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A feasibility study of using smartphone built-in accelerometers to detect fall portents

Ren-Jye Dzeng *, Yi-Cho Fang, I-Chung Chen

Department of Civil Engineering, National Chiao Tung University, 1001 Ta-Hsieu Rd, Hsinchu, Taiwan

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ABSTRACT

Fall accidents contribute to nearly half of all fatalities in the construction industry in Taiwan. Detecting fall portents using a smartphone, which many people carry daily, may help reduce fall accidents if the accuracy is acceptable. We designed two experiments with three algorithms to evaluate how well a smartphone can detect both falls and fall portents in a tiling operation scenario. The experiments show that work-related motions barely affected the detection of falls, and the result had a sensitivity and specificity of 100% and 96.1%, respectively. However, for detecting portents, the work-related motions had quite a large impact on the gyroscope-based algorithm, which demonstrated an accuracy rate of only 4.3%, but had only limited impact on the accelerometer-based algorithm, which still show acceptable accuracy rates of 73.5% and 88.5%. We conclude that using a smartphone to detect falls and portents in a construction site is feasible.

1. Introduction

1.1. Fall accidents in the construction industry

Fall accidents in the construction industry have been studied and identified as a common hazard and the leading cause of fatalities for several decades [1–7]. This problem is severe and common in many countries. The Council of Labor Affairs (CLA), the highest administrative office responsible for labor affairs and safety in Taiwan, reported that falls contributed to approximately 49.62% (930 of 1874) of construction work-related fatalities from 2000 to 2011 [8]. The U.S. Bureau of Labor Statistics reported that 33.45% of fatalities (4151 of 12,409) were related to falling from high elevations in the U.S. construction industry from 2000 to 2011 [9].

Falls from high elevations cause the highest number of fatalities in the European construction industry, accounting for 52% of all accidents [10]. Approximately 40% of fatal accidents are caused by falls in the Japanese construction industry [11]. Falls from high elevations also represent the largest share of work-related fatalities (181 of 606) in the Korean construction industry [12]. Falls were the most frequently occurring construction accidents resulting in fatalities or severe injuries. Furthermore, fall accidents accounted for the largest percentage of all recorded accidents, approximately 52%, and are often associated with workers on roofs, scaffolds, ladders, and floors with openings [13].

1.2. Loss of balance and falls

The factors contributing to fall accidents are numerous and complicated [6,14,15]. Previous research has reported the major contributors to fall accidents, including activities, the environment, safety facilities (e.g., guardrails, screens, and safety nets), equipment (especially personal protective equipment, PPE), management (e.g., training, education, and inspection), and individual factors (mental and physical demand). Most studies have focused on safety facilities and PPE (e.g., safety helmet and belt) inspection and have promoted training and education to increase safety and hazard awareness. However, minimal information is available on the physiological status of construction workers.

Due to the heavy physical requirements of construction activities, workers are liable to fatigue, distraction, drowsiness, muscle pains, and loss of balance (LOB), which may further impair performance and increase safety risk and fall accidents. Chi et al. [15] studied the causes of falls and observed that the individual factors included bodily actions, distraction, and insufficient capacities. Mao et al. [16] noted that the self-reported rates of "unsteady footsteps", "waist pain", and "dyspnea" are considerably higher in high-elevation workers than in ground-level workers, and differences were also observed between the two groups in measurements of balance function, calf circumference, and response time. Construction workers operating at high elevations experience fear, panic, and shivering, which often reduce their judgment capacity and increase the risk of falls [17].

With a growing body of evidence indicating the importance of physiological status to the safety of construction workers in addition to PPE and safety training, researchers have also reported that posture

* Corresponding author. Tel.: +886 916005996; fax: +886 35716257.
E-mail addresses: rjdzeng@mail.nctu.edu.tw (R.-J. Dzeng), ken74921@hotmail.com (Y.-C. Fang), md3240035@yahoo.com.tw (I.-C. Chen).

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stability and balance help prevent fall accidents. Thus, improving workers' balance may reduce the risk of fall accidents and injuries [1]. The ability to maintain balance and postural stability in upright postures is a critical factor for successful task performance and minimization of LOB and falls [18]. LOB or postural instability is often a contributing factor in fall accidents during construction work at high elevations, and postural sway generally increases when a healthy individual is on an elevated platform with a minimal risk of falling [19]. Indeed, falls from high elevations have received the most critical attention among the various LOB-related accidents [20]. The majority of fatal falls from scaffolding, building girders, and non-moving vehicles can be attributed to LOB [21]. The strong correlation between fall accidents and LOB demonstrated by the reviewed literature implies that the real-time monitoring and analysis of the balance conditions of workers may help identify fall portents and thus prevent falls from happening.

2. Scientific background

2.1. Fall detection algorithm

Researchers have successfully identified falls using devices such as accelerometers, and their fall detection models may be applied to this study even though they focus on falling on the ground instead of falling from elevated heights. Several researchers have used motion measurement systems, force plates, pressure-sensitive insoles, and kinematic sensors (accelerometers and gyroscopes) to detect falls [22,23]. Many studies have addressed fall detection using accelerometers [24–28]. The use of accelerometers to monitor daily activities or evaluate body kinematics has the advantages of low cost, portability, small size, and ease of operation [29].

In the detection of falls in real life or long-term monitoring, most researchers have used threshold algorithms. Bourke et al. [24] evaluated various algorithms for a waist-mounted-accelerometer-based system and concluded that using an algorithm that employs thresholds is the most suitable method. Nyan et al. [27] employed a threshold algorithm with accelerometers and gyroscopes to detect falls with an average lead time of 700 ms before an impact occurs, a sensitivity of 95.2%, and a specificity of 100%. Kangas et al. [30] used tri-axial accelerometers worn at the waist or on the head to detect falls, producing a sensitivity of 97–98% and a specificity of 100%. It should be noted that although these developments detect falls with high accuracy, they focus on predesigned falls from a still position instead of moving conditions. Moreover, they target elderly people or patients whose motions are not as dynamic as those of construction workers. As a result, the feasibility of applying these developments to construction workers is still questionable.

Several studies have begun to establish activity recognition and fall detection systems using smartphone-embedded accelerometers and gyroscopes for the elderly and patients. Ismail et al. [31] compared the abilities of 7 categories of classifier algorithms to classify human activities using a mobile phone. Fuentes et al. [32] implemented a motion recognition process using a mobile phone. Zhao et al. [33] established a smartphone-based fall detection and positioning system to provide healthcare to the elderly. Abbate et al. [34] presented a smartphone-based fall detection system that monitored the movements of patients.

2.2. On-site safety monitoring

In the construction industry, falls from high elevation often lead to fatality or serious injury. Unlike applications for the elderly or patients, in which detecting their falls helps notify their guardians, detecting falls in a construction site is much less meaningful. Thus, instead of only detecting falls, the goal of our research is to detect fall portents (i.e., behaviors preceding a fall) to predict and prevent falls. Additionally, whereas elderly persons and patients requiring fall detection systems usually have limited mobility, construction workers are usually in a state of constant motion during work, which creates signal noise, interfering with the accuracy of detection. These two factors make our research challenging and different from previous studies.

Construction sites are very complex working environments due to their dynamic nature and the concurrent involvement of numerous resources and supply components [35]. Furthermore, the characteristics of the working environment (e.g., high temperatures, large-scale jobsites, changeable workplaces, and high-motion activities) and the construction industry (e.g., many subcontractors and high labor mobility) are unfavorable for jobsite safety training and management. Traditional safety management approaches, such as education training, safety inspection, and surveillance cameras, have limitations. For example, checklists are commonly used on jobsites, but continuous checking and follow-up are abandoned after the list is checked. The detection of fall portents using surveillance cameras is also not feasible or economical due to the nature of the construction site, which features a large number of workers with different trades working in parallel over a wide area with continuous movement and a constantly changing environment.

Monitoring the movement of workers plays an important role in safety management on construction jobsites. Lee et al. [36] established a mobile safety monitoring system consisting of a mobile sensing device for detecting workers approaching hazardous areas. Park and Brilakis [37] presented a method for detecting the safety tools (e.g., vest) of construction workers in video frames. Cheng et al. [38] identified different types of worker activities (e.g., productivity, working, traveling, idling, and material handling) over time based on workers' spatial–temporal and thoracic posture data using ultra-wideband and physiological status monitoring technologies. Naticchia et al. [39] developed a real-time monitoring system to help health and safety inspectors. The system is able to log any unexpected behavior, such as moving to an unexpected area using, location-tracking technologies. Teizer and Vela [40] automated location tracking and monitoring of workforce using the proposed four types of algorithms based on video cameras.

2.3. Individual monitoring

Based on the literature review above, over half of construction occupational injuries and fatalities can be attributed to fall-related accidents. However, real-time individual safety monitoring systems are difficult to implement due to the dynamic nature of the construction site, and most fall prevention measures mainly focus on mitigating the injury after a fall instead of preventing the fall itself.

Several monitoring techniques have been proposed to improve safety or jobsite management using location-tracking technologies, such as RFID, GPS, and ultra-wideband, or pattern recognition technologies to monitor whether a worker is entering a hazardous area, wearing PPE, or moving. However, they cannot determine whether a worker is losing balance, suddenly swaying, or stepping unsteadily, which are good fall portents.

Alwasel et al. [41] helped construction workers to reduce their risk for musculoskeletal disorder by using anisotropic magnetoresistive sensors to track the angle of the upper arm relative to the trunk and to decrease the number of incidents resulting from prolonged, forceful overhead work. Similarly, predicting the physiological status of a worker based on motion monitoring and generating appropriate alerts may help workers maintain alertness and on-site safety.

Smartphones are currently gaining popularity, and built-in motion sensors have long become standard. The corresponding posture identification techniques are also well developed. Thus, individual motions can be monitored for workers who may already wear a smartphone, and fall portents can be detected without requiring them to wear additional sensors.

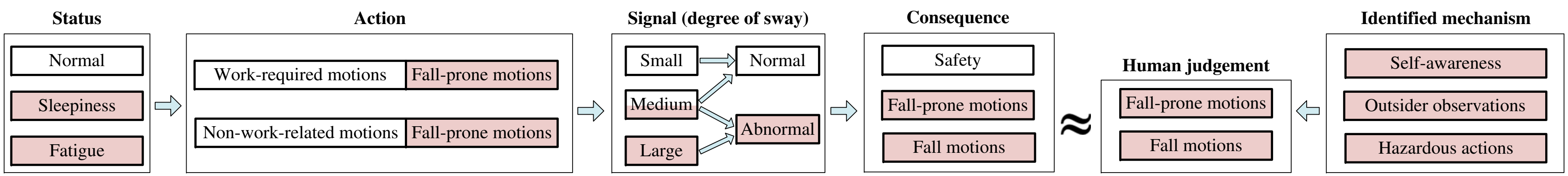

Fig. 1. Research assumption model.

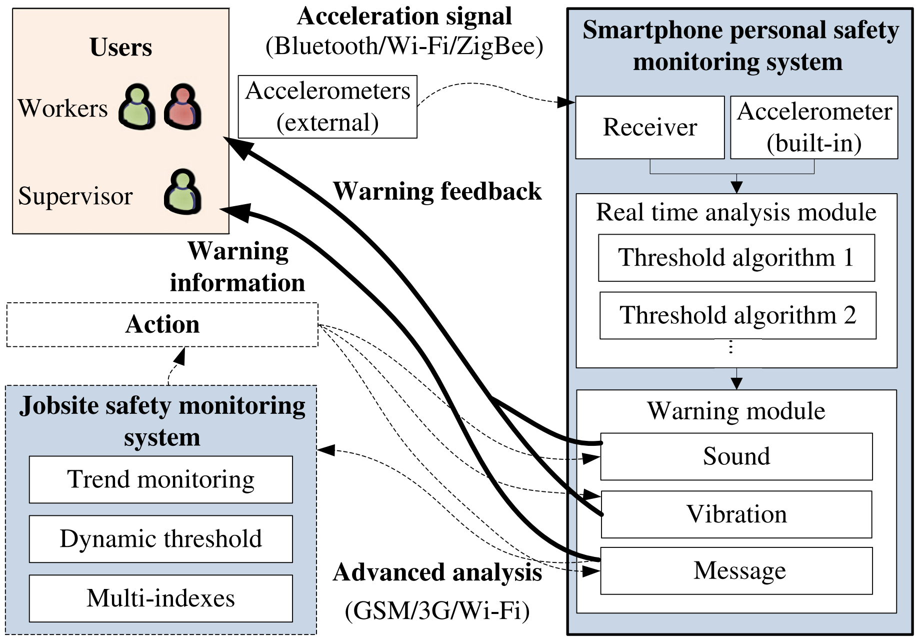

Fig. 2. System architecture and information flow.

3. Research objective

Fig. 1 depicts the factors and processes associated with fall hazards. A construction worker may be working under a given status, such as normal, fatigue, or sleepiness. At work, the worker may continuously perform motions, such as work-required motions (e.g., picking up a tile, tiling a tile, moving to a different work position) and non-work-related motions (e.g., smoking, coughing, chatting, scratching). Either type of motion may occasionally create dangerous situations (e.g., suddenly swaying, stepping unsteadily) for the worker and be considered as fall-prone motions. These motions create sways, which provide various types of signals (e.g., small, large, gradual, and abrupt) that can be detected by an accelerometer.

In the construction scenario, detecting fall portents is more meaningful than detecting falls because detecting falls cannot prevent falls. Thus, the primary objective of this study was to detect fall portents instead of falls. The difficulty of detecting portents lies in the fact that the existence of a portent may be ambiguous. However, some portents can still be identified by self-awareness, outsider observations, or actually performing hazardous actions. In this study, the portents

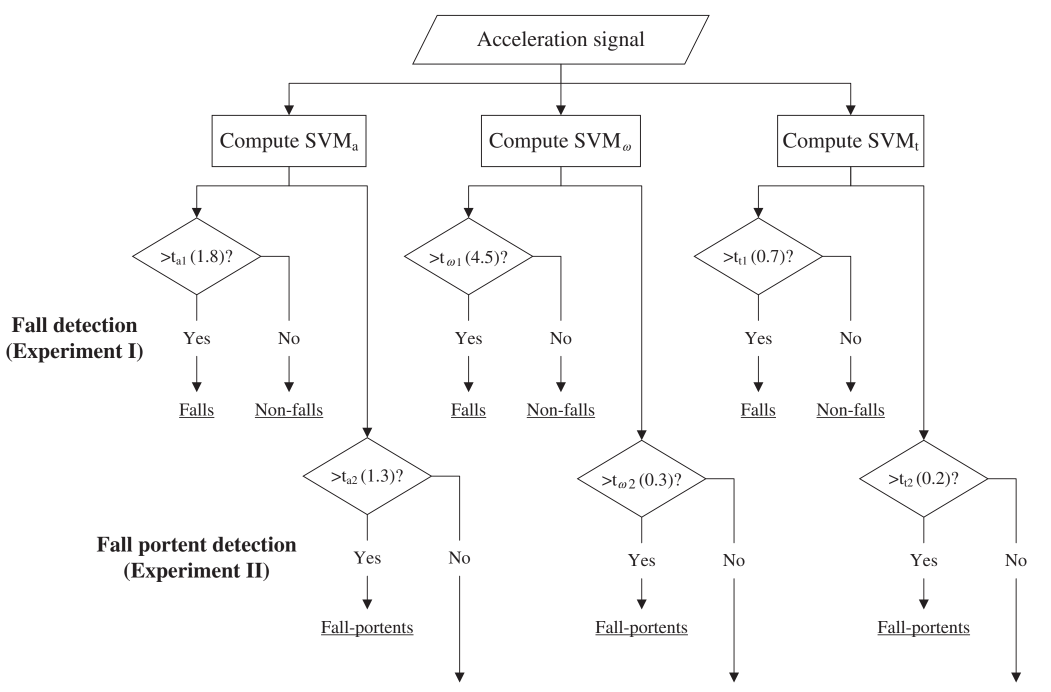

Fig. 3. Algorithm flowchart.

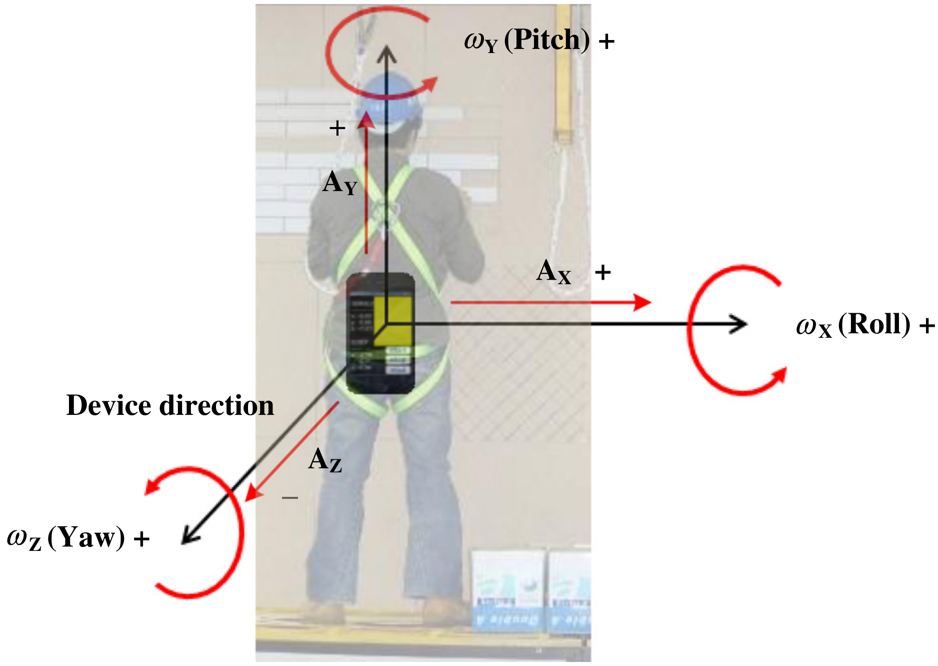

Fig. 4. Acceleration directions vs. device direction.

monitored were limited to those that can be detected by any of the aforementioned three approaches, which were used to evaluate the performance of accelerometer-based detection algorithms.

4. System model

4.1. Conceptual model

As shown by the thick-outlined rectangle in Fig. 2, this paper presents the first stage of research work towards the use scenario. This research focuses on using a smartphone (e.g., Apple's iPhone) consisting of an accelerometer, gyroscope, processor, wireless receiver, and alarm (with both sound and vibrating abilities) to detect the fall and fall portents of a construction worker. The objective is to detect potentially dangerous motions of a worker, such as sudden swaying, unsteady footsteps, and LOB, so that the worker or the supervisor may enact a prevention measure.

Fig. 2 shows the architecture of the proposed model and its information flow. The entire system consists of a personal safety monitoring system (PSMS) and jobsite safety monitoring system (JSMS). The target user of the PSMS is the worker with a task involving a fall risk, and the user of the JSMS is the supervisor or jobsite administrator. The worker is equipped with stand-alone external accelerometers or a smartphone installed with PSMS.

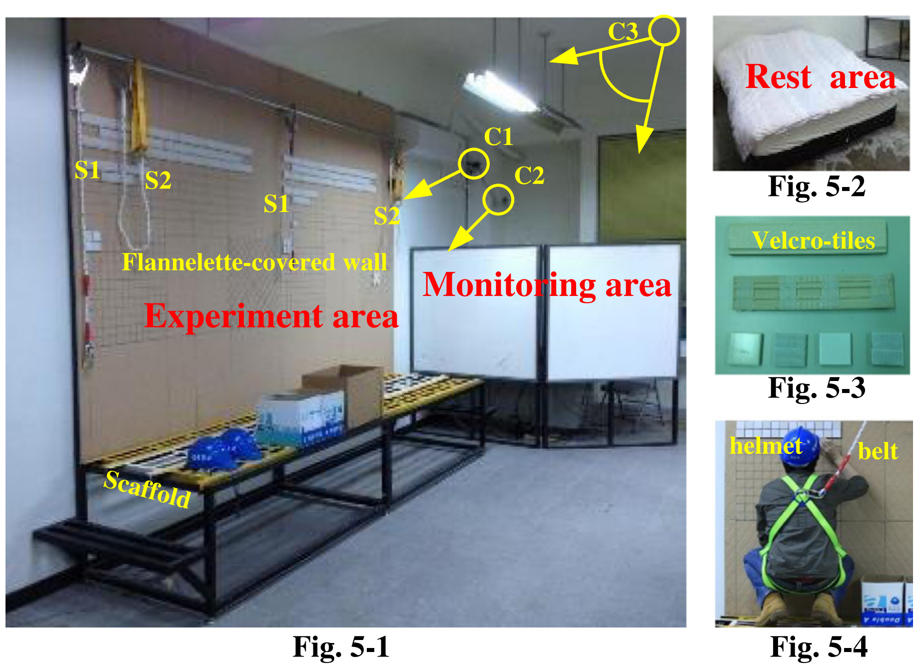

Fig. 5. Experiment environment.

The real-time analysis module continuously receives accelerometer data from more accurate exterior sensors wirelessly using Bluetooth technology and the sensors built into the smartphone, and analyzes the data based on the selected threshold algorithms. These data includes 3-axis accelerometer and gyroscope data and represent the physiological status of the worker. There are several different detection algorithms with different thresholds, as will be discussed later. The best threshold algorithm may vary depending on the type of job. When a fall or a fall portent is detected, the PSMS activates a warning signal comprising a series of sounds, vibration, or a message, and passes the data to the JSMS. The JSMS may consider multiple indexes (e.g., multiple accelerometers and gyroscopes) and performs a more complex analysis, such as trend analysis. The result is a recommended action for the supervisor.

4.2. Detection algorithms

As mentioned in the introduction section, most fall detection studies have used fall threshold (t) algorithms to detect falls and have proven to be effective. Threshold algorithms are based on a formula composed of sensor data, such as those from accelerometers or gyroscopes, and emit a warning when the formula value exceeds a threshold. Different researchers may use different weights for the data or different thresholds for the target use scenario.

Such an algorithm is also suitable for the proposed PSMS due to its simplicity and minimum computing power requirements. The algorithm could accurately represent the degree of sway and is thus suitable for detecting motion. We implemented three algorithms in the prototype system, as depicted in Fig. 3. It should be noted that the threshold values in parentheses are values adopted from those with the best accuracy in our experiments described later in Section 6.2 Results.

The first algorithm is adopted from Mathie et al. [28] and is shown in Eq. (1).

$$\mathrm{SVM_a\,(signalmagnitudevector)} = \sqrt{|A_X|^2 + |A_Y|^2 + |A_Z|^2}, \tag{1}$$

where A_X, A_Y, and A_Z are the acceleration in the x-, y-, and z-axes (shown in Fig. 4), respectively.

The second algorithm is adopted and modified from Bourke and Lyons [26] and is shown in Eq. (2). Bourke and Lyons [26] used a biaxial gyroscope to detect falls and found the thresholds for angular acceleration, angular velocity, and angular change. We only applied a part of this algorithm (i.e., the angular velocity) in the x (roll), y (pitch), and z (yaw) dimension. Although this algorithm may not be as effective as the first according to previous fall detection research, we still incorporate it in our system because we are focused on portents instead of direct falls.

$$\mathrm{SVM}_\omega = \sqrt{|\omega_X|^2 + |\omega_Y|^2 + |\omega_Z|^2}, \tag{2}$$

where ω_X, ω_Y, and ω_Z are the angular velocity along the x-, y-, and z-axes (shown in Fig. 4), respectively.

Table 1
Simulated fall types.

Falling type	Tiling posture	Pickup posture	Falling direction
I	Squat	Nil	Back
II	Squat	Nil	Lateral
III	Stand	Squat	Back
IV	Stand	Squat	Lateral
V	Stand	Stoop	Back
VI	Stand	Stoop	Lateral

We also developed a modified version of Eq. (1), as shown in Eq. (3), which monitors the change in the $\mathrm{SVM_a}$.

$$\mathrm{SVM_t} = \mathrm{SVM_{an}} - \mathrm{SVM_{an-1}}, \tag{3}$$

where $(\mathrm{SVM_{an}} - \mathrm{SVM_{an-1}})$ is the difference between two consecutively sampled accelerations. $\mathrm{SVM_t}$ is positive if the wearer's motion is increasing and negative otherwise.

4.3. Prototype implementation

The application that we developed for this study runs on Apple's iOS 5 on iPhone 4/iPod, which includes an LIS302DL accelerometer with a scale of $\pm 2/\pm 8$ g and a 100/400-Hz sample rate and an L3G4200D gyroscope with a scale of 250/500/2000 dps and a 100/200/400/800-Hz sample rate. These two sensors are capable of measuring acceleration and angular velocity in three directions (x, y, and z). The daily motion frequency of a human body is approximately 8 Hz [42]. Based on the Nyquist–Shannon sampling theorem, the equipped sample rate satisfies the experimental and analytical needs because the rate is more than twice the daily motion frequency of 8 Hz. The sensor data collected for each subject during the experiment was sent to a computer server via Wi-Fi.

5. Experimental setup

We designed two experiments to evaluate the effectiveness of the proposed system. Experiment I focused on the detection of falls during movement and compared the results with previous research targeting falls from a still position. The experiment was expected to answer the question regarding whether the signal noise emanating from working operations will significantly affect the detection accuracy. Experiment II focused on evaluating the effectiveness of detecting fall portents, such as swaying, unsteady footsteps, and LOB, and compared the detection accuracy under normal and abnormal statuses. The abnormal statuses in this experiment included sleepiness and fatigue.

Based on the report of CLA [43], workers in almost all construction trades are subject to a risk of falling. Because this is a pioneering study, a suitable operation for this experiment should be a common construction operation without a significant learning effect or overwhelming noise that is easily repeatable so that multiple subjects can perform the same task. We chose tiling as the primary task for the two experiments due to its simplicity and regularity in terms of gesture and movement. To facilitate repetition, we set up a wall covered with flannelette and prepared different types of tiles, each of which was glued with Velcro on the back so that the tile could be attached to the wall and later detached easily.

Fig. 5 shows the experimental environment setup, whose objective was to simulate a scenario in which a worker performs tiling on a scaffold. Fig. 5-1 shows an overview of the environment, including the experiment area, monitoring area, and rest area (separately shown in Fig. 5-2). In the experiment area, a flannelette-covered wall was set up for use with Velcro tiles (Fig. 5-3) so that different subjects could repeat the same tiling tasks. Each subject, equipped with a safety helmet and a belt (S1 and S2 in Fig. 5-1), was asked to attach the tiles to the wall according to the designed patterns using reference lines for guidance. The scaffold was painted white in the center and yellow on the sides. The white area (30 cm wide) represents the safe zone, and the yellow areas (20 cm and 30 cm wide) represent the watch zones.

The experiment facilitator, sitting behind the partition in the monitoring area, monitored the experiment using a computer and surveillance cameras (C1, C2, C3 in Fig. 5-1). The cameras monitored the experiment from different angles: C1 and C2 monitored from the top with a bird's-eye view and from the axial direction, focusing on the subjects' steps, respectively. A rest area was provided for subjects

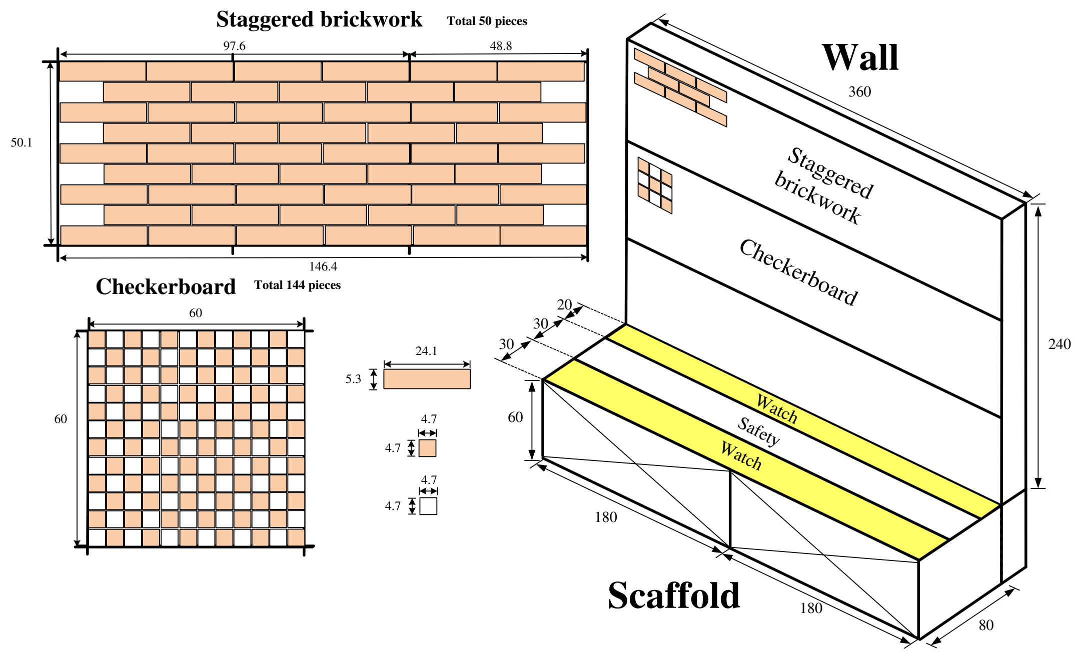

Fig. 6. Scaffold, tiling wall, and tile patterns (unit: cm).

who felt tired, fatigued, or uncomfortable during or after the experiment.

Four graduate students (three males and one female) from the construction management program of National Chiao-Tung University volunteered to participate in the experiments. The average age of the participants was 24.75, with a standard deviation of 1.30. The average height and weight were 170.75 cm (S.D. = 9.28) and 61.5 kg (S.D. = 14.31), respectively.

6. Experiments

6.1. Design of experiments

The objective of Experiment I was to detect falls. In Experiment I, each subject repeated six types of simulated falls three times onto a 24-cm-thick soft mattress attached to the side of the scaffold. Each of the subjects completed Experiment I within 30 min. Table 1 summarizes the six types of falls based on the subject's tiling postures (i.e., stand and squat), tile pick-up postures (i.e., squat and stoop), and falling direction (i.e., back and lateral).

Most experiments in the literature have focused on direct falls, i.e., asking subjects in a standing position to fall deliberately. Although vertical velocity is an important indication of fall detection [24], the dynamic nature of a construction worker's posture at work is also subjected to high and dramatic changes in vertical velocity. Therefore, we designed the simulated falls of Experiment I to include vertical posture transitions, such as from standing to squatting and from standing to stooping. The other objective was to examine the effect of these transition postures on the fall detection accuracy and collect signal patterns of these postures that may help distinguish normal postures such as squatting and stooping from fall portents in Experiment II.

The objective of Experiment II was to detect fall portents. In Experiment II, each subject executed a tiling task with two different design patterns in three different statuses (i.e., normal, sleepiness, and fatigue). To achieve the sleepiness and fatigue statuses, the subject was requested to stay up all night before the experiment (held at 7:00 AM) or to perform the tiling task twice to achieve relative fatigue.

The abnormal statuses were included because we expected few portents (e.g., swaying, unsteady footsteps, and LOB) for the normal status and more portents for the abnormal statuses. In addition, we were also interested in determining whether differences existed among the portent signal patterns induced by sleepiness and fatigue. It should be noted that working overtime and the night shift are common in Taiwan. As reported by the CLA [43], insufficient rest is common for high-elevation construction workers.

The tiling task environment was composed of a scaffold and a wall, as shown in Fig. 6. The scaffold was painted with two colors to distinguish between the safe (white) and watch (yellow) zones. Subjects were told to keep their feet within the safe zone during the task (as shown in the scaffold in Fig. 6). The task was to tile the wall according to the designated patterns (i.e., staggered brickwork and checkerboard) using the provided Velcro tiles (Table 2 and Fig. 6). A single task required a subject to attach 194 pieces of tiles in approximately 1 h.

Experiment II concerned two incidents, i.e., falls and fall portents. Whereas a fall was obvious and could easily be determined, we defined a fall portent as being any of the following three scenarios. First, a subject self-reported a portent by raising a hand when he/she lost balance or awareness during the experiment. Second, the experiment

Table 2
Tiling tasks.

Unit size	Color	Pattern	# of pieces
4.7 × 4.7 cm^2	White/beige	Checkerboard	144
24.1 × 5.3 cm^2	Brown	Staggered brickwork	50

Table 3
Results of Experiment I.

Fall type	Fall event	Accuracy (%)					
		SVM_a (t = 1.8)		SVM_ω (t = 4.5)		SVM_t (t = 0.7)	
		Sen.	Spe.	Sen.	Spe.	Sen.	Spe.
I	12	100	97.9	100	93.8	100	95.8
II	12	100	95.8	100	91.7	100	89.6
III	12	100	95.8	100	94.8	100	94.8
IV	12	100	90.6	100	88.5	100	94.8
V	12	100	97.9	100	94.8	100	95.8
VI	12	100	99.0	100	99.0	100	96.9
Overall	72	100	96.1	100	93.6	100	94.6

Sen: sensitivity and Spe: specificity.

Table 4
Fall-portent and non-fall-portent events in Experiment II.

Status	Number of events									
	Non-portent event						Fall portent			
	Squat	Stand-up	Stoop	Move	Tile	Total	Self-report	Obvious-sway	Cross-line	Union
Normal	610	621	239	1526	1943	4939	9	16	16	17
Sleepiness	456	480	189	1091	1379	3595	20	30	25	36
Fatigue	629	638	259	1564	1989	5079	22	40	33	47
Overall	1695	1739	687	4181	5311	13,613	51	86	74	100

facilitator identified an obvious sway using surveillance cameras. Third, a subject stepped over to the watch zone by more than 15 cm, which is more than half of the average man's foot length in Taiwan (26 cm). These portents indicated that a subject could not maintain balance or awareness, causing sudden swaying or unsteady footsteps, and was prone to falling.

6.2. Results

In Experiment I, we collected data for 72 (= 12 × 6) falls and 480 non-fall (including squatting, standing up, stooping, and tiling) events and applied different thresholds for each of the three algorithms. Table 3 shows the threshold for each algorithm with the best accuracy in terms of sensitivity and specificity. Sensitivity is the percentage of fall detections over the total number of falls that actually occurred, and specificity is the percentage of non-fall detections over the total number of non-fall events.

The "Overall" row shows the average performance of the six types of simulated falls. Under the best threshold, SVM_a, SVM_ω, and SVM_t reach 100% sensitivity. The primary performance difference is in specificity. SVM_a showed the highest specificity and SVM_ω the lowest, albeit with an acceptable value of 93.6%. SVM_t calculated the difference between two consecutive events and demonstrated a specificity similar to that of SVM_a.

The specificity of the system was not as good as its sensitivity. In other words, the problem with the fall detection was the false-detection rate instead of the hit rate. The best performer, SVM_a, demonstrated a false-detection rate of 3.9% (= 1−96.1%), whereas the worst performer showed a false-detection rate of 6.4% because it was more sensitive. Relative to previous studies on the detection of falls experienced by the elderly and patients in the healthcare domain, where the sensitivity and specificity are 95.2%–98% and 100%, respectively, all three algorithms exhibit satisfactory performance, even in the working scenario.

In Experiment II, each subject performed several motions to complete the tiling task, including squatting, standing, stooping, moving, and tiling. We counted the number of each type of event observed through surveillance data. Table 4 lists these numbers along with the number of identified fall portents for each designated status (e.g., normal and sleepiness). It should be noted that the union number records the number of incidents in which at least one self-report, obvious-sway, or cross-line sign occurred. An event was counted only when a subject changed motion. Thus, for example, a subject standing for 15 s, squatting, and standing for another 30 s is counted as 1 squatting and 1 standing occurrence.

Table 5 lists the sensitivity and specificity for each algorithm under different statuses with the best performing threshold. All three algorithms reached 100% sensitivity. SVM_a showed the highest specificity, and SVM_t showed a specificity similar to that of SVM_a. SVM_ω still exhibited the lowest specificity, unexpectedly.

Both SVM_a and SVM_t appear to have performed quite well in terms of specificity (99.9% and 99.7%, respectively). The worst performer, SVM_ω, had an 83.1% (16.9% false detections) specificity. However, this result is due to the bias from the extremely large number of non-portent events (3595–5079) compared to the small number of fall portents. This bias made the specificity less sensitive and discriminable.

To better evaluate the differences in performance, Table 6 provides a different measurement for accuracy. The number of detection targets (i.e., identified portents) is 100 for all three algorithms. The accuracy rate is the number of correct detections (column c) over the number of activated warnings (column b). The false-detection rate is the number of incorrect detections over the number of warnings. Based on the overall performance, the ranking of the algorithms in terms of performance is the same as that indicated in Table 5: $SVM_a > SVM_t > SVM_\omega$, as shown under the columns Accuracy rate and False-detection rate.

Based on Table 6, SVM_a still had a satisfactory accuracy rate (88.5%) and false-detection rate (11.5%). SVM_t had a 73.5% accuracy rate, and the worst performer, SVM_ω, had an unsatisfactory accuracy rate of 4.3%, with a false-detection rate of almost 95%. This finding indicates that detecting the target is much easier than avoiding false detection. Thus, the obstacle to overcome in applying this type of sensing technology in the problem is the problem of false detection.

Table 5
Results of Experiment II.

Status	Portent event	Accuracy (%)					
		SVM_a (t = 1.3)		SVM_ω (t = 0.3)		SVM_t (t = 0.2)	
		Sen.	Spe.	Sen.	Spe.	Sen.	Spe.
Normal	17	100	99.9	100	84.5	100	99.8
Sleepiness	36	100	99.9	100	76.4	100	99.5
Fatigue	47	100	99.9	100	88.5	100	99.8
Overall	100	100	99.9	100	83.1	100	99.7

Sen: sensitivity and Spe: specificity.

Table 6
Modified accuracy in Experiment II.

Algorithm	(a)	(b)	(c)	$\left(\frac{c}{b}\right)$	$\left(\frac{b-c}{b}\right)$
	Fall portents	# of warning	# of accurate detection	Accuracy rate	False-detection rate
Normal					
SVM_a	17	22	17	77.3%	22.7%
SVM_ω	17	785	17	2.2%	97.8%
SVM_t	17	24	17	70.8%	29.2%
Sleepiness					
SVM_a	36	39	36	92.3%	7.7%
SVM_ω	36	885	36	4.1%	95.9%
SVM_t	36	56	36	64.3%	35.7%
Fatigue					
SVM_a	47	52	47	90.4%	9.6%
SVM_ω	47	629	47	7.5%	92.5%
SVM_t	47	56	47	83.9%	16.1%
Overall					
SVM_a	100	113	100	88.5%	11.5%
SVM_ω	100	2299	100	4.3%	95.7%
SVM_t	100	136	100	73.5%	26.5%

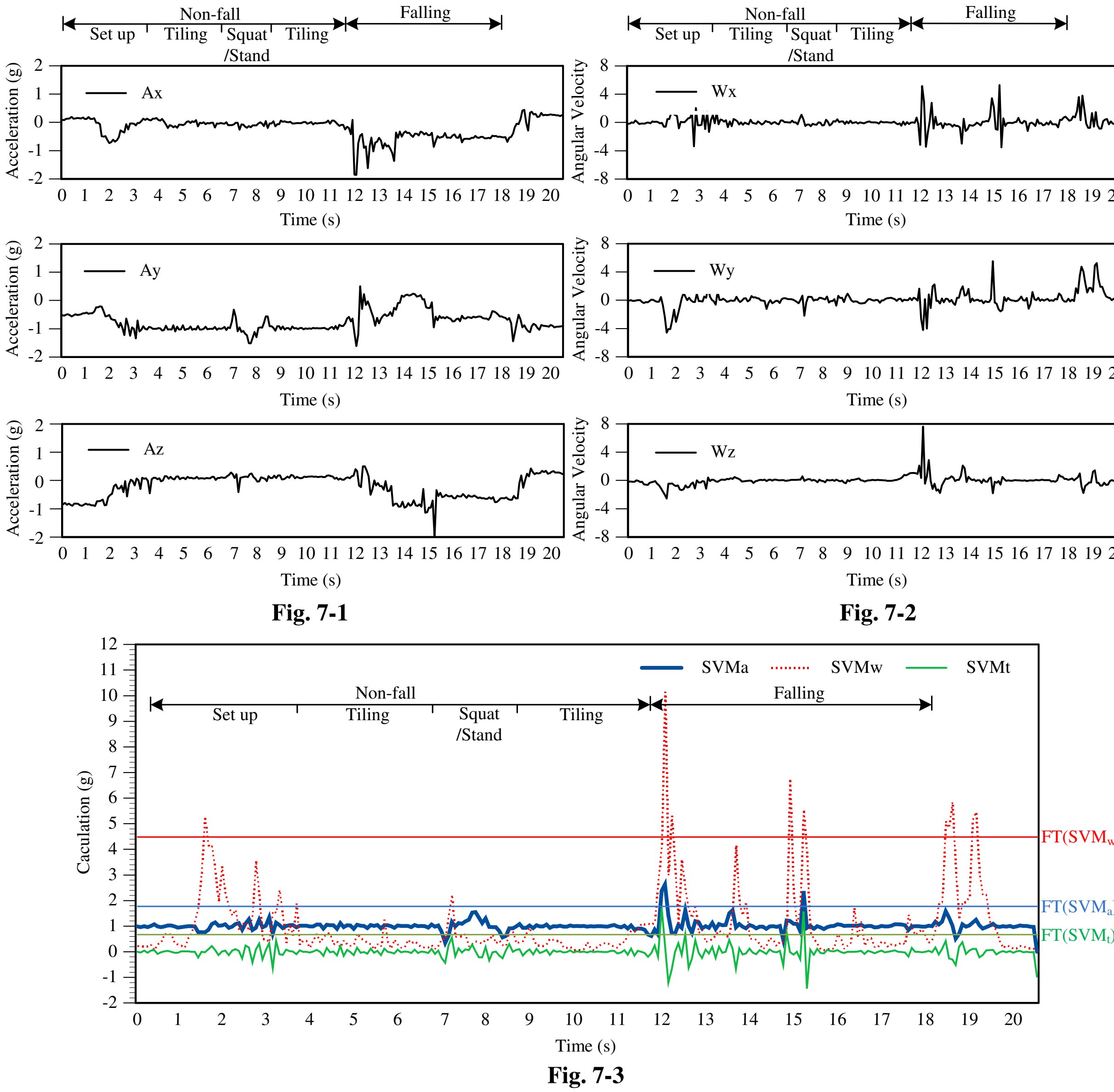

Fig. 7. Type IV simulated fall (Experiment I).

6.3. Discussion

In Experiment I, SVM_a and SVM_t performed better than SVM_ω in terms of specificity. This result indicates that the specificities for SVM_a and SVM_t were more stable than that of SVM_ω when facing a variety of tested motions in the experiment; thus, these algorithms may be more suitable for construction operations, which also feature a variety of motions. The calculation of SVM_ω is based on angular velocity and is thus more sensitive to different types of motion. As a result, the specificity fluctuates more widely, as shown in the example of Type VI (99.0%) vs. Type IV (88.5%). Although SVM_ω did not perform well in this experiment due to its sensitivity, we still used it in Experiment II in the hope that it would provide useful information regarding sudden sway motions.

Fig. 7 plots the raw acceleration (Fig. 7-1) and angular velocity (Fig. 7-2) signals for sampling data from Type IV simulated falls. Fig. 7-3 shows the results of the three algorithms in different colors, with horizontal lines representing the corresponding thresholds. An alarm was activated when the result exceeded the corresponding threshold.

In addition to the distinction between falls and non-fall motions, we can also further distinguish standing or squatting from tiling motions. Fig. 8 shows an example of the SVM_a and SVM_t values (blue and green lines, respectively) for the six types of fall processes, including set-up, tiling in squatting or standing positions, and back or lateral falling. As indicated for Types III and IV, both SVM_a and SVM_t show significantly different oscillation patterns for squatting or standing compared to tiling. In other words, squatting or standing could be distinguished by applying the appropriate threshold.

However, neither SVM_a nor SVM_t showed significantly different oscillation patterns between stoop and tiling (i.e., Type V and Type VI). Thus, stooping could not be as easily identified as squatting or standing. One possible explanation is that the accelerometer attached to the subject's waist swayed very little when the subject stooped.

For the same reason, none of the algorithms could detect tiling motions because they mainly involved hand motions instead of waist motions. As shown in Fig. 8, the waist-attached accelerometer only generated a slight oscillation in all six types of falls for the tiling motion. Therefore, a distinction between productivity and non-productivity

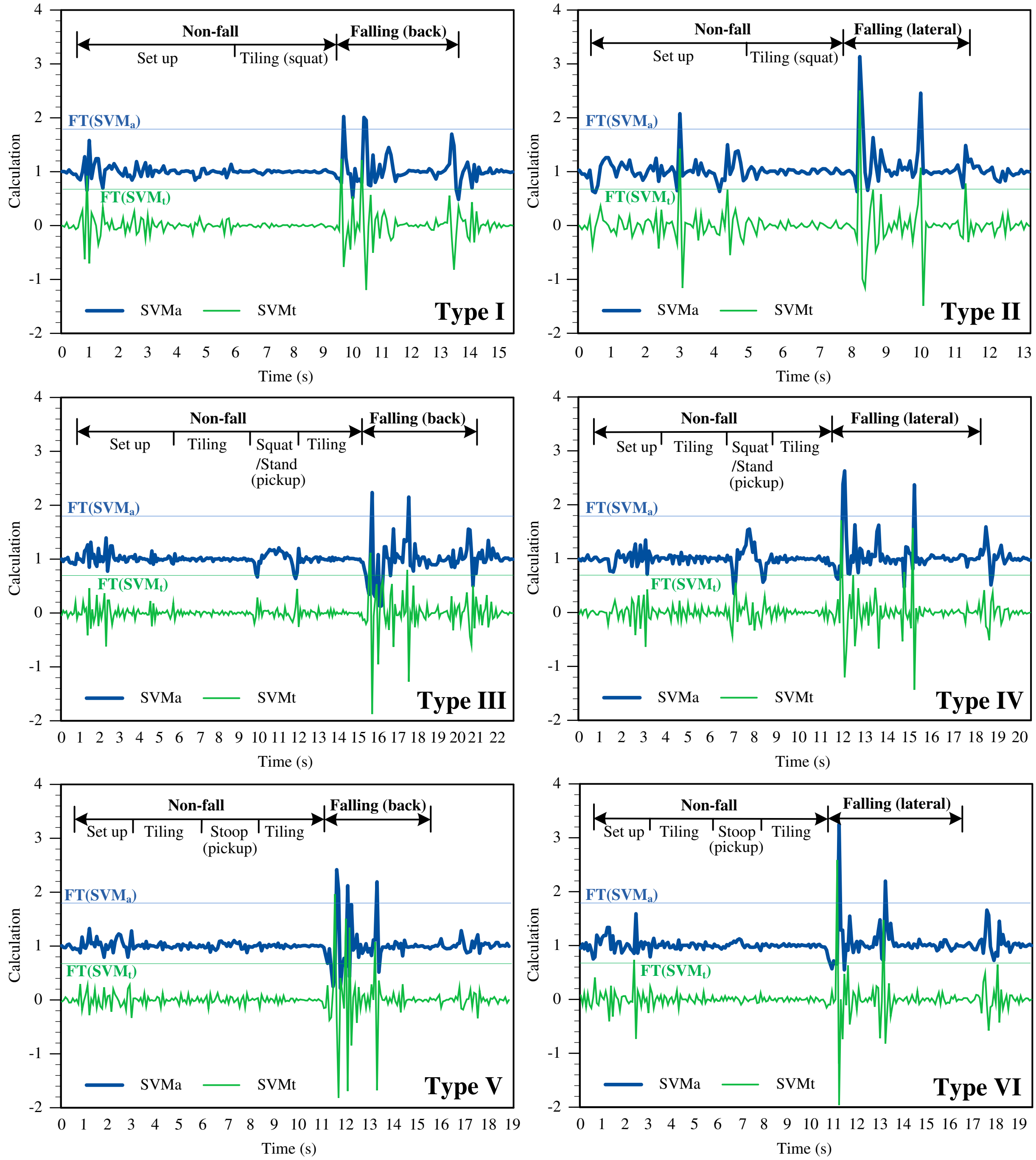

Fig. 8. SVM_a and SVM_t for six types of falls (Experiment I).

motions does not appear to be feasible using the waist-attached accelerometer and these algorithms.

Based on the results of Experiment I, SVM_a is more discriminating than SVM_t, which smoothed out the oscillation with its time-offset difference and thus reduced the distinction between different motions. Furthermore, SVM_a resulted in quite different oscillation patterns both between falls and non-falls and between motion states such as squatting and standing.

The results of SVM_t are similar to those of SVM_a in terms of oscillation, differing only in terms of vertical shift. The similarity is due to the subtraction of two SVM_a over very small intervals. Enlarging the time interval or applying a moving average may accentuate the difference in the oscillation and is worth exploring in the future.

In contrast, the results of SVM_ω (red signal in Fig. 7) were quite different from those of SVM_a and SVM_t. The results oscillated more acutely and produced more peaks, many of which were false detections (6.4%). Adjusting the threshold changed the accuracy by trading off sensitivity and specificity but did not result in a better performance than that of SVM_a and SVM_t.

Nevertheless, distinguishing each type of motion was not the concern of this research. Considering the large amount of data obtained from intensive sensor sampling and the comparatively slow computing

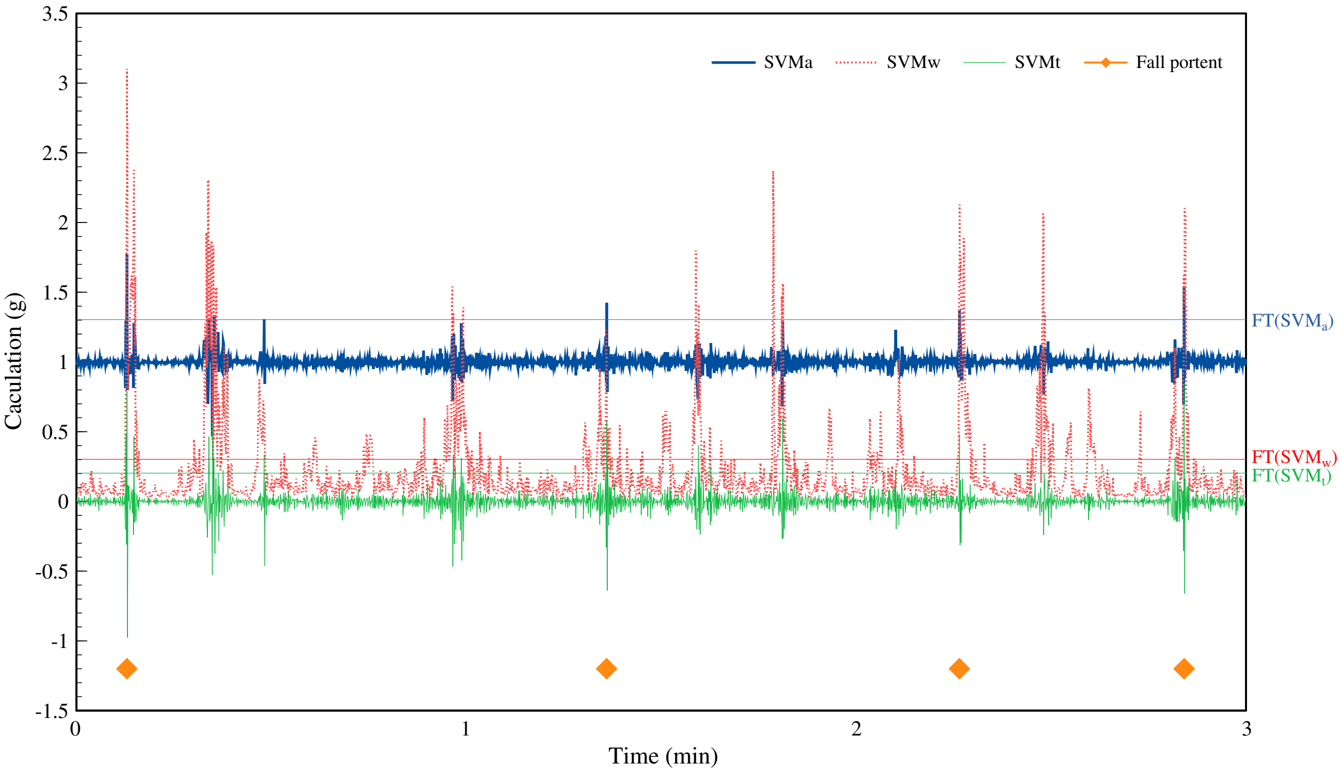

Fig. 9. An example of SVM_a, SVM_ω, and SVM_t for the sleepiness status (Experiment II).

power of current smartphones, we conclude that SVM_a is the best algorithm for use on current smartphones for Experiment I, providing satisfactory accuracy.

Fig. 9 shows an oscillation example of SVM_a, SVM_ω, and SVM_t for the sleepiness status of Experiment II. The associated threshold is also presented in the same color as each corresponding algorithm. Within the presented time frame, there were four identified portents, which are marked with orange diamonds. It is clear that, although three algorithms could detect all portents, the false detection rates were quite different among the three algorithms because of their degree of oscillation. SVM_a showed the lowest false detection rate, and SVM_t exhibited a similar false detection rate. However, SVM_ω demonstrated the worst false detection rate due to its over-sensitivity.

As shown in Table 6, the modified accuracies of the proposed algorithms in Experiment II were not as good as expected; in particular, the SVM_ω had an accuracy rate of only 4.3%. The errors may be attributed to at least the following two issues. First, the motion detected when the subject moved regularly is similar to the motion detected when the subject accidently crossed over the watch zone due to a temporary loss of alertness instead of LOB. Second, it was difficult to distinguish the motion of the subject's self-reported event, in which the subject, due to temporarily losing focus, slowed or stopped their motion briefly without any sudden sway. Both of these motions resemble regular movement at work, and motions without abrupt changes are difficult to detect. It should be noted that the objective of the thresholds presented here was to detect all identified portents. To this end, it was necessary to lower the thresholds, thus creating more false detections. In other words, if the algorithm was not required to detect all of the identified portents, increasing the thresholds may have improved its accuracy rate.

The best performer, SVM_a, exhibited higher accuracy rates under the sleepiness (i.e., 92.3%) and fatigue statuses (90.4%) than under the normal status (i.e., 77.3%). One possible explanation is that most of the portents of the subjects under the normal status were related to lost awareness without any sudden sway, whereas many portents of subjects under the abnormal statuses were related to sudden sways. In other words, the abnormal statuses produced many more portents, and those portents were often accompanied with obvious sways, thus increasing the accuracy rate.

SVM_a showed the highest accuracy and SVM_ω the worst in both experiments. The sudden sways of fall portents are not as obvious as falls. Therefore, fall portents cannot be detected as easily as falls. Although SVM_ω was the most sensitive algorithm among the three algorithms, this advantage became a disadvantage in both experiments because the sensitivity generated many unwanted noise signals. Therefore, the threshold algorithm based on angular velocity is not feasible for detecting fall portents. Nevertheless, this finding does not rule out the algorithm's application in other scenarios, such as the detection of productivity or work posture.

It should be noted that the subjects always had an iPhone attached to their waist throughout the entire experiments. Attaching the phone to a different body part results in different noise signals, and the accuracy and the best algorithm may also change. Like most studies using a single accelerometer attached to the waist to detect the falls of patients or the elderly, we also chose to attach the iPhone onto the belt because the waist is the center of body mass and results in less noise compared to that generated by other human parts such as the head or hand. Although the presented data demonstrate that attaching the device to the waist produces an acceptable accuracy rate for detecting fall-prone motions, the accuracy rate is unknown if the same device is attached to a different body part.

7. Conclusion and future developments

Fall accidents have been the leading cause of fatalities in the construction industry for decades. The objective of this research was to study the feasibility of detecting falls (Experiment I) and fall portents (Experiment II) in a construction work scenario, which involves more complicated motions than those explored in previous studies concerning healthcare scenarios for the elderly and patients. Three algorithms, SVM_a, SVM_ω, and SVM_t, were studied using a variety of thresholds, and the results of the best thresholds were presented in this paper.

In Experiment I (simulated falls), we designed six types of falls, which included work-related motions such as tiling, standing, squatting, and stooping, to evaluate whether those motions affect fall detection. In Experiment II (fall portents), we identified sudden swaying, unsteady footsteps, and LOB as fall portents and attempted to detect them during a normal tiling operation. We also performed the same experiment for subjects experiencing sleepiness and fatigue in addition to the normal status.

In both experiments, all three algorithms performed quite well, with 100% sensitivity, meaning that all falls or fall portents were successfully detected. The main difference observed among the algorithms was in their specificity. In Experiment I, all three algorithms exhibited acceptable overall specificity performance: SVM_a had the highest specificity (96.1%), and the specificities for SVM_t and SVM_ω were 94.6% and 93.6%, respectively. Thus, the false-detection rate ranged from 3.9% to 6.4%. We conclude that SVM_a is the best algorithm for use in current smartphones for Experiment I, and its accuracy is also satisfactory. Additionally, based on the good performance achieved in this study, which is similar to the results reported in previous studies regarding healthcare scenarios, we can also conclude that a more complicated working operation such as tiling barely affects the sensitivity and specificity performance of the algorithm in terms of detecting falls.

In Experiment II, both SVM_a and SVM_t also performed quite well overall, with a sensitivity of 100% and a specificity ranging from 99.7% to 99.9%. SVM_ω performed well in terms of sensitivity (i.e., 100%) but less well in terms of specificity (i.e., 83.1%). However, due to the extremely large amount of motion data collected from the long experiment, the specificity was actually insensitive and indiscriminative, which forced us to introduce a modified accuracy measurement from the perspective of detections instead of the entire sample. The modified accuracy values for SVM_a, SVM_ω, and SVM_t were 88.5%, 4.3%, and 73.5%, respectively. Taking the best performer, SVM_a, as an example, 88.5% of the triggered alarms were actually fall portents identified by self-report, obvious swaying, or line-crossing, and 11.5% were false detections. Thus, among the 113 alarms triggered by SVM_a, only 13 were false alarms. We therefore conclude that using SVM_a to detect portents in a tiling operation is feasible.

Based on this finding, on-going research will attempt to apply the algorithm to a variety of working operations exposed to falling hazards such as welding at high elevation or repair work in an elevator vault. We will also attempt to build a more complex, integrated sensor scheme that involves multiple individual accelerometers attached to a vest or different parts of the body other than the waist, such as the arms. The scheme will also include a brain wave sensor, such as EEG (electroencephalography), attached to the inside of a safety helmet. The signals recorded by these sensors can be wirelessly transmitted to a smartphone, which can act as an individual temporary data center and perform integrated analysis. Multiple smartphones worn by different workers may then transmit preliminary data wirelessly to a data center in a site office to perform further trend and team analysis. When those sensors detect a fall portent, the system should warn the worker and notify the supervisor, who may adjust the work schedule or tasks assigned to fall-prone workers.

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