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Foot Clearance Prediction using Wrist Acceleration and Gait Speed

Kodai Kitagawa[1], Chikamune Wada[2], and Nobuyuki Toya[3]

[1]Mechanical and Medical Engineering Course, National Institute of Technology, Hachinohe College, Hachinohe, Japan
[2]Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology, Kitakyushu, Japan
[3]Department of Medical Management and Informatics, Hokkaido Information University, Ebetsu, Japan

Corresponding author: Kodai Kitagawa (e-mail: kitagawakitagawa156@gmail.com).

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ABSTRACT Elderly individuals experience fall accidents due to tripping because recognizing foot clearance during walking is difficult for them. To prevent fall accidents, foot clearance should be measured and informed in daily life. Foot clearance is commonly measured using vision-based systems, such as optical motion capture systems. However, problem of these vision-based systems is that these systems cannot measure foot clearance in daily life because they have limitations due to obstacles and field of view. Based on this problem, we developed a wearable fall prevention system using smart devices, such as smartphones and smartwatches. This study aimed to evaluate the proposed prediction method for foot clearance using sensor data obtained from wearable smart devices which can be used in daily life. The proposed method will contribute to measure foot clearance in daily life. This method predicts foot clearance from wrist acceleration and gait speed using a machine learning-based regression model. The proposed method was tested in a computational simulation with a public gait dataset obtained using an optical motion capture system. The results showed that the correlations between the predicted and actual foot clearance were at least 0.65. In conclusion, this study indicates the possibility that the proposed method can be used to measure foot clearance and thus can be used in wearable fall prevention systems.

INDEX TERMS Foot Clearance, Wrist Acceleration, Fall Prevention, Machine Learning

I. INTRODUCTION

A. BACKGROUND

Fall accidents among elderly individuals often cause serious injuries, such as hip fractures [1]. Furthermore, studies have reported that elderly individuals who experienced fall accidents had reduced quality of life because of the fear of falling [2,3]. This background indicates the necessity of fall prevention in daily life for these individuals.

Tripping is considered important for fall prevention because a study reported that tripping caused 21% of falls in elderly individuals [4]. The risk of tripping depends on foot clearance, which is the vertical distance between the foot and ground [5]. In particular, decreases and changes in foot clearance increase the risk of tripping [5,6]. If elderly individuals recognize changes in their foot distance, they can avoid fall accidents due to tripping. However, knowing the foot position is difficult for elderly individuals because of their low proprioceptive sensation [7,8]. These studies have shown that fall prevention systems that measure and inform foot clearance are necessary for daily walking.

B. PREVIOUS STUDIES

Foot clearance is commonly measured using accurate vision-based systems, such as optical motion capture systems [9,10]. However, these vision-based systems cannot be applied to fall prevention in daily life because these systems have limitations due to obstacles and field of view. Electromagnetic tracking systems are also used to accurately measure foot clearance [6]. However, these systems are difficult to use in daily life because environmental preparations are necessary to avoid errors due to electromagnetic field distortions [11].

To overcome these limitations, studies have developed ubiquitous systems for measuring foot clearance using wearable sensors [12–16]. Arami et al. developed a shoe-type measurement system equipped with an infrared distance sensor and an inertial measurement unit (IMU) [12]. Furthermore, Jacob et al. developed a shoe-type measurement system that uses laser time-of-flight sensors [13]. Moreover, several studies have measured foot clearance using IMUs installed in shoes [14–16]. These shoe-type measurement systems can measure foot clearance in various fields. However, they require sensors attached to the user's shoes. Changes in the size or shape of the shoes due to sensor instrumentation might decrease gait performance, such as balance [17–19]. Thus, other areas where the sensors are attached other than the foot should be considered for users with low gait performances. The wrist is a recommended sensor attachment area. According to a previous investigation, the wrist is the most preferred sensor position for users [20]. Wrist-mounted devices, such as smartwatches, are preferred by users because they can be carried comfortably in daily life [21]. However, fall prevention systems using wrist-mounted sensors require gait prediction methods because wrist-mounted sensors cannot directly measure foot trajectory [21].

Based on this background, we developed a prediction method for gait parameters, such as foot clearance and step length, using wearable smart devices attached to the wrist [22–24]. We developed a gait classification method using inertial data on the wrist; however, this method could not provide quantitative information on gait parameters [22]. Furthermore, we developed a prediction method for quantitative step length using wrist acceleration although foot clearance could not be predicted [23]. Furthermore, our recent study proposed a prediction method for quantitative foot clearance using the wrist position. However, this method might be difficult to use in daily life because it requires accurate three-dimensional wrist position, which cannot be directly measured using smart devices [24]. To implement wearable fall prevention systems, developing prediction methods for foot clearance is necessary using acceleration that can be obtained from the inertial sensors in smart devices on the wrist.

C. OBJECTIVE

The objective of this study is to propose and evaluate a prediction method for quantitative foot clearance using only wrist acceleration, which can be measured using a wearable smart device.

II. PROPOSED METHOD

FIGURE 1 shows an overview of the proposed method. The proposed system predicts foot clearance using a machine learning-based regression model.

Wrist acceleration is considered to be useful information for predicting foot clearance because several studies have shown that wrist acceleration is affected by foot trajectory [25–27]. However, wrist acceleration is also affected by several other walking parameters, such as gait speed [28–30]. Thus, gait speed has also been used as a feature in the proposed method. Kindly note that a method for measuring gait speed using a smart device has already been proposed and that using this method in practice is possible [31,32].

Several review articles have indicated that machine learning-based regression models are useful for predicting kinematic values in gait analysis [33–36]. The k-nearest neighbor algorithm is selected as the machine learning algorithm for regression of the proposed method because this algorithm has shown great accuracy for gait analysis in previous studies [37–39].

The k-nearest neighbor algorithm of the proposed method is based on previous studies [40–42]. The k-nearest neighbor algorithm stores the entire training data consisting of actual foot clearance, wrist acceleration, and gait speed. As previously mentioned, Wrist acceleration and gait speed are used as features of prediction. Foot clearance is the target of prediction. The k-nearest neighbor algorithm finds data points in the training data that are most like the data point.

The k-nearest neighbor algorithm calculated foot clearance by the sum in responses for k neighbors. Note that the proposed method calculates only one response for each prediction because k value is set as 1 in this study. These responses are calculated as inversely proportional values to the Euclidean distance from the input data. The Euclidean distance is calculated by the following equation (1) [40].

$$ED = \sum_{i}^{N} (x_i - p_i)^2 \tag{1}$$

where, ED is the Euclidian distance, x_i is a query point, p_i is a case from the set of examples, and N is the number of data samples. The distance between the data point and its neighbor's data point in the training dataset is calculated using the Euclidean distance.

In this study, we evaluated whether the proposed method could predict foot clearance via wrist acceleration. Furthermore, we evaluated whether gait speed could improve the accuracy of the proposed method.

III. EXPERIMENT

A. DATASET

In this study, we used a public gait dataset [43] using an optical motion capture system to evaluate the proposed method with various characteristics (i.e., age, sex, weight, height, and gait speed) of the users. Simulated wrist acceleration data were calculated from the wrist trajectory obtained from the optical motion capture system (OQUS4, Qualisys, Sweden) [43]. Three-dimensional trajectory of wrist and foot were recorded by 10 cameras and reflective markers by 100 Hz sampling rate [43]. Kindly note that the proposed method will be implemented using a wearable accelerometer in a future study. Gait data for 10 participants, including elderly individuals, were extracted, and used in this study. The participants are described in Table 1. Schreiber and Moissenet mentioned that recording this dataset was approved by the Medical Ethics Committee of their institution [43].

B. DATA PROCESSING

This public dataset provides three-dimensional positions of full-body markers during a 10-metre straight walk at different gait speeds [43]. As mentioned previously, these position data were measured using the optical motion capture system with a sampling rate of 100 Hz [43].

We calculated three-axis linear acceleration as wrist acceleration data for the proposed method from the marker trajectory of the left radius styloid process coordinate. Furthermore, the vertical position of the left second metatarsal head coordinates was used as the foot clearance in this simulation. These foot clearance data were normalized using the body height of each participant (unit: %height). Normalized foot clearance data were used for the ground truth training and testing of machine learning. Three constant gait speeds (i.e., C1, C2, and C3) were used in this simulation, which were labeled using the public dataset [43]. The participants were instructed to perform each gait speed using a metronome. These three labels were used as a feature of the proposed method. The applied gait speeds are shown in TABLE 2. Note that the number of trials for each gait speed was different in several participants because of dataset differences. The number of trials for each participant is shown in TABLE 2. As presented in TABLE 2, all participants performed at least 3 walking trials for each gait speed. Note that specific features and sliding window techniques were not applied for the proposed method.

C. EVALUATION

The k-nearest neighbor algorithm for the proposed method was implemented using WEKA 3 [41,42]. Two feature patterns (“only wrist acceleration” and “wrist acceleration and gait speed”) were applied and compared to evaluate whether gait speed could improve the accuracy of the proposed method.

Pearson’s correlations and root mean squared error (RMSE) values between the ground truth and that predicted from the regression model were calculated as the accuracy of the proposed method. Correlation and RMSE values were calculated by the following equation (2) and (3).

$$Correlation = \frac{\sum(P_i - P_{ave})(GT_i - GT_{ave})}{\sqrt{\sum(P_i - P_{ave})^2 \sum(GT_i - GT_{ave})^2}} \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - GT_i)^2} \quad (3)$$

where, P_i is a predicted foot clearance, GT_i is a ground truth of foot clearance, GT_{ave} is average of ground truth of foot clearance, and N is the number of data samples. These values were calculated for each participant and each feature pattern. The training and testing for this evaluation were performed via a 10-fold cross-validation.

Spearman’s rank correlations (significant level: $p < 0.05$) between the RMSE and the specification of the participants (age, weight, and height) were calculated to investigate the relationship between accuracy and the specification of the users. These statistical tests were performed using the EZR software [46].

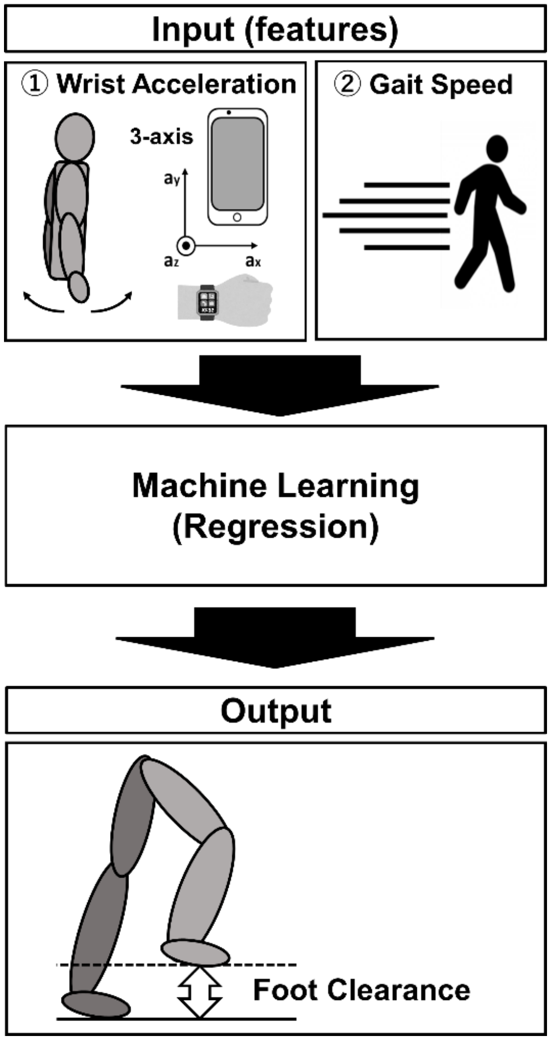

FIGURE 1. Overview of the proposed method.

TABLE 1
Extracted data on the participants from a public dataset

Participant	Sex	Age [years]	Weight [kg]	Height [m]
A	Male	31	67.0	1.66
B	Female	28	50.0	1.56
C	Male	67	98.0	1.83
D	Female	62	60.7	1.70
E	Male	21	74.0	1.78
F	Female	22	67.0	1.58
G	Male	57	86.0	1.88
H	Female	63	60.2	1.66
I	Male	48	89.4	1.90
J	Female	48	59.8	1.71
Mean ± S.D.	-	44 ± 17	71.2 ± 14.6	1.73 ± 0.112

TABLE 2
Gait speed of participants

Participant	Trial for each gait speed (10-m straight walking for each trial)		
	C1 [m/s] $0 < C1 < 0.4$	C2 [m/s] $0.4 \leq C2 < 0.8$	C3 [m/s] $0.8 \leq C3 < 1.2$
A	5	5	5
B	5	5	3
C	5	4	5
D	5	3	5
E	5	5	4
F	5	5	4
G	5	4	5
H	5	4	5
I	5	5	5
J	5	5	4

IV. RESULTS

A. ACCURACY OF THE PROPOSED METHOD

TABLES 3 and TABLE 4 show the correlation and RMSE between the ground truth and predicted values of foot clearance. The results showed that the proposed method using both wrist acceleration and gait speed provided greater correlation and smaller RMSE in all participants.

The results of Pearson's correlation showed that the proposed method using both wrist acceleration and gait speed could predict foot clearance with >0.65 correlation (0.669–0.868), with the ground truth being obtained from an optical motion capture system in case of all participants (TABLE 3). Furthermore, the RMSE values between the proposed method (using both wrist acceleration and gait speed) and ground truth were <1.1 %height (0.518–1.09 %height) in all participants, including both elderly and young individuals (TABLE 4).

B. RELATIONSHIP BETWEEN ACCURACY AND SPECIFICATION

The scatter plots and Spearman's correlation are shown in FIGURE 2, FIGURE 3, and FIGURE 4. The results of the statistical tests showed no significant correlation between the RMSE and the specification of the participants (i.e., age, weight, and height) ($p > 0.05$). These results indicate that the specification of the participants did not affect the accuracy of the proposed method.

C. EFFECT OF GAIT SPEED

The box plots of wrist acceleration in three gait speeds (participant D) are shown in FIGURE 5, FIGURE 6, and FIGURE 7. These results showed that wrist acceleration during faster gait speeds had a larger variation. These trends indicate that wrist acceleration was affected by not only foot clearance but also gait speed. Thus, predicting foot clearance using only wrist acceleration is difficult; however, we considered that the method of using both wrist acceleration and gait speed is more effective for prediction purposes.

TABLE 3
Correlation between predicted and ground truth

Participant	Correlation for foot clearance (Predicted vs. ground Truth)	
	Only wrist acceleration	Wrist acceleration and gait speed
A	0.610	0.713
B	0.705	0.754
C	0.751	0.807
D	0.812	0.868
E	0.780	0.852
F	0.564	0.716
G	0.793	0.826
H	0.529	0.669
I	0.682	0.773
J	0.744	0.796
Mean ± S.D.	0.697 ± 0.0941	0.777 ± 0.0613

TABLE 4
RMSE between Predicted and Ground Truth

Participant	RMSE for foot clearance [%height] (Predicted vs. ground truth)	
	Only wrist acceleration	Wrist acceleration and gait speed
A	1.27	1.09
B	0.719	0.662
C	0.861	0.757
D	0.633	0.532
E	0.628	0.518
F	1.04	0.847
G	0.686	0.629
H	1.00	0.839
I	0.773	0.654
J	0.688	0.614
Mean ± S.D.	0.831 ± 0.202	0.714 ± 0.165

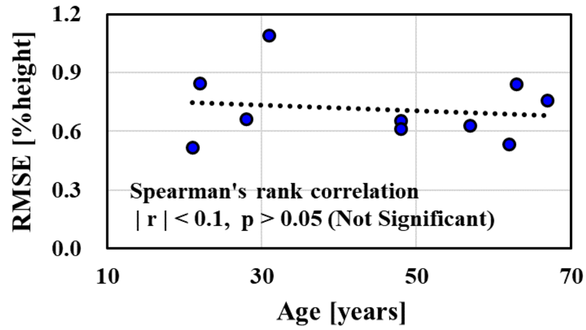

FIGURE 2. Relationship between RMSE and age of the participants.

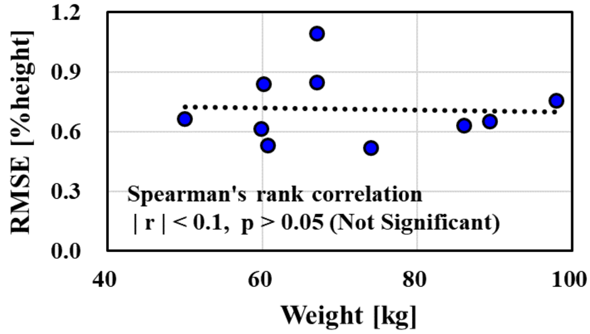

FIGURE 3. Relationship between RMSE and weight of the participants.

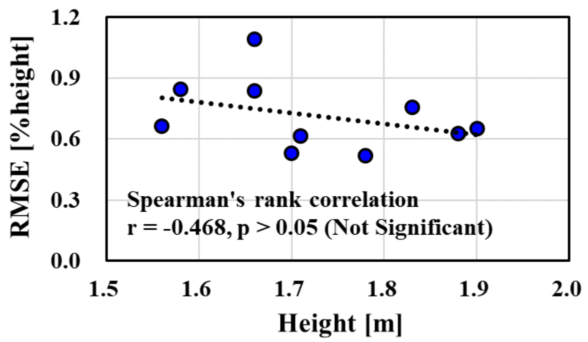

FIGURE 4. Relationship between RMSE and height of the participants.

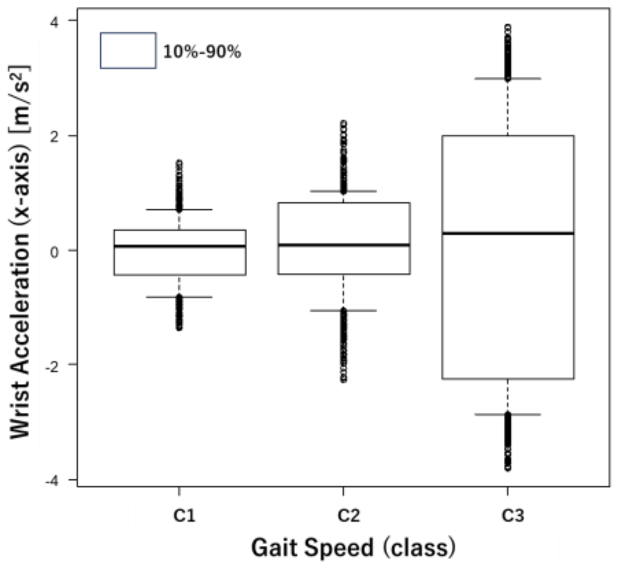

FIGURE 5. X-axis wrist acceleration in three gait speeds (participant D).

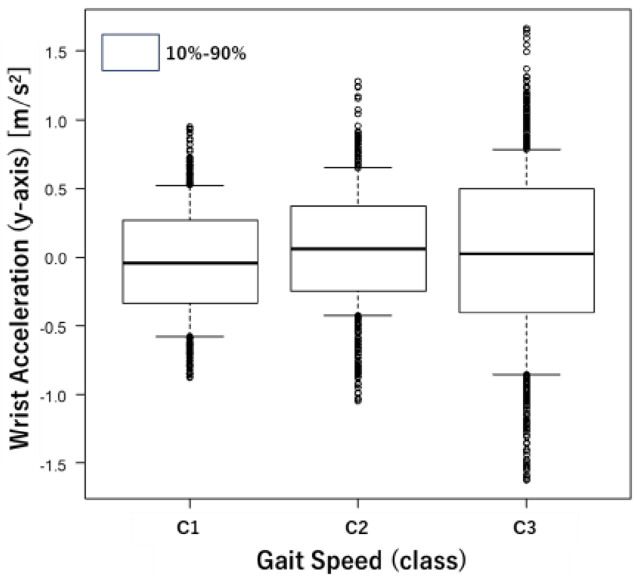

FIGURE 6. Y-axis wrist acceleration in three gait speeds (participant D).

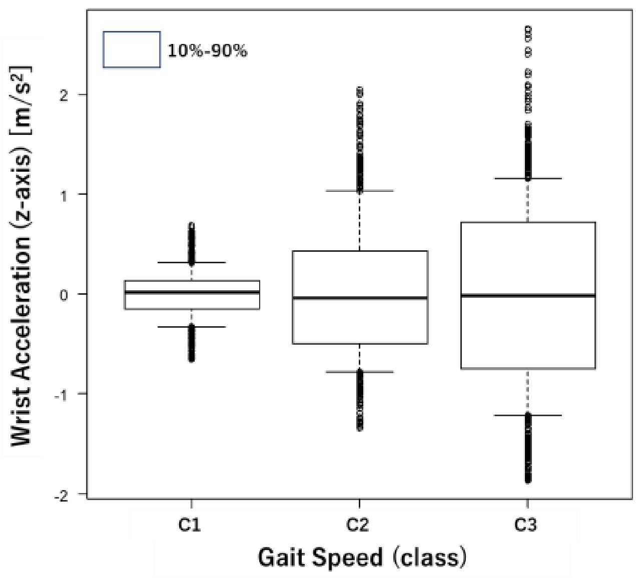

FIGURE 7. Z-axis wrist acceleration in three gait speeds (participant D).

V. DISCUSSION

The results showed that the proposed method could accurately predict foot clearance using wrist acceleration and gait speed. Furthermore, the proposed method had significant correlations and small RMSE with the ground truth in both young and elderly participants. Furthermore, the results of the statistical tests showed no significant correlation between RMSE and the specification of the participants (i.e., age, weight, and height). These results indicate the possibility that the proposed method can be used to monitor foot clearance in various users.

Comparison of feature patterns showed that the feature pattern using both wrist acceleration and gait speed was better than that using only wrist acceleration in all participants. These results suggest that gait speed is an effective feature for improving the accuracy of the proposed method. As mentioned previously, gait speed can be measured using smart devices and existing methods [31,32]. Therefore, the gait speed obtained from smart devices will be applied for the proposed method in future research. Previous wearable shoe-type system using infrared sensor and inertial sensor could measure foot clearance [12]. In addition, Jacob et al. developed wearable shoe-type system using multiple infrared Time-of-Flight (ToF) sensors [13]. Furthermore, Benoussaad et al. developed prediction method for foot trajectory using only foot-mounted inertial sensor [15].

These previous system could measure foot clearance with less than approximately 15 mm [12, 13, 15]. The error of the proposed method is larger than these previous studies. It is difficult to use the proposed method for accurate foot clearance measurement.

On the other hand, there is possibility that comfortability of the proposed method is greater than previous study because the wrist is sensor placement of this method. Previous systems require sensors attached to the user's shoes. Changes in the size or shape of the shoes due to sensor instrumentation might decrease gait performance [17–19]. Furthermore, the wrist is known as the most preferred sensor position for users [20]. From these comparisons, it is considered that the proposed method is suitable for rough monitoring for foot clearance in daily life.

A limitation of this study is that actual smart devices and inertial sensors were not used in the experiment. In future studies, wrist acceleration and gait speed obtained from actual smart devices will be used for evaluation. In the case using actual accelerometer, accuracy of the proposed method might be decreased from this simulation study since accelerometer has specific errors for dynamic measurement [47, 48].

The gait dataset of this evaluation was limited to only a 10-meter straight walk by healthy participants. There are differences between healthy and Parkinson's disease people for gait parameters including foot clearance [49]–[51]. In addition, it is known that gait is affected by various factors such as slope, obstacle, and long-term [52]–[55]. Thus, future studies should consider these conditions, such as slope, obstacle, and long-term walking.

As mentioned previously, accuracy of the proposed method is lower than previous wearable shoe-type systems. Thus, the accuracy of the proposed method should be improved. Siding window technique-based specific features such as average, median, variance, kurtosis, or skewness have possibility that improve accuracy of the proposed method [56]–[58]. In addition, machine learning algorithm such as artificial neural network, support vector machine, logistic regression, decision tree, and long short-term memory should be compared for finding most suitable algorithm for the proposed method [36].

VI. CONCLUSION

This study aimed to propose and evaluate the prediction method for foot clearance using sensor data obtained from wearable smart devices which can be used in daily life. The proposed method using both wrist acceleration and gait speed could predict foot clearance with >0.65 correlation (0.669–0.868), with the ground truth. Furthermore, the RMSE values between the proposed method and ground truth were <1.1 %height (0.518–1.09 %height). These results indicate the possibility that the proposed method can be used to measure foot clearance and thus can be used in wearable fall prevention systems. In the future works, the proposed method will be evaluated for actual wearable sensor and various situations. In addition, accuracy of the proposed method might be improved by selecting feature extraction techniques and machine learning techniques.

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Kodai Kitagawa received a Ph.D. in Engineering from Kyushu Institute of Technology, Japan, in 2022. Since 2022, he has been an assistant professor at the Mechanical and Medical Engineering Course, Department of Industrial Systems Engineering, National Institute of Technology, Hachinohe College. His current research interests include wearable sensors, human movement, gait measurement, physical therapy, and ergonomics. He is a member of the Institute of Electrical and Electronics Engineers (IEEE), the Society of Instrument and Control Engineers (SICE), and the Society of Physical Therapy Science (SPTS).

Chikamune Wada received a B.Eng. degree in Mechanical Engineering from Osaka University, Japan, in 1990 and a Ph.D. degree in Biomedical Engineering from Hokkaido University, Japan, in 1996. From 1996 to 2001, he was an assistant professor at the Sensory Information Laboratory, Hokkaido University. In 2001, he became an associate professor at the Human-Function Substitution System Laboratory, Kyushu Institute of Technology. Since 2016, he has been a professor at Human-Function Substitution System Laboratory. His research interests include assistive technology, particularly measuring human motion and informing disabled individuals of the necessary information to improve their quality of life. He is a member of the Institute of Electrical and Electronics Engineers (IEEE), the Society of Instrument and Control Engineers (SICE), the Japan Ergonomics Society, and the Human Interface Society. He is also a senior member of the Institute of Electronics, Information and Communication Engineers (IEICE).

Nobuyuki Toya received a Ph.D. degree in Engineering at Hokkaido University in 2000. From 2001 to 2005, he was an assistant professor at Kansai University. From 2005 to 2019, he was an associate professor of Advanced Course of Electronic and Information Systems Engineering at the National Institute of Technology, Kushiro College, Japan. In 2019, he became an associate professor at the Department of Medical Management and Informatics, Hokkaido Information University, Japan. Since 2023, he has been a professor at the Department of Medical Management and Informatics, Hokkaido Information University, Japan. His current research interests are in optical wireless communication, sensor network systems, and gait analysis. He is a member of the Institute of Electronics, Information and Communication Engineers (IEICE), the Japanese Society for Medical and Biological Engineering, and the Institute of Electrical and Electronics Engineers (IEEE).