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Automated detection and classification of construction workers' loss of balance events using wearable insole pressure sensors

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ABSTRACT

Fall on the same level is the leading cause of non-fatal injuries in construction workers; however, identifying loss of balance events associated with specific unsafe surface conditions in a timely manner remain challenging. The objective of the current study was to develop a novel method to detect and classify loss of balance events that could lead to falls on the same level by using foot plantar pressure distributions data captured from wearable insole pressure sensors. Ten healthy volunteers participated in experimental trials, simulating four major loss of balance events (e.g., slip, trip, unexpected step-down, and twisted ankle) to collect foot plantar pressure distributions data. Supervised machine learning algorithms were used to learn the unique foot plantar pressure patterns, and then to automatically detect loss of balance events. We compared classification performance by varying window sizes, feature groups and types of classifiers, and the best classification accuracy (97.1%) was achieved when using the Random Forest classifier with all feature groups and a window size of 0.32 s. This study is important to researchers and site managers because it uses foot plantar pressure distribution data to objectively distinguish various potential loss of balance events associated with specific unsafe surface conditions. The proposed approach can allow practitioners to proactively conduct automated fall risk monitoring to minimize the risk of falls on the same level on sites.

1. Introduction

Falls are the primary cause of construction workers' injuries [1]. In Hong Kong, statistics show that workers' injuries associated with falls accounted for almost half of the construction injuries [2], and about HK $ 40 million of total compensation in 2008 [3]. Especially, falls on the same level are one of the most significant causes of construction workers' injuries in Hong Kong, accounting for about 20% of construction accidents [4]. Compared with falls from height, the severity of injuries from falls on the same level is relatively low (generally leading to non-fatal injuries), but they are the most frequent types of injuries in construction, accounting for 40% of non-fatal fall injuries [5,6]. Given that these fall injuries can cause a delay in construction schedule, decrease productivity, and increase economic burden [7], the prevention of falls on the same level is an important priority in the construction industry [8].

Previous studies have shown that falls on the same level occur when workers suddenly lose their balance because of loss of balance events such as slips, trips, unexpected step-downs and twisted ankles [9–11]. Numerous intrinsic and extrinsic risk factors can lead to loss of balance events on construction sites [12]. While some intrinsic risk factors are non-modifiable (e.g., cerebellar problems) and modifiable (e.g., physical fitness, agility, fatigue, and attention etc.) [12], most of the extrinsic risk factors for falls on the same level on construction sites are related to unsafe environmental surface conditions such as uneven work surfaces, the presence of an obstacle or contaminant, and slippery surfaces [12,13]. For safety officers and managers at construction sites, identifying and detecting loss of balance events associated with unsafe environmental surface conditions are crucial to prevent same-level fall accidents. However, previous studies usually relied on experts' judgments and retrospective data (e.g., accident reports) for injury analysis and identifying loss of balance events associated with fall risk factors [14,15]. Despite the value these prior studies, their approaches not only might involve a subjective bias or missing data [16], but also might unable to prevent continuous monitoring of fall risk factors due retrospective nature of these studies [11].

To address these issues, we propose real-time detection and classification of loss of balance events by using wearable pressure insole

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sensors that measure foot plantar pressure distributions. Each loss of balance event (e.g., slips, trips, unexpected step-downs and twisted ankles) is associated with specific unsafe environmental surface conditions (e.g., slippery floors, uneven surfaces or obstacles on the path etc.), creating unique foot plantar pressure distribution patterns measured by using wearable insole pressure sensors. Supervised machine learning algorithms were developed to classify types of loss of balance events by using spatial and temporal features that reflect the unique plantar pressure data patterns. Detecting workers' loss of balance events provide useful information for (1) diagnosing potential causes (i.e., types of unsafe environmental surface conditions) of falls on the same level and (2) implementing appropriate interventions for construction workers who are more vulnerable to a loss of balance under given conditions. To test the detection performance, we conducted laboratory experiments to collect foot plantar pressure distribution data from simulated loss of balance events, and applied developed supervised machine learning algorithms. Based on the testing results, the feasibility of the proposed approach and its potential application areas were discussed.

2. Research background

2.1. Fall risk factors and preventive measures of falls on the same level

Understanding the underlying mechanisms of fall risk factors that may lead to falls on the same level is essential to identify and detect loss of balance events, and this could eventually help safety managers to implement effective preventive measures [17]. Fig. 1 presents the role of intrinsic and extrinsic risk factors that may lead to falls on the same level. As shown in Fig. 1, intrinsic risk factors are related to either an individual's perceptual ability to identify any existing unsafe conditions or motor control ability to recover from imbalance. Besides, extrinsic risk factors are associated with occupational environments and work organization [12]. Among the extrinsic risk factors (see Fig. 1) that may lead to falls on the same level, unsafe environmental surface conditions such as the presence of obstacles, uneven work surfaces, and slippery surfaces have been reported to be the most prevalent risk factors [18,19]. By analyzing more than 20,000 recorded falls in the United Kingdom, Manning [20] found that there are four major types of loss of balance events that could lead to falls on the same level: 1) slips; 2) trips; 3) unexpected step-downs; and 4) twisted ankles. These four events account for more than 90% of unsafe environmental surface conditions that resulted in falls on the same level [20]. They are directly associated with specific unsafe environmental surface conditions (i.e., extrinsic risk factors), such as a slippery surface (a slip), an obstacle on a walkway (a trip when striking it and a twisted ankle when stepping on it) and an uneven surface (unexpected step-down) [21]. As a result, identifying loss of balance events associated with specific unsafe environmental surface conditions are of importance to safety managers to propose appropriate interventions to prevent falls on the same level injuries.

Kaskutas et al. [22] reported that the two most effective preventive measures used to minimize the risk of falls on the same level are: (1) safety training programs [23,24], and (2) behavior-based management techniques such as goal-setting, motivational technique etc. [25,26]. However, current methods such as observations, surveys and retrospective reports that are used to assess the aforementioned preventive measures may encounter some inherent challenges on construction sites for identifying loss of balance events [16]. These challenges include but not limited to the: (1) dynamic and continuous changing of construction working environment; (2) differences in individuals' intuition, background, experiences and knowledge in reviewing these methods; (3) increase in resources and supply components at various stages of construction; and (4) inability of safety managers to assess the severity and frequency of occurrences of multiple risk factors in real time [27,28]. Taken together, there is a crucial need to introduce an efficient approach and a novel method for automated detection and classification of loss of balance events associated with specific unsafe environmental conditions that could help address such limitations and enhance the implementation of effective fall preventive measures.

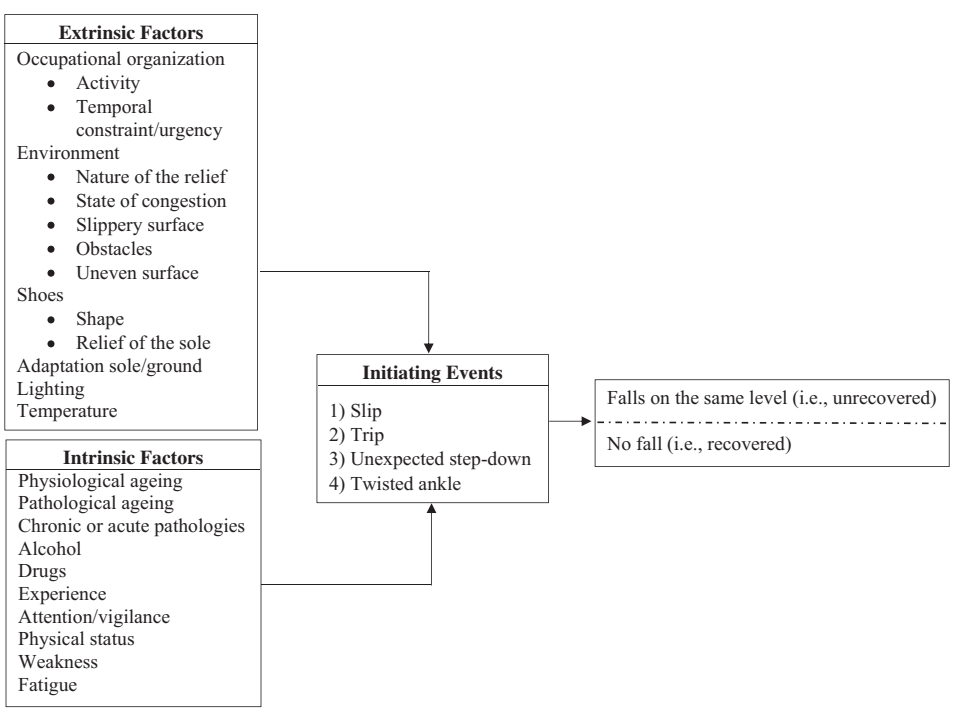


Fig. 1. Mechanisms of falls on the same level.
(Adopted from Gauchard et al. [12])

2.2. Wearable sensor-based approaches for fall risk detection and classification

Identifying potential fall risk factors at sites is challenging, especially in construction where work environments and workforce are continuously changing. Generally, fall risk detection relies on subjective and qualitative measures such as questionnaires or surveys on injured people [29]. For a more detailed investigation, quantitative measures such as motion sensors, force plates or electromyography sensors are required [30–32]. However, even though these measures provide useful information on fall risks, they are reactive and time-consuming, such that they may not be suitable for construction where working environments are continuously changing.

For a continuous and objective fall risk monitoring, body-worn accelerometers have gained attention in rehabilitation and clinical research areas [29,33–36]. Accelerometers attached to the body continuously measure body movements that can be used to detect any disturbance of body balance [29]. In construction, the use of accelerometers for detecting near-miss falls has been successfully validated through laboratory tests [37–39]. These studies developed fall risk assessment models to classify fallers and non-fallers, or assessment scores to predict the likelihood of future falls based on variables (e.g., position, angle, angular velocity, linear acceleration, gait speed etc.) from acceleration signals. However, despite the advantages of being lightweight, low-cost and easy to collect real-time data, acceleration-based approaches are limited to binary classification of fall risks (e.g., no-risk or fall-risk).

Even though foot plantar pressure measurement devices such as wearable insole pressure sensors have not been applied in construction, they have been widely used in diverse areas such as rehabilitation, sport science, daily activity monitoring and gait analysis [40–44]. Wearable insole pressure sensors measure the force acting on each sensor during foot contact [45]. Generally, multiple sensors are located at different areas of shoe insoles, providing pressure distribution data. As the pressure distribution pattern is an indicator of gait instability or body balance, these sensors can be used for detecting gait abnormality associated with falls [46]. Spatial and temporal pressure distributions could vary depending on types of loss of balance events, and thus these data have great potential for classifying different types of fall-initiating events (e.g., slips, trips, unexpected step-downs, and twisted ankles) that cannot be distinguishable by using accelerometers.

3. Methods

3.1. Participants

A convenience sample ($n = 10$) of healthy male volunteers ranging in age between 20 and 35 years (mean 26 ± 3.2 years), weight between 60 and 80 kg (mean 70 ± 10.5 kg), and height between 1.4 and 1.8 m (mean 1.6 ± 0.1 m) were recruited from the student population of the Hong Kong Polytechnic University. Exclusion criteria were: 1) a history of injuries on upper extremities, a low back, and lower extremities; and 2) a history of neurological disabilities or other conditions that could affect body balance functionality. All participants provided their informed consent forms in accordance with the procedure approved by the Human Subject Ethics Subcommittee of the Hong Kong Polytechnic University (reference number: HSEARS20170605001).

3.2. Experimental apparatus

Foot plantar pressure distribution data for each loss of balance event was collected at laboratory settings by using Moticon SCIENCE (Moticon GmbH, Munich, Germany, http://www.moticon.de), a wearable insole pressure sensor system. Fig. 2 shows an overview of Moticon SCIENCE. It provides a novelty in conducting research based on foot plantar pressure distributions in both laboratory and field conditions. It consists of two sensor insoles (containing 13 capacitive sensors each) that measure the foot plantar pressure distribution (Fig. 2a). Fig. 2b depicts an example of foot plantar pressure distribution patterns. Each insole sensor incorporates a wireless module for data transmission and sensor configuration control.

3.3. Experimental design and procedure

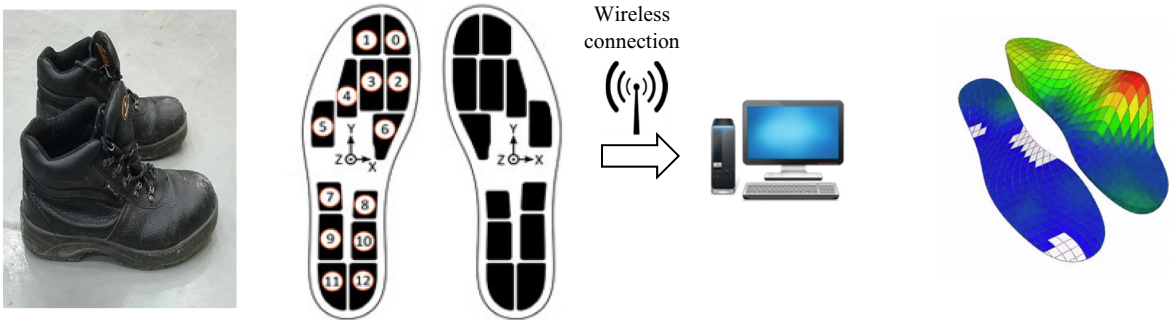
The current study adopted a randomized crossover study design in a single testing session. In particular, four different types of loss of balance events (i.e., slip, trip, unexpected step-down, and twisted ankle) were conducted in a laboratory setting to collect foot plantar pressure distribution data (Fig. 3). Before data collection, the experimental procedure was explained to the participants. Afterward, they provided their demographic data and informed consent. To simulate loss of balance events similar to real conditions, all participants were asked to wear safety boots and a hard hat during the testing sessions. Also, a safety harness and a 30-cm thick layer of high-density gymnasium mattress were provided to prevent any possible injuries (Fig. 3b). Before the testing sessions, they observed representative videos of real-life loss of balance events and were instructed to perform in a similar fashion. For more realistic simulations, specific unsafe environmental surface conditions such as a low-density polyethylene (#1. slips), concrete bricks on the path (#2. trips and #4. twisted ankles) and a platform with 20 cm height (#3. unexpected step-downs) were used in the present study (Fig. 3a).

During the testing session, the participant was instructed to walk at a comfortable pace and along a particular path even though there might be an unsafe environmental surface condition. In the slip event (Fig. 3a), the participant walked over a low-density polyethylene which caused a rapidly translating between the foot and the floor surface. In the trip event (Fig. 3b), the participant's foot naturally hit a concrete brick. In the unexpected step-down event (Fig. 3c), the participant suddenly lost their balance upon landing on a surface lower than expected. In the twisted ankle event (Fig. 3d), the participant naturally stepped on an unstable concrete brick. In all events, the participant did not have a prior knowledge of the unsafe environmental surface conditions and was instructed to look straight ahead during data collection. The sequence of the experimental trials was randomized. To measure the replicability of foot plantar pressure distribution data, each participant conducted ten repeated trials of each loss of balance event. Each trial was estimated for a duration of 6 s (4 s for normal gait plus 2 s for each loss of balance event). To reduce fatigue, the participants were allowed for 3 min rest between two successive trials.

3.4. Data processing and analysis

During data collection, each event was filmed using a video camera, and foot plantar pressure distribution data was synchronized. Based on the recorded video data and the walking steps (i.e., normal gait) of each event, time-series pressure data were labeled by types of events as the ground truth. The insole sensors collected foot plantar pressure distribution data at a rate of 50 Hz by a 16-bit analog to digital (A/D) converter and transferred the data via a wireless connection or a universal serial bus (USB) stick to the base computer. The sampling frequency was shown to be sufficient in previous experiments to measure foot plantar pressure distribution data [47].

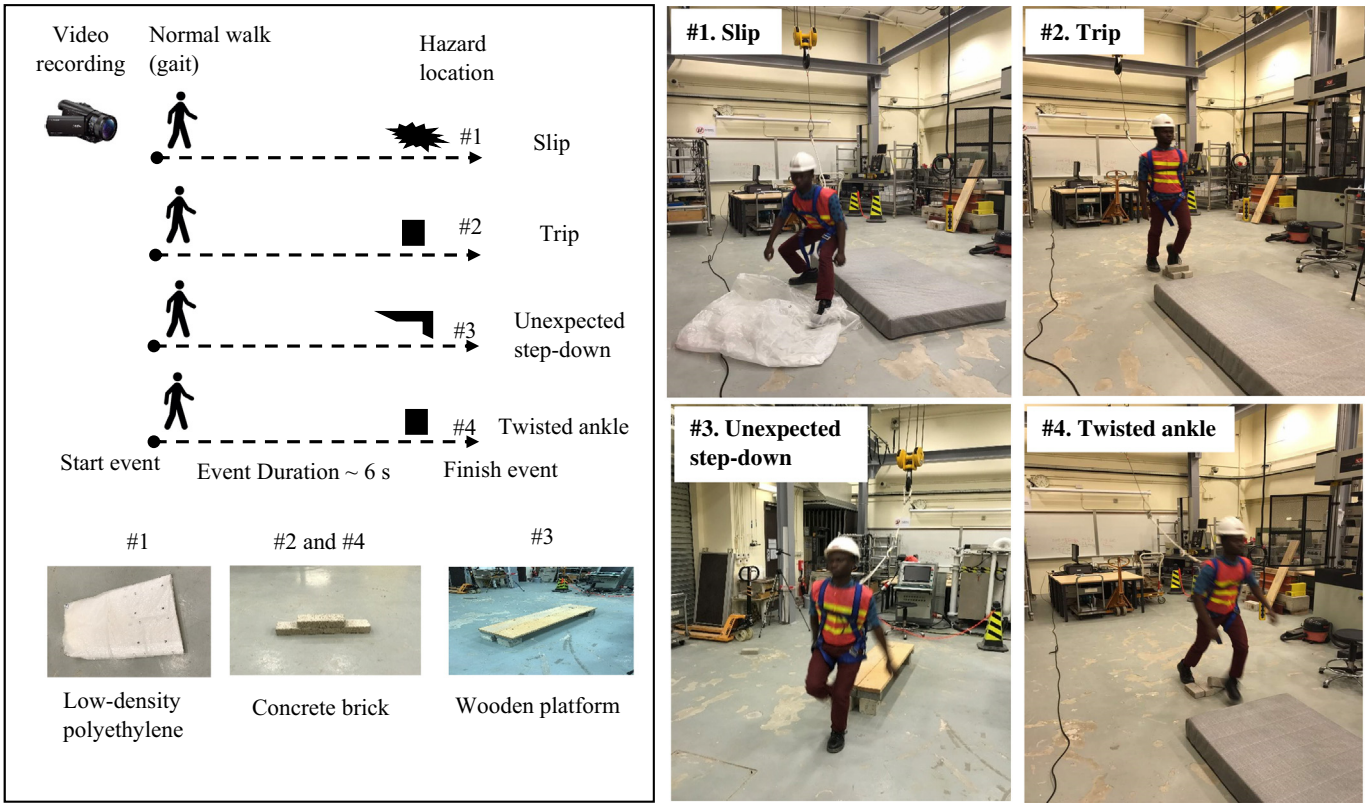
Fig. 4 shows examples of labeled pressure data from the sensors (i.e., pressure-time curves). The numbers of sensors indicate the positions on insoles as shown in Fig. 2a. For example, Sensor 1, 7, 8 and 12 represent different regions of interest such as toes, a mid-left foot, a mid-right foot and a heel foot, respectively. These data qualitatively support the hypothesis that each loss of balance event creates unique pressure patterns from insole sensors, and thus by analyzing the patterns, each event can be classified. Depending on types of loss of



(a) Sensor configuration

(b) Example of pressure data

Fig. 2. An overview of Moticon SCIENCE.



(a) Experimental setups

(b) Types of loss of balance events

Fig. 3. Experimental overview and data collection.

balance events, unique patterns on pressure-time curves are observed at each region, allowing us to understand mechanisms of these events. For example, during walking (graphs denoted as 'A'), cyclic alternating patterns on pressure-time curves are observed (Fig. 4). However, when loss of balance events (denoted as 'B', 'C', 'D' and 'E') occur, unique abnormal curve patterns are shown according to types of events. Generally, during a typical slip event, the foot slides forward against the floor, and thus a relatively long pattern of pressure data is found at the middle of the foot (e.g., Sensor 7 and 8). During a trip, the left foot hits an object (i.e., concrete brick), creating a very short peak pressure on Sensor 1, and shortly after this, higher peak pressure values on the right foot are observed as the subject tries to be recovered from a trip by supporting the body on the other foot. Unexpected step-down creates sudden body mass transfer, resulting in higher peak pressures on the foot contacting the ground. Twisted ankles could occur when a worker steps on a small or an unstable object. After landing, the pressure moves to the left to right as an ankle is rotated. As shown in Fig. 4, foot plantar pressure data implicitly reflect one's representative bodily reactions during the contact of the lower extremities with the ground. As a result, wearable insole pressure sensors can provide richer information than accelerometers to classify each loss of balance event.

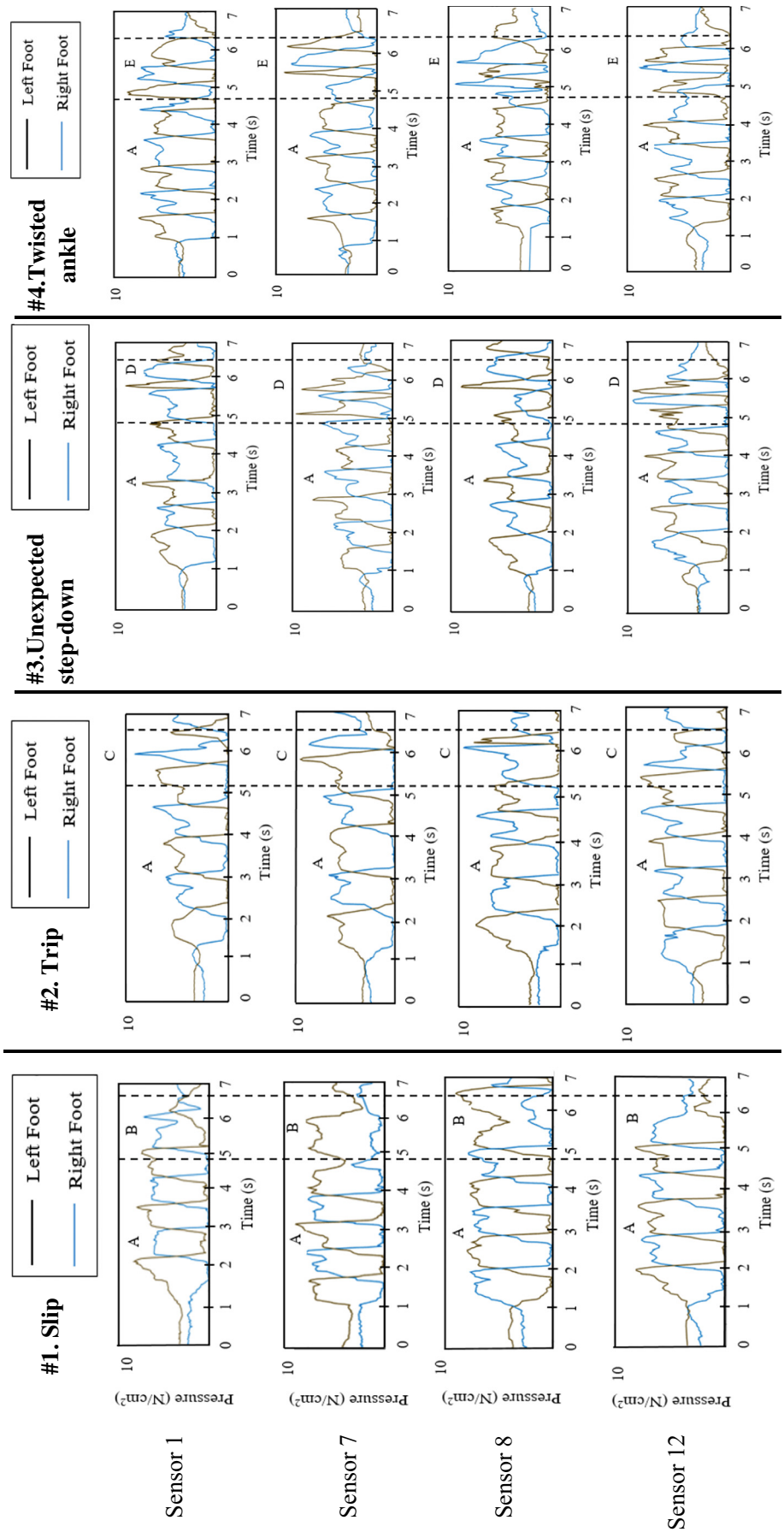


Fig. 4. Examples of labeled foot plantar pressure distribution data
Note: Dotted lines indicate regions of detecting loss of balance events in each pressure sensor. A = Normal walk; B = Slip; C = Trip; D = Unexpected step-down; E = Twisted ankle.

3.5. Developing supervised machine learning algorithms

Given unique foot plantar pressure patterns based on features that reflect both spatial (according to locations of pressure sensors in the wearable insoles) and temporal (dynamic loading patterns over time) changes of pressure data, classifying different types of loss of balance events from time-series foot plantar pressure data are sequential supervised machine learning problems. Even though sequential supervised machine learning algorithms have been widely applied in many fields, achieving adequate performance (i.e., accuracy) with computational efficiency is still an important research issue [48]. Generally, procedures for developing sequential supervised machine learning consist of 1) data segmentation, 2) feature extraction, 3) classifier learning, and 4) classifier model assessment and performance evaluation [49]. The goal of these steps is to determine an optimal combination of methods for data segmentation, feature extraction, and classifier learning.

3.5.1. Data segmentation

Data segmentation is a data preprocessing strategy to convert sequential supervised learning problems into traditional supervised learning problems [49]. A sliding window technique is one of the widely used methods for time-series data segmentation [48]. Specifically, for an observed time-series data $\mathbf{x_i} = (x_{i,1}, x_{i,2}, \ldots, x_{i,l})$, this method divides x_i into smaller time segments $< x_{i,t-d}, x_{i,t-d+1}, \ldots, x_{i,t}, \ldots, x_{i,t+d-1}, x_{i,t+d} >$ in a window of a fixed size w as the window slides through x (let $d = (w-1)/2$) [49]. Then, the classification can be performed for segmented data from each window independently through traditional supervise learning. Selecting an appropriate window size has a great impact on classification performance, especially in activity recognition problems [50]. As shown in Fig. 4, foot plantar pressure distribution data have unique patterns according to types of loss of balance events. Therefore, the window size should be large enough to include these patterns, and at the same time, should be smaller not to include noisy signals.

Previous research efforts on activity recognition have tested different window sizes, ranging from 0.1 s to over 10 s in steps of 0.25 s, 0.5 s or 1 s, and it has been concluded that short window sizes (e.g., less than 3 s) lead to better classification performance [50]. Also, the window sizes can be affected by types of features used in the algorithms. For example, one of the features widely used for sequential supervised learning is frequency-domain features using the fast Fourier transform (FFT) function, which will be described below. One of the limitations of using the FFT function is that the number of sample data points in the segment must be a power of two [51]. Considering the finding by Banos et al. [50] and the use of the frequency-domain features, we selected four different window sizes of 0.32 s, 0.64 s, 1.28 s and 2.56 s that corresponds to 16 (2^4), 32 (2^5), 64 (2^6) and 128 (2^7) data samples, respectively. In this study, a 50% overlap of the adjacent windows was used [52]. Su et al. [53] reported that data segmentation by overlapping adjacent windows reduces the error caused by transition state noise.

3.5.2. Feature extraction

Because of the high dimensionality of foot plantar pressure distribution data (26 data points from both feet per instance), it is important to extract relevant information subsets (i.e., features) from raw signals for better performance. As shown in Fig. 4, the pattern of foot plantar pressure data from each sensor differently changes over time depending on types of loss of balance events. The temporal changes and fluctuations can be reflected by time- and frequency-domain features. For time-domain features, we used seven time domain features (i.e., mean pressure, variance, maximum pressure, minimum pressure, range, standard deviation, and kurtosis) that have been commonly used for activity recognition and classification [51,54–56]. Also, to extract frequency-domain features, the raw data in time domain will be converted into frequency domain by using the FFT function, and then spectral energy and entropy were computed to be used as two frequency domain features [57].

In addition to time and frequency domain features, we applied a new feature extraction method based on pressure time integral (PTI). PTI is a variable that describes the cumulative foot loading over time, providing useful information on chronic foot problems [58]. In Fig. 4, each stride during the normal walks shows similar areas under the lines. However, during each loss of balance event, the cumulative foot loading that can be characterized by the area under the lines looks different because of the combined effect of body weight, movement of body mass and external forces acting of feet (e.g., hit by objects). As a result, the PTI can serve as a feature that reflects temporal changes of patterns over time, giving a distinguishable power for classifying different loss of balance events. The PTI was calculated by using the following equation:

$$PTI_{(i)} = \sum_{t=1}^{N} P_i(t) \times \Delta t \tag{1}$$

where N is the total number of data samples in a window, i is an index of sensors (i.e., 1 to 26 sensor streams), P_i is a pressure value at time t, and Δt is the duration of that data sample.

3.5.3. Classifier learning

To classify different types of loss of balance events, supervised machine learning classifiers were used to learn unique signal patterns from foot plantar pressure data based on extracted features. Howcroft et al. [29] investigated the best classification methods used in the studies for acceleration-based fall risk detection and found that neural networks, naïve Bayesian classifier, Mahalanobis cluster analysis and a decision tree have performed better than other classifiers. However, as the classifier performance could vary depending on types of data, window sizes and types of features, it is necessary to test diverse classifiers that fit best for detecting loss of balance events from foot plantar pressure data. In this research, classifiers to be tested include but not limited to 1) Artificial Neural Network (ANN), 2) Decision Tree (DT), 3) Random Forest (RF), 4) *K*-Nearest Neighbor (KNN), and 5) Support Vector Machine (SVM). Notably, a majority of studies have demonstrated that there is no single best classifier [59,60]. As such, a comparison of the different types of individual supervised machine learning classifiers may still be necessary to select the best model parameters that should be used in training a particular dataset. In this research, we selected the best model parameter from each type of individualized supervised machine learning classifier by training our experimental foot plantar pressure distribution data using Toolbox in MATLAB 9.2 software (Matlab, The MathWorks Inc., MA, USA). The following section describes the best-selected model parameters used in each supervised machine learning classifier.

3.5.3.1. Artificial neural network (ANN). An ANN is a robust method that can use training samples to learn dependencies in a dataset and then apply the trained model to recognize previously unseen dataset [61]. In this research, a multilayer feed-forward neural network or multilayer perceptron (MLP) was used [61]. The input layer consists of the different combinations of extracted features at a particular window size. By default, the number of hidden layers was set at 10. The number of output layer was equal to the five simulated events (i.e., four loss of balance events plus normal gait). In order to prevent over-fitting of dataset, a regularization parameter was used to decrease the magnitude of the trained model to recognize unseen dataset [61]. In this research, a scaled conjugate gradient backpropagation neural network was used for training the dataset. Also, a mean squared error was used for error evaluation during training [62]. In order to minimize the cost function during the training process, the Levenberg-Marquardt algorithm with a sigmoid transfer function was used in this study [63].

3.5.3.2. Decision tree (DT). DT is one of the most powerful classifiers for human activity classification and recognition [64]. This classifier works by examining the discriminatory ability of the extracted features one at a time to create a set of rules that ultimately leads to a complete classification system [36]. This research used the decision tree method of the classification and regression tree (CART) [51]. CART tree classifies patterns based upon sequence of questions in which the next question asked depends on the answer to the current question. Notably, CART was the best-selected model parameter because it is useful for analyzing nonparametric data that does not require any notion of metric [65]. In this research, the best optimization criterion (i.e., Gini diversity index) was used [51]. A node is considered as pure if it has a Gini index of zero. To prevent over-fitting of training dataset, the process of splitting leaf nodes is repeated continuously until a minimum number of observation of a class was reached.

3.5.3.3. Random forest (RF). The RF classifier is an ensemble learning technique for classification that consists of a combination of decision-trees [66]. The classification performance of each decision tree in a RF classifier is built by using a bootstrap aggregating (i.e., bagging) method and a random feature selection [67]. This approach helps in reducing the model variance and minimizing over-fitting of training dataset [66]. Since each node in a RF classifier is split into a limited number of randomly predicted variable, it is considered to be more powerful classifier when compared to other classifiers such as SVM and ANN [68]. There are only two model parameters that need to set when training a dataset with a RF classifier [69]. These are (1) mTry, which represents the number of input variables in the random subset at each node; and (2) nTree, which represents the number of trees to grow for each forest. By default values, mTry and nTree were set at 6 and 500 respectively. However, it is well-established that the classification outcome is not highly sensitive to the choice of these parameters [70].

3.5.3.4. K-Nearest Neighbor (KNN). The KNN classifier is a simple and straightforward classifier but requires no training time [68]. Training dataset is identified by an unknown window of class labels which are spread over the feature space [51]. A new dataset is assigned to a class label based on the single closest neighbor or *K*-nearest examples (i.e., *K*-neighbor of 1) considering the Euclidean distance [51]. Based on a heuristic method to achieve the best classification, this metric was selected in this research [63].

3.5.3.5. Support Vector Machine (SVM). The SVM constitutes a popular classifier which is based on finding optimal separating decision hyperplanes between classes with the maximum margin between patterns of each class [36]. It can benefit from a maximum margin hyperplane in a transformed feature space using a kernel function to map the dataset into an inner product space in order to create a non-linear structure [63]. For non-linear classification in this research, the Gaussian radial basis function (RBF) was used as the kernel function [51]. In order to enable a multi-class pattern recognition problem (i.e., identifying and detecting different types of loss of balance events) to be solved in a single optimization, this research used a multi-class one-against-one approach to train the SVM [71].

3.5.4. Classifier model assessment and performance evaluation

The final step is to determine the model parameters (e.g., window sizes, types of features and classifiers) to achieve the best performance for classifying the different types of loss of balance events. The performance of the classifiers was evaluated by a 10-fold cross-validation, which is a model validation technique to assess the accuracy and validity of statistical models. In the 10-folds cross-validation, the dataset is randomly split into 10 approximately equal size exclusive subsets. Then, each part is reserved as test datasets, and the remaining parts are performed as training datasets with a particular classifier [72]. According to Refaeilzadeh et al. [73], 10-fold cross validation is reliable to estimate the performance of classifiers because it makes predictions with 90% of dataset, which can be generalizable to the full dataset.

4. Results

We tested the proposed algorithms by using the data collected through laboratory experiments described above. The primary purpose of the test was to determine the best combination of window sizes, types of features and classifiers through cross-validation. Additionally, we also tested classification accuracy by varying the window positions to explore where the most distinguishing plantar pressure patterns exist during conducting each loss-of-balance event.

4.1. Best combination of window sizes, groups of features and classifiers

The proposed algorithms have three key parameters that would determine the classification performance: 1) window sizes; 2) types of features; and 3) types of classifiers. For window sizes, we selected four different window sizes of 0.32 s, 0.64 s, 1.28 s, and 2.56 s, considering both the optimal range of window sizes and the number of data samples required for extracting frequency-domain features. The proposed algorithms use three groups of features: 1) seven time-domain features; 2) two frequency-domain features; and 3) PTIs. Generally, supervised machine learning-based classification algorithms include feature selection that aims to identify optimal subsets of features not only for better classification accuracy but also for data understanding [74]. This paper applied the wrapper approach suggested by Kohavi and John [75] that assesses the subsets of features in terms of the prediction performance. Instead of an exhaustive search for all possible subsets, we tested subsets of combinations of three feature groups (e.g., time-domain, frequency-domain and PTI features) to understand the role of each feature group. As a result, seven subsets of three feature groups such as 1) time-domain features only (TF), 2) frequency-domain features only (FF), 3) PTI only (PTI), 4) time- and frequency-domain features (TF + FF), 5) time-domain and PTI features (TF + PTI), 6) frequency-domain and PTI features (FF + PTI), and 7) all three feature groups (TF + FF + PTI) were tested. For classifiers, we chose 1) ANN, 2) DT, 3) RF, 4) KNN, and 5) SVM.

Table 1 shows overall classification accuracies (i.e., the proportion of correct classifications in percentage) by cross-validation for five events (i.e., normal walking and four loss of balance events) based on combinations of different window sizes, feature group subsets, and classifiers. The testing results indicate that the classification performance could vary depending on the combination of algorithm parameters, emphasizing the need for finding the optimal parameters. The overall classification accuracies ranged from 20.3% to 97.1%, and each classifier shows the best performance on different combinations of feature groups and window sizes. For example, the best classification accuracy of each classifier was 74.7% (TF + FF and 0.32 s) in ANN, 82.7% (TF + PTI, 2.56 s) in DT, 97.1% (TF + FF + PTI, 0.32 s) in RF, 95.2% (PTI only, 0.32 s) in KNN, and 95.0% (FF + PTI, 2.56 s) in SVM, respectively (Table 1). Among five classifiers, the best performance was achieved by the RF classifier when using all feature groups with the smallest window size (0.32 s) (Table 1). One of the interesting results was that the RF classifier is less sensitive to selection of features and window sizes, showing over 90% overall accuracies regardless of types of features and window sizes. Regarding the effect of window sizes, contrasting results were observed according to types of classifiers. Specifically, the longer window sizes led to better performance in ANN, DT, and SVM while RF and KNN showed the best performance when using the smallest window size. In addition, using all feature groups would not always result in better performance. Except the RF classifier, the best performance was observed when using only subsets of feature groups in other four classifiers.

Fig. 5 shows how each loss of balance event was detected using RF classifier (best classifier) with all feature groups at 0.32 s window size

Table 1
Overall classification accuracies (%).

	ANN[a]				DT[a]				RF[a]				KNN[a]				SVM[a]			
	0.32 s	0.64 s	1.28 s	2.56 s	0.32 s	0.64 s	1.28 s	2.56 s	0.32 s	0.64 s	1.28 s	2.56 s	0.32 s	0.64 s	1.28 s	2.56 s	0.32 s	0.64 s	1.28 s	2.56 s
TF[b] only	30.6	25.4	20.4	56.5	67.4	61.7	58.7	82.2	96.0	95.1	94.9	94.9	87.8	86.8	85.9	92.1	56.8	85.6	84.1	93.3
FF[b] only	53.2	47.9	47.0	66.5	67.9	59.3	56.5	79.9	94.6	93.8	93.4	93.0	92.0	91.6	90.8	92.4	89.1	87.2	83.9	91.9
PTI[b] only	48.2	43.7	27.4	24.3	66.8	63.8	58.0	74.1	96.3	94.5	93.3	93.5	95.2	92.9	92.8	94.0	87.9	85.3	85.0	89.0
TF + FF	74.7	25.6	20.3	49.6	78.1	68.0	67.8	81.7	95.6	95.0	94.3	95.2	93.7	93.4	93.0	93.5	92.1	91.1	90.6	94.0
FF + PTI	58.4	30.7	28.2	53.9	69.5	62.3	85.3	80.5	96.8	95.4	95.0	94.4	93.9	93.2	92.2	94.3	90.9	89.8	87.7	95.0
TF + PTI	50.7	46.6	41.0	61.4	69.0	65.4	61.4	82.7	96.3	96.2	95.4	95.0	90.4	89.8	88.6	93.8	89.6	88.6	87.1	92.8
TF + FF + PTI	51.5	41.5	61.4	72.0	70.5	64.8	59.9	81.8	97.1	96.2	95.5	95.5	94.8	94.4	94.3	94.5	93.9	93.6	93.3	94.7

[a] ANN: Artificial Neural Network, DT: Decision Tree, RF: Random Forest, KNN: k-Nearest Neighbor, SVM: Support Vector Machine.
[b] TF: Time-domain features, FF: Frequency-domain features, PTI: Pressure Time Integral features.

data segment. As presented in Fig. 5, the rows show the percentage of true (i.e., actual) instances, and the columns reveal the percentage of predicted instances of loss of balance events. For example, while 97.7% of the actual instances was positively detected and classified as slip event, 0.1%, 0.2%, 1.4%, and 0.6% were predicted as normal walk, trip, unexpected step-down, and twisted ankle events, respectively (Fig. 5). Based on the confusion matrix, each event had more than 94.0% in correct detection of the instances (i.e., sensitivity) using all feature groups (Fig. 5). Fig. 5 also reveals that while normal walk was the most accurately classified and detected event (99.2%), the most confused events were the unexpected step-down and normal walk events (i.e., 2.40%). This might be attributed that unexpected step-down and normal walk events had similar foot plantar pressure patterns and magnitudes during the initial stride, which might have led to more misclassified and undetected instances.

4.2. Classification accuracy according to window position

Unlike walking that involves cyclic or repeated movements, loss of balance events such as slips, trips, unexpected step-downs and twisted ankles are one-off events, showing non-cyclic patterns of foot plantar pressure data (Fig. 4). Also, initial foot plantar pressure patterns could be similar for each loss of balance events, but corresponding foot plantar pressure patterns could vary depending on one's strategies to recover body balance. To understand where distinguishing foot plantar pressure patterns exist during loss of balance events, plantar pressure data during each event was divided into the first, second and third window from the start of the event without overlap, and the overall accuracy was tested by learning a classifier using data from each window, respectively. For this test, the algorithm parameters (RF, all feature groups, and 0.32 s window) that resulted in the best performance were used in this study.

Fig. 6 shows the overall accuracies according to the position of the windows. The first, second and third windows contain foot plantar pressure data from the start of each event to 0.32 s, from 0.32 s to 0.64 s, and from 0.64 s to 0.96 s, respectively. The RF classifier learned the data from each window only. The result showed that foot plantar pressure data from the first window has better distinguishing power, indicating foot plantar pressure data at the beginning of each event contain more unique and consistent plantar patterns to classifier loss of balance events.

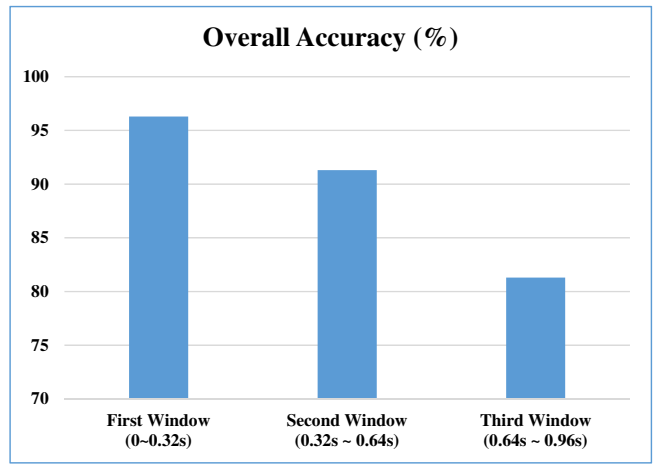


Fig. 6. Classification accuracies depending on window positions.

5. Discussion

This study examines foot plantar pressure distribution data for automated detection and classification of loss of balance events which are preceded by falls on the same level using wearable insole pressure sensors. An experimental study was conducted to design supervised machine learning algorithms to classify loss of balance events by analyzing foot plantar pressure data. From the comparative evaluation based on cross-validation, it was found that the RF classifier achieved

True class \ Predicted class	Normal walk	Slip	Trip	Unexpected step-down	Twisted ankle
Normal walk	99.2%	0.1%	0.2%	0.1%	0.4%
Slip	0.1%	97.7%	0.2%	1.4%	0.6%
Trip	0.5%	0.2%	96.9%	1.5%	0.9%
Unexpected step-down	2.4%	0.3%	0.5%	95.6%	1.2%
Twisted ankle	1.1%	0.8%	2.3%	0.9%	94.9%

Fig. 5. Confusion matrix when using RF with all feature groups at a window size of 0.32 s.

the best performance for detecting and classifying loss of balance events with an accuracy of 97.1%, and the sensitivity of more than 94% for each event using all feature groups and a window size of 0.32 s. Additionally, we performed hold-out validation by randomly splitting the data into two parts (70% for training, 30% for testing). The result also showed 95.9% overall accuracy when using same algorithm parameters, supporting the robustness of the proposed approach for independent test datasets. This result implies that foot plantar pressure distribution data obtained from wearable insole pressure sensors can effectively detect and classify loss of balance events, which may help to understand the causes of falls on the same level.

Despite the promising performance, the effects of different algorithm parameters such as types of classifiers, features, and window sizes are still not clear due to contrasting results according to different combinations of algorithm parameters. Determining best combination of classifiers, window sizes and features is a difficult task for many reasons such as the differences in experimental protocol, the objectives behind real-time falls on the same level applications, the types of wearable sensors used and their attachment to the human body, the performance evaluation and validation, and the nature of the fall activities conducted. Generally, the decision would be made based on classification performances [76–78]. For the problem that needs real-time analysis, the need for data pre-processing and computational time are also important factors to be considered.

The best accuracy achieved from the RF classifier confirmed the hypothesis that each loss of balance event creates unique patterns of foot plantar pressure distributions, even though other classifiers such as KNN and SVM showed comparable performance with slightly less accuracies. Recently, the RF classifier has been widely used in acceleration-based action recognition problems, showing better performance than other classifiers. Compared with other classifiers, several advantages of the RF classifiers have been revealed: 1) the RF can reduce computational time because it needs very little pre-processing of the data; 2) feature selection procedures are not necessary as the algorithm itself evaluates features on its own; and 3) it can minimize over-fitting issues [79]. In our results, the RF achieves the best performance when using all feature groups as it internally optimizes features used for training. Generally, the best classifier could vary depending on the selection of features. However, using the RF classifier can eliminate complicating feature selection problems, providing a comparative advantage over other classifiers.

The current study has established that the length of window size data segment and the type of features extracted from foot plantar pressure distribution while performing loss of balance events can influence the classifier performance. As a result, the window size is an important parameter to be considered in fall risk detection and classification studies. The window size of 0.32 s can be generally considered as optimum data segment for signals produced by wearable insole pressure sensor while loss of balance events are performed. In particular, the first window from the start of each event tends to contain distinguishable plantar pressure patterns for loss of balance event classification. With regards to extracted features, it was concluded that using all feature groups do not necessarily lead to better performance for all classifiers except the RF classifier. For instance, higher accuracies were achieved by the ANN, DT, and SVM classifiers during combining TF + FF, TF + PTI, and FF + PTI, respectively. For classifiers (e.g., RF, KNN, SVM) of which best performance is higher than 90%, PTI features have an important role as adding PTI as features increased the classification accuracy. It should be emphasized that PTI describes the cumulative effect of pressure over time in the certain area of the foot, and thus provides a value for the total load exposure of a foot sole area during one step [80]. This indicates that PTI is of added value to understanding temporal changes of foot plantar pressure distributions while performing loss of balance events.

Despite the promising result of the proposed approach, there are several potential issues when applying it in practice, which includes 1) data collection issues and 2) need for location data. First, identifying and removing unsafe environmental surface conditions (e.g., slippery floors) in a timely manner is essential to minimize the risk of falls on the same level. Toward this goal, continuous data transfer and real-time analysis are required. Most wearable sensors including pressure insole sensors use direct wireless network or a smartphone for data transfer. However, internet disconnection may occur in using wearable sensors and leads to failed data transfer in real time [81]. To minimize such risk, the reliability of wearable sensors data transfer should be tested, especially at construction sites where a signal blockage may commonly exist. Besides, the process of collecting foot plantar pressure distribution data measured by wearable insole pressure sensors during normal gait may be affected by the differences in individual risk factors (e.g., age, work experience, gender). To minimize such issues, repetitions of specific risk factor should be conducted to test data variability. Second, even though the proposed system can detect instances of loss of balance events, the location information where the event occurs is also required to be reported so that necessary interventions can be implemented. As such, additional location tracking systems should be used to proactively minimize the fall risks at construction sites.

6. Conclusions

This paper proposed a novel methodology for automated detection and classification of different types of loss of balance events that may lead to falls on the same level. Toward this goal, wearable insole pressure sensors were employed to collect participant's foot plantar pressure distribution data. Based on our experimental trials, the RF classifier obtained the best results with the accuracy of 97.1% and sensitivity of each loss of balance event above 94.0% using the window size of 0.32 s. The findings of this study suggest that foot plantar pressure distribution data measured by using wearable insole pressure sensors contain valuable information for identifying loss of balance events associated with specific unsafe environmental surface conditions. Overall, the proposed approach and novel method may help safety officers and construction managers to proactively conduct automated fall risk monitoring so as to implement effective fall preventive measures to minimize the risk of falls on the same level on construction sites.

Although the findings of this study showed potentials for detection and classification of loss of balance events in construction workers, there are some limitations that should be addressed in future studies. First, data collection of loss of balance events was conducted in a laboratory setting by a small sample of novice participants. Future research should compare our results to similar studies by conducting loss of balance events using a large sample of experienced construction workers. Second, despite its great potential as a tool for automated fall risk monitoring, this experimental study was conducted to involve workers' exposure to unsafe environmental surface conditions (i.e., extrinsic risk factors) that could exist on construction sites. Future research needs to detect and classify diverse intrinsic risk factors in construction workers (e.g., work experience, age, and fatigue). Also, it would be beneficial to integrate other sensing and localization technologies such as beacons, light sensors, and cameras into the proposed system in order to (1) provide more robust application solutions for construction workers' safety, and (2) analyze the type of activity being conducted by a worker, which may help in a worker's activity recognition and classification. Third, foot plantar pressure distribution data measured by using wearable insole pressure sensors were wirelessly transferred onto a desktop computer during data collection. Future research should conduct similar experiments using the proposed approach with an application running on a smartphone. This could better aid in both indoor and outdoor environmental settings during data collection.

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