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Semi-supervised near-miss fall detection for ironworkers with a wearable inertial measurement unit

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ABSTRACT

Accidental falls (slips, trips, and falls from height) are the leading cause of occupational death and injury in construction. As a proactive accident prevention measure, near miss can provide valuable data about the causes of accidents, but collecting near-miss information is challenging because current data collection systems can largely be affected by retrospective and qualitative decisions of individual workers. In this context, this study aims to develop a method that can automatically detect and document near-miss falls based upon a worker's kinematic data captured from wearable inertial measurement units (WIMUs). A semi-supervised learning algorithm (i.e., one-class support vector machine) was implemented for detecting the near-miss falls in this study. Two experiments were conducted for collecting the near-miss falls of ironworkers, and these data were used to test developed near-miss fall detection approach. This WIMU-based approach will help identify ironworker near-miss falls without disrupting jobsite work and can help prevent fall accidents.

1. Introduction

The construction industry is considered one of the most dangerous industries in the United States. Among construction-related accidents, fall accidents are one of the leading causes of fatalities and account for more than 30% of fatal accidents during recent decades [1]. Ironworkers are exceptionally susceptible to fall accidents and face the highest lifetime risk of fatal injuries among construction trades [2]. According to Beavers [3], between 2000 and 2005, more than 75% of fatal ironwork accidents were caused by fall accidents. Such high fatality rates among ironworkers are rooted in various factors: (1) most of the time, ironworkers are working on narrow surfaces of structural steel beams installed at high elevations and are thereby exposed to numerous open edges, and (2) ironwork construction consists of physically demanding tasks such as handling heavy steel materials (e.g., beams, columns, and steel plate) and equipment for steel erection. These work characteristics contribute to the risks that ironworkers face in their daily tasks.

Due to the high risk of fall accidents among ironwork erection projects in general construction, the Occupational Safety and Health Organization (OSHA) requires the use of fall protection measures such as guardrails, safety nets, and personal protective equipment to protect workers when working at elevation. The current safety measures for fall accidents are classified as active/primary protection measures (e.g., guardrails and covers), which physically prevent the occurrence of falls, and passive/secondary protection measures (e.g., personal fall arrest systems, safety nets), which help to prevent or minimize injury from falls [4,5]. While passive/secondary protection measures are generally employed for ironworkers, the use of active/primary fall protection measures is limited due to the constraints of ironworkers' working environments. This shortcoming faces particular criticism since current fall protection measures emphasize reducing the severity of an injury rather than proactively preventing a fall accident [6]. As an example, the use of a personal fall arrest system (PFAS) does not prevent the occurrence of fall itself during ironwork. Although the proper use of PFAS can save the life of workers who fall after losing their balance, being suspended in a harness may result in a suspension trauma, orthostatic intolerance, or other, more severe injuries [7]. Moreover, many workers still get injured due to using incomplete or inadequate fall protection devices [8].

In pursuit of a proactive approach for preventing accidents (including falls), researchers have turned their attention to collecting and utilizing accident leading indicators [9,10]. Leading indicators are conditions, events, or measures that are valuable in predicting the future occurrence of undesirable events, including accidents, incidents, or near misses [9]. Leading indicators are designed to monitor the safety process by identifying gaps between the current environment and the recommended settings [9,11]. The knowledge identified through this monitoring is then used to decrease the possibility of injury occurrence [11]. Thus, such indicators are associated with proactive approaches seeking to identify, assess, and eliminate a related risk [10]. A near

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miss is one such accident leading indicator [11,12] and is defined as an event that causes no damage or loss at the time of occurrence but could have materialized into an actual accident in a slightly different environment [13]. Near misses have been widely used to reduce the likelihood of future accidents in diverse industries (e.g., chemical, airline, nuclear, railroad, medicine, and construction) by detecting systemic flaws and managing such flaws by removing risk factors before accidents occur [14–17]. Thus, having knowledge about near misses (e.g., cause, worker, and location) can help identify hazardous elements and vulnerable workers. This knowledge can also provide opportunities to eliminate such hazardous conditions at the job site or to alert possible victims that they need to change their behavior before an accident. For this reason, identifying and collecting near misses is an important step in implementing proactive accident prevention measures.

Previous studies of utilizing near misses for occupational safety have emphasized the importance of near misses and introduced different applications of near-miss data [12,14,18–20]. In such cases, the collection of near-miss data mainly depends on a self-reporting system of workers. However, collecting near-miss data using a reporting system is not an easy task since such an approach is easily influenced by qualitative and retrospective decisions based upon the perceived attitudes of individual workers, such as, fear of discipline, acceptance of risk, and inconsistent perception of near-miss falls [18]. One of the available methods for collecting quantitative near-miss data is using a technology solution—such as Ultrasound or RFID—to acquire real-time information about workers' exposure to known jobsite hazards [21]. However, such a proximity-based approach is not sufficient to capture near misses that are caused by unknown hazards or not triggered by physical hazards. Alternatively, one promising technology is WIMUs, which can document subtle body movements (i.e., acceleration, angular velocity) with a 3-axis accelerometer, gyroscope, and magnetometer. In previous studies, WIMUs were widely used in fall detection [22–26], activity recognition [27–33] and gait analysis [34–36]. Due to its small size, a WIMU can be easily attached to the body of a subject and can transmit kinematic data through wireless communication. Thus, WIMUs have the potential to be widely deployed as a wearable tool on construction sites. To this end, this study utilizes WIMUs to document ironworkers' near-miss falls and developed a near-miss falls detection approach.

2. Research background

Many previous studies have focused on identifying fall accident risk factors to increase worker safety in construction. Chi [4] investigated accident patterns of previous fatal fall accidents and proposed accident prevention measures for each type of accidental scenario. Huang [8] identified factors related to fall accidents (i.e., cause of accident, fall height, and accident-related elements) based on accident records from OSHA, and Cattledge [37] studied injury records of nonfatal falls and identified problems with current fall accident prevention measures. As a proactive approach to accident prevention, Wu [12] developed a systematic model for identifying near-miss information from ongoing project using knowledge from historical accident database. Wu deduced knowledge from previous accidents and applied this knowledge to an ongoing construction project with a real-time near-miss tracking and reporting system that used RFID technology. Cambraia [19] provided near-miss guidelines utilizing near-miss information for accident prevention. Cambraia collected near-miss data from construction projects, analyzed the risks of identified near misses and suggested recommendations for implementing a near-miss system. Finally, Navon [38] introduced an automated fall-hazard monitoring system for construction sites. This study identified the risks of fall accidents in activities included in project schedules and proposed a guardrail installation measures to prevent fall accidents. Also, this study monitored the status of guardrail installation (e.g., missing or incomplete) through wireless communication to enhance worksite safety.

However, previous studies have only focused on investigating previous accidents to derive general recommendations [4,8,37] or on identifying potential accidents using previously known hazards and locations [12,19,38]. Moreover, previous techniques have failed to consider individual workers, who are actually at risk of accidents while working on construction sites. In particular, proximity-based systems [12,38] require substantial resources to prevent ironworker fall accidents since this population almost always works near open edges on narrow-surface steel beams. This exposure problem is compounded by the fact that ironworkers have only a small surface space to recover from even a small degree of balance loss, and current proximity-based systems do not address this issue in real time. These shortcomings of proximity-based systems emphasize the current challenge in implementing fall-prevention for ironworkers and highlight the reasons this population is still at the high risk of fall accidents in construction.

Information technology-based construction site data (e.g., about workers, work environment) collection measures assist in increasing the ability to store, retrieve, and manipulate data during the construction process [39]. As a possible alternative to capturing near-miss data, a WIMU, which includes an accelerometer, a gyroscope, and a magnetometer, can robustly document and wirelessly communicate human movement data. This advantage has led to the use of WIMUs for fall detection to increase the safety of patients and workers [22–26]. In biomedical studies, attaching accelerometers to the body is a widely used approach for detecting fall accidents, especially for the elderly [22,24]. Automated detection of fall accidents using wearable sensors has been considered a promising method for protecting the elderly or people with a disability from an unidentified fall risk. In previous biomedical studies [22–24], the key research objective focused on detecting fall accident situations or accident-related conditions such as accident location, severity of injury, or injured body parts. These previous studies approached fall accident detection by detecting strong accelerometer signals from when a subject actually fell to the ground rather than by identifying or monitoring dangerous movements (e.g., loss of balance) that reveal informative data about future or potential fall accidents. This limited focus is problematic for translating biomedical research to ironworkers since according to Beavers [3], loss of balance (LOB) is one of the major proximal causes of fall accidents for ironworkers, and LOB is cited as contributing to most unintentional falls even in spite of the lack of a quantitative definition [40].

There are a few studies that attempt to detect near-miss falls—sometimes called “near-falls”— automatically using body-attached sensors. In one such study, Weiss et al. [41] investigated subjects walking on treadmills to detect near-falls in normal activities. To generate near-fall data, different types of obstacles were placed in the walking path at random. In his study, he defined near-falls similarly with trip accidents. Many accelerometer-related features (e.g., signal vector magnitude, normalized signal magnitude area, and other derived features) were tested in his study with an 85% sensitivity and 88% specificity with one feature (i.e., vertical maximum peak to peak acceleration amplitude derivative). The study also showed an 85% sensitivity and 90% specificity with the combination of two features (i.e., vertical maximum peak to peak acceleration amplitude derivative and vertical maximum acceleration). This study reveals the possibility of near-miss fall detection using body-attached accelerometers in a controlled laboratory environment. In the construction domain, Dzeng et al. [42] used a smartphone accelerometer and gyroscope to detect fall portents (e.g., swaying, unsteady footsteps, and loss of balance), which are referenced by self-reporting and video observation. To detect fall portents, Dzeng et al. measured the signal magnitude vector using accelerometer or gyroscope and detected the fall portents using a threshold-based detection approach. As a result of this approach, Dzeng et al. acquired 88.5% accuracy for detecting fall portents from construction tiling workers on a scaffold.

Although previous near-miss fall detection methods demonstrate their feasibility for detecting fall-related near misses, they predominantly focus on detecting trip or fall-portent from tiling work. Weiss et al. [41] did not consider the different types of possible loss of balance scenarios, such as kicking or stepping over an obstacle, and lateral body sway in near-fall detection; additionally, the experiment in this study was performed by walking on a treadmill, which sends a constant walking speed to the sensor. The fall-portent detection method from Dzeng et al. [42] tested tiling work, which deals with more stationary work movements than ironworkers, whose tasks consist of diverse postures and movements such as walking, turning, squatting, bolting, reaching, and carrying a load on the narrow surface of an I-beam. Moreover, the detection methods from both previous studies mostly examine the magnitude of sensor signals to detect near miss during controlled walking speed or stationary work conditions. Our previous study [43], which used a threshold-based approach in near-miss fall detection, also revealed the challenges of threshold-based approaches using a single or minimal set of features. Such approaches necessitate a hierarchical detection model to classify all possible variations of workers' actions. Thus, to detect near-miss falls during ironworker tasks, an approach that can consider multiple features regarding body acceleration and angle to differentiate near miss from dynamic movements would be more effective than using a single feature. This study is extended from our earlier study [44] and proposes a semi-supervised learning algorithm that enables detecting near-miss falls from dynamic movements. Upon its validation in indoor and outdoor experimental settings, this study suggests its potential application to identify fall-prone workers and locations in iron work.

3. Methodology

This paper aims to develop a method for automatically collecting near-miss falls among ironworkers using kinematic data acquired from WIMUs attached to workers. This study applied a semi-supervised pattern-recognition algorithm (one-class support vector machine [OCSVM]) for near-miss fall detection and tested its feasibility and detection performance in a similar environment to ironworks. All computation in the study is processed through MATLAB (R2014, MATHWORKS), and OCSVM was implemented through the LIBSVM library [45], which is a popular support vector machine toolbox. The OCSVM semi-supervised algorithm is a support vector machine (SVM) that is one of the most promising machine learning tools for solving classification problems. Similar to the SVM algorithm, OCSVM transforms the original data to a feature space and seeks the appropriate hyperplane that contains only one class. Then OCSVM uses the hyperplane as the decision boundary to classify the binary data. Two different experiments were conducted to test the developed detection approach in laboratory and outdoor environments. The laboratory experiments were conducted to detect ironworkers' near-miss falls to show the feasibility of the developed approach. The outdoor experiments examined the performance of the developed method near a construction site environment. The developed near-miss fall detection approach can provide quantitative information about near misses and offers the foundations for utilizing near-miss fall data to alert ironworkers about their real-time fall risks. With this approach, unrecognized near-miss falls in a construction workplace can be identified, which gives researchers and safety managers the chance to better understand individual workers' near-miss falls and the locations or conditions that contribute to such accidents.

3.1. Data collection and processing

To test the developed near-miss fall detection method, this study conducted laboratory and outdoor experiments to collect near-miss fall data on the simulated ironworks environment with five subjects who participated in these experiments voluntarily. To create a test experience similar to ironworkers' experiences, all experiment subjects wore safety boots, a safety harness, and a hard hat during the experiments. During both experiments, each experiment subject wore a commercial WIMU (Shimmer 2R, Shimmer) sensor on his/her sacrum, which is the bottom of spine and also the point nearest to the human body's center of gravity. The WIMU documented the body movements of the worker through a 3-axis accelerometer and gyroscope. Data from the WIMU was wirelessly transported to a laptop computer in real-time using a Bluetooth connection. The overall process of the near-miss fall detection appears in Fig. 1 and is described in depth below.

In the laboratory experiment, a rectangular steel frame was installed to create a simulated, elevated work place of ironworker (See Fig. 2). Two pieces of 12′ 1″ (length) by 4″ (width) steel I-beams and two pieces of 6′ 6″ (length) by 2″ (width) angle beams formed the steel frame. This study intentionally designed the laboratory experiment to have narrow-width steel beams to encourage more instances of near-miss fall data, which we otherwise expected to appear at lower experimental frequencies because subjects would focus more on each step during the experiment.

Experiment subjects were asked to walk on this steel frame without interruption over a course of 5 min. During the experiment, body acceleration and angular velocity of subjects were documented using a WIMU with a 51.2-Hz sampling rate and the software provided by the WIMU manufacturer. In addition, a video recorder filmed the experiment to document any near-miss falls so the researchers could label and reference the data to identify detection results. Based on the recorded video data, the experiment organizer manually labeled the near-miss falls. In the outdoor experiments, a 56′ long steel I-beam with an 8″ width was installed in the backyard of an ironworker company. This installation was exposed to an outdoor environment to simulate the working conditions of an actual construction site. As with the laboratory experiments, five subjects were asked to walk continuously on the installed I-beam for 5 min. Since the I-beam installation was a single beam, the subjects were required to execute a 180 degree turn at both ends of the steel beam.

To synchronize the video data with the WIMU data, at the beginning and end of the experiment, the experiment organizer directly hit the sensor to insert a beginning signal and an ending signal into the WIMU data. Although the default WIMU sampling rate is 51.2 Hz, we reconstructed the WIMU data to use a 32-Hz sampling rate to ease the processing of the WIMU data because a 51.2 sampling rate mostly collected data with 51 sampling rate but once with 52 sampling rate every 5 s. Then using the video data synchronized with the WIMU data, the experiment organizer manually labeled the occurrence of near-miss falls to use the cross-reference as the ground truth in the machine learning classification.

It is important to note here that it is challenging to define near-miss falls—also known as near-falls or stumbles—due to the diverse conditions that influence these events. Weiss et al. [41] defined a near-fall as a loss of balance that would have resulted in a real fall if sufficient recovery process were not activated. Chehade [46] defined a stumble as a precondition of a fall that can contribute to a fall if the subject fails to recover his or her balance. Building upon these definitions, this study defines a near-miss fall as a loss of balance that results in a *visible* balance-recovery motion or decreased speed. Specifically, near-miss falls were labeled when experiment subjects on the I-beam had to use abnormal movements to recover their balance. Such movements included (1) not being able to maintain the speed of walking due to a loss of balance demonstrated by having to sway the body or swing an arm and (2) having obvious body sway or swing motions regardless of walking speed. In this study, actual falls (steps off of the beam) also occurred, but their corresponding data were eliminated manually since the scope of the study did not seek to classify actual falls.

To classify near-miss falls on the steel I-beam, the WIMU data were preprocessed before extracting features to reduce sensor noise and to improve the classification performance. This study used a third-order Butterworth low-pass filter with a cut-off frequency of 4 Hz to remove sensor noise because human movement energy is located below 3 Hz [47]. Also, this study used the “detrend” built-in function in MATLAB (R2014, MATHWORKS) to remove the influence of gravity in the

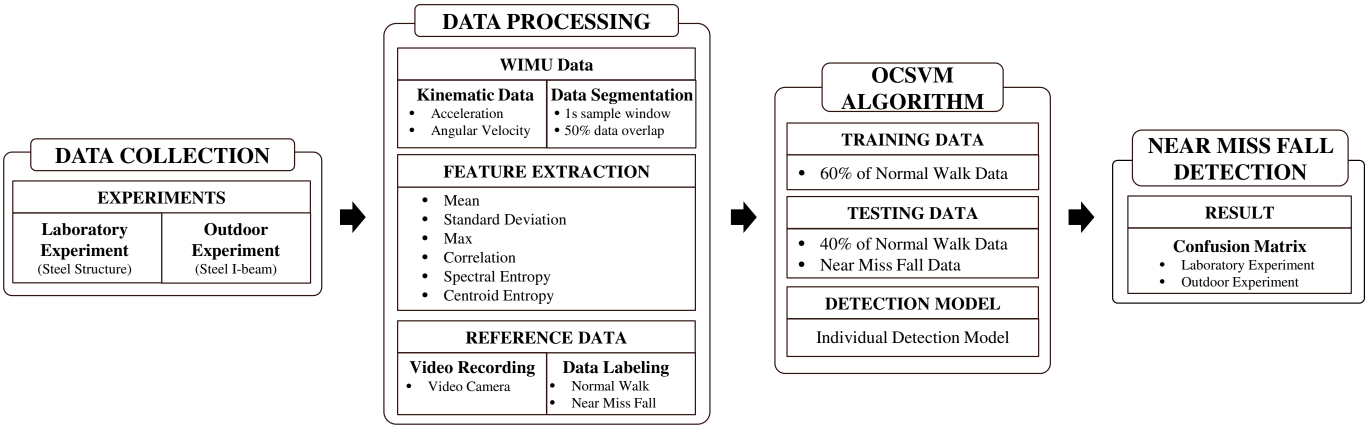

Fig. 1. Research process of near-miss fall detection.

WIMU data. Then this study sampled 32 raw data to create a single data window. Using a methodology developed by a previous classification study [30], we then overlapped multiple adjacent data windows at their 50% mark to increase the classification performance. Based upon this sample data, this study extracted 38 total features in the time and frequency domains. These features are widely used in WIMU-based studies examining daily activity classification and fall detection [30,48,49] and include the mean, max, standard deviation, correlation, spectral entropy, and spectral centroid from the x-, y-, and z-axes of both accelerometers and gyroscopes. These 38 features were used to classify near-miss falls (unstable) and normal walking motions (stable) through an OCSVM algorithm [45] (discussed in Section 3.2).

3.2. Semi-supervised near-miss fall detection

Due to the various factors (e.g., missteps, trip, wind, slippery surface) at play in a construction site, different types of near-miss falls can occur for the ironworker. This reality makes the use of a previous threshold-based fall detection algorithm [22,23] and general supervised pattern-recognition algorithm challenging since such an algorithm would have to be trained with every type of near-miss fall. Such a data-intensive requirement can be a huge barrier to the implementation of this method in a construction site due to the difficulties in collecting all near-miss data. With the current level of knowledge regarding near-miss falls—subjective definitions of near-miss falls will vary depending on the perception of each individual, and what some would qualify as a near miss may differ according to the ability of the subject to maintain stability or recover from a loss of balance.

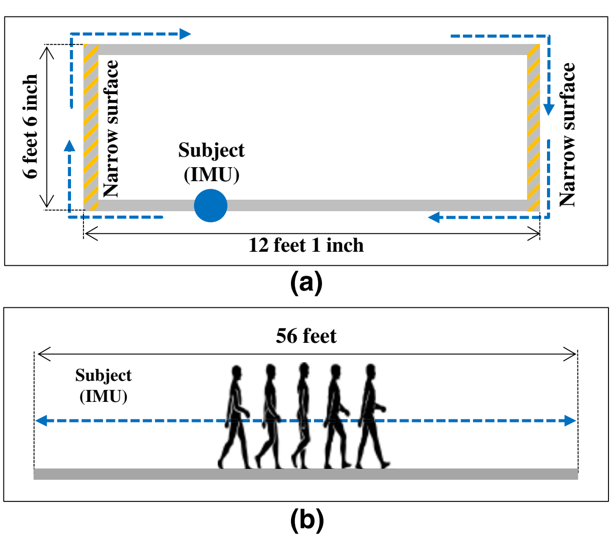

Fig. 2. Details of experiment environments: (a) laboratory experiment layout and (b) outdoor experiment layout.

To address this data acquisition challenge, this study examined a range of abnormal signals as stand-ins for near misses. Considering that near-miss falls generates abnormal signal patterns in WIMU data, the foundational premise of near-miss fall detection is the process of detecting which different types of abnormal signal patterns characterize different types of near-miss falls. For example, in Fig. 3, the accelerometer signal for a near-miss fall (see Fig. 3c, d, and e) and an actual fall (see Fig. 3b) shows a change in the medio-lateral axis and anterior–posterior axis acceleration as compared to normal walking (Fig. 3a).

However, there is a substantial difference between near-miss falls and actual falls in the acceleration of the vertical axis: As demonstrated in other fall detection studies [22], actual falls show a high vertical acceleration whereas near-miss falls do not show a similar difference across the vertical axis and only demonstrate such substantial differences in the anterior–posterior and medio-lateral axes when compared to normal walking. Moreover, near-miss falls do not show a similar pattern to each other in terms of their acceleration across the medio-lateral and anterior–posterior axis. This characteristic of near-miss falls makes a semi-supervised learning algorithm necessary for this study.

Considering the abnormal characteristics of WIMU signals for near-miss falls, this study selected to use an semi-supervised algorithm, one-class support vector machine (OCSVM) algorithm, which can detect all types of abnormal signals (near-miss falls) based upon their divergence from normal signal patterns (i.e., normal walking) (see Fig. 4).

According to this approach, every different near-miss fall signal does not need to be recorded and used to train the classifier. Rather, the OCSVM used in this study can classify two different classes based upon a classifier trained for only one class of data (here designated normal walking). Thus, this abnormal detection approach can be implemented by using only the normal signal data that can easily be collected in general working conditions. Instances for the algorithm are displayed by $x_i \in R^n$, and target values are $y \in \{-1,1\}^l$. To solve the training problem, our algorithm needed to solve this optimization problem (Eq. (1)) [50]:

$$\min_{w,\xi_i,\rho} \frac{1}{2}\|w\|^2 + \frac{1}{\nu n}\sum_{i=1}^{n}\xi_i - \rho \tag{1}$$

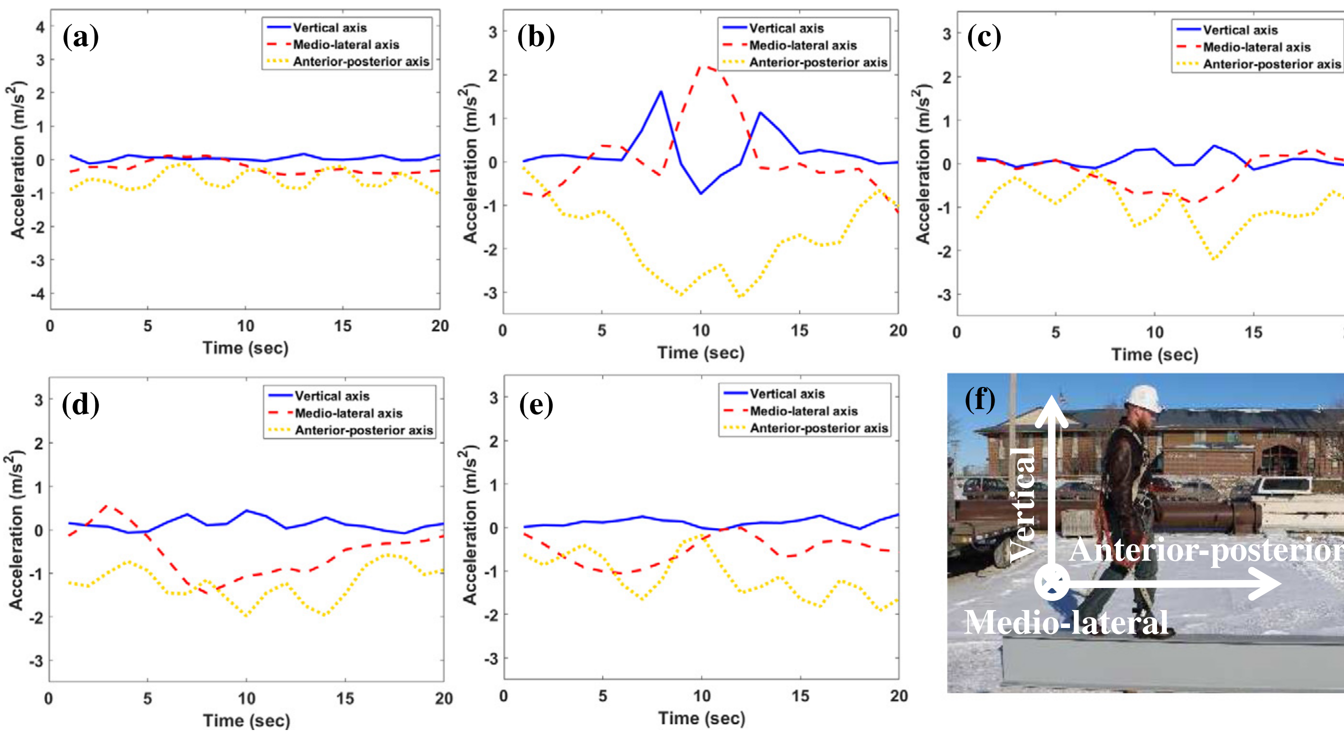

Fig. 3. Average value of acceleration in (a) normal walk, (b) actual fall, (c, d, e) near-miss falls, and (f) anatomical axes of human body movement.

Subject to $(w^t\phi(x_i))\geq\rho-\xi_i$ and $\xi_i\geq 0$

$$f(x)=sign((w\bullet\phi(x_i)-\rho) \tag{2}$$

Here, v is a introduced parameter between 0 and 1, which is an upper limit on the fraction of training errors and lower limit of the fraction of support vector [51], and ξ_i is a slack variable measuring the error of x_i. Function ϕ maps x_i to higher dimension, which results in support vectors forming a hyperplane that separates the classes. When solved optimization problem with w and ρ, class will be decided using decision function (Eq. (2)). In this study, various kernels have been studied, and the best results were achieved using a radial basis function (RBF):

$$K(X_i,X_j)=\exp\left(-r\|X_i-\|X_iX_j^2\|\|\right), r>0$$
$$K(X_i,X_j)=(\phi(x_i)\bullet\phi(x_j))$$

An RBF kernel is widely used to handle the nonlinear classification problem when the relationship between the target values and the attributes is nonlinear [52]. With this kernel, all kernel values sit in the range [0, 1], which results in a simplicity of computing vectors rather than polynomial kernels that can yield infinite values [53]. An RBF kernel needs to define the parameter (r) to perform better in training classification performance. To achieve the best values, we performed a grid search by exponentially increasing the parameter. Once an approximate

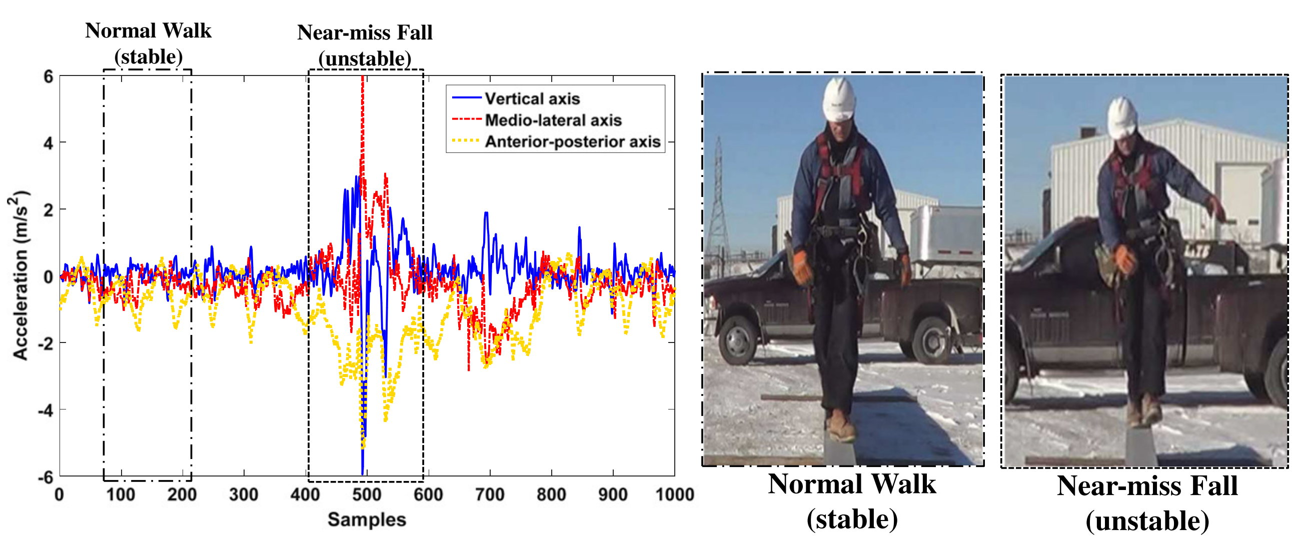

Fig. 4. Concept of near-miss fall detection using WIMU.

value for each parameter was found via a coarse grid, we narrowed down the search using a finer grid. Then we selected the parameter value that offered the best accuracy in near-miss fall detection. When it came to training the algorithm, all training data were selected from normal walking data that did not include a near-miss fall. In this study, 60% of the normal walking data was used for training the OCSVM classifier, and then the rest of the normal walking as well as the near-miss fall data were used to test the trained classifier. During the classification process, we adjusted the parameters of the algorithm to attempt to improve an accuracy of our algorithm.

4. Results

This study subsequently assessed the accuracy of the overall near-miss fall detection approach by producing a confusion matrix (see Table 1). According to the two different experiment conditions (i.e., the laboratory experiment and the outdoor experiment) and the outcomes of the five subjects, our resulting algorithm detected near-miss fall occurrences with 75.8% recall (TP/(TP + FN)) and 86.4% overall detection accuracy ((TP + TN) / (P + N)). During the laboratory experiment, the test subjects experienced a cumulative 183 near-miss falls on the installed steel frame. Among these near-miss falls, 137 data samples were correctly classified (74.9%) using the algorithm. In the outdoor experiments, a total of 69 near-miss falls occurred, and 54 of them were successfully detected (78.3%) through the implemented algorithm.

To foster near-misses in the data samples, this study installed narrow-surface beams in the laboratory experiment. As a result, more near-miss falls (183 samples) occurred compared to the outdoor experiments (69 samples), and it is expected to link to the better detection results in near-miss fall detection. However, despite the larger number of near-miss data, laboratory experiment shows slightly lower recall compared to outdoor experiment. In fact, the narrow-surface beams in the laboratory experiments presented a difficulty for subjects as they tried to perform their normal walking movements. Their walking movements thus included other simultaneous motions such as extensive arm swing, inconstant walking speed, and irregular balance-recovery motions. These motions caused ambiguity in labeling normal walking in the laboratory experiments. On the other hand, the outdoor experiments faced less ambiguity in the labeling of the normal walking due to simplicity of experiment layout (i.e., wider walking surface). This detail explains the slightly lower recall in the laboratory experiments (74.9%) as compared to the outdoor experiments (78.3%).

For walking activity classification, the developed approach achieved 86.4% recall in the two experiments, and the remaining 14.6% of walking data were misclassified as near-miss falls. The misclassified walking incidents occurred near the edge of the steel beam before/after subjects made a turning motion. At this point, the subjects' walk speed decreased as they prepared for the turn, or they started to walk, which may have given a similar signal to the near-miss fall defined in this study (i.e., when subjects reduced their walk speed and recovered their balance with an arm swing without significant body sway). Also, an irregular walk, such as wide/small step distance, steps with strong vertical force, and small degrees of body motion, were sometimes misclassified as near-miss falls using the developed approach. This result shows that irregular walking patterns, especially irregular steps and small body motions, have a similar signal pattern as defined near-miss falls when using a single WIMU (attached to the sacrum). This result illustrates that multiple WIMUs (e.g., attached to the head or upper body) may be necessary to better classify subtle movements. Also, a better definition or representation of near-miss falls would be beneficial to clearly differentiate between near-miss falls and irregular walking movements.

In the laboratory experiments, near-miss falls were detected with similar accuracy (71.9% to 77.6%) across experiment subjects. However, outdoor experiments had a varied near-miss fall detection rate (73% to 87.5%) depending on the experiment subjects. Such a high variability of near-miss fall detection rates manifested in-part due to the low incidences of near-miss falls in the outdoor experiment setting. For example, Subjects 2 and 5 had fewer near-miss falls compared to Subjects 1, 3, and 5 during the outdoor experiments, and the near-miss fall detection rates in Subjects 2 and 5 were found to be higher than other subjects. It should be noted that Subjects 2 and 5 also had fewer near-miss falls even in the laboratory experiments. Such a consistency of

Table 1
Near-miss fall detection results achieved through the OCSVM.

Activity	Subject no.	Number of occurred near-miss falls	Number of detected near-miss falls	Confusion matrix		
					Near miss fall (predicted)	Normal walk (predicted)
Laboratory	1	58	45	Near miss fall	77.6%	22.4%
				Normal walk	9.7%	90.3%
	2	25	18	Near miss fall	72%	28%%
				Normal walk	13.4%	86.6%
	3	46	35	Near miss fall	76.1%	23.9%
				Normal walk	16.4%	83.6%
	4	22	16	Near miss	72.7%	27.3%
				Normal walk	11%	88.9%
	5	32	23	Near miss fall	71.9%	14.4%
				Normal walk	10%	90%
	Total	183	137	Recall	74.9%	
				Accuracy	86.8%	
Outdoor	1	28	22	Near miss fall	78.6%	21.4%
				Normal walk	15.7%	84.3%
	2	7	6	Near miss fall	85.7%	14.3
				Normal walk	14.3%	85.7%
	3	12	9	Near miss fall	75%	25%
				Normal walk	12.1%	87.9%
	4	5	4	Near miss fall	80%	20%
				Normal walk	11.8%	88.2%
	5	17	13	Near miss fall	76.5%	23.5%
				Normal walk	16.3%	83.7%
	Total	69	54	Recall	78.3%	
				Accuracy	85.2%	

individual vulnerability to near-miss falls across different experimental settings indicates that the frequency of detected near-miss falls could be used as a predictor of the fall risks of individual workers.

5. Discussion

As a proactive fall accident prevention measure for ironworker, this study developed a near-miss fall detection approach that uses wearable inertial measurement units (WIMUs) to gather data about bodily motions. The data are then applied to an algorithm that monitors bodily gestures for abnormal movements (near misses). In particular, this study successfully used WIMUs to document the signals of subjects losing their balance (near-miss falls) and detected these signal using a well-known abnormality detection algorithm (OCSVM). To verify the developed near-miss fall detection approach, this study conducted two different experiments in laboratory and outdoor settings. By applying the OCSVM algorithm, this study achieved moderate near-miss fall detection accuracies regardless of the experimental environment.

Previous studies to detect a near-miss fall based on WIMU data mostly used a threshold approach based on the sum of total body acceleration [30,31]. While such studies demonstrated the feasibility of their approach in limited settings (e.g., during treadmill walking, stationary motions), the threshold approach requires collecting and analyzing all possible forms of near-miss fall data and normal activity data to define the threshold values of near-miss falls. This task may not be feasible considering the nature of near misses in construction. The proposed approach based on the OCSVM algorithm is able to detect different types of near-miss falls based on workers' normal activity data, which is relatively easy to obtain. In addition, unlike previous studies, which focused on detecting trip/slip or detecting near-miss fall during stationary actions, this study is an initial attempt at detecting near-miss falls, loss of balance, during non-stationary actions (i.e., moving along the steel frame). Such non-stationary actions included more diverse motions (e.g., turning at the edge of steel frames, acceleration, and deceleration of walking speed), and irregular movements of other body parts (e.g., extensive arm swings), all of which posed a greater challenge in detecting near-miss falls and would explain the slightly lower accuracy of the proposed approach compared to previous studies.

Locational information regarding near-miss fall occurrences in the proposed method provides a fruitful point of discussion. By synthesizing the detected near-miss fall information for multiple subjects walking along the steel beams, the locations that appear to contribute to making workers fall-prone can be identified (see Fig. 5). To document the locations of the collected near-miss falls on the steel structure, each turning motion was labeled with video data. Then the near-miss fall data were identified as before or after the turning motion and the total number of data samples between each turning motion were resized to have same length for each steel beam. As a result, the narrow-surface beams—marked as A and C—show relatively higher occurrences of near-miss falls even when utilizing data from only one subject. With the current accuracy of the OCSVM algorithm, the figure shows a clear difference between the wide surfaces and the narrow surfaces in the laboratory experiment. This outcome indicates that when synthesizing the near-miss fall data of multiple workers in a particular location, this fall-prevention approach could help identify hazardous conditions automatically. Thus, by combining the localization techniques, this near-miss fall detection approach has the high potential to detect hazardous conditions and to contribute to reducing the risk of fall accidents by decreasing the exposure time workers face hazards detected within the collected locational information.

However, there are still many challenges to addressing the diversity of construction job tasks. For example, carrying a symmetrical or asymmetrical load may affect to the IMU signals of normal walking and near-miss falls. In response, this study also tested the detection performance of the algorithm for a case in which subjects carried a side load (25 lb). All other experimental settings were maintained exactly as those of the previous outdoor experiments. Although this new experiment included an asymmetrical load, we first trained the OCSVM classifier using normal walking data collected from the outdoor experiments in which the subjects carried no loads—this choice allowed us to examine the importance of building out a comprehensive training data set. Our results showed that when we trained the classifier using the no-load data, the recall of near-miss detection dropped by 18% compared to previous outdoor experiments. However, when the classifier was trained with data collected from the walking with a side-load experiment, its recall accuracy proved to be slightly better than previous outdoor experiments. This preliminary result indicates the need for building a comprehensive training data set to address the diversity of construction job tasks.

An additional consideration that expands the need for a robust and automated approach to fall accident prevention has to do with the variability of workers' balance. For example, different people have different abilities to maintain their balance while working on a small surface area (specifically working on a narrow steel beam). Furthermore, even an individual worker may experience variability in his/her abilities to maintain a balance depending on his/her workload or fatigue level. Some types of hazards—such as slippery surfaces, obstacles on the beam, strong wind, or uneven or moving surfaces—can also impact workers' balance, but such hazards are often ignored in current hazard identification processes. Collecting and analyzing near-miss fall data using this proposed approach will help identify workers who are fall-prone due to excessive workload or fatigue and/or will help locate hidden fall hazards that are not identified by current hazard analysis practices.

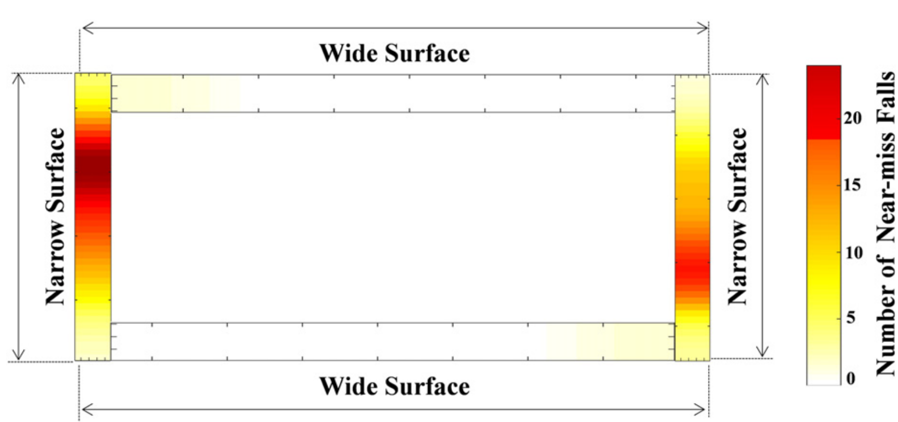

Fig. 5. Near-miss fall locations in laboratory setting.

6. Conclusion

This study developed and tested an approach to detect the near-miss falls of ironworkers based on WIMU data attached to workers' bodies. An OCSVM algorithm was implemented to detect the near-miss falls based upon a binary assessment of the normal walking movements. The results demonstrated the performance of this approach by achieving a 75.8% recall and 87.5% accuracy in detecting near-miss falls with two different experimental conditions that simulate ironworker working environments.

This study validated the feasibility of the developed approach in detecting near-miss falls and demonstrated its usefulness as a proactive fall-prevention method for ironworkers. With the advantage of a semi-supervised algorithm that classifies near-miss falls using only normal walking data, the developed approach has substantial benefits in real-world implementation compared to previous approaches. The developed approach will contribute to providing near-miss fall information that can be used for proactive fall-prevention measures of ironworkers in response to their high risk of fall accidents. Also, this approach is expected to help safety managers identify individual fall risks by counting the total number of near-miss falls for each worker and predicting risky locations or hazards based upon the detected locations of near-miss falls. Specifically, collected near-miss fall locations would beneficial for analyzing the relationship between ironworkers' behavior patterns and the construction site environment. The proposed WIMU-based approach also has application and financial benefits due to the small sensor size and the low operation costs.

As a limitation to the approach, the near-miss fall detection accuracy varies depending upon the experiment subject and the performed task. Further studies on near-miss fall detection during diverse ironworker activities, including squatting, bolting, reaching, and carrying a load, need to be conducted to improve the applicability of this approach. Also, additional field experiments in actual building structures are necessary to validate the effectiveness of the developed approach in identifying potential problems (e.g., hazards) in a real-world setting. Finally, future studies should test the applicability of this fall detection approach in different construction trades to expand the reach of this study.

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