Abstract

The construction industry accounts for nearly half of all industrial-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 employment, workers are prone to loss of awareness and balance, increasing safety risk and fall accidents. Previous literatures have indicated that loss of awareness may be the major cause of occupational injuries or fatalities, and identified the strong correlation between fall 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 of 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 of a helmet, and transmit these signals to a monitoring server for further analysis. The paper also presents an experiment with preliminary findings of detecting fall portents using internal motion sensors of a smartphone. In the experiment, participants performed a tiling task under four physiological statuses on a scaffold. We identified the fall portents based on subjects' self-awareness and actually performing hazardous actions, and outsider observations from experiment administrators. An accelerometer-based threshold algorithm was tested and its performance was evaluated against the identified fall portents.

The result indicates that the work-related motions had limited impact on the detection algorithm. The accuracy under the sleepiness, fatigue, normal, and inebriation statuses were 92.3%, 90.4%, 77.3%, and 68.8%, respectively. With the algorithm exhibiting an overall accuracy of 86%, we conclude that using a smartphone to detect fall portents in a working scenario is feasible and worthwhile studying further.

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

1. Introduction

Construction jobsites account for nearly half of all industrial-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 attributed to fall accidents from 2000 to 2012. Moreover, fall accidents contributed to approximately 67.07% (110 of 164) and 62.5% (90 of 144) fatalities in 2011 and 2012, respectively (CLA, 2014). This indicates the prevention of fall may be still insufficient or ineffective.

Fall accidents are common in the construction industries of many countries. The U.S. Bureau of Labor Statistics reported that 33.76% of fatalities (284 of 817) were related to falls in the U.S. construction industry (BLS, 2012). Falls also contributed to approximately 40% fatalities in the Japanese construction industry (Ohdo et al. 2011). Furthermore, falls represented the highest number of fatalities in the European and Korean construction industry, accounting for 52% and 30% of all work-related accidents (Carbonari et al. 2011; Min et al. 2011), respectively.

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

According to the report of CLA, approximately 54% of all workers attributed loss of awareness as the major cause of occupational injuries or fatalities, while only 25% attributed it to equipment failure and the surrounding environment. The strong correlation between fall accidents and loss of balance has been also 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. EEG (electroencephalography) can represent mental condition including fatigue, drowsiness, attention, and alertness. Researchers have successfully applied EEG monitoring to detect driving fatigue for aircraft pilots and car drivers (Borghini et al. 2012). On the other hand, motion sensors such as accelerometers and gyroscope 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, especially in fall detection for the elderly and patients (Bourke et al. 2010).

Nowadays a smartphone with built-in accelerometer and gyroscope has emerged as a popular, carry-on personal belonging. Several studies have begun to establish smartphone-based fall detection or activities recognition system (Abbate et al. 2012). Mellone et al. (2012) indicated that smartphone is capable of becoming a pervasive and low-cost tool for the quantitative analysis of balance and mobility. Dai et al. (2010) used a smartphone to detect fall, and the proposed system achieved strong detection performance and power efficiency. He et al. (2012) 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, smartphone can also integrate external motion sensors and EEG sensors using Bluetooth or Wi-Fi, and transmit the data to a monitoring server (Wang et al. 2012). Stopczynski et al. (2013) developed a smartphone that displayed real-time images of brain activities. Szu et al. (2013) 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), they cannot determine whether a worker is losing awareness or balance. The inability to monitor the physiological status of workers makes the jobsite safety management difficult, and workers working under inappropriate or even dangerous physiological condition without the supervisor knowing it. As aforementioned, the loss of awareness and balance can be appropriate signs for fall portents, and some researchers have successfully detected the mental status of drivers and the fall for the elderly and patients. Such result provides valuable information on developing real-time personal safety monitoring system in a more complex environment such as in the construction industry, which features a large number of interacting workers working simultaneously over a wide area with continuous movement and a constantly changing environment. This paper presents a framework of developing a personal safety monitoring system based on a smartphone, and shows the initial result of our on-going research with the preliminary findings of an experiment designed to evaluate the accuracy of detecting fall portents using internal motion sensors of a smartphone.

2. Smartphone-based detection system

2.1. Conceptual model and use scenario

This study attempts to develop a real-time personal safety monitoring system consisted of an EEG helmet, motion sensing vest, and smartphone, that can predict falls by identifying the fall portents of a construction worker who is wearing it and notify the worker and supervisor if necessary to prevent falls. As depicted in Fig. 1, a construction worker is normally required to wear safety gear, including a helmet, vest, and belt. A variety of sensors, such as EEG sensors, accelerometers, gyroscopes, or smartphone, can be hooked up to this gear. These sensors can detect the physiological condition of the worker and send signals to the smartphone for primary analysis. The smartphone will transmit the signals to administration center for further analysis. When the system detects a fall portent, it should warn the worker with a series of sound and vibration, and notify the supervisor with text message.

The administration center on a jobsite monitors all workers wearing such safety gear and performs personal and group trend analyses, as 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 different sensors as a spectrum to show the worker's physiological or fall-prone trends. Based on this information, the supervisor may adjust the work schedule or tasks assigned to fall-prone workers. It should be noted that the dynamic nature of working condition (e.g., changeable workplaces and high-motion activities) of construction workers is significantly different from the use scenario of the drivers, elderly, and patients. The dynamic condition produces noises and makes the fall portent detection challenging.
2.2. Prototype implementation with a smartphone

We developed an application, which runs on Apple’s iOS 6, to 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 (e.g., iPhone 4/iPod) attached to the subject’s waist to detect the fall portents. The smartphone consisted of an accelerometer (i.e., LIS302DL), gyroscope (i.e., L3G4200D), processor, wireless receiver, and alarm (with both sound and vibrating abilities).

Threshold algorithms received considerable attention in the field of fall detection and daily activity monitoring due to its simplicity and minimum computing power requirements. Furthermore, the algorithm can accurately represent the degree of sway and is thus suitable for detecting motion. The target detection is determined based on whether the value of the formula composed of sensor data (e.g., accelerometers and gyroscopes) exceeds the threshold. The weight of each data and threshold may be different for different target use scenarios. We adopted several threshold algorithms, including accelerometer-based, gyroscope-based, and hybrid-based ones. For brevity, this paper presents only the best performer in our experiment, which is the accelerometer-based threshold algorithm originally proposed by Karantonis et al. (2006), as shown in Eq. 1.

\[
SVM^{\text{acc}}(\text{signal magnitude vector}) = \sqrt{|A_X|^2 + |A_Y|^2 + |A_Z|^2}.
\]  

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 system architecture is shown in Fig. 2. The recording module acquires raw data from the built-in accelerometer and gyroscope, and then stores such data in the text format in the smartphone. The calculating module applies threshold algorithms such as accelerometer-based, gyroscope-based, and hybrid-based ones. Besides, the user can adjust the weight of each axis of the motion data depending on the characteristics of the target-motion (e.g., sudden sway or loss of balance).
The warning module is activated when the SVM value exceeds the corresponding threshold. Furthermore, the user can adjust the threshold depending on the type of job to control the alarm sensitivity. It should be noted that adjusting threshold results in a trade-off between accuracy and false-detection rate. The result of the experiment described in the next section assumes the threshold with the best accuracy in our experiment. Transmitting module sends the stored data to a monitoring server via Wi-Fi or Bluetooth for further advanced analysis that involves multiple workers.

Figure 3 shows the interface of the App, including “Start Guarding” and “Options” pages. In the “Start Guarding” pages (Fig. 3-1), data recording can be activated or terminated by clicking the “Start” and “Stop” buttons. The traffic lights icons dynamically show the real-time calculation result of three different algorithms depending on how much percentage of the threshold the SVM value exceeds. When the SVM exceeds the fall-prone threshold, the light is on red and sends out a sound warning with vibration. When the SVM exceeds 80% of the threshold without exceeding the threshold, the light is on yellow without warning. Otherwise, the light remains green. Note that, although the yellow signals do not send out any personal warning, their occurrences are monitor in the server and an appropriate warning can be sent to the supervisor if the frequency exceeds a certain threshold.

In addition, the page also shows the recording status as well as the setting information. The user can adjust the setting in the “Options” pages (Fig. 3-2). For instance, changing e-mail address, which the data would be sent to, activating both accelerometer and gyroscope, adjusting sampling rate (i.e., 0.007 second approximately equals 1000/7=140Hz). The user can determine if the header and time tag should be attached to each sampling data in the exported file.

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 subject 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 experiment process was recorded by surveillance cameras.

The experiment defined an occurrence of fall portent if any of the following three scenarios occur. First, a subject felt loss of awareness or balance, and self-reported by raising a hand. Second, a subject produced an obvious sway that was identified by the experiment facilitator. Third, a subject crossed over the watch zone on the scaffold board that was painted with a highlighted color. Since we expected few portents could be produced in a normal status, subjects were required to participate in the experiment in different statuses including normal, and other abnormal statuses such as fatigue, sleepiness, and inebriation. The identified portents were assumed to be the detection targets and used to be compared with the detection result of the tested algorithm to determine its accuracy.

Four graduate students from the construction management program of 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 alcohol beverage (350ml with 5% alcohol content) to induce inebriation.

Table 1 shows the experiment results. The number of actual portents identified is 111 (Column a). The number of warning activated based on the SVM algorithm is 129 (Column b). Column e shows the accuracy rate, which 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 (Column d) over the number of warnings. Based on the accuracy rate under each status, the algorithm performed satisfactory accuracy under the sleepiness (92.3%) and fatigue (90.4%) statuses, a mediocre accuracy under the normal status (77.3%), and the worst accuracy under inebriation status (68.8%). The algorithm performed an overall accuracy rate of 86% with a false-detection rate of 14%. The result indicates that the tiling work-related motions had limited impact on the detection algorithm. The result also indicates that all portents can be detected by the SVM algorithm, and detecting the target is much easier than avoiding false detection. Thus, choosing an appropriate threshold value is important to reduce the false-detection rate while maintaining a high detection rate.

The algorithm had a lower accuracy rate under the normal and inebriation statuses (77.3% and 68.8%) compared to 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 experiment facilitator based on the obvious sways. The regular motions of participants became smaller under the sleepiness and fatigue statuses, and enlarge the difference between the work-related sways and fall-portent sways. Consequently, it was easier for the facilitator to identify the fall portents and define them as the targets. In the normal and inebriation statuses, the difference between the work-related sways and fall-portent sways was not so obvious for the
facilitator to identify. As a result, some fall portents might not have been identified as the targets. If these fall portents were included as the 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 be detected using a motion sensor. Adjusting the threshold value to accommodate for this type of targets will result in large amount of false detections. Figure 4 depicts an oscillation example of SVM for sleepiness status, marked with the threshold of 1.3 in a red horizontal line and four identified portents marked with red diamonds. Obviously, the algorithm can detect all fall portents. However, the algorithm also generates three false alarms.

Table 1. Results of experiment

| Status     | (a) | (b) | (c) | (d) | (e) | (f) |
|------------|-----|-----|-----|-----|-----|-----|
|            | Fall | # of | # of | # of | Accuracy | False- |
|            | portents | warning | accurate detection | false detection | rate (c/b) | 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%   |

Figure 4. An example of SVM for the sleepiness status

4. Conclusion

Fall accidents have been identified the leading cause of fatalities in construction industry for several decades. Previous literatures 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 and the fall for the elderly and patients. Such successful result provides a foundation for developing real-time personal safety monitoring system in the construction industry.

This paper has described the conceptual model of a real-time personal safety monitoring system consisted of 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 detect 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 to 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) with a smartphone attached to their waist. Fall portents were identified based on any of the three methods, namely self-report, obvious-swaying, and line-crossing behaviors. The identified portents were compared with the detection result of the tested algorithm.

The experiment result indicated that the detection accuracy for the SVM algorithm under the sleepiness, fatigue, normal, and inebriation statuses were 92.3%, 90.4%, 77.3%, and 68.8%, respectively. The algorithm performed quite well under sleepiness and fatigue statuses, but not so good under the normal and inebriation statuses. The decrease of the detection quality may be attributed to the situation where the experiment facilitator failed 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) under four statuses were successfully detected, but with additional false alarms that result 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 worthwhile studying further.

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