Digital Life

*Journal of Digital Life 2025,5,S5*

*Special Issue: Measurement, control, and analysis of motion using ICT and AI*
*Article*

# Detecting Near-Miss Actions and Estimating Physical Fatigue among Construction Workers Using Wearable Sensors

Yoshimasa Umehara [1], Toshio Teraguchi [2], Yuhei Yamamoto [3], Taiga Kobayashi [4] and Ryuichi Imai [5]*

[1]Faculty of Business Administration, Setsunan University, 17-8 Ikeda-nakamachi, Neyagawa-shi, Osaka 572-8508, Japan
[2]Faculty of Economics, University of Marketing and Distribution Sciences, 3-1 Gakuen-nishimachi, Nishi-ku, Kobe-shi, Hyogo 651-2188, Japan
[3]Faculty of Environmental and Urban Engineering Department of Civil, Kansai University, 3-3-35 Yamate-cho, Suita-shi, Osaka 564-8680, Japan
[4]Graduate School of Engineering and Design, Hosei University, 2-33 Ichigaya-tamachi, Shinjuku-ku, Tokyo 162-0843, Japan
[5]Faculty of Engineering and Design, Hosei University, 2-33 Ichigaya-tamachi, Shinjuku-ku, Tokyo 162-0843, Japan

**Abstract**
Labor shortages in the construction industry have become a serious issue in developed countries, particularly in Japan, where workforce aging and declining recruitment of young workers are significant challenges. In this context, ensuring worker safety has become increasingly critical. While occupational accidents in Japan's construction industry have decreased annually due to proper safety measures, the construction industry still has the highest number of fatalities among all industries. Falls from height and falls on the same level are the leading causes of injuries and fatalities. Therefore, detecting near-miss incidents (such as tripping and slipping) that precede falls, along with physical fatigue, could help prevent occupational accidents. This study investigated the feasibility of detecting near-miss incidents and estimating fatigue levels using wearable sensors suitable for continuous monitoring at construction sites. We conducted validation experiments simulating near-miss actions and fatigue conditions. Results showed that applying a Convolutional Neural Network (CNN) to data collected from an iPhone® placed in workers' trouser pockets achieved an F1-score of 0.95 in detecting near-miss actions. Additionally, by comparing body sway magnitudes before and after fatigue, we confirmed the potential for estimating physical fatigue.

**Keywords:** *Machine Learning, Human Activity Recognition, Fatigue Estimation, Wearable Sensor, Near-Miss Action*

## 1. Introduction

While global economic growth has led to increased construction demand, the construction industry in developed countries faces severe labor shortages. In the United States, the Infrastructure Investment and Jobs Act of 2021 has outlined a $1.2 trillion infrastructure development plan. However, 88% of U.S. construction companies are experiencing difficulties in securing construction workers (Associated General Contractors of America, 2023). Under these circumstances, Japan's Ministry of Land, Infrastructure, Transport and Tourism is promoting i-Construction to improve safety and labor productivity in the construction industry, resulting in a 6.6% decrease in workplace accidents compared to 2018 (Ministry of Health, Labour and Welfare, 2023a). This reduction can be attributed to the implementation of safety measures, such as KY (*Kiken Yochi*, or hazard prediction) activities that anticipate potential dangers at construction sites and 5S (Sort, Set in order, Shine, Standardize, and Sustain) activities that focus on organization and cleanliness, which are well-known among site managers. Moreover, the Ministry of Health, Labour

Received: 21 November 2024, Revised: 29 January 2025, Accepted: 27 February 2025, Published: 26 March 2025
* Correspondence: imai@hosei.ac.jp

and Welfare formulated the 14th Occupational Safety & Health Program (Ministry of Health, Labour and Welfare, 2023b) in April 2023, which emphasizes the promotion of digital transformation. This program encourages the introduction of cutting-edge technologies for safety measures, such as proximity detection of workers using ICT construction machinery and management of workers' locations and vital data using wearable sensors. These initiatives are believed to contribute to the reduction in the number of occupational accidents. However, the construction industry still has the highest number of fatalities among all industries (Ministry of Health, Labour and Welfare, 2023a). This can be attributed to the inherently high-risk nature of construction work, which involves tasks such as working at heights and operating heavy machinery. Furthermore, physical fatigue resulting from manual labor is believed to affect workers' attentiveness and concentration levels, potentially leading to accidents. According to Heinrich's Law (Heinrich, 1931), a well-known empirical rule in occupational safety, for every serious accident, there are 29 minor accidents, and behind these, there are 300 near-miss incidents. Near-miss incidents in the construction industry include reports of cargo collapse during material loading and cases where outriggers, used to ensure the stability of mobile cranes, sink into the ground (Ministry of Health, Labour and Welfare, 2012). Furthermore, focusing on the factors of occupational accidents that occur in the construction industry, falls from height are the most frequent, followed by falls on the same level (Ministry of Health, Labour and Welfare, 2023a). Therefore, it can be inferred that safety management through dynamic monitoring of construction workers is important. Thus, detecting near-miss actions such as stumbles and slips, which are precursors to falls and trips, could enable the prevention of occupational accidents before they occur. Moreover, estimating the fatigue level of construction workers could help reduce the risk of occupational accidents. By detecting near-miss actions and estimating worker fatigue, the number of occupational accidents can be decreased, and fatalities can be prevented, thereby contributing to the improvement of safety at construction sites. Moreover, estimating the fatigue level of construction workers could help reduce the risk of occupational accidents. By detecting near-miss incidents and estimating worker fatigue, the number of occupational accidents can be decreased, and fatalities can be prevented, thereby contributing to the improvement of safety at construction sites.

In existing research, detecting near-miss actions and estimating physical fatigue have been approached through distinct methodologies. First, focusing on the detection of near-miss actions among construction workers, given that occupational accidents in the construction industry frequently involve falls from height and falls on the same level (Ministry of Health, Labour and Welfare, 2023a), the implementation of wearable sensors has been proposed as a means of detecting falls. Notable examples of wearable sensors currently deployed at construction sites include the Spot-r by Triax Technologies, Inc., and the fall detection device by Takenaka Engineering Co., Ltd. On the other hand, fall detection methods using cameras and LiDAR, which offer higher visibility compared to wearable sensors, have become widespread in the healthcare and welfare sectors, notably the mirAI-EYE by GLORY Ltd., and fall detection sensor for elderly people by FAJ Inc. However, these methods are designed for care recipients and can only be applied in stable environments without blind spots, with a detection range of within 7 meters. Therefore, their adoption in construction sites is hindered by the occurrence of blind spots due to complex structures and the difficulty of wide-area detection. Murata Manufacturing Co., Ltd., has developed a worker safety monitoring system as a wearable sensor capable of detecting near-miss incidents such as trips and slips that may precede falls on construction sites. However, the specific definitions of near-miss actions and their detection algorithms have not been made public. Therefore, we focus on fall and near-miss action detection methods in the sports and welfare fields, where action recognition research has been advancing. In the field of sports, a method for detecting falls of soccer players using the deep learning model LSTM (Naruo et al., 2023) has been devised. The reason this method is effective is that soccer has a limited duration and range of movement, and the players' motion patterns are relatively consistent. On the other hand, LSTM learns patterns from long-term time-series data. Therefore, we infer that it would be difficult to apply this method to construction workers, whose behavior varies greatly depending on differences in site terrain, structure, equipment used, and job type. In the welfare field, methods for detecting near-miss actions using machine learning models, such as SVM and Decision Tree, as well as thresholds (Pang et al., 2019), have been devised. However, these methods are limited to elderly individuals during walking or daily activities. Consequently, they are difficult to apply to construction workers, who exhibit a wide range of complex behaviors, such as working at heights or operating heavy machinery. Therefore, we believe that by proposing a method suitable for detecting near-miss actions of construction workers who perform a wide variety of tasks, we can contribute to the prevention of occupational accidents.

Next, we focus on estimating the fatigue level of construction workers. Generally, in fatigue level estimation, analyses based on physiological indicators from vital sensors, such as heart rate, electromyography, and oxygen consumption, are conducted. However, the utilization of vital sensors remains challenging on construction sites due to factors such as the impact on heart rate for specific occupations (Akagawa et al., 2020) and the contact between fall protection equipment and vital sensors. Consequently, there are still issues hindering their widespread adoption. In the field of sports, where research on fatigue level estimation has been advancing, it is possible to estimate fatigue levels based on exercise load by calculating the amount of exercise from the distance and speed of movement during play, measured using wearable sensors (Yamada et al., 2023). However, the amount of exercise used for estimating fatigue levels is currently calculated from the distance traveled obtained by GNSS positioning (Yamada et al., 2023). This method is difficult to apply to construction sites with complex structures where multipath effects are likely to occur. As a fatigue estimation method that does not use GNSS positioning, there is a method for estimating fatigue levels by measuring body sway using a force plate, since body sway increases with muscle fatigue (Paillard, 2012). Specifically, body sway is measured by having subjects stand upright on a force plate for 30 seconds before and after fatigue. The fatigued state is reproduced by running on a treadmill for 30 minutes, and the results of the experiment show that body sway significantly increases after fatigue (Derave et al., 2002). However, current methods for measuring body sway are limited to precise methods using force plates or cameras, and a method for measuring body sway using wearable sensors has not yet been established. Therefore, if it becomes clear that the fatigue level of construction workers can be estimated based on body sway, which can be measured by wearable sensors, it will be possible to take breaks and reallocate workers according to their fatigue level, which is expected to help prevent the risk of occupational accidents.

Based on the above, this study aimed to investigate the possibility of detecting near-miss actions and estimating fatigue levels by measuring body sway using wearable sensors that enable continuous monitoring even on construction sites where environmental conditions change daily due to ongoing construction work.

## 2. Methods

### *2.1 Methods for Detecting Near-Miss Actions*

Near-miss action detection is performed utilizing a deep learning model that has been trained to recognize near-miss action patterns. Our approach to near-miss action detection draws upon anomaly detection methodologies from medical and mechanical domains (Masetic et al., 2016), as well as action recognition techniques employing wearable sensors (Inoue, 2016). In accordance with the methodologies, our study employed wearable sensors to acquire triaxial acceleration and triaxial angular velocity measurements. Subsequently, machine learning models were applied to the acquired data. The study evaluated two candidate machine learning models—Random Forest and Convolutional Neural Network (CNN) classifiers—through empirical experimentation to determine the most effective approach for near-miss action detection. The rationale for employing Random Forest lies in its dual advantages: superior generalization performance with overfitting prevention, and computational efficiency. Our Random Forest data application process involves converting and standardizing integer raw data. During the segmentation phase, we calculate statistical features such as maximum, minimum, mean, standard deviation, and interquartile range. In addition to these features, the unit-converted raw data is used as explanatory variables. The reason for using these features is that previous research (Bao et al., 2004) suggests the possibility of classifying operations with high accuracy. Furthermore, although previous research (Bao et al., 2004) indicates the potential effectiveness of FFT-based features, we do not use them in this study because our preliminary experiments showed that similar features were obtained during near-miss incidents and work operations, which could negatively affect model training. The Random Forest parameters were set according to previous research (Breiman, 2001) as follows: the number of trees was set to 100, the random seed was fixed at 42, the Gini function was used as the split criterion, while both the maximum tree depth and the number of features were set to auto-tune.

The adoption of Convolutional Neural Network (CNN) is justified by their capability to effectively learn spatiotemporal features from sensor data through convolutional and pooling layers, as well as their superior performance in action and image recognition tasks. The data processing pipeline for CNN implementation involves unit conversion of raw integer data followed by standardization to generate the explanatory variables. The CNN architecture consists of three convolutional layers and two fully connected layers, following the structure proposed by Zeng (2014). The CNN hyperparameters were configured based on Zeng (2014) as follows: learning rate was set to 0.001 with Adam optimizer for learning rate decay, ReLU was used as the activation function, and cross-entropy was employed as the loss function. The batch size was set to 10, and the model was trained for 1,000 epochs. For early stopping, we set the patience parameter to 30 with a delta value of 0.00001.

### *2.2 Methods for Estimating Fatigue Levels*

In this study, fatigue levels are defined as the amount of change in body sway before and after exercise, and evaluated by comparing the measurement results of body sway before and after exercise. The method for measuring body sway draws from measurement techniques in medical research, including postural sway measurement during quiet standing (Demura et al., 2006) and gait analysis methods based on long-duration walking rhythm patterns (Higashi et al., 2011). These methods analyze parameters such as the geometrical patterns of the center of gravity sway plotted in two dimensions and peak acceleration during the swing phase. However, these methods are difficult to apply to measuring construction workers' body sway as they were conducted under stable conditions that substantially differ from construction site environments. Therefore, this study aims to investigate the feasibility of fatigue estimation by developing a robust and easily applicable method for measuring body sway that can accommodate the variable conditions of construction sites, considering fatigue induced by construction work. The body sway measurement method proposed in this study calculates the mean of differences between moving maximum and minimum values at 3-second intervals from tri-axial acceleration and tri-axial angular velocity data obtained through wearable sensors. If this mean value changes in accordance with the accumulation of worker fatigue and increased physical load, we hypothesize that fatigue levels could potentially be estimated through body sway measurements.

## 3. Experiment

### *3.1 Detecting Near-Miss Actions Experiment*

The objective of this experiment was to investigate the feasibility of detecting near-miss actions by having participants perform simulated near-miss actions while wearing three different types of wearable sensors.

#### *3.1.1 Experimental Setup and Procedure*

The experiment was conducted in front of the Hosei University Shinmitsuke building, under experimental conditions, where near-miss actions and work actions were simulated and performed. By applying Random Forest and CNN to the tri-axial acceleration and tri-axial angular velocity data acquired by three types of wearable sensors during the execution of each action, we verified the wearable sensor and machine learning model suitable for detecting near-miss actions. Table. 1 shows the defined near-miss actions and work actions. Near-miss actions were defined as fall, trip, slip, stagger, and run, which are the most common precursors to falls from height and falls on the same level, which are the most frequent causes of occupational accidents. In addition, there are a vast number of types of work actions performed by construction workers. Therefore, in this study, in order to verify the usefulness of the proposed method, work actions similar to near-miss actions were selected. The work actions were defined as stand up, squat down, sit down, get on all fours, lie down, walk, walk while squatting, crawl under obstacles, and step over obstacles. By simulating the execution of these defined actions and classifying them into two categories: work actions and near-miss actions, we attempted to detect near-miss actions. The number of measurements was 5 times for each of the 9 types of work actions and 10 times for each of the 5 types of near-miss actions per person. By visually checking the videos taken during these measurements and extracting the moments of action, ground truth labels were assigned. The

Table.1 Defined work action and near-miss action

| Category | Action |
|---|---|
| Near-Miss Action | Fall |
| | Trip |
| | Slip |
| | Stagger |
| | Run |
| Work Action | Stand up |
| | Squat Down |
| | Sit down |
| | Get on all fours |
| | Lie down |
| | Walk |
| | Walk while squatting |
| | Crawl under obstacles |
| | Step over obstacles |

measurement time of the extracted work actions and near-miss actions was approximately 3 minutes per person for both.

### *3.1.2 Materials and Participants*

The three types of wearable sensors used in this experiment were: the xG-1 (Yamada et al., 2023) by xSENSING Co., Ltd., as a sports activity tracker used for analyzing exercise and play activities; the iPhone® 12 Pro by Apple Inc. as a smartphone sensor integrated into daily life; and the Apple Watch® Ultra by Apple Inc. as a smartwatch capable of measuring vital signs. The positioning of the wearable sensors is shown in Fig. 1. These three types of wearable sensors were selected because each possesses distinct characteristics, allowing us to determine which wearable sensor is most suitable for detecting near-miss actions. The specific characteristics of each wearable sensor are as follows: the xG-1, attached to the back of the body using a dedicated vest, can acquire high-precision motion data during physical activities; the iPhone® can easily collect everyday motion data; and the Apple Watch® can capture hand movement data during tasks. These wearable sensors were used to collect three-axis acceleration and three-axis angular velocity data at a sampling rate of 50 Hz. The subjects were eight male university students in their 20s, all of whom performed near-miss actions and work actions.

### *3.1.3 Data Processing and Evaluation*

When applying machine learning models, segmentation must be performed on the wearable sensor data where action boundaries are ambiguous before data can be processed. The segmentation process is conceptually illustrated in Fig. 2. As reported in existing literature (Inoue, 2016), conventional segmentation methods typically employ fixed-size windows with constant overlap ratios for data processing. In previous research (Huynh et al., 2005), daily actions were identified by fixing the window slide width to 250ms and setting the window size to 250ms, 500ms, 1,000ms, 2,000ms, and 4,000ms. However, it has been shown that the optimal window size varies for each action, and appropriate settings for the detection target are important. Similarly, the window overlap ratio also requires settings appropriate for the detection target (Inoue, 2016). Based on these findings, since near-miss actions are instantaneous actions, we set the window size to 200ms, 500ms, 1,000ms, and 2,000ms, which are narrower than those in previous research (Huynh et al., 2005), and the overlap ratio to 0%, 30%, 60%, and 90%. We constructed 16 models for each of Random Forest and CNN, for a total of 32 models. By verifying the detection accuracy of near-miss actions using these 32 models, we aim to identify the machine learning model and the window size/overlap ratio during segmentation that are suitable for detecting near-miss actions. The training data for model construction consisted of 7 out of 8 subjects, and the test data consisted of the remaining 1 subject.

For detection accuracy evaluation, we use the F1-score, which is the harmonic mean of precision and recall, with values closer to 1 indicating higher accuracy. The evaluation method compares predicted labels from each window with ground truth labels at each data point. When windows overlap, resulting in multiple predictions for a single data point, the final prediction is determined by majority voting.


Fig.1 Placement of wearable sensors

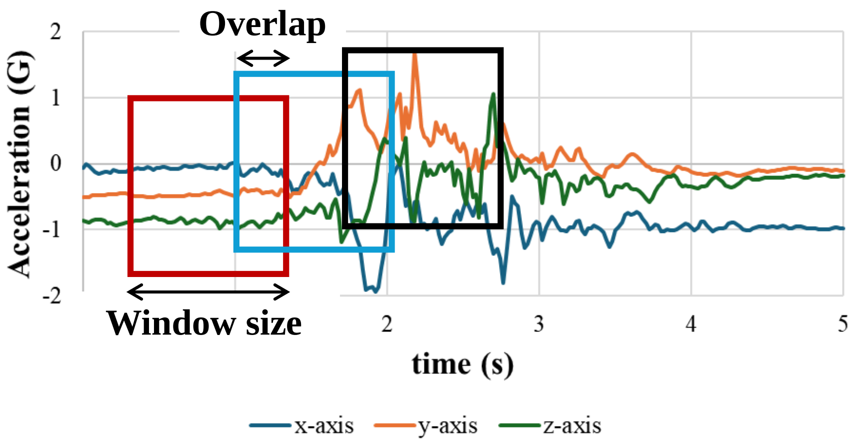


Fig.2 Segmentation image during data loading

### *3.2 Estimating Fatigue Levels Experiment*

The objective of this experiment is to investigate the possibility of estimating fatigue levels by measuring and comparing body sway before and after fatigue using wearable sensors.

#### *3.2.1 Experimental Setup and Procedure*

The experiment was conducted in front of the Hosei University Sinmitsuke building. The subject ran 5 km in approximately 20 minutes to induce a state of fatigue. The same actions were performed before and after fatigue, and the change in the amount of body sway was compared. The actions for measuring body sway before and after fatigue were walk, transport, upstairs, and downstairs, which were considered easy to measure body sway due to periodic movements, assuming actual operation at construction sites. Each action was performed at the same pace for 30 seconds before and after fatigue, and data on triaxial acceleration and triaxial angular velocity were acquired.

#### *3.2.2 Materials and Participants*

We used xG-1 (Yamada et al., 2023) from xSENSING Co., Ltd., as the wearable sensor. The xG-1 is a sports activity tracker used for analyzing exercise and play patterns, making it suitable for measuring body sway. The sensor placement and data collection methods are identical to those described in Section 3.1.2. The subject was one male student in his 20s.

#### *3.2.3 Data Processing and Evaluation*

Since the acquired raw data of triaxial acceleration and triaxial angular velocity are integer values, the integer value of acceleration is converted to G, and the integer value of angular velocity is converted to deg/s. Then, using the proposed method, body sway before and after fatigue is compared, and if a difference is observed between before and after fatigue, it is evaluated that it is possible to estimate the fatigue levels.

## 4. Results & Discussion

### *4.1 Experimental Results and Discussion on Detecting Near-Miss Actions*

The results of Random Forest application are shown in Fig. 3. In Fig. 3, the left horizontal axis represents the window size, the right horizontal axis shows the overlap rate, and the vertical axis indicates the F1-score, where higher plot points represent higher detection accuracy. The highest detection accuracy was achieved with the xG-1 sensor, using a window size of 200ms and an overlap rate of 90%, resulting in an F1-score of 0.45, indicating that Random Forest could hardly detect near-miss actions. These results suggest that near-miss action detection using Random Forest is challenging. The low detection accuracy of Random Forest can be attributed to two main factors: insufficient utilization of time-series data characteristics and inadequate feature extraction and selection. While Random Forest excels at handling correlations between individual features, it struggles to directly model temporal dependencies. This limitation likely resulted in missing crucial information when detecting near-miss actions, which involve subtle movement changes over short periods. The results of the CNN implementation are presented in Fig. 4. The highest

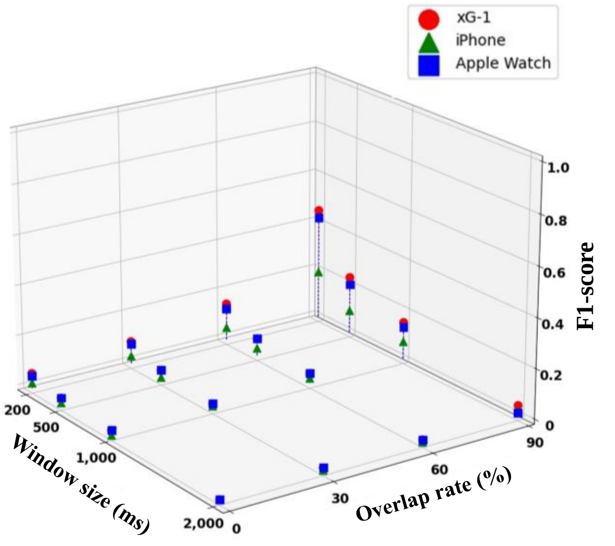


Fig.3 F1-scores for each parameter obtained during Random Forest validation

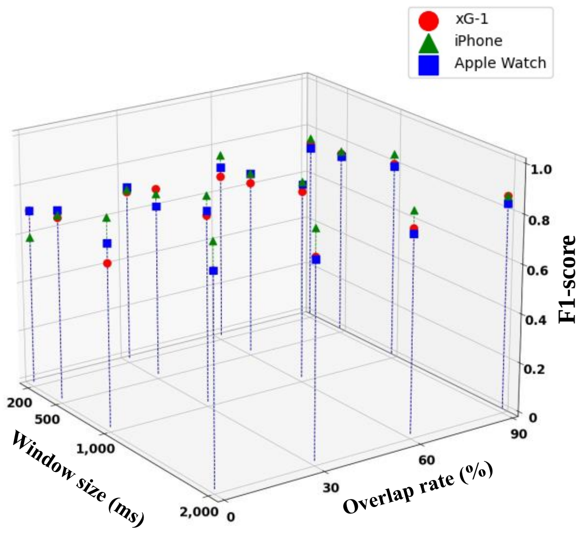


Fig.4 F1-scores for each parameter obtained during CNN validation

detection performance was obtained when using an iPhone® with a window size of 2,000ms and a 0% overlap, achieving an F1-score of 0.95, indicating that CNN effectively detects near-miss actions with high precision. The substantial enhancement in F1-score through CNN implementation can be explained by CNN's inherent capability to recognize local patterns within multidimensional data. The improvement in F1-scores with larger window sizes can be attributed to the increased number of data points, enabling the learning of more features and recognition of overall motion patterns. The F1-score peaked at 0% overlap because each window remains independent, preventing prediction labels from being influenced by other windows. Conversely, when overlap exists, identical data points may be included in multiple windows, potentially resulting in different prediction labels for each window. In this case, prediction labels for identical data points are determined by majority voting, causing incorrect predictions to affect the overall results and decrease accuracy. Therefore, when different prediction labels are obtained for the same data point, alternative methods to majority voting should be considered for label determination. Among wearable sensors, the iPhone® showed the highest detection accuracy when applying CNN. This is likely because near-miss action characteristics are more prominently displayed around the waist area. Furthermore, when comparing detection accuracy across different types of near-miss action, falling motions showed the lowest accuracy. This can be attributed to the similarity between falling motions and lying down actions performed during work tasks.

### *4.2 Experimental Results and Discussion on Estimating Fatigue Levels*

Fig. 5 and 6 present quantitative analyses of relative changes in body sway magnitude, measured via three-axis acceleration and angular velocity, comparing pre- and post-fatigue conditions. The coordinate system establishes the x-axis as an anteroposterior, y-axis as vertical, and z-axis as mediolateral directions. Analysis revealed a consistent pattern of increased post-fatigue body sway across multiple movement patterns, with particular emphasis on carrying out tasks designed to simulate construction worker activities. Stair descent movements exhibited a pronounced susceptibility to increased body sway magnitude. Differential analysis of fatigue-induced changes across individual axes demonstrated minimal perturbation along the vertical y-axis, while substantial variations were observed in both the anteroposterior (x-axis) and mediolateral (z-axis) directions. This axis-specific response pattern can be attributed to the inherent stability of vertical components versus the heightened susceptibility of horizontal plane movements to fatigue-induced oscillations. Of particular significance, stair descent movements demonstrated markedly elevated fatigue-induced body sway compared to other assessed movements, suggesting enhanced sensitivity to physical fatigue. This heightened response during stair descent can be mechanistically linked to the substantial energetic demands associated with controlled vertical displacement during the movement sequence.

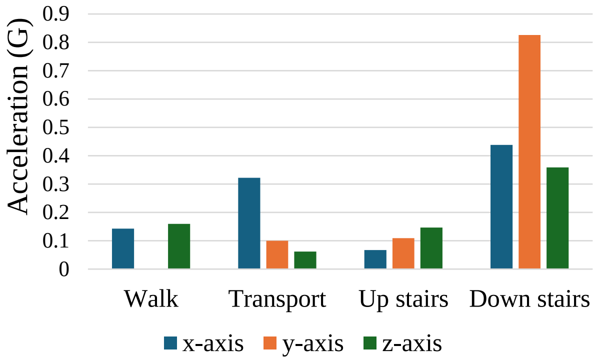


Fig.5 Relative changes in acceleration before and after fatigue

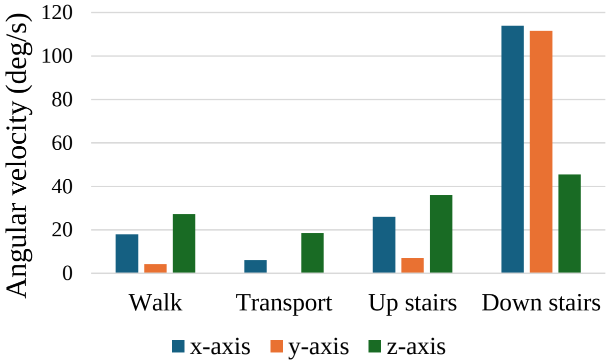


Fig.6 Relative changes in angular velocity before and after fatigue

***4.3 Discussion on Generalizing to Actual Construction Environments***

In this study, we verified the possibility of detecting near-miss actions and estimating fatigue levels in an experimental environment with limited actions. However, since actual construction sites involve a vast variety of actions and diverse environments, we will discuss how the findings obtained in this study can be generalized.

In detecting near-miss actions, actual construction sites involve work at heights, work in unstable locations such as scaffolding, and work performed by multiple people. Therefore, even if the same action is performed, the actual behavior may differ. Thus, we infer that the robustness of near-miss actions detection can be improved by collecting comprehensive action data of actual construction workers and building a model.

In estimating fatigue levels, this study measured body sway for periodic actions. Since it was shown that body sway increases after fatigue in the action of going down the stairs, the proposed fatigue level estimation method may be applicable to actions that are periodic and require balance at actual construction sites. However, this study used student subjects in their 20s, and it is necessary to consider individual differences due to the diverse age groups and physiques of construction workers in actual operation. Therefore, it is considered that it is possible to estimate the fatigue levels corresponding to individual differences by measuring the body sway data in the state before fatigue of each individual and calculating the amount of increase in body sway by comparing it with that.

**5. Conclusion**

In this study, we investigated the feasibility of detecting near-miss actions and estimating physical fatigue levels using wearable sensors suitable for continuous monitoring at construction sites. Initially, we evaluated various wearable sensors, machine learning models, and segmentation methods appropriate for near-miss action detection. The results demonstrated that applying CNN to data collected from an iPhone® placed in a trouser pocket achieved near-miss action detection with an F1-score of 0.95. This suggests that our proposed detection method could effectively identify near-miss actions at construction sites. Furthermore, the use of smartphones as familiar, unobtrusive sensors integrated into daily life could facilitate widespread adoption among construction workers, potentially contributing to accident prevention in construction environments.

Subsequently, we examined the possibility of fatigue estimation using the xG-1 sports activity tracker. The results indicated that physically demanding activities, such as descending stairs and carrying loads, exhibited notably increased body sway under fatigue conditions. This suggests the potential for estimating construction workers' fatigue levels during their duties. Such fatigue estimation could enable improved site management through appropriate worker allocation, particularly for those prone to fatigue, thereby preventing accidents proactively.

Future research will focus on validating near-miss action detection and fatigue estimation capabilities using data collected from actual construction sites. Additionally, we plan to estimate near-miss action locations through GNSS positioning and correlate them with site conditions to establish the practical applicability of our detection method. Furthermore, we will assess the effectiveness of our fatigue estimation approach by comparing estimated fatigue levels with subjective fatigue assessments obtained through worker questionnaires.

**Author Contributions**

Conceptualization, Y.U., T.T., Y.Y., T.K. and R.I.; methodology, Y.U., T.T., T.K. and R.I.; validation, Y.U., T.T., Y.Y., T.K. and R.I.; formal analysis, Y.U., T.T., Y.Y., T.K and R.I.; investigation, T.K.; resources, R.I.; data curation, T.K.; writing—original draft preparation, T.K.; writing—review and editing, Y.U., T.T., Y.Y., T.K. and R.I.; project administration, R.I.; All authors have read and agreed to the published version of the manuscript.

**Funding**

This research received no external funding.

**Institutional Review Board Statement**

The study was conducted according to the Declaration of Helsinki.

**Informed Consent Statement**

Informed consent was obtained from all subjects involved in the study.

**Acknowledgments**

We would like to express our gratitude to xSENSING Co., Ltd., for providing valuable insights into the data characteristics of wearable sports sensors during the execution of this study.

**Conflicts of Interest**

The authors declare no conflicts of interest.

**References**

Akagawa, H., Kasai, Y., Iizuka, K., Yamada, S. and Morikawa, N. (2020). Study on Heart Rate Characteristics of Construction Workers Under Hot Conditions. *Report of Obayashi Corporation Technical Research Institute*, *84*(1). (in Japanese)

Bao, L. and Intille, S. S. (2004). Activity Recognition from User-Annotated Acceleration Data. *Lecture Notes in Computer Science*, 3001, 1-17.

Breiman, L. (2001). Random Forests. *Machine Learning*, *45*(1), 5-32.

Demura, S., Kitabayashi, T. and Noda, M. (2006). Measurement and Evaluation of Healthy People's Body-sway. *The Journal of Education and Health Science*, *51*(3), 223-233. (in Japanese)

Derave, W., Tombeux, N., Cottyn, J., Pannier, J. L., and De Clercq, D. (2002). Treadmill Exercise Negatively Affects Visual Contribution to Static Postural Stability. *International Journal of Sports Medicine*, *23*(1), 44-49.

Heinrich, H. W. (1931). *Industrial Accident Prevention: A Scientific Approach*, McGraw-Hill.

Higashi, H., Shigeoka, T., Itokawa, T., Kitasuka, T. and Aritsugi, M. (2011). A Consideration of Features for Fatigue Estimation by Gait Analysis Using Accelerometer. *The Special Interest Group Technical Reports of IPSJ*, 2011-MBL-57(27), 1-8. (in Japanese)

Huynh, T. and Schiele, B. (2005). Analyzing Features for Activity Recognition. *Proceedings of the 2005 Joint Conference on Smart Objects and Ambient Intelligence: Innovative Contextaware Services: Usages and Technologies (sOc-EUSAI '05)*. 159-163.

Inoue, S. (2016). Human Sensing with Wearable Sensors. *Journal of Japan Society for Fuzzy Theory and Intelligent Informatics*, *28*(6), 170-186. (in Japanese)

Ishioka, H. (2020). AI for Digitization of Construction Management: Single Camera Worker Detection, Tracking and Action Recognition in Construction Site. *Technical Research Report of Shimizu Construction Co., Ltd.*, *98*(1), 21-30. (in Japanese)

Masetic, Z. and Subasi, A. (2016). Congestive Heart Failure Detection Using Random Forest Classifier. *Computer Methods and Programs in Biomedicine*, *130*, 54-64.

Ministry of Health, Labour and Welfare. (2012). Visualization of Near-Miss Cases for Participation in Safety and Health Activities, https://safeconsortium.mhlw.go.jp/anzenproject/concour/2012/sakuhin4/images/n096_2.pdf (in Japanese)

Ministry of Health, Labour and Welfare. (2023a). Analysis of Occupational Accidents in 2023. https://www.mhlw.go.jp/content/11302000/001099504.pdf (in Japanese)

Ministry of Health, Labour and Welfare. (2023b). The 14th Occupational Safety & Health Program. https://www.mhlw.go.jp/content/11200000/001253683.pdf

Naruo, T., Yamamoto, Y., Jiang W., Sakamoto, K., Nakamura, K., Tanaka, S., Okazaki, Y. and Yamazaki, Y. (2023). "Research for Detecting Falling of Soccer Players from IMU using LSTM". *Proc. 85th National Convention of IPSJ*, 331-332. (in Japanese)

Paillard, T. (2012). Effect of General and Local Fatigue on Postural Control: A Review: *Neuroscience & Biobehavioral Reviews*, *36*(1), 162-176.

Pang, I., Okubo, Y., Sturnieks, D., Lord, S. R. and Brodie, M. A. (2019). Detection of Near Falls Using Wearable Devices: A Systematic Review. *Journal of Geriatric Physical Therapy*, *42*(1), 48-56.

Yamada, T., Masaki, H., Matsubayashi, Y., Tanaka, S., Imai, R., Naruo, T., Nakamura, K., Yamamoto, Y., Jiang, W. and Tanaka, C. (2023). Development of Sensing Unit "xG-1" for Visualizing Team Plays. *Journal of Digital Life*, *3*, 10.

Zeng, M., Nguyen, L. T., Yu, B., Mengshoel, O. J., Zhu, J., Wu, P. and Zhang, J. (2014). Convolutional Neural Networks for Human Activity Recognition Using Mobile Sensors. *Proceedings of the 6th International Conference on Mobile Computing, Applications and Services (MobiCASE)*, 197-205.