An Intelligent App for Safely Texting-while-Walking in Indoor Environments

Shih-Yu Huang

Department of Computer Science and Information Engineering, Ming Chuan University

ABSTRACT

People are increasingly inseparable from their smartphones. People often use smartphones during fragmented free time, such as when sitting or standing around with little to do. There is a trend whereby users will often write text messages as they walk around indoors. In this situation, the device can block out a large part of the user's field of vision, and take away their attention from the periphery of their vision, and so accidents may occur. However, it is difficult to prevent users from texting while they walk. This paper therefore proposes and outlines the design, development and testing of a smartphone App, which utilizes the three-axis accelerometer and camera on a smartphone to detect unsafe corridors and warns users immediately to avoid accidents. When an obstacle is detected or the environmental light level is dangerously low, the proposed App will give a warning message to the user. The experimental results indicate that the danger detection rate of the proposed App is over 95%. The proposed system may help reduce the dangers of walking indoors while using a mobile device such as a smartphone.

Keywords: smart phone, three-axis accelerator, video processing, dangerous road

一個適用於室內環境防止邊走路邊滑手機之智慧型 App 設計

黃世育

銘傳大學資訊工程系

摘　要

在這人手一機的時代，使用者除了坐著或站著使用行動裝置之外，甚至還會邊走路邊滑行動裝置，這樣的情況產生不少的意外事件，本論文利用三軸加速器與手機相機等手機上的感應器資訊設計一智慧型 App 來降低類似的意外事故，當環境光線昏暗或前方路面有障礙物時，所設計的 App 會產生告警訊息提醒使用者，實驗數據顯示所提演算法的偵測率高達 95%，本論文所提的 App 是一個提供安全通勤好的選項。

關鍵詞：智慧型手機，三軸加速器，視訊處理，危險路面。

文稿收件日期 106.3.17;文稿修正後接受日期 106.9.26; *通訊作者
Manuscript received March 17, 2017; revised September 26, 2017; * Corresponding author

I. INTRODUCTION

In the era of smart phone, people use mobile devices not only in sitting or standing. While walking, it is very common for users to watch videos on the phones, text, or swipe phones. However, the scenario could be perilous because the smart phones easily block the users' visions when they walk and concentrate on the screen at the same time. Pedestrians get injured or even lose their lives on the sidewalk or at an intersection due to such behavior. The trend indicates that since the screen size of smart phone tends to be bigger and bigger, the number of similar incidents is growing [1, 2].

NTT DOCOMO, Japan's largest mobile service provider, has developed a mobile-application software (App) to deal with the issue. When the App detects that the user is playing smart phones when they move, the App will automatically issue signals to warn them [3]. In 2012, another Japanese company, Softbank, has developed a similar App for the same purpose [4]. Zhou and others also proposed a Heads Up system to solve the problem [5]. In Zhou's research, the system utilized data from gyroscope sensor, accelerometer, and GPS on the smart phone to determine whether a user is watching and walking at the same time . If the system confirms the watching-and-walking status, the phone screen will be locked to prevent further use of the phone.

Conceptually, these Apps should be effectual. Nevertheless, swiping smart phones while walking is an inevitable trend. It will be very annoying for any phone user to keep receiving warning messages or to have their service stopped. As a consequence, these Apps are rarely used. Therefore, a more perceptive App is proposed in this paper. The App is not only able to sense if users are walking and swiping phones at the same time, but also determine if the road condition is hazardous in front of the users. If there is an obstacle, an uneven road, or a risky condition on the way, a warning message will then be issued.

To design a smarter safe-walking-reassuring App, two major subjects need to be focused on. The first subject is how to accurately determine if a user is texting while walking, and the second is how to efficiently identify the upcoming threat. The first subject can be addressed by using the information from the tri-axis accelerometer embedded on the smart phone. The second subject can be solved by analyzing images taken from smart phone's video camera. Subjects concerning how to determine a phone user's behavior by using the three-axis accelerometer have been popular research topics [6-17]. The event in the first subject in this paper is relatively straightforward. It concerns only if a user is texting while walking.

On the other hand, applying image processing techniques to detect hazardous roads has been extensively studied in helping blind people to find safer paths [18-23]. One major contrast between earlier study and this research is that the earlier ones were mainly based on computer platform, yet this research adopts smart phone. Not only that the computing power of a smart phone is inferior to that of a computer, but that the real-time response cannot be compromised particularly in our study to detect risky roads. Hence, the dense algorithms that serve blind people to find safer paths are not suitable for our study. Fortunately, our goal is just to identify risky road, which is simpler than assisting blind people to find safer paths. Therefore, the feasibility of this research increases.

The remainder of this paper is organized as follows. Section 2 presents the related works in tri-axial accelerometer to determine phone users' behavior and safe-path detections. The technology for safely texting-while-walking is described in Section 3. Section 4 shows the experimental results of the proposed App. Finally, the conclusions and future works are given in Section 5.

II. RELATED WORKS

In this section, we will review the existing studies of the use of tri-axial accelerometer to determine phone users' behavior, and the use of image processing techniques to detect hazardous road condition.

Determining phone users' behavior by means of tri-axial accelerometer has been a popular research topic [6-10]. Research in [6] indicated that the Nyquist rate for gravity sensor to collect data should be in the range of 15 - 16 Hz. This means that the maximal signal frequency allowed is 8Hz, which is considered to be sufficient to assess human body activity. Android operating system has four frequency modes: general mode (5Hz), interface mode (15Hz), game mode (50Hz), and high-speed mode (100Hz). Many important features might not be observed if the frequency is too low. On the contrary, if the frequency is too high, excessive data sampled will increase the chance of false positives. Hence, the suitable frequency to analyze human body activity should be at 15Hz.

Davide Anguita et al. [7] extracted 17 features from the smart phone tri-axial sensor. Those features were utilized in Support Vector Machine (SVM) classifier to identify 15 basic human body activities. Also, in a research of mobile media content, Abayomi and Andrade [8] indicated that the average, minimum, maximum, and standard deviation of the signals from three axes respectively were enough to represent basic states of human body activities. Adopting F-score as the standard, various states of human body activities were used in training and testing via distributed dataset. Together with GPS positioning, the system was capable of recommending media content on the basis of phone users' current behavior and locations.

Siirtola et al. [9] employed decision trees to recognize human body activities in both real-time and off-line conditions. The system was developed on Android operating system. The system classifies the activities by their own characteristics. The results showed that the minimum 98% recognition rate was achieved in off-line case, while the lowest real-time recognition rate was 84.5%.

Liu et al. [10] extracted data of the average, standard deviation, average acceleration, frequency of a periodic wave, and binomial distribution of the three axes respectively in the tri-axial sensor. Different classification algorithms were applied subsequently to identify human body activities. The algorithms included Random Forest, Instance-based Learning, Neural Network, Rule Induction, Naive Bayes, Voting Feature Intervals, and Logistic Regression. The experimental results showed that the Random Forest algorithm achieved the maximal recognition rate.

In addition to analyzing human body behavior, the tri-axial accelerator is also widely used in fall detection [11-17], especially for senior citizens. Similar studies can be divided into two types: the smart phone that is fixed on the human body in a specific direction, and the smart phone that is placed randomly on the body. Yi He et al. [11] proposed to carry the smart phone on the waist in an upright position with the screen facing outward. The Signal Magnitude Area (SMA) of the three axes in the tri-axial sensor was then calculated as the threshold to determine the state of human body activities.

Abbate [12] claimed that a human being changed from a static body position to an active state would cause at least 3G force to the smart phone gravity sensor. Using the Finite State Machine to accomplish sensing process would reduce the possibility of false positives outcome. Neural Network classification was subsequently applied to recognize human body activities.

Cao et al. proposed a fall detection system E-FallD [13]. Users were required to enter personal information such as body weight, height, age, and emergency contact number. Threshold values would then be generated accordingly. Data from the tri-axial sensor would be used by SVM classifier to identify the user's current state. If a user fell but could not stand up, the system would generate a message to the corresponding emergency contact phone.

Yavuz et al. [14] proposed the use of Discrete Wavelet Transform (DWT) to reduce the noise of the tri-axial accelerometer, and data mining approaches would then be applied on the SQLite database to determine whether the signal pattern indicated that the user had fallen down. If it was confirmed that the users has fallen, a message would be sent to Twitter, together with Google maps to show the location of the incident.

Hou et al. [15] proposed a real-time fall detection system by means of the tri-axial accelerometer. In order to assess the fall condition, the smart phone would be attached on the user. Then SVM classification was applied to monitor the user's activity. If the user fell, the acceleration would trigger the system. Mellone et al. [16] developed an uFall App to detect the fall situation by using the mobile phone sensors. He et al. [17] adopted the SMA techniques, together with the tri-axial accelerometer to determine whether the user's status is lying down, standing up, falling, moving horizontally, or moving vertically.

In the study of using image processing technology to help blind people finding safe paths, the following two categories have been widely used: the first is the reconstruction of the three-dimensional spatial structure; the second is the object identification. In the first category, the structure from motion (SFM) is one of the most commonly techniques used. The method is to locate corresponding objects from multiple images. The objects are used to reconstruct the three-dimensional space with Epipolar geometry. Although the method has relatively high accuracy, it takes a lot of computing power.

In the year of 2007, Davison et al. proposed monocular simultaneous localization and mapping technique [18] so that the SFM could be computed in real-time. Engin Tola et al. reconstructed the three-dimensional space of an actual scene by the filming of a video camera [19] . The RANSAC-based F-matrix was used to compute the displacement of each of the images. The F-matrix of each pair of images was converted into a corresponding projection matrix. The matrixes were used to reconstruct the 3D scene. Alberto et al. adopted a dual camera for a 3D scene reconstruction. The research utilized the tri-axial accelerometer to measure the camera angle. By filtering out the noisy background and obstacles beyond reach, areas of normal road condition would be obtained. In this way, tremendous amount of computation in the image processing was reduced.

The SFM strategy was then applied to determine the relative position of each video image through comparing multiple successive images. Speeded up robust features (SURF) algorithm was used in the corresponding image shooting position. Compared with scale invariant feature transform (SIFT), SURF could save quite amount of time in extracting feature points. Although in comparison, slight deviations did exist among feature points, the SURF algorithm was able to identify the location corresponding to the coordinates. Linear combination was then adopted to generate the transformation matrix H of the images taken. The matrix H of each image was calculated to build the real scene so that each pixel would have coordinates in the 3D space. After getting the coordinates of each pixel, the potential area of the road surface could be obtained. Thus, whether there was an obstacle on the road could be quickly identified.

The object identification strategy is capable of detecting obstacles by features of background, shape, color, and edge. The features of the background and the shape aren't suitable since they demands tremendous efforts in training. In contrast, the use of color information and edge features to learn and identify obstacles on the path is more practical. The color histogram feature is commonly used due to its simplicity and efficiency. It is particularly suitable for the use in real-time image processing. Tan et al. [20] established color histogram model of a road by collecting the color of the small area in front of a car. En Pen et al. [21] defined a preset height and angle to calculate the flat road surface in the image. They set the small area in front of the user as a safe area and established the quantized color histogram of the area. After that, they compared the color histogram with that of the flat road surface, and then a possible obstacle in the safe area could then be identified. Furthermore, the image was divided into three zones. According to the distance from the obstacles to the user, a recommended traveling direction would be provided to the user.

Taylor et al. [22] used the edge features to detect a safe path. The study assumed that stairway was a single-colored obstacle. The RGB videos were converted to HIV signals, preventing the impact of light on color to secure safe navigation. Qing Lin et al. [23] applied the torque converter to transfer image perspective to vertical overlooking view. Edge detection techniques were then utilized to locate the shape of edges in the image. Obstacles, in contrast to flat road surface, could be identified by pattern filter. The use of polar operation to locate the obstacle position in the real world would allow users to be warned of possible collisions.

III. THE PROPOSED ALGORITHM

This section first analyzes the potential hazardous situation when users walk and swipe smart phones simultaneously. Secondly, details of the proposed detection technique for walking-and-texting scenarios will be introduced.

3.1 Analysis Of Potential Hazardous Situation When Users Texting While Walking

Generally speaking, most of the users who walk and text belong to young age group. The practice can be seen at all locations such as campuses, companies, and bus stations. In many circumstances, the smart phones are used inside a building. Hence, in this paper, we focus on indoor environment. Three common scenarios are discussed as follows.

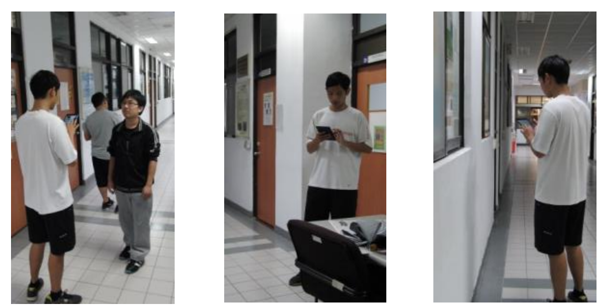
3.1.1 Walking in roomy interior corridors

Figure 1. (a) shows the side-view of a user who is using a smart phone while walking in a roomy interior corridor. Figure 1. (b) displays the captured image of the smart phone's camera. Floor tiles in the image suggest that the situation is considerably safe.

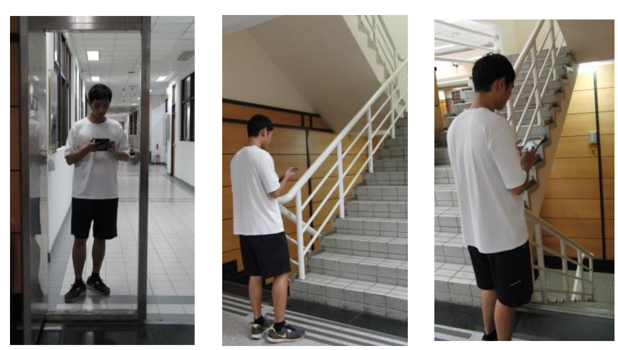
(b) (a)

Figure 1. Using a smart phone while walking in a oomy interior corridor: (a) Photo of the user (b) Captured image of the smart phone's camera

3.1.2 Encountering obstacles on the way



(a) (b) (c)

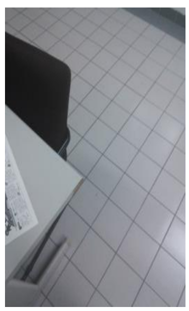


(d) (e) (f)

Figure 1. Obstacles on the way

The situation is that when a smart phone user walks on a path, the obstacles are located directly in front of the user, or on the side. Types of obstacles are varied, including pedestrians, walls, door steps, stairs, or other objects. Figure 1 (a) - (f) were images showing a variety of obstacles. Figure 2 (a) - (f) are images of corresponding situations captured by the smart phone's camera. Usually, in these situations, users will focus on using their smart phones and accidents may easily happen. Among them, staircase is most life-threatening. Careless fall may be fatal. Furthermore, not aware of upcoming objects on the way will easily lead to a sprained ankle.

(a)

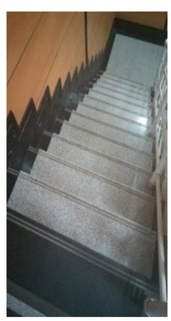


(b)

(c)

(d)

(e)



(f)

Figure 2. Images captured by the smart phone's cameras of corresponding situations in figure 2

3.1.3 Walking in an environment of insufficient light

Figure 4 shows the captured image of the smart phone's camera in an insufficiently illuminated environment. Evidently, insufficient light can be dangerous to any person, not limited to smart phone user, even in a roomy corridor.

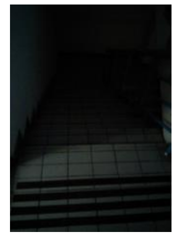


Figure 4. Image captured by the smart phone's camera in an insufficiently illuminated environment

3.2 Proposed System

Figure 5 shows the proposed system, which consists of two modules: one is texting while walking detection module (TWDM); the other is dangerous road detection module (DRDM). The system starts with TWDM module. Data from the smart phone tri-axial accelerometer will be collected. Then the SVM classifier is employed to determine whether the user is texting while walking. If the answer is positive, the system will enter DRDM modules. Images will be taken immediately by the smart phone's camera, followed by a road condition analysis. If the captured image indicates a hazardous condition in front, the system will generate a warning message. The following paragraphs will discuss the designs of TWDM modules and DRDM modules.

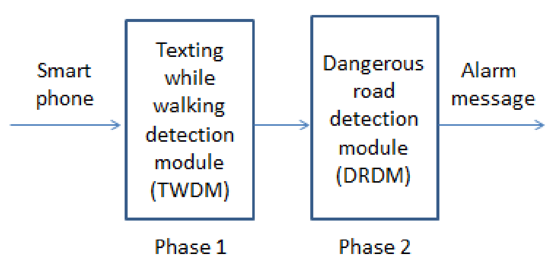


Figure 5. Structure of the proposed system

A. Texting while Walking Detection Module (TWDM)

The motion of the tri-axial accelerometer in a smart phone when a user is walking is shown in Figure 6. The movement of walking of a human being is composed of lifting up the foot, stretching forward, and then dropping the foot. The actions form a certain pattern which makes the value of Z-axis accelerometer change regularly as shown in Figure 7. In addition, while a user is walking and texting at the same time, the smart phone is in a face-up position, which naturally tilts upward. Charts in Figure 8 present the value of Z-axis accelerometer in six different circumstances.

Figure 8 (a) shows the situation when a smart phone is used in a shaking condition. The tri-axial accelerometer receives violent forces in all directions. Therefore, the change in the Z-axis accelerometer is huge. Figure 8 (b) shows that the smart phone is still and the user is not using the phone. Hence, Z-axis accelerometer is in a steady state. Figure 8 (c) shows that the user is using the smart phone when it is in a stationary state. The value of Z-axis accelerometer changes irregularly. Figure 8 (d), (e), (f) display motion of Z-axis accelerometer when using the smart phone in different circumstances on public transportation. Since primary force comes horizontally, the major value variations are observed in Y-axis accelerometer and Z-axis accelerometer. The changes of value in Z-axis accelerometer are mainly due to the bumpiness of the road.

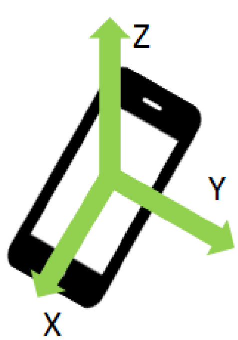


Figure 6. Motion of the tri-axial accelerometer in a smart phone when a user is walking

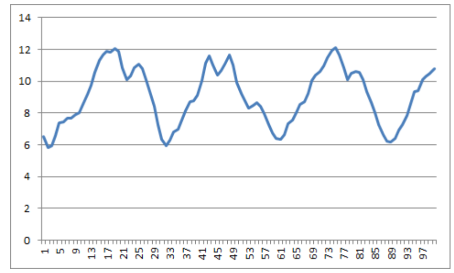
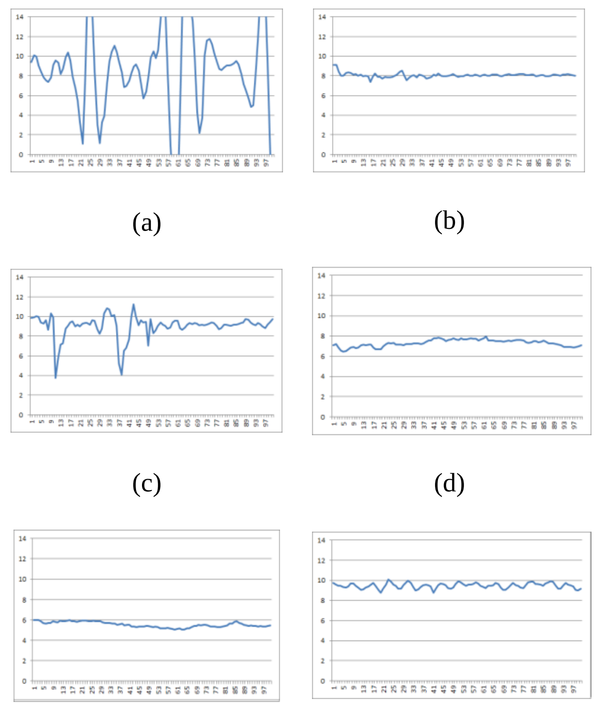


Figure 7. Value of the Z-axis accelerometer while walking



(a) (b)

(c) (d)

(e) (f)

Figure 8. Value of Z-axis accelerometer in six different circumstances: (a) Shaking, (b) Still; smart phone not in use, (c) Still; smart phone in use, (d) Car Decelerating, (e) Car Accelerating, (f) On the Subway

In this paper, the above mentioned pattern emerged in the value of Z-axis accelerometer is used to detect whether the user is texting while walking. We adopt the average of wave length (WLA), the number of the waves (WC), the variances of wave length (WLV), and the variances (ZV) respectively of the value of Z-axis accelerometer to design SVM classifier. The first three features are able to discriminate the regularity of the value of Z-axis accelerometer. The fourth is able to discriminate the scale of force. Table 1 shows the values of WLA, WC, WLV, and ZV in different situations. Each situation has three different test values. The values of WLA, WC, WLV, and ZV of walking are quite different from these of other circumstances. Table 1 demonstrates that the four adopted features can effectively detect the texting-while-walking events.

B. Dangerous Road Detection Module (DRDM)

In this paper, we classified the potential threatening road condition when the smart phone user is walking and texting simultaneously into two levels. The first level of danger (most dangerous) situation is when light is insufficient. The second level is when obstacles such as pedestrians, chairs, stairs, doorstep, or any other items block the way. When the texting-while-walking event is detected, the proposed algorithm will start to detect the first level of danger. If the danger is detected, the system will generate a warning on the screen immediately. Otherwise, the proposed algorithm will proceed to detect the second level of danger. If the second level of the danger is detected, the system will generate a warning on the screen. The following paragraphs will discuss how those two detection algorithms work to assist the smart phone users walk safely.

The Support Vector Machine (SVM) is used to detect texting-while-walking event, which is a machine learning algorithm that utilizes multi-dimensional vectors to train a data model. So the model is able to predict the category of the current usage. There are two categories in this research: Texting While Walking Category (TWWC) and Non Texting While Walking Category (nTWWC). When the wave pattern of Z-axis accelerometer is categorized as TWWC by the SVM of TWDM, the proposed system will enter DRDM module. Otherwise, the system will remain in TWDM module, and continue to monitor activity of the Z-axis accelerometer.

Table 1. Features in different using situations: (A)Walking, (B) Shaking, (C) Still; smart phone not in use: (D) Still; smart phone in use, (E) Car Accelerating, (F) On the Subway

Situations	Features			
	WLA	WC	WLV	ZV
(A)	25.50	2	2.25	1.31
	25.50	2	2.25	1.51
	27.33	3	2.22	1.53
(B)	11.86	7	26.12	33.47
	11.67	6	24.56	23.46
	10.63	8	21.73	30.49
(C)	0.00	0	0.00	0.02
	0.00	0	0.00	0.02
	0.00	0	0.00	0.01
(D)	85.00	1	0.00	0.76
	51.00	1	0.00	0.15
	10.00	1	0.00	1.29
(E)	0.00	0	0.00	0.21
	0.00	0	0.00	0.21
	0.00	0	0.00	0.21
(F)	0.00	0	0.00	0.01
	0.00	0	0.00	0.01
	0.00	0	0.00	0.01

- **The detection algorithm of the first level of danger**

Insufficient ambient light is classified in this paper as the first level of danger. Video image captured by the smart phone is usually RGB signal. It is more difficult to estimate the light intensity of signals in RGB Domain. Therefore, in this algorithm, the RGB signals will be converted to YUV signals. The average value of the Y-Channel signals is calculated. If the average value is less than a threshold value, it is an indication of insufficient light. The system will alert the user by generating a warning on the screen. The formula converting RGB signals to Y-Channel signals is shown in Equation (1).

$$Y = 0.299R + 0.587G + 0.114B \tag{1}$$

- **The detection algorithm of the second level of danger**

In this system, it is permitted for users to use smart phones while walking in an indoor environment. However, the contents in the captured images of the smart phone's front camera are mostly floor (as shown in Figure 9). The second level of danger of road condition is when there is an obstacle on the floor. Figure 10 shows common indoor environments that are classified as the second level of danger. The obstacles presented in the images are respectively, a trash can, a pedestrian, a wall, a doorstep, stairs going up, and stairs going down.

These obstacles usually form irregular edge points in the image, as illustrated in Figure 11. Therefore, edge points are used as features in this research to determine whether the road condition is in the second level of danger. However, using the edge points alone to determine if obstacles exist is not sufficient. In many circumstance, seams between floor tiles possess tremendous amount of edges and edge points, which will cause significant interference. The following describes the removal of the edge points formed by tiles.

(a) (b)

Figure 9. Clear image of road surface: (a)Small tile seams, (b) Large tile seams

(a) (b) (c)

(d) (e) (f)

Figure 10. Common hazardous road conditions: (a) Trash can, (b) Pedestrian, (c) Wall, (d) Doorstep, (e) Stairs going up, (f) Stairs going down

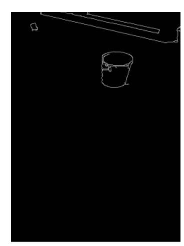


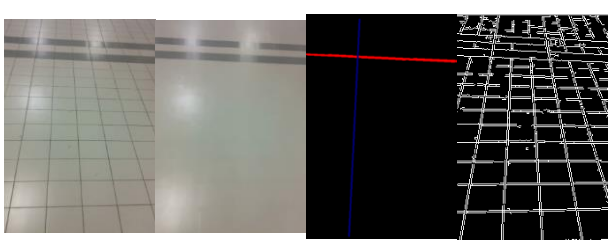
Figure 11. Edge points caused by obstacles

We adopt image morphology to remove the edges of the tiles. Because the tile seams occupy far less space than the tiles in proportion, by applying dilate function repeatedly on the same image, the tile seams will be deleted from the image. Figure 12 shows an example of the floor before and after the performing dilating. When the tile seams vanished, the only edge points left are that of the wall as shown in Figure12(c).

(a) (b) (c)

Figure 12. Example of removing tile seams by dilate function

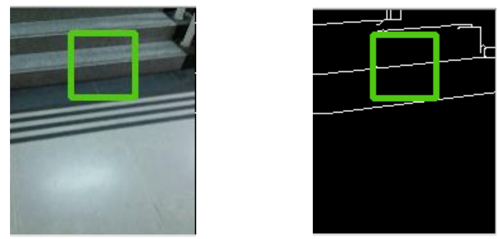
However, a certain case needs to be taken into consideration. In order to visually alert pedestrians, tiles of a different color are commonly inserted between certain distances of the floor as shown in Figure 13(a). In such cases, the above algorithms will fail as shown in Figure 13(b). Fortunately, the different-color tiles usually generate distinct horizontal lines in the captured image. In addition, the tile seams form either horizontal or vertical lines. If the lines formed by the tile seams run perpendicularly to the distinct horizontal lines, it is a suggestion that the distinct lines are produced by different color tiles. In Figure 13(c), the red line represents the different-color tiles while the blue line represents the tile seams obtained by Figure 13(a) whose edge points are shown in Figure 13(d).



(a) (b) (c) (d)

Figure 13. Different color tiles in a roomy corridor

When the problem caused by the tiles is removed, the amount of edge points in the image can be used to determine whether the road condition is dangerous. However, not the entire image is influential. We assign the upper area of the image to be our Region of Interest (ROI) as shown in Figure 14(a). If excessive edge points appear in the ROI as shown in Figure 14(b), the road ahead will be considered dangerous.



(a) (b)

Figure 14. Demonstrative example of ROI

The proposed algorithm of DRAM module is summarized as follows. First, the brightness in the environment is detected by the algorithm. If the brightness is below a threshold TH_1, a warning indicating insufficient light will be issued. Next, the proposed algorithm starts the removal of tile seams. The edge points formed by different color tiles are further removed. Finally, the algorithm calculates the number of edge points in ROI. If it is greater than the threshold TH_2, the system will generate a warning message, showing that there is an obstacle in front of the user.

IV. EXPERIMENTAL RESULTS

In this research, the New Nexus 7 launched by ASUS and Google is used for the experimental platform. Its processor is a Qualcomm Snapdragon S4 Pro APQ8064. It has 2GB memory and the operating system is Android 4.4.4. Because the proposed system should run in real-time, the camera image resolution is set to 176×144 pixels so that New Nexus 7 can handle up to 13 images per second. The image at the up left corner in Figure 15 is the captured snapshot from the New Nexus 7's camera. The black and white image shows the outcome of edge detection. White lines indicate edges of obstacles. If there is an obstacle in front or if the ambient light is insufficient, the heads-up Notifications provided with Android will be used to issue warning messages. Either Figure 16(a) "Light not enough" or Figure 16(b) "Obstacles Detected" will pop up on the screen. The following is the analysis of the results of TWDM module and DRDM module.

Figure 15. A snapshot captured by the smart phone while walking

(a) (b)

Figure 16. Warning Messages: (a) Light not enough, (b) Obstacles Detected

A. Texting while walking detection module (TWDM)

TWDM's performance depends heavily on the SVM classifier. The experiment of this module has three scenarios: using but not moving; texting while walking, and using in a moving vehicle. In all three situations user can touch the smart phone screen. Each scenario has 100 sets of training data to train the SVM classifier. Another 100 sets of testing data are prepared to test the accuracy of SVM classifier. Table 2 shows the accuracy of the SVM classifier. In the first scenario, 93 out of the 100 testing data were classified in nTWWC category. Seven were mistakenly identified as TWWC category. In the second scenario, 99 testing data were recognized to be in TWWC category, one was misclassified in nTWWC category. In the third scenario, all testing data were categorized as nTWWC. Overall accuracy of SVM was 97.33%.

Table 2. The accuracy of the SVM classifier

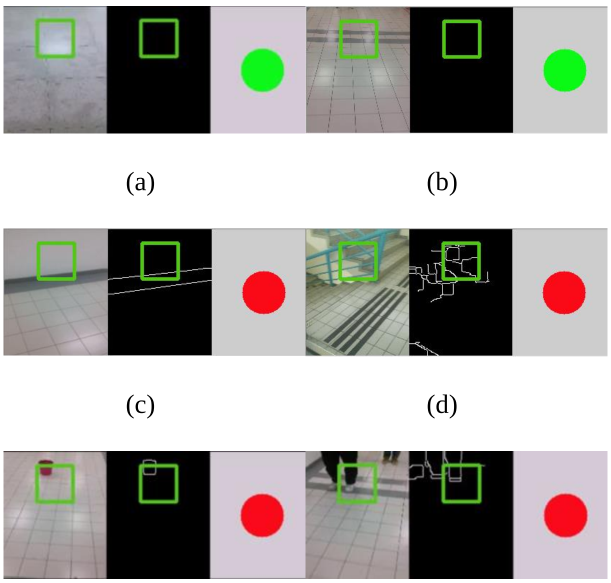
		nTWWC	TWWC	Accuracy
Testing data	Still	93	7	93%
	Walking	1	99	99%
	In a moving vehicle	100	0	100%
	Average	99.48%	93.40%	97.33%

B. Dangerous road detection module (DRDM)

In order to verify the ratio of correctness of the proposed algorithm of DRDM, we used 11 testing videos filmed in different situations. When the user was texting while walking, the smart phone camera started video recording the front view of the user for about 1 to 2 minutes. In order to conduct in-depth analysis of DRDM, DRDM and the 11 videos were simulated on a personal computer, which was ASUS X550V, featuring Intel Core i5-3230M 2.6GH processor, 4G memory, and Win 8.

Images in Figure 17 are some results of the computer simulations. Each picture is separated into three parts. The part on the left is the image captured by the smart phone's camera. White lines in the middle black image are edge points generated by DRDM process. The green frames are ROIs. The circle on the right is a signal: red circle indicates a hazardous road in the front, and green circles represent that the road ahead is safe. Figure 17(a) shows simple tiled floors, and the proposed algorithm can identify correctly that the road is safe. Figure 17(b) shows floors with different-colored tiles; the algorithm can also indicate the road is safe.

Figure 17(c) shows upcoming walls; the algorithm is able to produce a warning red circle. Figure 17(d) shows the encountered stairs; the red circle is produced by the algorithm. Figure 17(e) and Figure 17(f) shows obstacles on the way in different situations; in both situations, the algorithm can generate red alarm effectively.



(a) (b)

(c) (d)

(e) (f)

Figure 17. Demonstrative examples of DRDM results

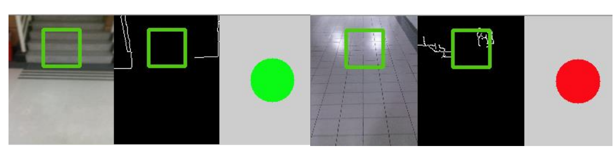
In order to verify the accuracy of the proposed algorithm in DRDM, all images recorded by the Asus Nexus 7 smart phone will also be verified by an expert to decide whether the road condition in each image is safe or dangerous. In this research, R is denoted the percentage that the expert and DRDM module have the same judgment on images.

Take the first video as an example. In the experiment, 1080 images and 1100 images were identified by the expert as safe road and dangerous road respectively. Among the 1080 safe road images, the proposed algorithm could identify 1057 of them. Among the 1100 dangerous images, 1024 image were classified in the identical category by the proposed algorithm. Thus, R_1= (1057+1024)/(1080+1110) = 0.96. Generally speaking, the accuracy of the proposed system is higher than 0.93. And the average of R is 0.95. Table 3 gives the details of results.

Table 3. Accuracy rate of the proposed algorithm in DRDM, where N1 is the number of safe road judged by the expert, N2 is the number of safe road judged by the proposed algorithm, N3 is the number of dangerous road judged by the proposed algorithm, N4 is the number of dangerous road judged by the expert, N5 is the number of safe road judged by the proposed algorithm, and N6 is the number of dangerous road judged by the proposed algorithm

Video	R	N1	N2	N3	N4	N5	N6
1	0.96	1080	1057	23	1100	76	1024
2	0.96	940	913	27	980	60	920
3	0.95	780	753	27	800	47	753
4	0.96	1080	1050	30	1120	51	1069
5	0.95	1120	1072	48	1320	71	1249
6	0.96	620	605	15	660	40	620
7	0.95	1140	1118	22	1180	85	1095
8	0.94	960	921	39	980	78	902
9	0.96	1220	1201	19	1280	72	1208
10	0.93	680	651	29	700	74	626
11	0.94	960	927	33	980	80	900

Figure 18 shows the examples of false positives. Figure 18(a) is a case that the system has failed to issue a warning message due to insufficient light, which has made the edge points of the stairway unrecognizable. Figure 18 (b) demonstrates a warning message, issued in a safe road condition. It is because fluorescent lamp has created uneven reflection of light on the floor. Spots on the floor caused by excessive brightness have created irregular edge points. These mistakes were mainly resulted from the ambient light.



(a) (b)

Figure 17. Demonstrative examples of DRDM results

V. CONCLUSIONS

The main contribution of this paper is to propose and outline an intelligent App that helps to increase the safety of users when they text-and-walk indoors. The system in this paper effectively utilized a tri-axial accelerometer to determine when the user is texting while walking. Then, image processing techniques were applied to detect if there were dangerous corridor conditions in front of the smart phone user. The results show that the system has 95% accuracy, both in judging the user's status (walking / not-walking) and detecting the safety of the corridor conditions in terms of obstacles. The proposed system therefore has the potential to increase safety when texting-while-walking in indoor environments. In our future work, we hope to develop a further system to help address the problems of safety while walking outdoors.

ACKNOWLEDGMENT

This research is under the support of the National Science Council for project number MOST 103-2221-E-130-018. We also give our thanks for Mr. Yi-Hsuan Lin’s kindly help in developing of the prototype.

REFERENCES

[1] Huang, S. Y., Lin, Y. H., and Wang, L. T., “A Safe Walking App for Pedestrians”, The International Conference on Digital Information Processing, Data Mining, and Wireless Communications, Jan. 2015.

[2] Nasar, J. L., and Troyer, D.,“ Pedestrian injuries due to mobile phone use in public places”, Accident Analysis & Prevention, Volume 57, pp. 91–95, 2013.

[3] https://www.nttdocomo.co.jp/service/safety/anshin_mode/

[4] http://www.softbank.jp/corp/group/sbm/news/press/2014/20140523_01/

[5] Zhou, Z., “Heads Up: Keeping Pedestrian Phone Addicts from Dangers using Mobile Phone Sensors”, International Journal of Distributed Sensor Networks, June 2014.

[6] Anjum, A., and Ilyas, M. U., "Activity recognition using smartphone sensors", IEEE Consumer Communication and Networking Conference , pp. 914-919, Jan. 2013..

[7] Anguita, D., et al., "A Public Domain Dataset for Human Activity Recognition Using Smartphones", 21th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, 2013.

[8] Otebolaku, A. M., and Andrade, M. T., "Recognizing High-Level Contexts from Smartphone Built-In Sensors for Mobile Media Content Recommendation", IEEE 14th International Conference on Mobile Data Management (MDM), 2013.

[9] Pekka, S., and Röning, J., "Ready-to-Use Activity Recognition for Smartphones", IEEE Computational Intelligence and Data Mining , Sep. 2013.

[10] Jiayang, L., et al., "uWave: Accelerometer-based personalized gesture recognition and its applications", IEEE Symposium on Pervasive and Mobile Computing, pp. 657-675, 2009.

[11] Yi, H., Li, Y., and Bao, S., "Fall Detection by built-in tri-accelerometer of smartphone", IEEE Symposium on Biomedical and Health Informatics, 2012.

[12] Stefano, A., et al., "A smartphone-based fall detection system", IEEE Symposium on Pervasive and Mobile Computing , 2012 .

[13] Yabo, C., Yang, Y., and Liu W., "E-FallD: A fall detection system using android-based

smartphone", IEEE International Conference on Fuzzy Systems and Knowledge Discovery (FSKD), 2012.

[14] Yavuz, G., et al., "A smartphone based fall detector with online location support", International Workshop on Sensing for App Phones;, Zurich, Switzerland. 2010.

[15] Yibin, H., Li, N., and Huang, Z., "Triaxial accelerometer-based real time fall event detection" , IEEE International Conference on Information Society, 2012.

[16] Mellone, S., et al., "Smartphone-based solutions for fall detection and prevention: the FARSEEING approach", Zeitschrift für Gerontologie und Geriatrie, pp. 722-727, 2012.

[17] He, Y., Li, Y., and Yin, C., "Falling-incident detection and alarm by smartphone with Multimedia Messaging Service", E-Health Telecommunication Systems and Networks , pp. 1-5, 2012.

[18] Davison, A.J., Reid, I.D., Molton, N.D., and Stasse, O., “MonoSLAM: real-time single camera SLAM”, IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), pp. 1052–1067 2007.

[19] Tola, E., Knorr, S., Imre, E., Alatan, A.A., and Sikora, T. “Structure from motion in dynamic scenes with multiple motions”, Workshop on Immersive Communication and Broadcast Systems, 2005.

[20] Tan, C., Hong, T., Chang, T., and Shneier, M., “Color model-based real-time learning for road following”, IEEE Conference of Intelligent Transportation Systems, 2006.

[21] Peng, En, et al., "A smartphone-based obstacle sensor for the visually impaired." Ubiquitous Intelligence and Computing”, Springer Berlin Heidelberg, pp.590-604, 2010.

[22] Taylor, T., Geva, S., and Boles, W.W., “Monocular vision as a range sensor”, Proceedings of International Conference on Computational Intelligence for Modelling, 2004.

[23] Qing, L., and Han, Y., "Safe Path Estimation for Visual-Impaired People Using Polar Edge-Blob Histogram", Proceedings of the World Congress on Engineering and Computer Science. 2013.