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Brief Report

Foot Position Recognition Using a Smartphone Inertial Sensor in Patient Transfer

Kodai Kitagawa [1,*], Ryo Takashima [1], Tadateru Kurosawa [1] and Chikamune Wada [2]

1 Department of Industrial Systems Engineering, National Institute of Technology, Hachinohe College, 16-1 Uwanotai, Tamonoki, Hachinohe 039-1192, Japan; kuro-m@hachinohe-ct.ac.jp (T.K.)
2 Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology, Hibikino 2-4, Wakamatsu-ku, Kitakyushu 808-0135, Japan; wada@brain.kyutech.ac.jp
* Correspondence: kitagawakitagawa156@gmail.com

Abstract: Caregivers experience lower back pain due to patient transfer. Foot position is an important and adjustable posture for reducing lumbar loads during patient transfer. Specifically, a suitable foot position provides the use of the lower limbs instead of the lumbar region in patient handling. Thus, we have developed a monitoring and feedback system for foot positioning using wearable sensors to instruct suitable foot positions. However, existing measurement methods require multiple specific wearable sensors. In addition, the existing method has not been evaluated in patient transfer, including twisting and lowering. Thus, the objective of this study was to develop and evaluate a measurement method using only a smartphone-installed inertial sensor for foot position during patient transfer, including twisting and lowering. The smartphone attached to the trunk measures the acceleration, angular velocity, and geomagnetic field. The proposed method recognizes antero-posterior and mediolateral foot positions by machine learning using inertial data. The proposed method was tested using simulated patient transfer motions, including horizontal rotation. The results showed that the proposed method could recognize the two foot positions with more than 90% accuracy. These results indicate that the proposed method can be applied to wearable monitoring and feedback systems to prevent lower back pain caused by patient transfer.

Keywords: wearable sensors; inertial sensor; smartphone; caregiver; patient transfer; foot position; posture recognition; machine learning; occupational health

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1. Introduction

Caregivers experience lower back pain owing to lumbar loads during patient transfer. Patient transfer causes lumbar loads due to lowering, twisting, and lifting [1–6]. Thus, several assistive devices have been developed to avoid musculoskeletal loads during patient transfer [7]. These devices can reduce lumbar loads and the risk of lower back pain [7,8]. However, several devices, such as mechanical lifts, require remarkable effort for operation [7]. In addition, awkward postures related to the risk of lower back pain remained in several facilities using these assistive devices [8]. From this background, it is considered that instruction on suitable posture during patient transfer is needed to prevent lower back pain among caregivers.

The instruction of a suitable posture based on ergonomics and body mechanics is effective in reducing musculoskeletal loads on caregivers [9–11]. However, these instructions cannot be applied to real-time and continuous prevention of lower back pain because they require observation of the posture of the caregiver. Thus, measurement systems using vison-based systems for posture during patient handling were developed for real-time and continuous intervention to prevent lower back pain [12,13]. Vision-based systems can accurately measure human posture [14]; however, the measurement area of these systems is limited by several factors, such as field of view and occlusion. Wearable sensor-based systems can measure posture during patient handling without limiting the measurement area. These systems could measure and provide feedback on the trunk angle related to lumbar loads during patient handling by wearable sensors [15–17]. However, a feedback system of only the trunk angle requires a trainer to observe and instruct the lower limb posture in the implementation of a suitable posture [17]. Body mechanics recommends using the lower limb instead of the lumbar region to reduce the lumbar load during patient handling [18]. From these studies, it is considered that lower limb postures should be measured and fed back in real time and everywhere by wearable sensor-based systems.

The foot position is an adjustable and effective posture for implementing suitable patient transfer using lower limb movement [19–21]. A previous study showed the possibility that foot position with long anteroposterior distance could reduce lumbar load by prompting the usage of lower limb muscles instead of lumbar [21]. In addition, other previous studies used commands such as "use legs instead of back" to improve patient handling motion [17]. Thus, we have been developing a measurement method for foot position using wearable sensors to determine a suitable foot position [22,23]. Our previous method could measure foot position during patient lifting motion (assistance for sit-to-stand), which is part of patient transfer, using inertial sensors and shoe-type force sensors. However, this method cannot be applied to patient transfer, including twisting and lowering [22,23]. The posture during twisting and lowering should be measured and monitored because twisting and lowering cause lumbar loads on caregivers [5,24]. In addition, our previous method required the preparation of additional devices because this method requires shoe-type force sensors, which are not common devices [22,23]. On the other hand, inertial sensors can be used by many caregivers because they are installed on common smartphones. Furthermore, many previous studies have indicated that the inertial sensors of smartphones could be applied for the measurement of human movements, such as walking and activities of daily life [25–31]. Based on these facts, it is considered that a novel measurement method for foot position using only an inertial smartphone sensor might be useful for preventing lower back pain due to patient transfer. Thus, the objective of this study was to develop and evaluate a measurement method for foot position in patient transfer using only an inertial sensor installed on a smartphone.

2. Materials and Methods

2.1. Proposed Method

Figure 1 presents an overview of the proposed method. The smartphone on the trunk measures acceleration, angular velocity, and geomagnetic on the 3-axis during patient transfer motion. These inertial data are known to be effective signals for activity recognition [28]. The trunk was selected for sensor placement because a previous study indicated that an inertial sensor on the trunk could measure movement related to lumbar loads in manual handling [32]. The combination of the proposed method and existing methods using only a single inertial sensor will measure various kinematic values, such as trunk movement and foot position, to prevent lower back pain.

The machine learning-based classifier recognizes the anteroposterior (AP) and mediolateral (ML) foot positions during patient lifting using inertial data. Our recent study indicated that the lumbar loads of the AP foot position were lower than those of the ML foot position in patient lifting [20]. Thus, these foot positions during patient lifting should be recognized and fed back to caregivers to reduce lumbar loads. This study considers that the feedback system prompts AP foot position when the proposed method recognizes ML foot position. The features (maximum, minimum, mean, median, standard deviation, root-mean-square, variance, kurtosis, and skewness) of the machine learning were calculated from the time waveform of each sensor signal. These features are effective for activity recognition using the inertial sensors of smartphones [28]. Previous studies have shown that an artificial neural network (ANN), decision tree (DT), and support vector machine (SVM) are common algorithms used for human activity recognition using sensor data [33]. A suitable combination of algorithms and sensor signals depends on the movement or activity. In this study, a suitable combination of algorithms and sensor signals for the proposed method was explored experimentally. In addition, the usefulness of the proposed method is evaluated experimentally.

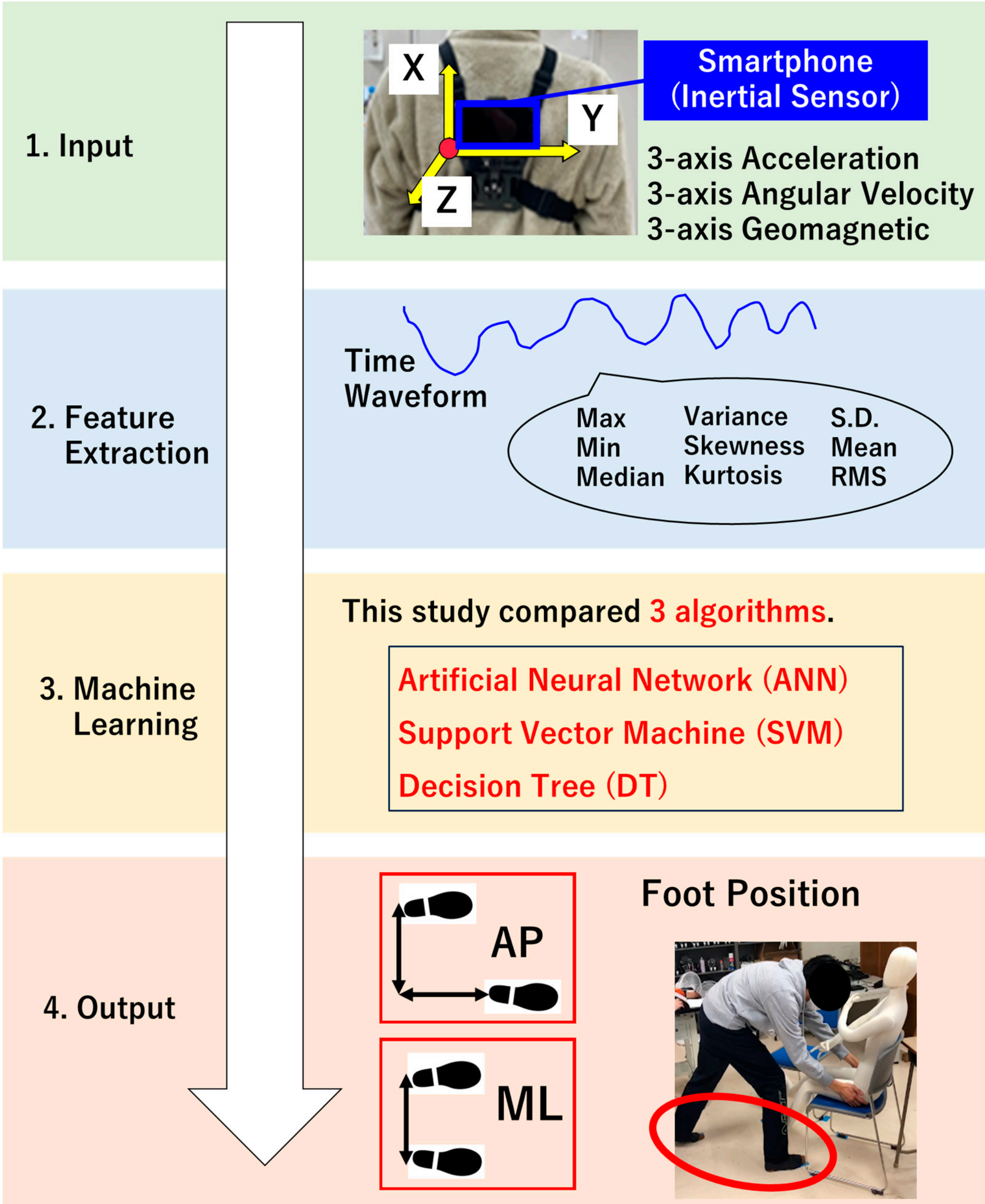

Figure 1. Overview of the proposed method. AP: anteroposterior; ML: mediolateral; ANN: artificial neural network; DT: decision tree; SVM: support vector machine.

2.2. Experiment

In the experiment, the accuracy of foot position recognition using the proposed method was evaluated to verify the usefulness of the proposed method. Furthermore, the accuracies of different combinations of sensor signals (acceleration, angular velocity, and geomagnetic) and machine learning algorithms (ANN, DT, and SVM) were compared to determine a suitable combination for the proposed method.

The participants were 10 young males (age 19.4 $\pm$ 0.663 years; height, 169 $\pm$ 4.98 cm, weight 64.2 $\pm$ 13.3 kg, mean $\pm$ standard deviation). The experimental procedures were conducted in accordance with the Declaration of Helsinki and the Ethics Committee for

Human Research of the National Institute of Technology, Hachinohe College (approval number R4-2).

A smartphone (iPhone 8, Apple Inc., Cupertino, CA, USA) for the proposed method was attached to the trunk of the participant, as shown in Figure 1. iPhone 8 implemented an inertial sensor (Bosch Sensortec, Reutlingen, Germany). The participants performed patient transfer motion for 5 trials for both the AP and ML foot positions (a total of 10 trials for each participant). Figure 2 shows the foot positions and seat placements for patient transfer. The patient was transferred from seat 1 to seat 2 with horizontal rotation (Figure 2). The horizontal angle between seat 1 and seat 2 was fixed to 30 degrees. The forefoot (left foot) of the participants was fixed to the same position in both the AP and ML foot positions (Figure 2). Foot position was defined by the length and width between the heels of both feet. The foot angle was not fixed during patient transfer. The doll (height 140 cm, weight 4.8 kg) used as a simulated patient was lighter than humans because the lumbar loads of participants should be controlled compared to actual patient transfer. The posture of the simulated patient was kept in a sitting posture during patient transfer. The smartphone measured 3-axis acceleration, angular velocity, and geomagnetic during patient transfer with a 100 Hz sampling frequency by the phyphox applications [34]. From these procedures, 100 trials (AP: 50 trials, ML: 50 trials) were measured by all participants.

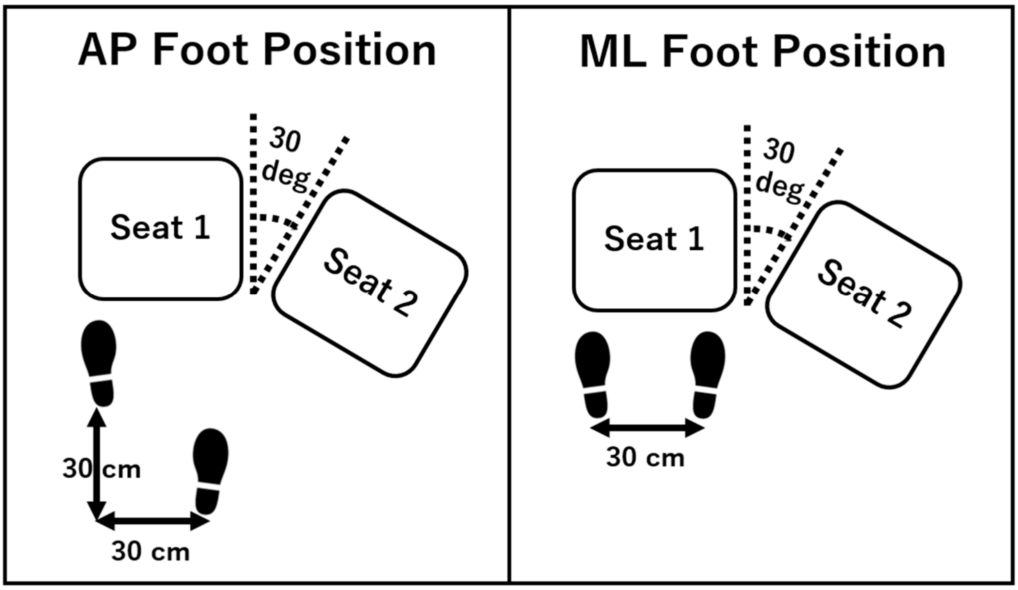

Figure 2. Foot positions of the experiment. AP: anteroposterior; ML: mediolateral.

2.3. Analysis

A total of 100 trial data points obtained from the experiment were used for the training and testing of the proposed method. Features (maximum, minimum, mean, median, standard deviation, root-mean-square, variance, kurtosis, and skewness) for machine learning were calculated from the time waveform during patient transfer for each sensor signal (acceleration, angular velocity, and geomagnetic on each axis). As mentioned previously, the performances of the proposed method using different combinations of sensor signals and machine learning algorithms were compared. The ANN, DT, and SVM were selected as machine learning algorithms. Tables 1–3 list the specifications of each algorithm. The sensor signals were trio, pair, or solo acceleration, angular velocity, and geomagnetic.

Table 1. Specifications of the artificial neural network (ANN).

Specifications		Values
Number of Layers	Input Layer	1
	Hidden Layer	1
	Output Layer	1
Number of Nodes/Neurons (Due to the Number of Signals)	Input Layer	27 to 81
	Hidden Layer	27 to 81
	Output Layer	1
Activation	Hidden Layer	Sigmoid
	Output Layer	Linear
Training		Back Propagation
Loss Function		Mean Squared Error
Momentum		0.2
Learning Rate		0.3

Table 2. Specifications of the decision tree (DT).

Specifications	Values
Minimum Number of Observations at each Leaf	2
Data to Use for Pruning Tree	1/3 of the Data
Data to Use for Growing Tree	2/3 of the Data

Table 3. Specifications of the support vector machine (SVM).

Specifications	Values
Kernel	Linear Kernel
Training	Sequential Minimal Optimization
Hyperparameter c	1.0

Training and testing of the proposed method were trained and tested via leave-one-out cross-validation (LOOCV). The accuracy, precision, recall, and F-measure of foot position recognition as evaluation values were calculated as follows:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$\text{F-measure} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

where TP is true positive, TN is true negative, FP is false positive, and FN is false negative. These evaluation values were calculated by training and testing using LOOCV. The LOOCV for each machine learning algorithm was performed using WEKA [35,36].

3. Results

Tables 4–7 show the accuracy, precision, recall, and F-measure of foot position recognition. The proposed method using an ANN or SVM with all sensor signals (acceleration, angular velocity, and geomagnetic) could correctly recognize all foot positions. The proposed method, using two sensor signals, could recognize foot positions with an accuracy of 0.780–0.990.

Table 4. Accuracy of the proposed method.

Sensor Signal	Accuracy		
	ANN	DT	SVM
Acceleration, Angular Velocity, Geomagnetic	1.00	0.890	1.00
Acceleration, Angular Velocity	0.870	0.780	0.860
Acceleration, Geomagnetic	0.960	0.940	0.970
Angular Velocity, Geomagnetic	0.990	0.890	0.980
Acceleration	0.830	0.690	0.710
Angular Velocity	0.880	0.810	0.850
Geomagnetic	0.990	0.900	0.950

ANN: artificial neural network; DT: decision tree; SVM: support vector machine.

Table 5. Precision of the proposed method.

Sensor Signal	Precision					
	ANN		DT		SVM	
	AP	ML	AP	ML	AP	ML
Acceleration, Angular Velocity, Geomagnetic	1.00	1.00	0.915	0.868	1.00	1.00
Acceleration, Angular Velocity	0.894	0.849	0.818	0.750	0.833	0.891
Acceleration, Geomagnetic	0.942	0.979	0.958	0.923	0.961	0.980
Angular Velocity, Geomagnetic	1.00	0.980	0.933	0.855	0.980	0.980
Acceleration	0.851	0.811	0.667	0.721	0.723	0.698
Angular Velocity	0.880	0.880	0.804	0.816	0.843	0.857
Geomagnetic	0.980	1.00	0.955	0.857	0.941	0.959

AP: anteroposterior; ML: mediolateral; ANN: artificial neural network; DT: decision tree; SVM: support vector machine.

Table 6. Recall of the proposed method.

Sensor Signal	Recall					
	ANN		DT		SVM	
	AP	ML	AP	ML	AP	ML
Acceleration, Angular Velocity, Geomagnetic	1.00	1.00	0.860	0.920	1.00	1.00
Acceleration, Angular Velocity	0.840	0.900	0.720	0.840	0.900	0.820
Acceleration, Geomagnetic	0.980	0.940	0.920	0.960	0.980	0.960
Angular Velocity, Geomagnetic	0.980	1.00	0.840	0.940	0.980	0.980
Acceleration	0.800	0.860	0.760	0.620	0.680	0.740
Angular Velocity	0.880	0.880	0.820	0.800	0.860	0.840
Geomagnetic	1.00	0.980	0.840	0.960	0.960	0.940

AP: anteroposterior; ML: mediolateral; ANN: artificial neural network; DT: decision tree; SVM: support vector machine.

Table 7. F-measure of the proposed method.

Sensor Signal	F-Measure					
	ANN		DT		SVM	
	AP	ML	AP	ML	AP	ML
Acceleration, Angular Velocity, Geomagnetic	1.00	1.00	0.887	0.893	1.00	1.00
Acceleration, Angular Velocity	0.866	0.874	0.766	0.792	0.865	0.854
Acceleration, Geomagnetic	0.961	0.959	0.939	0.941	0.970	0.970
Angular Velocity, Geomagnetic	0.990	0.990	0.884	0.895	0.980	0.980
Acceleration	0.825	0.835	0.710	0.667	0.701	0.718
Angular Velocity	0.880	0.880	0.812	0.808	0.851	0.848
Geomagnetic	0.990	0.990	0.894	0.906	0.950	0.949

AP: anteroposterior; ML: mediolateral; ANN: artificial neural network; DT: decision tree; SVM: support vector machine.

The accuracy of all the patterns, including geomagnetic signals, was at least 0.89. The proposed geomagnetic method tends to be more accurate than the proposed method using acceleration or angular velocity. In addition, the accuracy of the decision tree using only geomagnetic data is greater than that of the decision tree using both angular velocity and geomagnetic data. The results showed that the accuracies of the proposed methods using an ANN and SVM were greater than those of the proposed methods using a DT.

The results showed that there were almost no differences in the precision, recall, and F-measure between the AP and ML foot positions. Furthermore, the precision, recall, and F-measure of the proposed methods using an ANN and SVM were greater than a DT.

4. Discussion

In this study, we propose and evaluate a foot position recognition method using a smartphone-installed inertial sensor for patient transfer. The results showed that the proposed method, using several combinations of multiple sensor signals and machine learning, could recognize foot positions with an accuracy of more than 0.97. The inter-observer agreement of lower limb posture recognition by humans was approximately 0.97 in a previous study related to occupational health [37]. These results and reports suggest the possibility that the accuracy of the proposed method is comparable to that of human observations. Additionally, the proposed method can be applied for monitoring and feedback on foot position to prevent lower back pain due to patient transfer.

The results showed that the proposed methods using an ANN or SVM with all sensor signals (acceleration, angular velocity, and geomagnetic) were the most accurate in all combinations. If there is no limitation for implementation, combinations of all sensor signals and an ANN or SVM are recommended for the proposed method.

The results showed that multiple sensor signals contributed to a greater accuracy of foot position recognition. These results indicate that acceleration, angular velocity, and geomagnetic are effective for the proposed method. In particular, geomagnetic contributed the most to accurate recognition compared to the other signals. From these results, it is considered that geomagnetic is the most effective signal for the proposed method. However, geomagnetic signals are affected by magnetic disturbances owing to environmental conditions [38]. Thus, the proposed method should be combined with existing methods for estimating magnetic disturbances, such as the Kalman filter [39], customized for inertial and geomagnetic data. In addition, the improvement of the proposed method using only acceleration and angular velocity is considered another solution. In future work, the proposed method will be applied in various environments through these improvements.

A comparison of machine learning algorithms showed that the accuracies of the ANN and SVM were greater than those of the DT. From these results, it is considered that the DT is difficult to use for the proposed method because the DT-based if–then rules are not flexible for data distributions. Therefore, the ANN and SVM are recommended for use in the proposed method.

The results of precision, recall, and F-measure showed that there were almost no differences in the recognition performance between the AP and ML foot positions. These results show that the proposed method can recognize the two foot positions evenly. From these results, it is considered that the proposed method is useful for wearable applications to implement a suitable posture for patient transfer to prevent lower back pain.

As mentioned previously, our previous study suggested the possibility that the AP foot position contributes to reducing lumbar loads during patient transfer [20]. Thus, the proposed method can be applied to the recognition of the AP and ML foot positions. When the proposed method recognizes the ML foot position, the caregiver is informed to use the AP foot position.

The limitation of this study was that patient transfer was a simulated motion. In addition, the simulated patient in this study was lighter than the actual human because patient transfer with an actual patient carries a risk of lumbar loads for participants. Moreover, further motion analysis is required because motion analysis contributes to explaining reasons for accuracy or error of activity recognition. Furthermore, the foot positions of this study were limited to only two positions for the repeatability of the experiment. Therefore, various foot positions with different foot distances must be applied for future evaluations of the proposed method.

The experimental environment and participants were limited to young males and a laboratory environment. There are differences in patient handling motion between males and females. For example, the patient handling motion of males is faster than females' motion [40]. There is a possibility that these differences affect the accuracy of the proposed method. The results of this study can be generalized for patient transfer for patients who are sitting. However, the results of this study cannot be applied to other patient handling motions, such as turning supine patients on the bed. Thus, the proposed method should be tested for other patient handling motions. In future studies, the proposed method should be evaluated for various patient handling and actual caregivers or nurses in the clinical field. Additionally, the feedback system using the proposed method was not implemented and evaluated. Finally, the effect of intervention using the implemented feedback system should be investigated in future works.

5. Conclusions

In this study, we proposed and evaluated a foot position recognition method using a smartphone-installed inertial sensor and a machine learning technique for wearable applications to implement a suitable posture for patient transfer. The experimental results showed that the proposed method could recognize foot positions during patient transfer with high accuracy. These results indicate that the proposed method can be applied for the monitoring and feedback of foot position to prevent lower back pain due to patient transfer.

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Informed Consent Statement: Informed consent was obtained from all the participants involved in the study.

Data Availability Statement: Data are stored in a password-protected PC at the National Institute of Technology, Hachinohe College.

Conflicts of Interest: The authors declare no conflicts of interest.

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