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A smartphone-based detection of fall portents for construction workers

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Abstract

The construction industry accounts for nearly half of all industry-related fatalities in Taiwan. Identified as the leading cause of such fatalities for several decades, falls also contribute to almost half of work-related fatalities. Given the strenuous nature of construction work, workers are prone to loss of awareness and balance, increasing the safety risk and number of fall accidents. Previous studies have indicated that loss of awareness may be the major cause of occupational injuries or fatalities, and identified the strong correlation between falls and loss of balance. Thus, real-time monitoring of the mental and balance conditions of workers may help identify fall portents, and thus prevent falls from happening.

This paper describes a framework for developing a personal safety monitoring system based on a smartphone, which receives external signals wirelessly from motion sensors and brain wave sensors attached to a vest and inside a helmet, and transmit these signals to a monitoring server for further analysis. This paper also presents an experiment with preliminary findings regarding the detection of fall portents, using the internal motion sensors of a smartphone. In the experiment, participants performed a tiling task on a scaffold under four physiological statuses. We identified the fall portents based on the self-awareness of the participants, hazardous actions performed by the participants, and outsider observations by experiment administrators. An accelerometer-based threshold algorithm was tested, and its performance was evaluated against the identified fall portents.

The results indicated that the work-related motions had a limited impact on the detection algorithm. The accuracy for the sleepiness, fatigue, normal, and inebriation statuses were 92.3%, 90.4%, 77.3%, and 68.8%, respectively. The algorithm exhibited an overall accuracy of 86%, thus, we conclude that using a smartphone to detect fall portents in a working scenario is feasible, and deserves further investigation.

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Keywords: accelerometer; construction safety; fall portent detection; smartphone; threshold algorithm.

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1. Introduction

Construction jobsites account for nearly half of all industry-related fatalities in Taiwan. Fall accidents have been identified as the leading cause of such fatalities for several decades. According to statistics of the Council of Labor Affairs of Taiwan (CLA), approximately 50.55% (1,020 of 2,018) of construction work-related fatalities during 2000–2012 were attributed to fall accidents. Moreover, fall accidents represented approximately 67.07% (110 of 164) and 62.5% (90 of 144) of fatalities in 2011 and 2012, respectively [1], indicating that the prevention of falls may be still insufficient or ineffective.

Fall accidents are common in the construction industries of many countries. The US Bureau of Labor Statistics reported that 33.76% of fatalities in the US construction industry (284 of 817) were related to falls [2]. Falls also contributed to approximately 40% of fatalities in the Japanese construction industry [3]. Furthermore, falls represented the highest number of fatalities in the European and Korean construction industries, accounting for 52% and 30% of all work-related accidents [4,5], respectively.

Given their heavy physical requirements and irregular lifestyle (e.g., alcohol abuse, night shifts, and an insufficient rest period), construction workers are prone to fatigue, drowsiness, and loss of balance, increasing safety risks and fall accidents. However, most studies have focused on safety facilities and personal protective equipment (PPE) inspection, which only mitigate the injuries after a fall, instead of preventing the fall itself from happening. Moreover, other conventional measures such as safety training and education also have limitations because of the characteristics of the industry (e.g., many subcontractors and high labor mobility).

According to the CLA report, approximately 54% of all workers considered loss of awareness as the major cause of occupational injuries or fatalities, whereas only 25% attributed accidents to equipment failure and the surrounding environment. The strong correlation between fall accidents and loss of balance has also been demonstrated. These evidences imply that real-time monitoring and analysis of the physiological status (such as mental and balance condition) of workers could help identify fall portents, and thus prevent falls from happening.

Real-time physiological monitoring and analysis have been extensively studied and evaluated. Electroencephalography (EEG) can indicate the mental condition, including fatigue, drowsiness, attention, and alertness. Researchers have successfully applied EEG monitoring to detect driving fatigue in aircraft pilots and car drivers [6]. By contrast, motion sensors such as accelerometers and gyroscopes can represent the degree of body sway, and several researchers have used accelerometers with threshold algorithms to monitor daily activities and distinguish each type of motion, particularly for detecting falls among the elderly and infirm [7].

Nowadays, smartphones with built-in accelerometers and gyroscopes have emerged as popular, carry-on personal belongings. Several studies have begun to establish smartphone-based fall detection or activity recognition systems [8,9]. Mellone et al. [10] indicated that smartphones could become a pervasive and low-cost tool for the quantitative analysis of balance and mobility. Dai et al. [11] used a smartphone to detect falls, and the proposed system achieved excellent detection performance and power efficiency. Some studies [12,13] have proposed a smartphone-based fall detection system that automatically sends a warning message including the time, GPS coordinate, and Google map of the location when a fall is detected. In addition, smartphones can also integrate external motion sensors and EEG sensors, using Bluetooth or Wi-Fi, and transmit the data to a monitoring server [14]. Stopczynski et al. [15] developed a smartphone that displayed real-time images of brain activity. Szu et al. [16] proposed a wireless, real-time, and smartphone-based EEG system for homecare applications.

Although several monitoring techniques have been proposed to improve safety or jobsite management, using location-tracking (e.g., RFID and GPS) or pattern recognition technologies (e.g., PPE and worker inspection), these technologies cannot determine whether a worker is losing awareness or balance. The inability to monitor the physiological status of workers makes jobsite safety management difficult, implying that workers could be laboring under inappropriate or even dangerous physiological conditions without their supervisor knowing it. Thus, the loss of awareness and balance can be appropriate signs for fall portents. Indeed, some researchers have successfully detected the mental status of drivers, as well as fall among the elderly and patients. Such results have provided valuable information for developing a real-time personal safety monitoring system in a complex environment such as the construction industry, which features numerous workers interacting in a wide area with continuous movement and a constantly changing environment. This paper presents a framework for developing a personal safety monitoring system based on a smartphone, and shows the initial results of our ongoing research, with the preliminary findings of an experiment designed to evaluate the accuracy of detecting fall portents, using the internal motion sensors of a smartphone.

2. Smartphone-based detection system

2.1. Conceptual model and use scenario

Figure 1 conceptually shows our proposed Cloud Jobsite Monitoring System, which is composed of three layers of data management: smartphones, fog server, and cloud server. Workers wear sensors, so that their physiological status including EEG, motion, and location data can be detected. The information is used to determine whether their physiological status is suitable for the work environment, based on the pre-assessed risk rating of the related work zone. The EEG sensor may be attached to a helmet, whereas motion sensors could be sensors built in a smartphone or stand-alone sensors attached to a vest. The RFID or GPS sensor built in a smartphone could be used to track the location.

The physiological status and location data of a worker is collected and transmitted to a smartphone worn by the worker. The smartphone is equipped with an App that analyzes the data and produces a warning to the worker or supervisor if an inappropriate action or unsafe status occurs. The individual data of each worker of a crew is transmitted to the fog server as a data logger through Wi-Fi or Bluetooth for further analysis. Each fog sever is responsible for analyzing the crew data as a group, and adjusting the warning trigger threshold for the crew when necessary. The fog is introduced to the system as an intermediate layer to scale down the real-time data that needs to be managed by the cloud [17]. The fog also serves as a self-learning unit that controls the risk profile of the corresponding crew according to the involved trades, operations, and environment, and thus the exposed risks vary for each crew, and different warning thresholds may be necessary for different crews. The data of all fogs are then transmitted to the cloud server, which could be a portable computer server. Additional in-depth analyses such as trend analysis or cross analysis can be performed.

The risk profile of each fog effectively controls the corresponding warning mechanism by considering the individual health condition and characteristics of the involved trades, operations, location, and working environment. For example, workers at high elevations have a greater risk to suffer fall accidents than do those on the ground. Older workers have a longer response time than do young workers. Thus, the warning mechanism should be adjusted correspondingly for monitoring the movement and balance condition of workers at high elevations or the EEG of older workers. As the trades, operations, and work environment change during the construction process, the fog automatically improves the accuracy of the warning mechanism according to the risk profile updated by the responses of the crew member and supervisor. The attributed-location-based system also helps the site manager monitor workers' daily physiological status (e.g., maximum workloads and work hours) to enhance individual health management and reduce cumulative trauma disorders, which lead to a chronic reduction in competence at work.

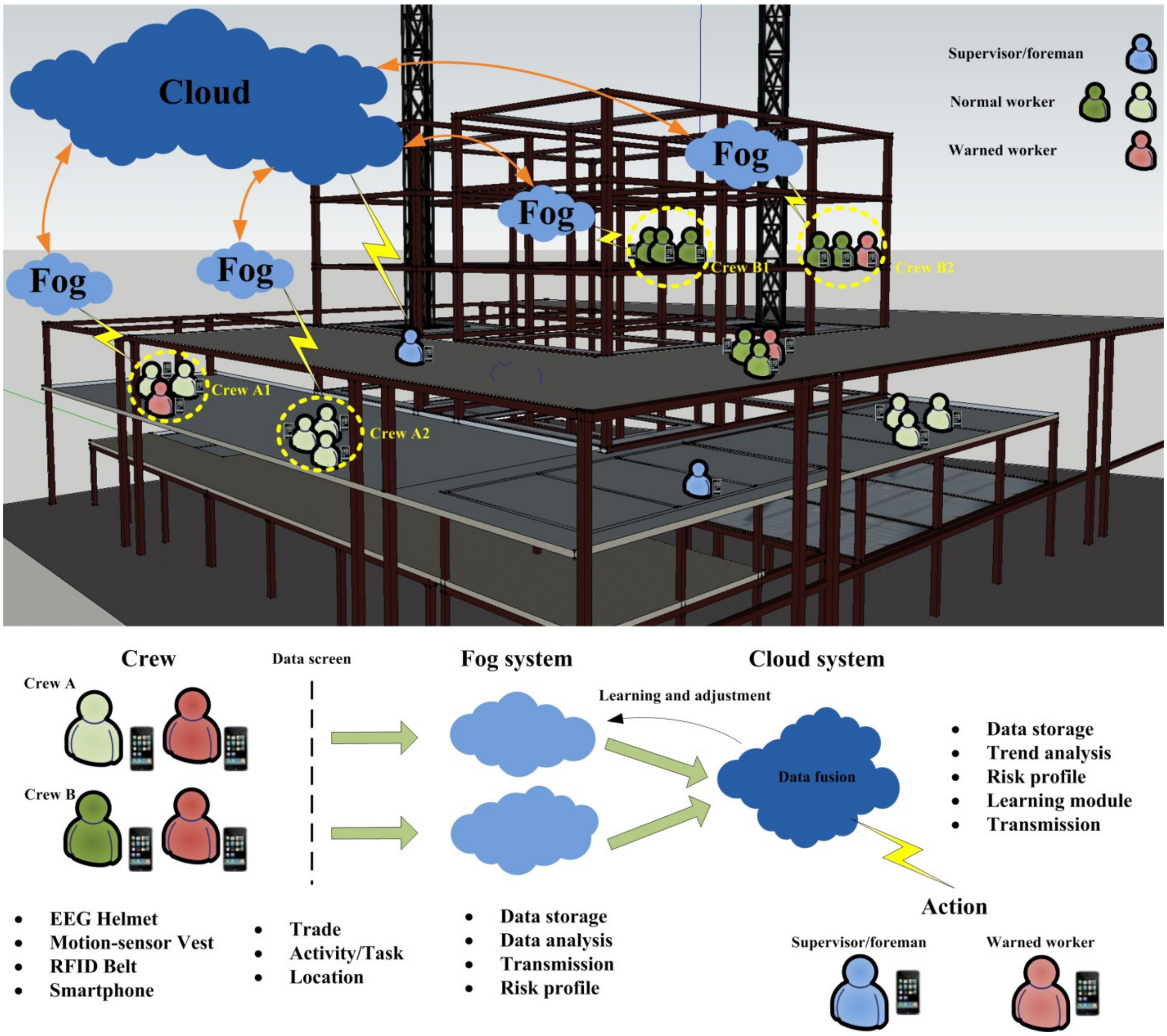

Fig. 1. Cloud Jobsite Monitoring System

This paper describes the ongoing development of the prototype of the proposed real-time personal safety monitoring system consisting of an EEG helmet, motion sensing vest, and smartphone, which can predict potential falls by identifying the fall portents of a construction worker who wears it, and notify the worker and supervisor if necessary to prevent falls. As depicted in Fig. 2, a construction worker is normally required to wear safety gear, including a helmet, vest, and belt. Various sensors, such as EEG sensors, accelerometers, gyroscopes, or a smartphone can be attached to this gear. These sensors can detect the physiological condition of the worker, and send signals to the smartphone for primary analysis. The smartphone transmits the signals to an administration center for further analysis. When the system detects a fall portent, it should warn the worker with a series of sounds and vibration, and notify the supervisor with a text message.

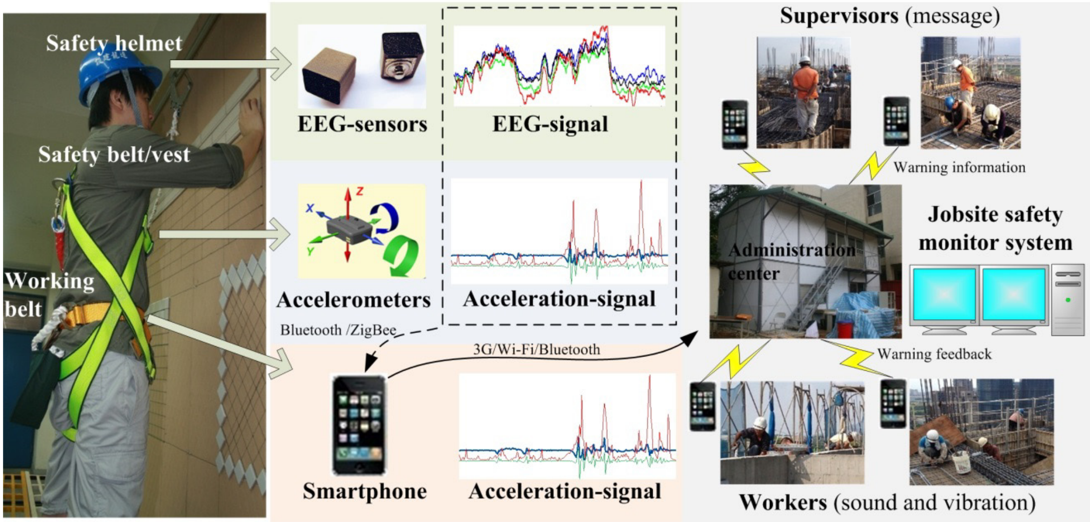

Fig. 2. Use scenario

The administration center on a jobsite monitors all workers wearing such safety gear, and performs personal and group trend analyses, because different workers may require different warning thresholds depending on the level of falling risk to which they are exposed. Statistical data can be represented in several ways using various sensors as a spectrum to show the physiological or fall-prone trends of a given worker. Based on this information, the supervisor may adjust the work schedule or tasks assigned to fall-prone workers. Nevertheless, the dynamic nature of the working conditions (e.g., changeable workplaces and high-motion activities) of construction workers is substantially different from the use scenario of drivers, the elderly, and patients. This dynamic condition produces noises and makes the fall portent detection challenging.

Currently, using a smartphone to process EEG and motion-sensor signal exhibits a primary limitation. The EEG (four channels) and motion-sensor (two tri-axial accelerometers) signals are received through Bluetooth and Wi-Fi, and their required sampling rates are 256 Hz and 64 Hz, respectively. However, most smartphones could process only the motion-sensor data using threshold algorithms, but could not process the numerous EEG data using the corresponding fast Fourier transform analysis, resulting in a substantial delay. Although few smartphones could process both EEG and motion-sensor data, the power could only be maintained for approximately 10 min. In summary, most current smartphones are capable of dealing with motion sensor data; however, they are not appropriate for processing EEG data because of limitations in the computing and battery capacities. Therefore, our prototype uses a smartphone to collect and analyze motion data, and uses a data logger to directly collect EEG data.

2.2. Prototype implementation using a smartphone

We developed an application, which runs on the iOS 6 of Apple, can record the data of a built-in accelerometer and gyroscope, perform a real-time analysis using threshold algorithms, and transmit the original data to the server for further analysis. In the prototype implementation, we used a smartphone (iPhone 4/iPod) attached to the waist of the participant to detect the fall portents. The smartphone included an accelerometer (LIS302DL), gyroscope (L3G4200D), processor, wireless receiver, and alarm (with both sound and vibrating abilities).

Threshold algorithms have received considerable attention in the field of fall detection and daily-activity monitoring because of their simplicity and minimum computing power requirements. Furthermore, the algorithms can accurately represent the degree of sway, and are thus suitable for detecting motion. The target detection is determined based on whether the value of the formula for processing sensor data (e.g., accelerometers and gyroscopes) exceeds the threshold. The weight of each data and threshold may differ for different target use scenarios. We adopted three threshold algorithms: accelerometer-based, gyroscope-based, and hybrid-based algorithms. For the sake of brevity, this paper presents only the optimal performer in our experiment, which was the accelerometer-based threshold algorithm originally proposed by Karantonis et al. [18], as shown in Eq. (1).

$$SVM_a(signal\ \ magnitude\ \ vector) = \sqrt{\left|A_X\right|^2 + \left|A_Y\right|^2 + \left|A_Z\right|^2} \tag{1}$$

where A_X, A_Y, and A_Z are the acceleration in the x-, y-, and z-axes, respectively.

The application consisted of recording, calculating, warning, and transmitting modules. The architecture of the system is illustrated in Fig. 3. The recording module acquires raw data from the built-in accelerometer and gyroscope, and then stores such data in text format in the smartphone. The calculating module applies threshold algorithms (accelerometer-based, gyroscope-based, and hybrid-based algorithms). Moreover, the user can adjust the weight of each axis of the motion data depending on the characteristics of the target motion (e.g., a sudden sway or loss of balance).

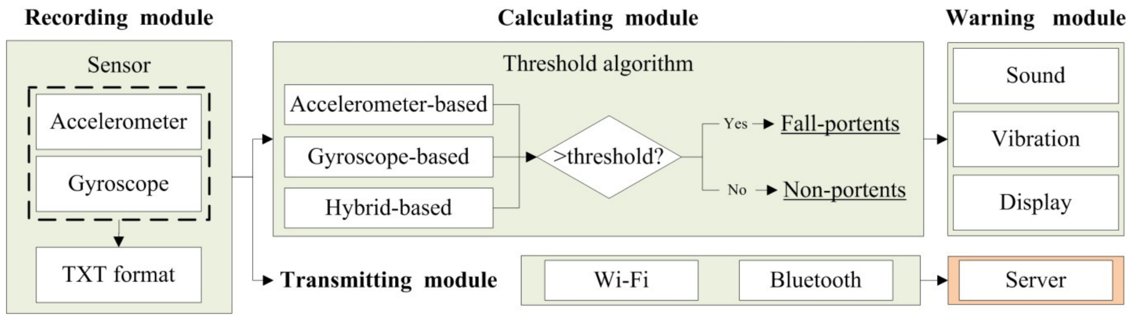

Fig. 3. Architecture of the phone-based system

The warning module is activated when the SVM_a value exceeds the corresponding threshold. Furthermore, to control the alarm sensitivity, the user can adjust the threshold depending on the type of job. Nevertheless, adjusting the threshold results in a trade-off between accuracy and a false-detection rate. The results of the experiment described in the next section applied the threshold with the optimal accuracy. The transmitting module sends the stored data to a monitoring server through Wi-Fi or Bluetooth for advanced analysis involving multiple workers.

Figure 4 presents the interface of the App, including the "Start Guarding" and "Options" pages. In the "Start Guarding" pages (Fig. 4-1), data recording can be activated or terminated by clicking the "Start" and "Stop" buttons. The traffic light icons dynamically display the real-time calculation results of the three algorithms, depending on how much the threshold of the SVM_a value is exceeded. When the SVM_a exceeds the fall-prone threshold, the light becomes red, and sends out a sound warning with vibration. When the SVM_a reaches 80% of the threshold, without exceeding it, the light becomes yellow, without a warning. Otherwise, the light remains green. However, although the yellow signals do not send out any personal warning, their occurrences are monitored in the server, and an appropriate warning can be sent to the supervisor if the frequency exceeds a certain threshold.

In addition, the page displays the recording status and settings. The user can adjust the settings in the "Options" pages (Fig. 4-2). For instance, changing the e-mail address to which the data is sent, activating both the accelerometer and gyroscope, adjusting the sampling rate (i.e., 0.007 s approximately equals 1000/7 = 140 Hz).

Furthermore, the user can determine if the header and time tag should be attached to each sampling data in the exported file.

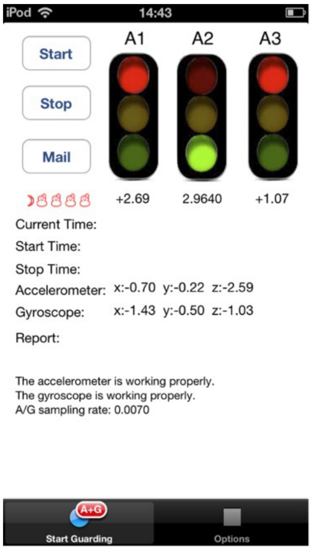

Fig. 4-1

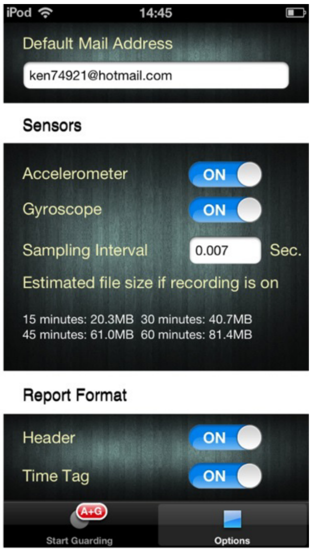

Fig. 4-2

Fig. 4. App interface

3. System evaluation

We designed an experiment to evaluate the effectiveness of the smartphone-based detection system. The experiment simulated a construction working environment where a participant can perform a designated tiling task on a scaffold. To facilitate the experiment, we prepared a flannelette-covered wall and tiles that were glued with Velcro on the back. The experimental process was recorded by surveillance cameras.

The experiment defined an occurrence of a fall portent if any of the following three scenarios occurred. First, a participant felt loss of awareness or balance, and self-reported by raising a hand. Second, a participant produced an obvious sway that was identified by the experiment facilitator. Third, a participant crossed over the watch zone on the scaffold board, which was painted with a highlighted color. Because we expected that few portents could be produced when the workers were in a normal status, participants were also required to participate in the experiment in abnormal statuses (fatigue, sleepiness, and inebriation). The identified portents were assumed to be the detection targets, and used for comparing with the detection result of the tested algorithm to determine its accuracy.

Four graduate students from the construction management program of the National Chiao-Tung University volunteered to participate in the experiments. Each participant was required to perform the tiling task under four different statuses (i.e., normal, fatigue, sleepiness, and inebriation). To achieve these statuses, the participants were requested to perform the tiling task twice to induce fatigue, stay up all night before the experiment to induce sleepiness, and consume an alcoholic beverage (350 mL, 5% alcohol content) to induce inebriation.

Table 1 summarizes the results of the experiment. One hundred eleven actual portents were identified (Column a). One hundred twenty-nine warnings were activated based on the SVM_a algorithm (Column b). Column e shows the accuracy rate, which is the number of correct detections (Column c) divided by the number of activated warnings (Column b). The false-detection rate is the number of incorrect detections (Column d) divided by the number of warnings. Based on the accuracy rate for each status, the algorithm exhibited a satisfactory accuracy for the sleepiness (92.3%) and fatigue (90.4%) statuses, a mediocre accuracy for the normal status (77.3%), and the lowest accuracy for the inebriation status (68.8%). The algorithm attained an overall accuracy rate of 86%, with a false-detection rate of 14%. This result indicated that the tiling work-related motions had a limited impact on the detection algorithm. This result also indicated that all portents could be detected by the SVM_a algorithm, and detecting the target was much easier than avoiding a false detection. Thus, choosing an appropriate threshold value is crucial to reduce the false-detection rate, while maintaining a high detection rate.

Table 1. Results of experiment

Status	(a) Fall portents	(b) # of warning	(c) # of accurate detection	(d) # of false detection	(e) Accuracy rate (c/b)	(f) False-detection rate (d/b)
Normal	17	22	17	5	77.3%	22.7%
Sleepiness	36	39	36	3	92.3%	7.7%
Fatigue	47	52	47	5	90.4%	9.6%
Inebriation	11	16	11	5	68.8%	31.3%
Overall	111	129	111	18	86%	14%

The algorithm exhibited a lower accuracy rate for the normal and inebriation statuses (77.3% and 68.8%) than for the fatigue and sleepiness statuses (90.4% and 92.3%). One possible explanation is that, among the three proposed identification methods of fall portents, most portents were identified by the experiment facilitator, based on obvious sways. The regular motions of the participants decreased under the sleepiness and fatigue statuses, increasing the difference between the work-related sways and fall-portent sways. Consequently, under such conditions, it was easier for the facilitator to identify the fall portents, and define them as the targets. Under the normal and inebriation statuses, the difference between the work-related sways and fall-portent sways was not so obvious for the facilitator. As a result, some fall portents might have not been identified as targets. If these fall portents were included as targets, the false-detection rates would be decreased, and the accuracy rates would be increased. We also noticed that the portents related to loss of awareness without any sudden sway, or the motions without abrupt changes were difficult to detect using a motion sensor. Adjusting the threshold value to accommodate for this type of target may result in numerous false detections.

Figure 5 depicts an oscillation example of SVM_a for the sleepiness status, marked with a threshold of 1.3 in a red horizontal line, and exhibiting four identified portents marked with red diamonds. Obviously, the algorithm could detect all fall portents. However, the algorithm also generated three false alarms.

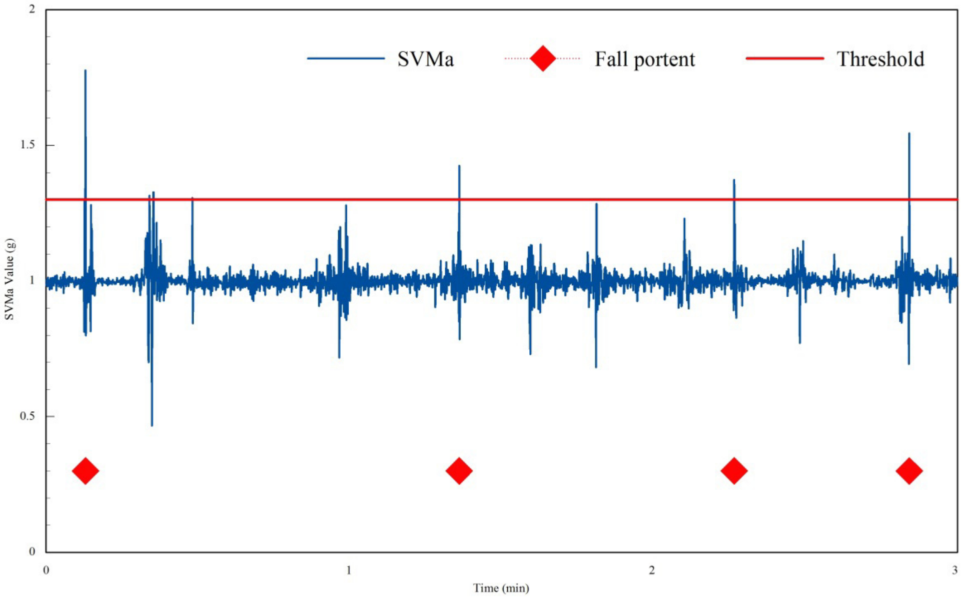

Fig. 5. An example of SVMa for the sleepiness status

4. Conclusion

Fall accidents have been identified as the leading cause of fatalities in the construction industry for several decades. Previous studies have indicated that loss of awareness and balance is the major cause of such injuries and fatalities, and several researchers have successfully detected the mental status of drivers, as well as the fall among the elderly and infirm. Such successful results provide a foundation for developing a real-time personal safety monitoring system for the construction industry.

This paper describes the conceptual model of a real-time personal safety monitoring system comprising an EEG helmet, motion sensing vest, and smartphone. The physiological signals recorded by these sensors can be wirelessly transmitted to a smartphone, which can act as an individual temporary data center, and perform primary analysis. The smartphone can also transmit the preliminary data wirelessly to a monitoring server for further analysis. When the system detects a fall portent (e.g., loss of awareness or balance), it should warn the worker and notify the supervisor, who may adjust the work schedule or tasks of the fall-prone workers.

This paper also presents the preliminary findings in detecting fall portents using a smartphone. We developed an App (iOS 6), which can record the data of the built-in motion sensors, perform a real-time analysis using threshold algorithms, and transmit the original data to a monitoring server. To evaluate the effectiveness of the smartphone-based detection system, the participants performed a simulated tiling task under four different statuses (i.e., normal, sleepiness, fatigue, and inebriation), while carrying a smartphone attached to their waist. Fall portents were identified based on any of the three methods (self-report, obvious-swaying, and line-crossing behaviors). The identified portents were compared with the detection result of the tested algorithm.

The results of the experiment indicated that the detection accuracy of the SVM_a algorithm for the sleepiness, fatigue, normal, and inebriation statuses were 92.3%, 90.4%, 77.3%, and 68.8%, respectively. The algorithm performed satisfactorily for the sleepiness and fatigue statuses, but unsatisfactorily for the normal and inebriation statuses. The decrease in the detection quality may be attributed to failure of the experiment facilitator to identify some portents, because they were not as obvious in the normal and inebriation statuses as in the sleepiness and fatigue statuses. Overall, all portents (i.e., 111 detection targets) were successfully detected in all statuses, but with additional false alarms that resulted in an accuracy rate of 86% and a false-detection rate of 14% (i.e., 18 false detections). We conclude that using a smartphone to detect fall portents in a working scenario is feasible, and deserves further investigation.

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References

[1] Council of Labor Affairs (CLA), Construction industry accidents knowledge platform, Institute of Occupational Safety & Health, 2014, http://www.iosh.gov.tw/CIAKP/ReportIndex.aspx?NID=575.
[2] Bureau of Labor Statistics (BLS), Occupational injuries and illnesses and fatal injuries profiles, 2012, http://data.bls.gov/gqt/InitialPage.
[3] K. Ohdo, Y. Hino, S. Takanashi, H. Takahashi, Y. Toyosawa, Study on fall protection from scaffolds by scaffold sheeting during construction, Procedia Engr. 14 (2011) 2179–2186.
[4] A. Carbonari, A. Giretti, B. Naticchia, A proactive system for real-time safety management in construction sites, Autom. Construct. 20 (6) (2011) 686–698.
[5] S.-N. Min, J.-Y. Kim, M. Parnianpour, The effects of safety handrails and the heights of scaffolds on the subjective and objective evaluation of postural stability and cardiovascular stress in novice and expert construction workers, Appl. Ergon. 43 (3) (2012) 574–581.
[6] G. Borghini, L. Astolfi, G. Vecchiato, D. Mattia, F. Babiloni, Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness, Neurosci. Biobehav. Rev. (2012), http://dx.doi.org/10.1016/j.neubiorev.2012.10.003.
[7] A.K. Bourke, P. van de Ven, M. Gamble, R. O'Connor, K. Murphy, E. Bogan, et al., Evaluation of waist-mounted tri-axial accelerometer based fall-detection algorithms during scripted and continuous unscripted activities, J. Biomech. 43 (15) (2010) 3051–3057.
[8] S. Abbate, M. Avvenuti, F. Bonatesta, G. Cola, P. Corsini, A. Vecchio, A smartphone-based fall detection system, Pervasive and Mobile Computing 8 (6) (2012) 883–899.
[9] D. Fuentes, L. Gonzalez-Abril, C. Angulo, J.A. Ortega, Online motion recognition using an accelerometer in a mobile device, Expert Syst. Appl. 39 (3) (2012) 2461–2465.
[10] S. Mellone, C. Tacconi, L. Chiari, Validity of a smartphone-based instrumented timed up and go, Gait Posture 36 (1) (2012) 163–165.
[11] J. Dai, X. Bai, Z. Yang, Z. Shen, D. Xuan, PerFallD: A pervasive fall detection system using mobile phones, IEEE Int'l Conf. on Pervasive Computing and Communications Workshops, Mannheim, 2010, pp. 292–297.
[12] G. Yavuz, M. Kocak, G. Ergun, H.O. Alemdar, H. Yalcin, O.D. Incel, et al., A smartphone based fall detector with online location support, Int'l Workshop on Sensing for App Phones, Zurich, Switzerland, 2010, pp. 31–35.
[13] Y. He, Y. Li, S.-D. Bao, Fall detection by built-in tri-accelerometer of smartphone, IEEE-EMBS Int'l Conf. on Biomedical and Health Informatics (BHI), Hong Kong, China, 2012, pp. 184–187.
[14] Y.-T. Wang, C.-K. Cheng, K.-C. Huang, C.-T. Lin, Y. Wang, T.-P. Jung, Cell-phone based drowsiness monitoring and management system, IEEE Biomedical Circuits and Sys. Conf. (BioCAS), Hsinchu, Taiwan, 2012, pp. 200–203.
[15] A. Stopczynski, C. Stahlhut, J.E. Larsen, M.K. Petersen, L.K. Hansen, The smartphone brain scanner: A mobile real-time neuroimaging system, arXiv:1304.0357 (2013), http://www.plosone.org/article/info%3Adoi%2F10.1371%2Fjournal.pone.0086733
[16] H. Szu, C. Hsu, G. Moon, T. Yamakawa, B.Q. Tran, T.P. Jung, et al., Smartphone household wireless electroencephalogram hat, Applied Computational Intelligence and Soft Computing (2013), http://dx.doi.org/10.1155/2013/241489
[17] F. Bonomi, R. Milito, J. Zhu, S. Addepalli, Fog computing and its role in the internet of things, The first edition of the MCC workshop on mobile cloud computing, Helsinki, Finland, 2012, pp. 13–16.
[18] D.M. Karantonis, M.R. Narayanan, M. Mathie, N.H. Lovell, B.G. Celler, Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring, IEEE Transactions on Information Technology in Biomedicine 10 (1) (2006) 156–167.