STEP LENGTH ESTIMATION BASED ON ARM ACCELERATIONS FOR WEARABLE FALL PREVENTION SYSTEMS

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ABSTRACT

Elderly people have experienced falling accidents due to progressive loss of visual, sensual, and muscular functions. To prevent falls, gait monitoring, and gait parameter improvement, such as step length, are necessary. Thus, in this study, we developed a wearable and ubiquitous fall prevention system to monitor gait parameters by utilizing arm acceleration obtained using a smartphone or smart watch. We proposed a step length estimation method using a regression algorithm that utilizes features obtained from arm acceleration. We evaluated the accuracy of the proposed method by assessing the gait of ten young participants using a treadmill. The results showed that the proposed method could estimate step length with an error rate of less than 8% of the body height. Therefore, we suggest that the proposed method can detect differences in step length due to aging.

Keywords: step length, wearable sensor, arm acceleration, machine learning, falling prevention

1. INTRODUCTION

1.1 Falling accidents in elderly people

The World Health Organization reported that many elderly people have experienced falling accidents [1]. Falling accidents in elderly people could adversely affect the quality of life (QOL) because they cause serious injuries such as head injuries, which require hospitalization [2]. A study reported that elderly patients who were hospitalized because of falls often die in the hospital [2]. In addition, elderly people who experienced falls had decreased physical functions and QOL due to fear of falling accidents [3]. These studies indicated that most elderly people who have experienced falling accidents have decreased QOL both during hospitalization and in daily life. Therefore, fall prevention is necessary for the preservation of the QOL of elderly people.

1.2 Falling prevention

To prevent falls, many methods, such as questionnaires, physical tests, exercises, and environmental safety modification in clinical fields, could be employed [4]. For example, the Timed Up and Go test is effective for clinically assessing posture, balance, cognition, and vision [4]. However, these interventions and treatments could not be employed in real time during walking in daily life. In addition, questionnaires have problems due to subjectivity and low accuracy [4]. Therefore, an objective gait measurement system in real time is necessary to prevent falling accidents in daily life. Optical motion capture systems are used as a highly accurate gait measurement system in some specific hospitals [5]. Optical motion capture systems can evaluate body motion using infrared cameras and reflective markers with high accuracy [5]. However, these systems have limitations such as a high cost, the need for an expert to operate, and the laboratory environment [5]. Wearable motion capture systems based on an inertial measurement unit (IMU) can measure body motions without environmental limitations [5-6]. Nevertheless, wearing many IMUs could cause discomforts due to many straps and belts [6]. Moreover, long-term use of most IMU-based systems leads to low accuracy due to magnetic field, drift, and integral errors [7]. Thus, gait measurements that do not use additional devices and can be used for a long time are required. Some falling detection systems use smartphones or smart watches, addressing the issue of requiring additional devices and environmental limitations [8-9]. For example, Yoo and Oh proposed a real time falling detection method using arm acceleration obtained from a smart watch and artificial neural network [8]. In addition, Abbate et al. developed a smartphone-based falling detection system [9]. This system could automatically extract a falling event from activities such as jumping [9]. These systems could detect falls using smart watches or smartphones, but they could not predict and prevent falling accidents. From these backgrounds, we propose a gait monitoring and feedback system for real time fall prevention.

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1.3 Related studies

We have developed a monitoring and feedback system for gait parameters related to falls due to tripping [10-12] because tripping is the most frequent cause of falling [13-14]. Most elderly people trip because they could not recognize their gait parameters such as step length and foot–ground clearance due to a progressive loss of visual and sensual functions [15-18]. These gait parameters, which change with age, affect the ability to step over obstacles and stability related to tripping [15-18]. Thus, we considered that if elderly people are informed of their gait parameters in real time, falling accidents related to tripping could be prevented. Therefore, we have developed a monitoring and feedback system for gait parameters for fall prevention.

Our previous system estimated gait parameters by utilizing a machine learning algorithm using sensor data obtained from a wearable device on the arm. If the estimated gait parameters indicate risk of falling, this system informs the users to improve their gait by vibration. In our studies, we proposed an automatic classification method of rough gait conditions, which were normal, long, and high steps [10-12]. This classification method could classify gait conditions with an approximately 0.66 accuracy by utilizing a machine learning algorithm using three-axis acceleration obtained from a single wearable device on the arm [11]. However, our previous system could not quantitatively measure the gait parameters in detail. In this study, we propose a quantitative estimation method for step length.

Step length is an important parameter for tripping prevention. Step length should be stabilized continuously because destabilized step length disturbs the trajectory of the foot [19-20]. A disturbed trajectory of the foot leads to tripping even without obstacles [19-20]. Thus, continuous monitoring of step length is important for tripping prevention. In addition, quantitative measurement for step length is required. Insufficient step length reduces the flexion of the ankle because this step length shortens swing time [21]. When the flexion of the ankle is reduced, the risk of tripping increases because of toe contact [21-23]. Alternatively, excessively long step length is a risk factor for tripping since step length should be shortened to increase foot–ground clearance when crossing high obstacles [24-26]. Suitable step length depends on several factors such as age, disease, and motor function [27]. For example, a study reported that differences in step length between young people, elderly individuals, and those with Parkinson's disease were more than 10% of the body height [27]. From these investigations, continuous measurement of quantitative step length is necessary to prevent falling accidents due to tripping. Therefore, we propose an estimation method for quantitative step length using a wearable sensor.

The proposed method estimates step length using a single wearable device, either a smart watch or smartphone, on the arm. We considered that arm movement could track gait since studies found the relationship between arm movement and trunk rotation, energy expenditure, and gait parameters such as foot–ground clearance [28-32]. In addition, a study reported that users of gait monitoring systems preferred to wear sensors on the wrist rather than on the sole, ankle, or back [33].

Studies examined the estimation of step length using a smart device on the upper limb [34-35]. Kamisaka's method could estimate each step length with approximately 5-cm error using an accelerometer and a magnetometer on the arm [34]. Furthermore, Wang's method could estimate each step length with approximately 4-cm error using an accelerometer and a gyroscope attached to the arm [35]. However, the surrounding external magnetic field interfered with the magnetometer [7]. Furthermore, long-term use of a gyroscope could result in gyro drift issues [7]. Therefore, long-term measurement and the place of use are limited in these methods. Thus, in this study, we propose a novel estimation method for step length using arm acceleration that could be used in every place.

1.4 Objective

This study proposes and evaluates an estimation method for step length for a wearable falling prevention system. In addition, we compared the accuracy of 12 machine learning algorithms for the proposed method.

1.5 Outline of this paper

This section describes the backgrounds, related works, and objective of this paper. The rest of this paper is organized as follows. Section 2 describes the proposed step length estimation method. Section 3 describes the experimental procedures for evaluating the proposed method. Section 4 describes the results and discussions. Finally, Section 5 describes the conclusions of this paper.

2. PROPOSED METHOD

The proposed method estimates the step length of each step using regression algorithms with arm acceleration. In the proposed method, a three-axis arm acceleration is acquired once for each step, with the forearm placed across the side of the body. Figure 1 shows timing detection for data acquisition. This timing is detected using a proximity sensor of a smart device.

Figure 2 shows a block diagram of the step length estimation. A machine learning algorithm is used for the regression of step length. A machine learning algorithm could generate a regression function that will be used to estimate step length (output) using the three-axis arm acceleration data as the features (input). Then, the generated regression function estimates step length for each step using arm acceleration and a machine learning algorithm such as an artificial neural network. Comparing these algorithms is necessary for finding a suitable algorithm for the proposed method since each algorithm has different advantages [36-38]. In this study, we compared 12 machine learning algorithms to determine a suitable algorithm for the proposed method.

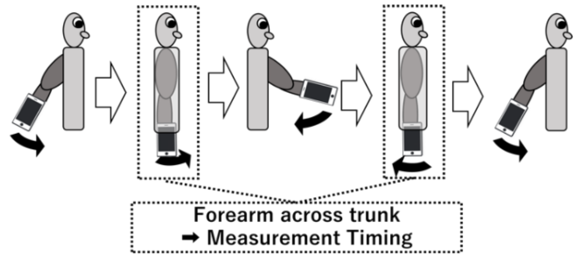

Figure 1. Timing for the measurement of arm acceleration

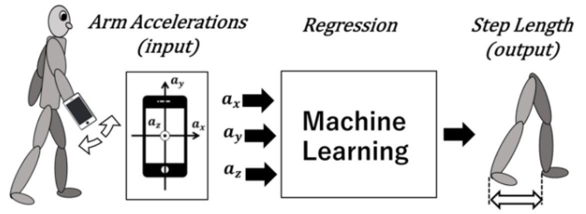

Figure 2. The proposed step length estimation method

3. EXPERIMENT

In this experiment, we evaluated whether the proposed method could estimate step length during walking. In addition, we compared the accuracy of 12 algorithms to find a suitable algorithm for the proposed method.

For the study's participants, we enrolled ten healthy young males aged 20.8 ± 0.1 (mean ± standard deviation (SD)) years with a mean body height of 171.4 ± 6.3 cm. All experimental procedures were approved by the ethics committee for human research of the National Institute of Technology, Kushiro College (approval number: 27-1). All participants received an explanation of the objectives and description of this study and signed a written informed consent form before participating in the experiment.

Figure 3 shows the experimental setup used in this study. The participants were instructed to walk 120 steps with two subjective step lengths (60 steps for each step length) on a treadmill: the normal and long step lengths. The short step length was not performed because there was a possibility that it leads to falling accidents due to stability loss of the participants [32]. In total, 1,200 data of acceleration and step lengths were obtained from all participants. The walking speed was set for each participant to walk comfortably and each step length using a treadmill. A digital camera (iPhone 5S; Apple Inc., Cupertino, California, USA) was used to record each participant's gait. The three-axis arm acceleration data were recorded for each step using the self-made software for with accelerometer and proximity sensors installed on a smartphone (Nexus 5; LG Electronics, Seoul, South Korea) attached on the wrist. The accelerometer of smartphone (range: ±2G) measured arm acceleration data with 100 Hz sampling rate.

Step lengths were calculated using the walking speed set on the treadmill and the number of steps counted using the videos obtained from the digital camera. The ratio between the measured step length and body height was calculated as the normalized step length [%Height].

The 12 machine learning algorithms (Bagging, Kstar, Decision Stump, M5P, REP Tree, Ibk, Additive Regression, Gaussian Processes, Support Vector Machine, Linear Regression, Isotonic Regression, and Artificial Neural Network) were tested and compared. Bagging and Additive Regression were performed using REP Tree, a decision tree algorithm. These machine learning algorithms were implemented by Weka [39]. Weka is open library and software for machine learning algorithm. Weka is implemented by Java programing language.

We evaluated the mean absolute error (MAE) of the estimated normalized step length between estimated value and actual value. The MAE values were evaluated as accuracy of the proposed method. In addition, the MAE values were calculated for each machine learning algorithm. The MAE values were calculated via 10-folds cross validation process. In 10-fold cross validation, the 1,200 data were randomly separated into 10 subsamples (120 data for each subsample). One subsample is used for test data, and other nine subsamples is used for training of machine learning. This process was repeated 10 times with changing combination of subsample between test and training. From these processes, all data were used for both test and training. Calculation of the MAE via 10-fold cross fold validation was performed for each machine learning algorithm. Furthermore, computational times during 10-fold cross validation for all algorithms were also calculated and compared. These processing were performed by the system with the following characteristics: Intel® Core™ i7-4500U CPU @ 2.70 GHz, 8.00 GB RAM, x64 based processor.

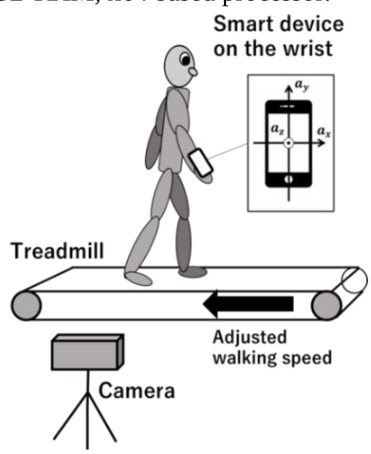

Figure 3. Experimental setup

4. RESULTS AND DISCUSSIONS

Table 1 shows the MAE values and computational times of the proposed method via 10-fold cross validation. The results showed that the proposed method using the Bagging algorithm could estimate step length with the smallest MAE value. The Bagging algorithm is a method for generating multiple functions and using an aggregate function decided from a plurality vote for generated multiple functions [40]. In addition, decision tree-based algorithms such as Decision Stump, M5P, and REP Tree had high accuracy. The reason for these results was that the decision tree could obtain a highly generalized regression function with a threshold-based range, and therefore, achieving high accuracy was possible even when there were variations in acceleration pattern in one step length [38]. The Bagging algorithm using REP Tree could estimate step length more accurately than REP Tree only. This result showed that a combination of the Bagging algorithm and a decision tree algorithm is effective for the proposed method. Moreover, the Bagging algorithm is robust for perturbed data because this algorithm uses an aggregate function obtained from multiple functions. [40]. This advantage of the Bagging algorithm is effective for estimating step length using the proposed method. From these results, the Bagging algorithm using REP Tree is considered the most suitable machine learning algorithm for the proposed method.

The result showed that the proposed method could estimate step length with less than 8 [%Height] error in all algorithms. In addition, computational times were less than 20 [s] in almost algorithms without Gaussian Processes. A study reported that differences in step length between young people, elderly individuals, and those with Parkinson's disease are more than 10 [%Height] [27]. Therefore, our proposed method could detect differences between normal and abnormal step lengths, which indicate an increased risk of falling due to aging or disease. However, these differences or thresholds depended on each disease. Thus, the accuracy of the proposed method should be discussed for each disease and situation. Furthermore, there is possibility that Gaussian Processes is not suitable for real-time application due to computational time.

Table 2 shows a comparison between our proposed method and related studies [34-35]. According to the body height of the participant, the estimation error of the proposed method is approximately 10.3 ± 0.4 cm (mean ± SD). The results showed that the errors of the other two methods were lower than that of our proposed method. The reason for these results was that these methods used much data obtained from a magnetometer or gyroscope [34-35]. However, the surrounding external magnetic field interfered with the magnetometer [7]. Furthermore, long-term use of a gyroscope could result in gyro drift issues [7]. Therefore, the use of these methods regarding the place of use and long-term measurement is limited. From this comparison, our proposed method could be used in a fall prevention system in the long-term and in every place compared with the other methods.

One potential limitation of this study was that the accuracy of the proposed method was tested in the walking condition set on a treadmill only. The utility of the proposed method should be tested in the long-term and in various places to confirm its advantages. Moreover, an evaluation of several conditions such as slope walking is necessary. Another limitation of this study is that we only enrolled young healthy male participants in this study. In future works, the use of the proposed method to evaluate the gait of elderly and female individuals is necessary.

The proposed method has an estimation error for step length. If a fall prevention system requires more detailed step length, improving the accuracy of the proposed method is necessary. According to Truong's study, arm acceleration during forward and backward swings is different [41]. Therefore, the accuracy could be improved using separated arm acceleration for forward or backward swing. Moreover, other machine learning algorithms could improve the accuracy of the proposed method. For example, the Boosting algorithm could improve the accuracy because it could be used as an alternative for the Bagging algorithm that incorporates weights [42]. Furthermore, the Bagging and Boosting algorithms can use several machine learning algorithms other than decision tree algorithms [42]. Therefore, a combination of the Bagging and other machine learning algorithms should be tested. To improve accuracy, consideration of wearable accelerometers is also important. For example, inertial sensor of Xsens (Enschede, Netherlands) could be used for clinical gait analysis due to its accuracy [43]. Furthermore, previous study reported that Apple Watch (Apple, Cupertino, CA) has also high accuracy for gait analysis [44].

For the implementation of a fall prevention system, estimation methods for other gait parameters such as foot–ground clearance are necessary. In addition, notification method of gait parameters is required.

Table 1. MAE and computational time

Machine Learning Algorithm	**MAE [%Height]**	**Computational Time [s]**
Bagging	**5.07**	**1**
Kstar	5.18	17
Decision Stump	5.26	< 1
M5P	5.39	5
REP Tree	5.39	1
Ibk	5.68	15
Additive Regression	5.98	< 1
Gaussian Processes	6.12	93
Support Vector Machine	6.33	15
Linear Regression	6.38	< 1
Isotonic Regression	6.42	2
Artificial Neural Network	7.58	15

Table 2. Comparison of the step length estimation methods [34-35]

Method	Error [cm]	Signal Source
Kamisaka's Method [34]	5.0	Accelerometer Magnetometer
Wang's Method [35]	3.6	Accelerometer Gyroscope
Proposed Method	10.3 ± 0.4	Accelerometer

5. CONCLUSIONS

In this study, we proposed a step length estimation method using arm acceleration obtained from a smart device attached on the wrist for a wearable fall prevention system. The results showed that the proposed method could estimate step length with an estimation error of less than 8% of body height. This result suggests that the proposed method detects rough differences in step length due to aging. In future works, improving the accuracy of the proposed method is necessary. Furthermore, we will propose an estimation method for other gait parameters and information method for a fall prevention system. Finally, we will integrate these methods and implement a wearable fall prevention system.

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REFERENCES

[1] World Health Organization; World Health Organization. Ageing, Life Course Unit. WHO Global Report on Falls Prevention in Older Age. 2008.

[2] Cartagena LJ, Kang A, Munnangi S, Jordan A, Nweze IC, Sasthakonar V, Boutin A, Angus LG. Risk factors associated with in-hospital mortality in elderly patients admitted to a regional trauma center after sustaining a fall. Aging clinical and experimental research. 2017 Jun 1;29(3):427-33.

[3] Schmid AA, Van Puymbroeck M, Knies K, Spangler-Morris C, Watts K, Damush T, Williams LS. Fear of falling among people who have sustained a stroke: A 6-month longitudinal pilot study. American Journal of Occupational Therapy. 2011 Mar 1;65(2):125-32.

[4] Genovese V, Mannini A, Guaitolini M, Sabatini AM. Wearable inertial sensing for ICT management of fall detection, fall prevention, and assessment in elderly. Technologies. 2018 Dec;6(4):91.

[5] Chen S, Lach J, Lo B, Yang GZ. Toward pervasive gait analysis with wearable sensors: A systematic review. IEEE journal of biomedical and health informatics. 2016 Sep 22;20(6):1521-37.

[6] McAdams ET, Gehin C, Noury N, Ramon C, Nocua R, Massot B, Oliveira A, Dittmar A, Nugent CD, McLaughlin J. Biomedical sensors for ambient assisted living. InAdvances in Biomedical Sensing, Measurements, Instrumentation and Systems 2010 (pp. 240-262). Springer, Berlin, Heidelberg.

[7] Ahmad N, Ghazilla RA, Khairi NM, Kasi V. Reviews on various inertial measurement unit (IMU) sensor applications. International Journal of Signal Processing Systems. 2013 Dec;1(2):256-62.

[8] Yoo S, Oh D. An artificial neural network–based fall detection. International Journal of Engineering Business Management. 2018 Jul 20; 10:1847979018787905.

[9] Abbate S, Avvenuti M, Bonatesta F, Cola G, Corsini P, Vecchio A. A smartphone-based fall detection system. Pervasive and Mobile Computing. 2012 Dec 1;8(6):883-99.

[10] Kitagawa K, Taguchi Y, Toya N. Proposal and evaluation of the gait classification method using arm acceleration data and decision tree. In Proceedings of The 2017 International Conference on Artificial Life and Robotics 2017 (pp. 104-107).

[11] Kitagawa K, Taguchi Y, Toya N. A Study on Classifiers in a Gait Classification Method Using Arm Acceleration Data. International Journal of Biomedical Soft Computing and Human Sciences: the official journal of the Biomedical Fuzzy Systems Association. 2017;22(2):49-56.

[12] Toya N, Sakamoto Y, Taguchi Y, Kitagawa K. Fundamental study of a simple walking support system using smart devices. InWorld Congress on Medical Physics and Biomedical Engineering 2018 2019 (pp. 739-743). Springer, Singapore.

[13] Kim H, Yoshida H, Suzuki T, Ishizaki T, Hosoi T, Yamamoto S, Orimo H. The relationship between fall-related activity restriction and functional fitness in elderly women. Nihon Ronen Igakkai zasshi. Japanese journal of geriatrics. 2001 Nov;38(6):805-11. (in Japanese)

[14] Overstall PW, Exton-Smith AN, Imms FJ, Johnson AL. Falls in the elderly related to postural imbalance. Br Med J. 1977 Jan 29;1(6056):261-4.

[15] Saito S, Muraki S. Study on tracks and sense of feet position while stepping over an obstacle in the elderly. Japanese Journal of Ergonomics. 2010; 46:172-9. (in Japanese)

[16] Kobayashi Y, Fujimoto H, Nakazawa K, Akai M. Foot position tends to be sensed as more medial than the actual foot position. Journal of motor behavior. 2009 Oct 8;41(5):437-43.

[17] Shin S, Demura S, Watanabe T, Kawabata H, Sugiura H, Matsuoka T. Relationship between the obstacle height cognition and step movement in the elderly. Journal of Physiological Anthropology. 2012 Dec 1;31(1):27.

[18] Alcock L, Galna B, Perkins R, Lord S, Rochester L. Step length determines minimum toe clearance in older adults and people with Parkinson's disease. Journal of biomechanics. 2018 Apr 11; 71:30-6.

[19] Forner Cordero A, Koopman HF, van der Helm FC. Multiple-step strategies to recover from stumbling perturbations. Gait & posture, 2003, 18.1: 47-59.

[20] Sessoms PH, Wyatt M, Grabiner M, Collins JD, Kingsbury T, Thesing N, Kaufman K. Method for evoking a trip-like response using a treadmill-based perturbation during locomotion. Journal of biomechanics. 2014 Jan 3;47(1):277-80.

[21] CHOU, Li-Shan; DRAGANICH, Louis F. Placing the trailing foot closer to an obstacle reduces flexion of the hip,

knee, and ankle to increase the risk of tripping. Journal of biomechanics, 1998, 31.8: 685-691.

[22] JudgeRoy JO, Davis III B, Õunpuu S. Step length reductions in advanced age: the role of ankle and hip kinetics. The Journals of Gerontology Series A: Biological Sciences and Medical Sciences. 1996 Nov 1;51(6):M303-12.

[23] Saito, T. Suganuma, K. Saito, Y. Aoyagi, T. Kaneko, C. Comparison of heel raise repetitions and maximum step length and their relation to falls: Rigakuryoho Kagaku, 2016; 31; 907-910 (in Japanese)

[24] Lu TW, Chen HL, Chen SC. Comparisons of the lower limb kinematics between young and older adults when crossing obstacles of different heights. Gait & posture. 2006 Jun 1;23(4):471-9.

[25] Chen HC, Ashton-Miller JA, Alexander NB, Schultz AB. Stepping over obstacles: gait patterns of healthy young and old adults. Journal of gerontology. 1991 Nov 1;46(6):M196-203.

[26] Muir BC, Haddad JM, Heijnen MJ, Rietdyk S. Proactive gait strategies to mitigate risk of obstacle contact are more prevalent with advancing age. Gait & posture. 2015 Jan 1;41(1):233-9.

[27] Halliday SE, Winter DA, Frank JS, Patla AE, Prince F. The initiation of gait in young, elderly, and Parkinson's disease subjects. Gait & posture. 1998 Aug 1;8(1):8-14.

[28] Pontzer H, Holloway JH, Raichlen DA, Lieberman DE. Control and function of arm swing in human walking and running. Journal of Experimental Biology. 2009 Feb 15;212(4):523-34.

[29] Yizhar Z, Boulos S, Inbar O, Carmeli E. The effect of restricted arm swing on energy expenditure in healthy men. International journal of rehabilitation research. 2009 Jun 1;32(2):115-23.

[30] Olshen R, Cooper L, Woo SL. The development of mature gait. Journal of Bone and Joint Surgery. 1980:336-53.

[31] Kitagawa, K. Taguchi Y. Toya, N. Effect of foot-ground clearance during walking on acceleration of the upper limbs: Rigakuryoho Kagaku, 2017; 32; 549-552 (in Japanese)

[32] Young PM, Dingwell JB. Voluntary changes in step width and step length during human walking affect dynamic margins of stability. Gait & posture. 2012 Jun 1;36(2):219-24.

[33] Zhong R, Rau PL, Yan X. Gait assessment of younger and older adults with table motion-sensing methods: A user study. Mobile Information Systems. 2019 Jan 1;2019.

[34] Kamisaka D, Muramatsu S, Iwamoto T, Yokoyama H. Design and implementation of pedestrian dead reckoning system on a mobile phone. IEICE transactions on information and systems. 2011 Jun 1;94(6):1137-46.

[35] Wang Q, Ye L, Luo H, Men A, Zhao F, Ou C. Pedestrian walking distance estimation based on smartphone mode recognition. Remote Sensing. 2019 Jan;11(9):1140.

[36] Specht DF. A general regression neural network. IEEE transactions on neural networks. 1991 Nov 1;2(6):568-76.

[37] Shevade SK, Keerthi SS, Bhattacharyya C, Murthy KR. Improvements to the SMO algorithm for SVM regression. IEEE transactions on neural networks. 2000 Sep;11(5):1188-93.

[38] Zhan C, Gan A, Hadi M. Prediction of lane clearance time of freeway incidents using the M5P tree algorithm. IEEE Transactions on Intelligent Transportation Systems. 2011 Sep 8;12(4):1549-57.

[39] Machine Learning Group at the University of Waikato, Weka 3: Machine Learning Software in Java, https://www.cs.waikato.ac.nz/ml/weka/index.html, Accessed September 2020.

[40] Breiman L. Bagging predictors. Machine learning. 1996 Aug 1;24(2):123-40.

[41] Truong PH, Nguyen ND, Ho NH, Jeong GM. Nonparametric regression-based step-length estimation for arm-swing walking using a smartphone. International Journal of Computers Communications and Control. 2018 Aug 1;13(4):566-73.

[42] Sutton CD. Classification and regression trees, bagging, and boosting. Handbook of statistics. 2005 Jan 1; 24:303-29.

[43] Wolff A, Sama A, Lenhoff M, Daluiski A. The use of wearable inertial sensors effectively quantify arm asymmetry during gait in children with unilateral spastic cerebral palsy. Journal of hand therapy: official journal of the American Society of Hand Therapists. 2020 Jun 19.

[44] Sama AJ, Hillstrom H, Daluiski A, Wolff A. Reliability and agreement between two wearable inertial sensor devices for measurement of arm activity during walking and running gait. Journal of Hand Therapy. 2020 Aug 20.

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