ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)

https://doi.org/10.17559/TV-20241013002055
Original scientific paper

Automated Detection of Construction Worker Inattention Using IMU Sensors and Visual Focus of Attention

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Abstract: Worker inattention is a major contributor to accidents in the construction industry, particularly falls. This study presents a novel method for automatically detecting and monitoring worker inattention in construction training simulations using Inertial Measurement Unit (IMU) sensors and Visual Focus of Attention (VFOA). The proposed system distinguishes between inattention during work tasks and movement, utilizing quaternion data from IMU sensors to infer head pose direction. A custom software program was developed to track inattention in real-time and communicate with work management systems. Validation through simulations with 20 participants demonstrated high correlations (r > 0.93) between predicted and actual measures of inattention. The system accurately detected instances of inattention during both work tasks and movement. This research provides a foundation for enhancing construction safety through automated, real-time inattention monitoring, potentially reducing fall-related accidents in construction environments.

Keywords: fall prevention; human pose; inattention monitoring; inertial measurement unit sensor; quaternion; user datagram protocol

1 INTRODUCTION

The construction industry experiences a higher rate of injuries and fatalities than other sectors due to various hazards, elevated work, and the use of heavy, cumbersome equipment. According to the number of fatal industrial accidents by private industry sector in 2022 announced by the U.S. Bureau of Labor Statistics in Fig. 1, construction had the most accidents with 1,069.

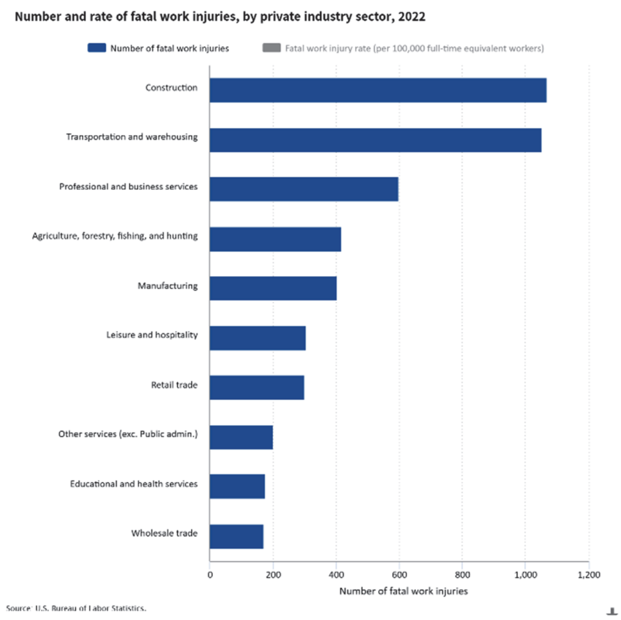
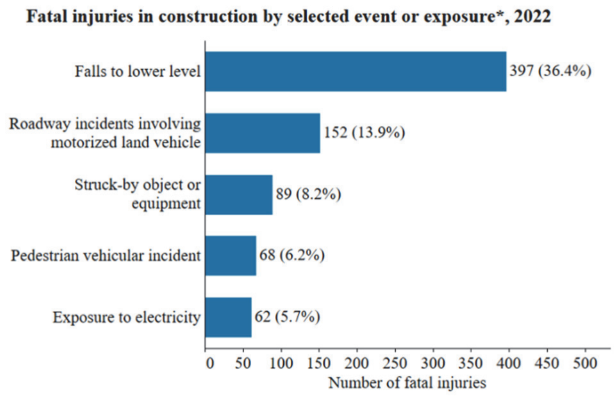


Figure 1 Number of fatal work injuries by private industry sector

In the UK, the Health and Safety Executive (HSE) reported that, out of 138 workplace fatalities between 2023 and 2024, 51 occurred in construction, representing over a third of all cases. Falls are a leading cause of fatal injuries on construction sites, as shown in Fig. 2, based on the 2022 U.S. Bureau of Labor Statistics report published in 2024.

The construction sector is particularly vulnerable to such accidents, with falls posing significant danger on construction sites. In the United States, in 2020, 351 of the 1,008 construction industry fatalities were due to falls [1].

In Korea, falls similarly represent a major cause of fatalities across accident types; as shown in Tab. 1, falls accounted for over half of all construction-related deaths, at 54.2% in 2021 and 52.8% in 2022 [2].



Source: U.S. Bureau of Labor Statistics, 2022 Census of Fatal Occupational Injuries. Calculations by the CPWR Data Center.
*Event and exposures limited to two-digit OIICS codes.

Figure 2 Fatal injuries in construction by selected event or exposure

Table 1 Trends in accident fatalities by major accident types

Accident Type	2021		2022	
	Number of fatalities	Fatality rate / %	Number of fatalities	Fatality rate / %
Falling	147	54.2	115	52.8
Crushing	56	20.7	47	21.6
Hitting objects	25	9.2	21	9.6
Burns	0	0	0	0
Crush injuries	13	4.8	15	6.9
Collision	8	3	4	1.8
Traffic accident	4	1.5	1	0.5
Electrocution	3	1.1	3	1.4
Asphyxiation	1	0.4	1	0.5
Other	14	5.2	11	5

Source : Korea MOLIT, 2023,CSI Data.

Given that two-thirds of fall accidents result in death, the risk of falls is a significant global issue, posing a constant threat to the safety and lives of workers. Visser et al. (2012) highlighted that distracted workers operating cranes can lead to serious collision-related injuries, delays in work progress, and damage to other plant, equipment, and personnel on site [3]. According to the analysis of domestic fall accidents posted on the Construction Safety Management Integrated Information Network, 35 out of 80 fall accidents (more than 40%) were caused by worker negligence. As such, one of the main causes of fall accidents is momentary inattention of workers, which can lead to fatal consequences. Therefore, inattention detection is essential to effectively prevent fall accidents. Inattention detection can help reduce cases of worker negligence whenever it occurs, which can ultimately affect the reduction of falls.

OSHA has taken steps to mitigate this risk by revising Washington State's vertical fall prevention standards, overhauling OSHA's fall prevention regulations, updating scaffolding safety standards, and revising steel construction safety standards. These actions are part of broader efforts to establish and revise industrial safety rules and standards. According to Xinyu Huang and Jimmie Hinze (2003), comprehensive fall prevention training is essential, arguing that effective worker training can significantly reduce unsafe behaviors [4]. However, Albert et al. (2014) noted that risk recognition largely depends on the individual worker's experience and personality, suggesting a need for an objective measure to evaluate subjective risk assessments [5].

Objectively assessing and alerting workers to inattentive situations could help reduce fall-related accidents. To address this, numerous studies have been conducted on detecting inattentive situations. Methods include monitoring personal protective equipment usage through real-time object detection algorithms [6], using sensors to alert workers and detect physical anomalies [7], and implementing computer vision-based automated systems that identify worker positions to detect potential hazards [8].

This paper explores quantitative methods to calculate and communicate risk, focusing on inattention, a major cause of falls. While quantitatively measuring inattention is challenging, indicators such as changes in head direction could serve as objective measures. Visual Focus of Attention (VFOA), defined as the direction of the head in space, has been identified as a reliable indicator of a person's attentiveness. Pang & Cho (2015) demonstrated that VFOA can effectively indicate actual inattention by correlating eye movement with head direction [9, 10]. The study confirmed the utility of VFOA in understanding the relationship between eye movement and head direction [9, 11, 12]. The introduction of IoT technology at construction sites aims to preemptively detect situations that may lead to accidents and prevent worker negligence [13-16]. Traditional sensors, often cumbersome and expensive, posed challenges, but the advent of inexpensive and wearable Inertial Measurement Unit (IMU) sensors offers a practical solution. These sensors allow workers to operate without hindrance and provide alerts in environments where cameras are infeasible.

Existing studies have largely focused on fall prevention strategies through structural safety measures, adherence to safety guidelines, and worker training. However, a notable gap remains in the objective and real-time detection of worker inattention an immediate cause of many fall incidents. Traditional approaches often emphasize compliance and awareness but lack effective tools to detect and address inattention as it occurs. Current solutions are also limited by their reliance on subjective self-assessment or on bulky, impractical equipment that can hinder movement and fail to provide timely alerts. Wearable monitoring technology is in its infancy in the construction industry, but it has great potential to enable personalized safety monitoring [17].

This study seeks to address this research gap by developing an unobtrusive system capable of objectively monitoring inattention through Visual Focus of Attention (VFOA), measured via IMU sensors. By automatically detecting inattention in real time, this approach aims to offer a proactive solution to prevent falls by immediately alerting workers to potential risks arising from inattentive behaviors.

Therefore, this paper proposes a method to automatically detect and monitor worker inattention by inferring VFOA based on the direction of the worker's head using an IMU sensor. A program was developed to test the methodology's applicability in real-world settings. Section 2 reviews existing studies on detection systems for fall causes and inattention, including automated detection of worker risk factors. Section 3 outlines the methodology employed by the automatic inattention detection system developed in this study. Section 4 presents the testing results of the proposed method. The study concludes with Section 5, which summarizes the findings and suggests directions for future research.

2 RELATED WORKS

2.1 Visual Focus of Attention

VFOA can serve as a metric for assessing safety by detecting interactions between humans and computers. When observing an object, both the eyes and head typically rotate in the same direction. The rationale for employing head direction as an indicator of attention focus is its non-invasive measurement ease compared to pupil tracking. Technologies that infer gaze direction from head orientation are applied in various fields, such as advertising, driver safety enhancement, and construction site accident prevention [18]. Research on driver inattention, in particular, has made significant advances in studying VFOA. Lee utilized a camera to monitor 18 real-time gaze areas based on the driver's head direction, aiming to detect inattention and suggested a collision warning system [19]. Moreover, Stiefelhagen (2002) developed a technique for tracking meeting participants' visual attention by estimating head direction from facial images [9], achieving a 73% accuracy rate in identifying the VFOA across multiple evaluation sessions. Liu et al. (2008) introduced a vision-based method to estimate drivers' head posture by calculating the head rotation between two consecutive frames [11]. Soumitry and Teizer (2012) presented an automated method to approximate equipment operators' rough head orientation using distance cameras, aiming to mitigate construction accident risks associated with equipment blind spots [20]. Hasanzadeh et al. (2017) identified a correlation between eye movement metrics and attention [21]. Debnath et al. (2017) utilized gaze and head movement direction to detect and analyze VFOA [22], while Afroze et al. (2022) explored deep learning techniques for multi-object scenarios [23]. Chilukamari (2017) developed computational models based on focal regions and human visual system sensitivity [24]. Cai et al. (2021) designed a CNN-based multitask learning framework to automatically estimate worker VFOA using low-resolution construction images [25]. Furthermore, studies such as Francis & Suresh (2017) applied VFOA in various domains, including neurological assessment [26]. These methods typically involve face detection, head pose classification, and object localization to estimate focus of attention. These studies demonstrate the extensive use of head orientation in detecting inattention through VFOA.

2.2 Inertial Measurement Unit Sensor

Research on wearable sensors for analyzing human motion and quantifying movement has been vigorous. In recent years, numerous studies have focused on motion capture systems utilizing IMU sensors [27-29]. Unlike camera-based methods, IMU sensors offer the advantage of being easily attachable to various body parts due to their lightweight nature, facilitating the collection of worker motion data in diverse environments, whether indoors or outdoors. These sensors, when positioned over key joints such as the knee, hip, elbow, toe, shoulder, neck, and ankle, allow for highly accurate and precise clinical analyses of walking patterns [32]. IMU-based systems are particularly valuable for evaluating limb movements and gait in both the upper and lower body [33]. In the construction industry, efforts to detect worker inattention through IMU sensors are ongoing. Choo developed a threshold-based model for assessing workers at heights by monitoring safety hook fastening using a barometer and IMU sensor, as well as a model for detecting hook loosening based on acceleration signals from the belt and hook, achieving accuracies of 96% and 86%, respectively [34]. Lee employed a pressure sensor insole to identify gait pattern disruptions and safety risks based on deviations in Ground Reaction Force (GRF) [35]. Preliminary tests using IMU and pressure sensors to assess workers' balance abilities succeeded in identifying individuals who lost balance, though not specifically fall-like behaviours. Additionally, the semi-supervised algorithm One-Class Support Vector Machine (OSSVM) has been applied to detect near-miss falls by attaching an IMU sensor to the sacrum, near the body's center of gravity [36]. Fang has utilized hierarchical threshold-based algorithms, including Support Vector Machines (SVMs) and vertical acceleration (VA), to detect fall indicators by attaching IMU sensors to belts and vests [37]. Fang & Cho developed an algorithm to estimate a worker's VFOA by measuring head direction and rotation speed using IMU sensors [10].

As demonstrated in the studies mentioned, wearing IMU sensors proves effective in capturing human motion, making them suitable for application in various sports and activities involving significant movement [38]. IMUs are particularly useful for gait analysis and sports performance assessment, and have advantages over other measurement systems [39]. However, further research is needed to standardize metrics and sensor placement for more generalizable results [40, 41].

The ease of placement on body parts, combined with their non-invasiveness and independence from lighting conditions, enables their use in detecting fall indicators in diverse work environments, both indoors and outdoors. A survey by Zhao, J., Obonyo, E., & G. Bilén, S. (2021) highlighted significantly lower ratings of physical and mental discomfort among users, as well as minimal impact on work performance, underscoring the minimal interference of IMU sensors with work activities [42]. This evidence supports the utility of IMU sensors as a valuable tool for measuring worker movements at construction sites without significantly impeding work processes.

2.3 Accident Risk Detection System

The advancement of technology in detecting accident risks has significantly benefited from the integration of computer vision and artificial intelligence. Research has predominantly focused on two main approaches: employing camera-based computer vision technology [43-48] and sensor-based methods [35-37, 44, 49]. Real-time vision-based systems have been created for worker localization and hazard detection [50]. Integration of computer vision and Building Information Modeling has been explored for automatic fall hazard detection [51]. Mixed reality-based visual warning systems have been designed to provide real-time safety information to workers [52].

With the evolution of Convolutional Neural Networks (CNNs) and machine learning, computer vision has enabled the estimation of workers' postures and the detection of objects, identifying potential fall hazards due to unstable postures [43-45] and verifying the use of Personal Protective Equipment (PPE) [46-48]. However, camera-based techniques are susceptible to motion blur, occlusions, varying lighting conditions [46], information bias due to camera positioning [43], and errors from camera shake in scenarios such as power pole or bucket work [53].

Sensor-based methodologies have introduced innovations such as alarm systems utilizing Ultra-wide Band (UWB) technology to warn of proximity to predefined hazardous zones [54] and mobile devices that differentiate between inanimate objects and humans, offering 24-hour monitoring in risk areas with time-sensing capabilities [55]. The development of diverse sensor technologies has spurred research into risk detection systems designed to prevent access to hazardous areas based on the user's location and the work environment.

Research on fall prevention has also diversified. While initial studies focused on devices such as airbags and helmets to detect and mitigate fall impact, recent attention has shifted towards identifying precursors to falls [56, 57], primarily within the realm of computer vision. For instance, Han employed a Kinect sensor, equipped with a 3D camera, infrared, and depth sensors, to map 13 joint data into 3D space, using Dynamic Time Warping (DTW) for detecting unsafe movements during ladder climbing, achieving high recall (90.9%) and precision (57.9%) rates [58]. Zhang utilized a 3D pose estimation model to identify fall indicators between steady and fallen states, achieving an 85.02% accuracy rate, alongside findings that frequent posture adjustments increase fall likelihood from elevated surfaces [43]. Daun applied the OpenPose model to gather posture and duration features from real-time image-based key point coordinates of the operator's posture, employing

Gaussian and Gaussian mixture models for posture instability detection, forming a two-stage safety monitoring framework with an accuracy of 84.38% and a precision of 81.25% [44]. Another study proposed a hybrid model combining CNN and Long Short-Term Memory (LSTM) networks to automatically classify unsafe behaviors [45]. Additionally, computer vision research has been conducted to ensure workers at heights wear PPE, separate from fall prevention [46-48]. Nonetheless, the susceptibility of computer vision technologies to issues like lighting, occlusion, and camera placement bias necessitates a fall detection system that can overcome these challenges.

3 PROPOSED METHOD

This study introduces a novel approach to fall prevention through the use of IMU sensors. An IMU sensor combines accelerometers, gyroscopes, and magnetometers; the accelerometer captures acceleration and gravitational force data, while the gyroscope measures body part rotation using Euler angles or quaternions based on angular velocity. This allows for precise monitoring of body movement and rotation. IMU sensors, employing a contact-based method, offer several advantages over camera-based systems. They are not affected by motion blur or occlusion, can be easily attached to body parts due to their lightweight nature, and operate independently of lighting conditions. These features enable the effective collection of worker motion data across various indoor and outdoor environments [59, 60], crucial for analyzing workers' postures and positions accurately.

Building on this technology, the study developed a software program that leverages data from IMU sensors to automatically identify workers' inattentive behaviors. The program is integrated with a work management system via UDP (User Datagram Protocol) for network communication, facilitating real-time analysis of IMU sensor data. An algorithm capable of recognizing inattention instantaneously analyzes the data, with results automatically relayed to the work management system. This allows managers to make informed decisions promptly and provides immediate feedback to workers on their inattention. Designed as an effective tool for fall prevention, the program's efficacy in detecting inattentive behavior during work and movement was evaluated, utilizing VFOA as a reliable indicator of inattention. A schematic of the methodology of this paper is presented in Fig. 3.

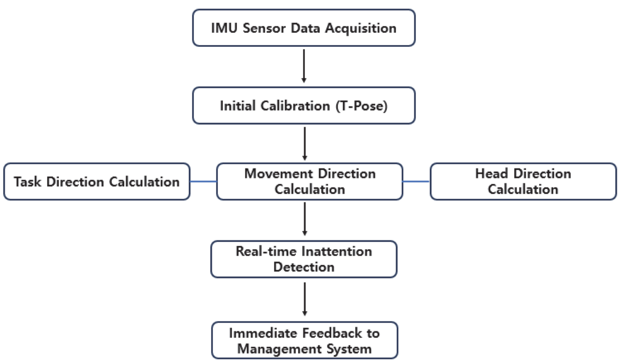


Figure 3 A schematic flowchart of the methodology of this paper

3.1 Acquisition of IMU Sensor Data

This research utilized SigmaMotion's IMU sensors, provided by the ipop company, to collect data on workers' positions and movements [61]. As illustrated in Fig. 4, sensors were affixed to 15 key body joints, with each sensor dedicated to capturing motion data for its respective location. This data encompasses quaternion rotations and relative position coordinates along the x, y, and z axes. The IMU sensors dispatch motion data packets utilizing the UDP (User Datagram Protocol), which are then transmitted to a CS observer program developed on the Unity engine. This setup enables the visualization of 3D movements and the monitoring of user motion, as demonstrated in Fig. 5. The real-time data acquisition was enabled by parsing code crafted in Python, serving as input for the aforementioned program. The structure of the gathered motion data is organized into 15 rows and 7 columns, with the 15 rows corresponding to the major body parts where the sensors are mounted, adhering to the index order relayed by the IMU sensors. The seven columns contain three-dimensional position coordinates and four-dimensional quaternion data. Fig. 6 visualizes the outcomes, depicting the 15 three-dimensional position coordinates derived from the motion data, utilizing matplotlib for visualization.

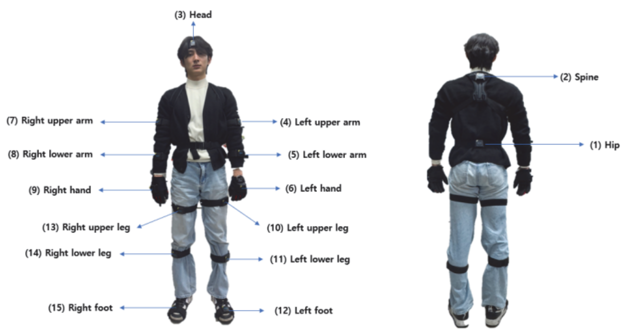


Figure 4 A worker attaching an IMU sensor to major joints of the body: The major joints are as follows in order of index of sensor data(1) hip, (2) spine, (3) head, (4) left upper arm, (5) left lower arm (6) left hand, (7) right upper arm, (8) right lower arm, (9)) right hand, (10) left upper leg, (11) left lower leg, (12) left foot, (13) right upper leg, (14) right lower leg, (15) right foot

Figure 5 Appearance of a 3D avatar in the Unity engine program mapped based on sensor data of 15 major joint points

Motion data was calibrated by having workers wearing sensors perform a T-pose, as depicted in Fig. 7. Although IMU sensors demonstrate minimal error in short durations, they are prone to accumulating errors over extended periods [62]. In this study, workers were instructed to assume a T-pose at the beginning of each task, initiated by start and end signals from the work management system during worker simulations. This calibration process effectively minimized the impact of error accumulation on the task simulation results.

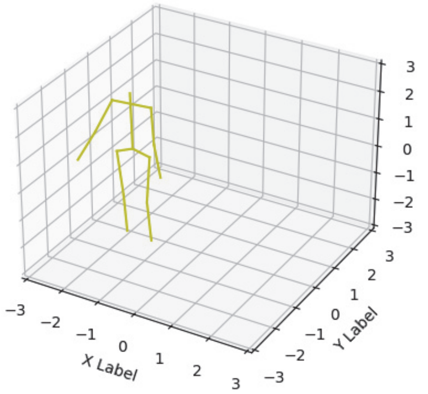


Figure 6 Visualization of 3D position coordinates of motion data

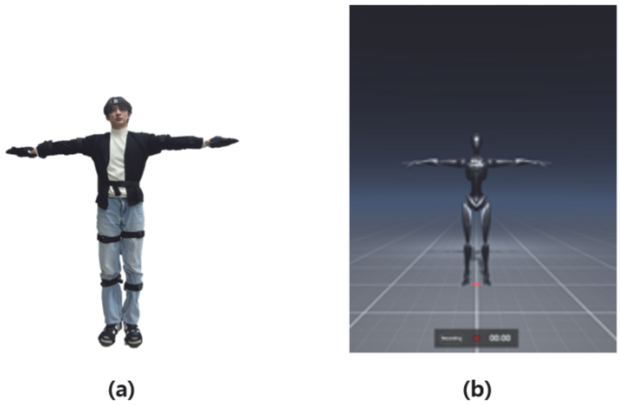


Figure 7 (a) T-pose of the worker wearing the sensor, (b) T-pose of the 3D character in the Unity program

3.2 3D Coordinate-Based Vector Extraction for Inattention Detection

Fall accidents, even from low heights, commonly result in severe injuries and significant costs. Consequently, developing a system that analyzes the causes of fall accidents and mitigates the risk by reducing the likelihood of falls is crucial. Inattention is identified as a primary factor contributing to falls [63]. This research introduces a method utilizing IMU sensors to evaluate workers' inattention, distinguishing between inattention during work and movement.

Inattention during work is gauged by comparing the angle between the task direction and the worker's head pose direction. The task direction is defined by a vector from the sensor on the worker's head to the central point of the sensors on both hands, indicating the task's location. This is determined by the vector between the position coordinates at the 2nd index and the midpoint of the coordinates at the 5th and 8th indexes from the IMU sensor motion data. The worker's head pose direction, another measure of inattention, denotes the vector direction where the worker is looking attentively. An angle close to 0 degrees between these vectors signifies that the worker's gaze is focused on the task, whereas a larger angle indicates a deviation from the task. This methodology ensures that attentive observation of the task area by workers, as reflected by the angle between the worker's head pose direction and the task direction approaching 0 degrees, is based on IMU sensor data.

Inattention during movement is assessed by the angle between the movement direction and the worker's head pose direction. The movement direction is calculated using the position coordinates from the IMU sensor to determine the center of mass, incorporating the relative mass of body parts as specified by Eq. (1). This calculation considers the relative mass, allocating weights to each body part to reflect body balance and minimize the influence of movements from lighter parts, like the arms, on the center of mass movement [64]. The three-dimensional position coordinates from IMU sensors on 15 body parts, sampled at approximately 30 Hz, are analyzed using a sliding window method with a 1-second window length. This method recalculates every second, averaging the center of mass within the window and establishing the direction vector by comparing the current window's average center of mass to the previous one. An angle nearing 0 degrees between these vectors indicates attentive movement, whereas a larger angle suggests inattention.

$$CM = \sum_{i}^{n} \left(Weight_i \cdot Keypoint_i \right) / n \tag{1}$$

In Eq. (1), n represents the number of body parts measured by the IMU sensor. $Weight_i$ denotes the relative mass of the ith body part, and $Keypoint_i$ refers to the three-dimensional position coordinates of the IMU sensor attached to the ith body part. By assigning weights to each body part based on their relative mass, the equation allows for the calculation of a centor of mass that reflects the worker`s actual physical balance. This provides more precise results than calculating the center of gravity based only on the position coordinates of the sensor, and since it can consider the balance of the body, it can minimize the impact of posture changes or position shifts on the center of gravity by assigning relatively lower weights to body parts that are easy to move, such as arms and legs. This allows the precise center of gravity position of the worker to be calculated.

3.3 Extracting Worker's Head Direction Based on Quaternion Information

In this study, the head pose direction was utilized as a critical indicator for measuring workers' inattention. This was calculated based on quaternion rotation information from motion data transmitted by the IMU sensor attached to the head, specifically from the 2nd index. Quaternions are excellent for expressing rotations, offering great utility in representing rotations within four-dimensional space and being free from the gimbal lock problem, which is why they are widely used in various fields for calculating orientation. To handle the quaternion rotation information obtained from the IMU sensor on the head, the quaternion was first transformed into a rotation object. This transformed rotation object was used to rotate the unit vector of the head direction acquired during the T-pose, which is taken for motion data calibration. The rotation change of the actual head direction was calculated based on the rotated vector reflecting the rotation information represented by the quaternion, from which the head pose direction was extracted. Fig. 8 visualizes the result of the worker's appearance during an actual work simulation and the head pose direction extracted in three-dimensional coordinates.

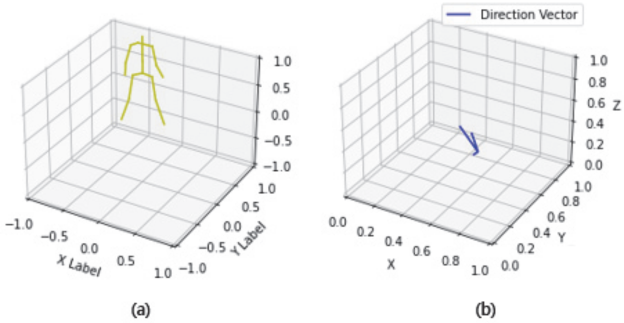


Figure 8 (a) The appearance of the worker in the actual work simulation, (b) The result of visualizing the worker's head pose direction in three-dimensional space

3.4 Calculate Work Inattention Direction and Work Movement Inattention Direction

This study proposes a method for detecting workers' inattention using IMU sensors. This method primarily relies on motion data to calculate the task direction vector, movement direction vector, and head pose direction. Utilizing these, inattention during work and movement was detected. As shown in Fig. 9, inattention during work is determined by calculating the angle between the working direction and the direction of the worker's head. If this angle exceeds a specific threshold angle (θ) for 3 seconds or more, it is considered as an inattentive state during work. In addition, to detect inattention during movement, the angle between the moving direction and the head direction is calculated every second. If the calculated angle exceeds the threshold angle for 3 seconds or more, as shown in Fig. 10, it is determined as an inattentive state during movement. In this paper, the threshold angle is empirically set to 30 degrees. The movement of a worker was defined as a situation where the distance moved by the center of mass exceeds a threshold within 1 second, and the movement inattention direction vector was calculated only when the distance was greater than the threshold. The angles for inattention during work and movement were calculated as per Eq. (2), with larger angles indicating a closer state to inattention. The program developed in this study automatically detects the degree of workers' inattention by real-time monitoring of these angles.

Inattention during work and movement is calculated using Eq. (2), where w represents the direction vector of the worker performing a task and the direction vector of the worker moving, respectively, and the head pose vector indicates the direction of the worker`s head. The calculated inattention angle (θ) is converted to degrees by dividing by π and utilized for the automatic detection of inattention.

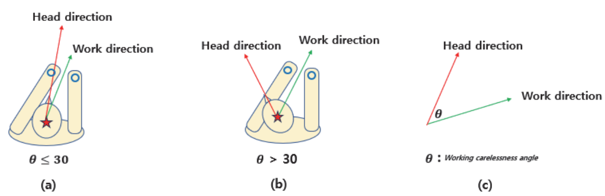


Figure 9 (a) Example of worker's normal working condition, (b) Example of worker's inattention during work, (c) Angle of inattention during work

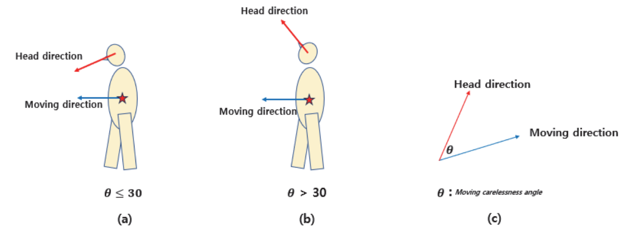


Figure 10 (a) Example of worker's normal movement, (b) Example of worker's inattention during movement, (c) Angle of inattention during movement

$$\theta = \cos^{-1}\left(\frac{head\ pose\,vector \cdot w}{head\ pose\,vector \cdot w}\right) \tag{2}$$

4 RESULTS

We verified the method for automatically detecting inattention proposed in this study by performing task simulations with 20 workers equipped with IMU sensors. Considering that the IMU sensor requires considerable time and precision for equipment wearing and setup in the process of collecting data from each participant, we set the number of participants to 20. The verification consisted of four stages. 1) We evaluated the accuracy of the angle between the worker's working direction and head direction estimated in real time by the program. 2) We evaluated the accuracy of the angle between the worker's moving direction and head direction. Through these steps, we verified how accurately the program can track the changes in the inattention angle of real workers. In addition, 3) a list of potential inattention behaviors during task performance was defined (For example, when a worker is talking freely with another worker, talking on the phone, using a smartphone, observing the surroundings, staring blankly, looking for necessary tools, adjusting safety equipment, etc.). The workers were asked to perform inattention behaviors randomly from this list during the task. The performance of inattention detection was evaluated by comparing the number of inattention behaviors requested during the task simulation with the number estimated by the program. Finally, 4) the number of inattention behaviors requested during movement was compared with the number estimated by the program. The simulation for verification utilized the program developed in this study.

4.1 Real-Time Inattention Angle Assessment

To evaluate the performance of the program developed in this study, the angle between the worker's head direction and task direction (inattention angle during work) estimated using IMU sensors was compared with the actual angle measured using a goniometer (ground truth). Fig. 11 presents a time-series graph showing the changes in the inattention angle during work over time, with the x-axis representing the data index and the y-axis representing the inattention angle during work. Similarly, an analysis comparing the program's prediction results with actual measurements was conducted for the angle between the worker's head direction and movement direction (inattention angle during movement). The inattention angle during movement is predicted at 1-second intervals, and these results are displayed in a time-series graph in Fig. 12, where the x-axis represents time (seconds) and the y-axis indicates the inattention angle during movement.

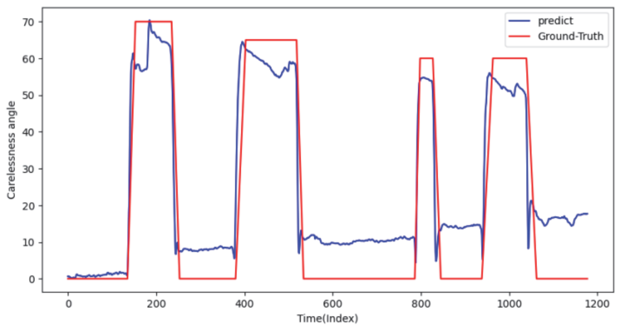


Figure 11 The angle of inattention during the task estimated by the program and the angle of inattention during the actual task using the joint protractor

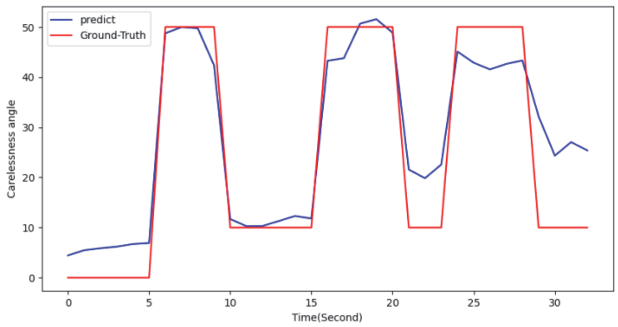


Figure 12 The program-estimated movement inattention angle and the actual movement inattention angle using the joint protractor

Analysis of the developed program's predictions revealed that the correlation coefficient between predicted and actual angles for inattention during work averaged 0.9397, with a mean absolute error (MAE) of 9.7 degrees. For inattention during movement, the correlation coefficient was 0.9478, with an MAE of 6.2 degrees. Pearson correlation tests showed p-values below 0.001 for both work and movement, confirming statistical significance. These results indicate that the predicted angles for inattention based on the proposed method are strongly correlated with actual angles, ensuring high reliability. Furthermore, the MAE results validate the program's capability to accurately estimate real-time angles. The detailed results are summarized in Tab. 2.

Table 2 Performance metrics summary

	Correlation (p-value)	MAE
Work inattention	0.9397 (< 0.001)	9.7
Movement inattention	0.9478 ($6.72e^{-17}$)	6.2

4.2 Assessing the Level of Inattention During Work

This study evaluated the detection rates of careless behavior during tasks and movement separately. To evaluate careless behavior during tasks, workers were instructed to engage in random careless behaviors during a task simulation. The detection rate of careless behavior during tasks was determined by comparing the number of careless events identified by the program after the simulation with the total number of careless behaviors that the worker was asked to perform. Additionally, the evaluation of careless behavior during movement included having workers perform randomly selected careless behaviors while moving throughout the task simulation. Workers moved along a predefined direction vector, and the program tallied the number of inattention events during movement at the end of the simulation and compared this number to the number of inattention behaviors initially requested. For example, in the scenario shown in Fig. 11, workers were asked to exhibit three inattention behaviors during work, and the program successfully identified three instances of inattention, indicating persistent inattention lasting more than three seconds. Similarly, in the scenario shown in Fig. 12, three instances of inattention during movement were requested, and the program accurately detected all three instances, calculating the inattention angle once per second during movement. The results of the task simulation analysis with 20 participants confirmed high detection performance, as the program's inattention detection predictions accurately matched the number of requested behaviors. These results confirm that there were no false positives or false negatives that missed inattention when there was no sensor error, as the sensors were periodically calibrated for each simulation.

5 DISCUSSION

This study presents the potential to enhance safety on construction sites by detecting worker inattention using IMU sensors and VFOA and providing real-time feedback. The system can contribute to accident prevention by issuing immediate alerts when a worker's risk of falls increases due to inattention. However, several challenges are anticipated when applying these findings from a controlled simulation environment to actual construction sites. First, IMU sensors tend to accumulate errors over time, making it difficult to maintain accurate data during continuous tasks. Periodic calibration movements, such as a T-pose, are required to adjust the sensor data. However, these calibration procedures may hinder task efficiency and require worker cooperation. Future research aims to improve field applicability by introducing an automatic calibration algorithm that adjusts sensor data in real time without worker intervention. Second, unlike simulations, real construction environments are subject to irregular external factors, sudden movements, and unexpected impacts, which may reduce sensor data reliability. To address this, a deep learning-based anomaly detection model could be implemented to detect and correct external factors in real time by learning normal patterns. This approach minimizes noise caused by external factors, thereby increasing data accuracy and allowing the model to maintain consistent performance even in unpredictable environments.

Additionally, the IMU sensor-based inattention monitoring system only tracks joint movements without recording location data or movement paths, significantly reducing privacy concerns. It does not collect facial, identity, or precise location data, offering advantages for privacy protection. In conclusion, this IMU sensor-based real-time inattention monitoring system can effectively complement traditional safety management methods, which rely on pre-task training and supervision during tasks. Without the need for cameras, the system helps improve safety without infringing on worker privacy and can naturally integrate with existing safety management systems to enhance worker safety. This is expected to reduce interruptions due to accidents, decrease medical costs, and positively impact productivity.

Acknowledgements

This work was supported by the NRF (National Research Foundation) of Korea, funded by the Korean government (Ministry of Science and ICT) (RS-2024-00340935).

6 CONCLUSION

This study introduces an innovative approach to automatically detect and monitor worker inattention in a construction training simulation using IMU sensors and VFOA. The developed system demonstrates high accuracy in identifying inattention during work tasks and movements, and there is a strong correlation between predicted and actual inattention measurements. This technology has the potential to improve safety practices in the construction industry, especially in fall prevention, by providing real-time feedback on worker inattention. Future research will focus on implementing and validating this system in a real construction environment, and exploring ways to integrate it with existing safety protocols, and will move forward with research that addresses the limitations of real-world applications.

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