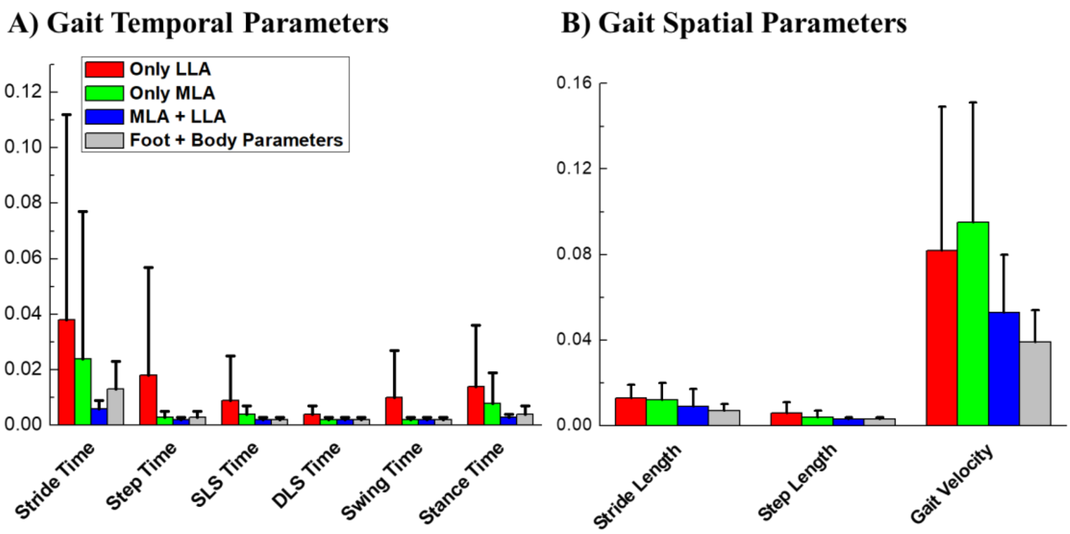

Figure 3: Mean square errors and their standard deviations in the spatiotemporal gait parameters

Table 1. Estimation accuracy according to the different group compositions

	Group 1	Group 2	Group 3	Group 4
Stride Length	98.46	98.61	98.95	99.05
Step Length	98.52	99.08	99.34	99.33
Gait Velocity	91.59	90.21	94.55	96.20
Stride Time	96.43	97.75	99.39	99.54
Step Time	96.69	99.42	99.69	99.74
SLS Time	98.06	99.14	99.62	99.62
DLS Time	94.86	97.45	97.94	98.21
Swing Time	97.83	99.63	99.66	99.74
Stance Time	97.57	98.55	99.56	99.64

The spatiotemporal gait parameters of stride time, step time, single-limb-support (SLS) time, double-limb-support (DLS) time, swing time, stance time, stride length, step length, and gait velocity were calculated from ten strides in the middle of the 30-meter walkway.

A machine-learning-based regressor was built to estimate the spatiotemporal gait parameters. A fully-connected feed-forward neural network model consisting of two hidden layers with 'Adam' optimizer and 'ReLU' activation function was used to predict the spatiotemporal variables of walking. The number of neurons for each layer was the same as the number of input variables. Input variables for the regressor were the foot feature parameters as measured by the foot scanner for sitting, standing, and one-leg-standing conditions, and body anthropometric data. The input variables were classified into four groups to investigate the most optimized input set among the foot and body anthropometric data: only LLA related parameters were selected for the group 1, only MLA related parameters for group 2, a combination of MLA and LLA parameters for group 3, and all foot parameters and body anthropometric parameters for group 4. The outcomes were the estimation of the spatiotemporal gait parameters at preferred walking speed. The performance of the regressor model was evaluated by the mean square error (MSE).

RESULTS: The MSEs and SDs of spatiotemporal gait parameters at the preferred speed were shown in Figure 3. The prediction errors of the spatiotemporal gait parameters decreased with increasing number of inputs of the regressor. The errors in group 1 were the largest, while the errors in group 4 were the lowest. However, there was no remarkable difference between the errors in groups 3 and 4. The prediction accuracies in groups 3 and 4 were above 97% except for the gait velocity estimation which was around 95% accuracy.

DISCUSSION: We present a machine-learning based regressor to estimate 9 spatiotemporal gait parameters with use of foot characteristics and body anthropometric data. The prediction accuracy of the machine-learning-based regressor on gait temporal parameters was relatively poor in the LLA-only group showing average accuracy ranging from 94.86 to 98.06%. The accuracy percentages were greatly increased in the MLA-only group (from 97.45 to 99.63%) compared to the LLA-only group. This considerable increases in prediction accuracy in the MLA-only group might be explained by the characteristics of input sets. Our previous study showed that the MLA characteristics are significantly correlated to the feature of gait temporal parameters while those of LLA are related to gait spatial parameters. However, the prediction errors were further reduced when both MLA and LLA variables are used. It might be because the MLA and LLA can react independently against different movement conditions although they are a close proximity of each other, thus obtaining both foot characteristics helps the regressor to improve the prediction accuracy of the gait temporal characteristics. The prediction accuracies were marginally increased in group 4. For the gait spatial parameters, the MSEs and SDs on the gait spatial parameters were relatively high in LLA-only group and MLA-only group than the other groups. The MSEs when both MLA and LLA variables were used (group 3) were the most efficient in performing the estimation although it was relatively simple and less complex than group 4. Besides, the input variables applied to group 3 did not require manual measurement of the body anthropometric data and in turn, demanded less human labour. When the results of group 3 were compared to those of group 4, little difference was found. From this, we can conclude that foot characteristics serve as more dominant factors than the body anthropometric data in estimating personalized gait patterns. As a study adopting neural network method, a limitation was the use of black-box approach which provides little understanding of the generating mechanisms. Consequently, the results of this study are highly dependent on the training datasets. Subjects with various conditions including elderly and neuro-muscular disorders will be included in the future to generalize the model.

CONCLUSION: The feasibility of the machine-learning-based regressor to estimate gait spatiotemporal parameters using the foot structural features including MLA and LLA characteristics measured in a various static condition such as sitting, standing, and one-leg-standing was developed in this study. The machine-learning-based regressor showed high accuracy and precision for estimating human gait parameters. Therefore, the gait pattern can be easily assessed by only measuring the foot features without using complex and expensive traditional methods if the data pools including different populations such as elderly and muscular-skeletal disorders are significantly increased.

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