International Journal of New Computer Architectures and their Applications (IJNCAA) 3(1): 11-21
The Society of Digital Information and Wireless Communications (SDIWC) 2013 (ISSN: 2220-9085)

Real Time Injury and Related Activities Monitoring with Single Rotatable Infrared Sensor

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ABSTRACT

This paper proposed a system to perform injury recognition to assist people with multiple disabilities using single infrared sensor with rotatable capability. Our system will be installed in a room to monitor the disabled for fall, inactivity and help request to recognize injury of people with multiple disabilities. This system alerts the caregiver with alarm, short message (SMS) and a scene snapshot (email), the snapshot assists in verifying false alerts. The designed system is sustainable as it is computationally inexpensive and efficient. The system has the abilities to recognize common human activities. Besides, the system is non-intrusive as there is no wearable device required on the person under monitoring. The system is intuitive as the person or subject under monitoring does not have to press any button for informing and verifying a possible injury.

KEYWORDS

Fall detection, disabled, infrared sensor technology, injury recognition, Computer Vision, sustainable technology, activity recognition.

1 INTRODUCTION

People with Cerebral Palsy, stroke and mental disorders suffered from multiple difficulties [1], [2]. These include difficulty in walking around and doing simple exercises, difficulty in communicating with others, and having trouble in sitting, walking, or speaking clearly.

In general, these people fall frequently and easily, most of the falls cause injury. In some cases, unintentional fall may even bring them to death [3], [4]. Furthermore, people with multiple disabilities have difficulty to communicate with others using comprehensible speech [5]. Hence, asking for help verbally when required is a tiresome task for them.

When we searched for systems to prevent injuries for people with multiple disabilities, we found most of them focus on fall detection. Some of the systems used wearable devices designed mainly for the elderly community with motor skills and capability to operate the devices. As for vision based systems, they required real time video streaming that are computationally expensive and hardware consuming.

The scarcity of the systems for preventing injury of the people with multiple disabilities leads this research to source for a good contemporary solution.

2 RELATED WORKS

Recent studies [3], [6], [7], [8] has highlighted there is a need to develop fall detection system to trigger alarm whenever a person under monitoring fall and need assistance. According to Mubashir [4], fall detection can be divided into three categories: wearable device based, ambience sensor based and vision based.

Most of the fall detection models detect fall using wearable device i.e. pendant, watch or mobile phone. These includes commercialized produces i.e. “Alert 1”, “MobileHelp”, “LifeAlert” [9], [10], [11] while some are still under development i.e. “Design of a Fall Detection and Prevention System for the elderly” [12], “Wireless System for Fall Detection” [13], and “Fall Detector using Smart Phone on Android Platform” [14]. These developments are not designed for people with multiple disabilities. However, there are some common features on their architecture such as the use of accelerator meter to measure tri-axial on the device and gyroscope to measure the pitch and roll of the device through angular velocities.

As people with multiple disabilities have physical and motor impairment, some wearable devices may not be suitable as they still need to trigger and verify the alarm physically if they fall. If they lost consciousness, the devices become useless as the alarm cannot be triggered. Besides, wearable devices required some motor skills and knowledge which people with multiple disabilities may not be empowered with [7]. User may feel unpleasant (intrusive) wearing the devices all the time and chooses to discontinue [3], [6]. In some instances, they might forget to put it on [8], [15].
On the other hand, Doulamis et al. [16] uses vision based monitoring to detect fall. Zweng, Zambanini & Kampel [3] proposed statistical behavior fall detection which captures the human subject’s behavior using multiple cameras. Mastorakis & Makris [8] uses Kinect’s infrared sensor to detect human fall by measuring the velocity based on the contraction or expansion of the width, height and depth of the 3D bounding box expressed in world coordinate system. Mubashir, Shao, & Seed [4] commented that vision based approach in comparison to the other two approaches i.e. wearable devices based and ambient based, is certainly the area to look forward to as it deals with intrusion and robustness better.

Throughout the literature review, most of the models focus on fall detection and neglect other possible threats that occur without a prior fall such as the loss of consciousness while sitting. Recognizing the user’s gesture to seek help before or without a fall is also neglected.

3 RESEARCH PROBLEM

A sustainable injury recognition model is required to serve the needs of people with multiple disabilities to recognize injury. They need an injury recognition model that is capable of detecting fall, inactivity, and gesture of requesting immediate assistance.

4 INJURY RECOGNITION PROTOTYPE

In this paper, we proposed an injury recognition system using single infrared sensor with 180 degree rotation capability to monitor a human subject. The illustration of our injury recognition system is shown in Figure 1. It consists of two external devices i.e. the infrared (IR) sensor and GSM modem as well as an injury recognition application.

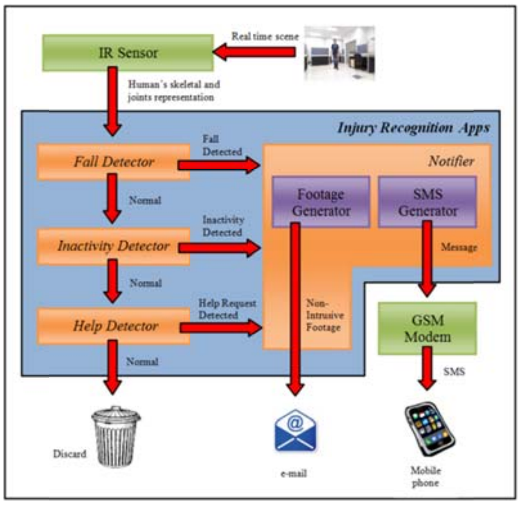

Figure 1. Injury Recognition Prototype System

The IR sensor module is responsible for capturing real time scene and localizing human's skeletal and joints in three dimensional coordinates (x, y, z). Later, the human's skeletal and joints representation will be forwarded to injury recognition application for further processing and notification if needed. The representation will be analysed by three different modules namely fall detector, inactivity detector and help detector. Activity recognition module enables our system to identify subject current activity and keep a list of activities performed in a log. Notification module is responsible to pass critical message to guardian once alarm is triggered.

When a fall detector receives skeletal and joints representation, it checks if the subject is in a falling gesture. If the status of falling remains for 30 seconds, an alarm will be triggered. This is to avoid the system from sending false alarm such as the human subject could be performing an exercise instead of falling.

If the subject is in a normal state, the representation is passed to inactivity detector to check if the subject has been inactive for more than 30 seconds. If human inactivity state is true, an inactivity alarm will be triggered. This indicates that the subject has lost consciousness or ability to maneuver.

In the case where both fall detector and inactivity detector did not detect any unusual state, the representation will be passed to help detector to check if the human is seeking help. If the gesture of seeking help is detected, an alarm will be triggered. If no incidents being detected by all three modules, the representation will be discarded.

When an alarm is triggered, the notifier module performs two tasks. 1) Generate and send a snapshot of the current scene through email and 2) Generate and send a short message through SMS.

4.1 Skeletal and Joints Detection

Our human's skeletal and joints are localized using infrared (IR) sensor as recommended in [17]. This sensor uses infrared beam to detect skeletal structure with 20 important joints. An infrared image with human's skeletal and joints representation is produced, these representations are utilized for fall, inactivity and help request recognition.

4.2 Fall Recognition

In fall detector module, we mark and use "Y coordinate range limit (MYRF – Maximum Y Range for Falling) as falling area" to detect the gesture of falling. If the located Y coordinates for four joints (head - H, shoulder center – SC, spine – S and hip center – HC) remain idle for 30 seconds within MYRF, then it will be considered as a fall as shown in Figure 2.

Figure 2. All joints found within MYRF.

Since MYRF value is correlated with subject's distance from the sensor, automated MYRF adjustment is proposed to address it. Through the observations, the MYRF value decreases when the distance between subject and sensor increases. For instance, MYRF value for falling at optimum nearest distance (OND) i.e. 1500 mm is around 380 pixels while the MYRF value for falling at the optimum furthest distance (OFD) i.e. 3700 mm is around 320 pixels. We calculated the distance of 1500 mm as the OND because the sensor loses skeleton trace after 1500 mm. The variation of MYRF value between OND and OFD is 60 pixels. Thus, for every 36 mm increment of distance, MYRF value decreases by 1 pixel.

$$MYRF^1 = MYRF^0 - \left(\frac{D^0 - OND}{36}\right) \quad \text{Eq. 1}$$

The equation to get the best possible MYRF to detect the fall on various distances from sensor is shown in Eq. 1 where *MYRF* is the Maximum Y Range coordinate for falling while D^0 is the current human distance from sensor (or depth) and *OND* is the optimum nearest distance (or depth).

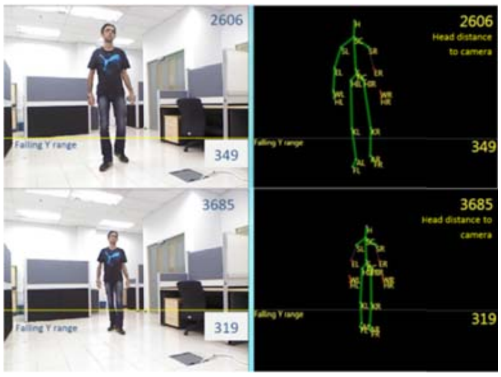

Figure 3. Determination of MYRF.

An example of MYRF determination is shown in Figure 3. Numbering on the top right of each frame e.g. 2606 indicates the distance (in mm) of head from camera while number in the middle of each frame i.e. 349 indicate the value of MYRF (in pixel).

4.3 Inactivity Recognition

Inactivity detector is developed to detect other crucial event such as the loss of consciousness without any prior fall. This module helps to trigger alarm if the subject is under inactivity state. When inactivity detector is activated, it keeps track on the X and Y coordinates for 12 joints (Figure 4) except shoulder centre – SC, spine – S, left and right wrist– WL & WR, left and right ankle– AL & AR, as well as left and right hip – HL & HR. If the X and Y coordinates for each joint remain the same for 30 seconds, the system will trigger alarm to indicate the person has not been active for some time.

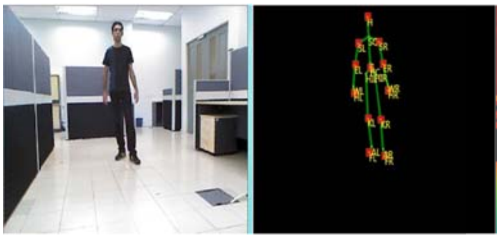

Figure 4. 12 Detect joints within the ROI of fall detector

To improve the verification accuracy, we define region of interest (ROI) for each important joints to allow some variation of joints coordinate. The size of ROI for each joint is 20 X 20 pixels at the depth of 2 meters where the joint is located in the middle of ROI. As for the depth of 3.7 meters (maximum distance from camera), the ROI is 10 X 10 pixels. Hence, our system determines ROI when different depth with Eq. 2 where $D^0$is the current depth. It indicates an inactivity if a joint remain in the ROI for 30 seconds that is after 900 frames being recorded.

$$2\left(10-\left(\frac{D^0 - 2000}{340}\right)\right)$$

Eq. 2

4.4 Help Request Recognition

Generally, a person will wave his hands spontaneously as a gesture to request assistance. We detect and recognize waving of hand(s) then trigger an alarm. We define another ROI for help detector and recognize hand(s) wave pattern within the ROI. We utilize head's (H) coordinate as a reference point where left hand ROI will be determined with Eq. 3 below:

$$StartPoint(x,y) = \left((H+70),(H+100)\right), EndPoint(x,y) = \left((H-200),(H-80)\right)$$

Eq. 3

Figure 5 shows how to determine the ROI for left hand, the starting point coordinate is (120, 20) whereas ending point coordinate is (390, 200) if the head coordinate is (320, 100). Based on this, a help request will be detected if the subject wave his or her left hand three times within the specified ROI. The ROI for help detector shrinks when a subject moves further way from the camera, for every 36 mm increment in depth, 1 pixel is decreased from each side of the ROI.

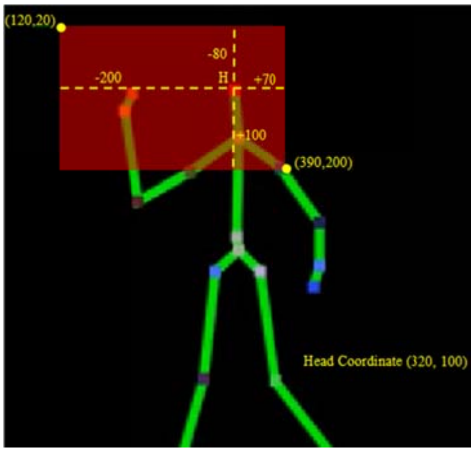

Figure 5. Detecting joints with the ROI of help detector

4.5 Activity Recognition

The activity recognition module keeps track of activities in real time. It manages to identify 14 common activities which include standing, walking, running, sitting, bending, waving left hand, waving right hand, brushing teeth, drinking, eating, writing, reading, combing hair as well as shaking head. It sends the last ten recent activities as shown in Figure 6 to guardians in the form of SMS and email if a critical event such as inactivity state occurs. Hence, a guardian can make use of the activity log to investigate the cause of an injury.

```
Status       Date/Time
--------------------------------
Walking      16/2/2013   4:16:20pm
Running      16/2/2013   4:17:01pm
Walking      16/2/2013   4:17:18pm
Sitting      16/2/2013   4:17:52pm
Reading      16/2/2013   4:17:58pm
Writing      16/2/2013   4:20:14pm
Reading      16/2/2013   4:22:27pm
Standing     16/2/2013   4:30:49pm
Running      16/2/2013   4:30:57pm
Fall         16/2/2013   4:31:30pm
```

Figure 6. User activity log

4.6 Notifier

An alarm will be triggered when any of the above mentioned critical events being detected. The camera will take a snapshot of the scene then send it to the guardian's email address. The reason for choosing email is because it provides faster speed and lower cost for image transfer, push mail and Wi-Fi access features are available in most of the mobile phones. Guardians can use the snapshot received for verification before taking necessary action.

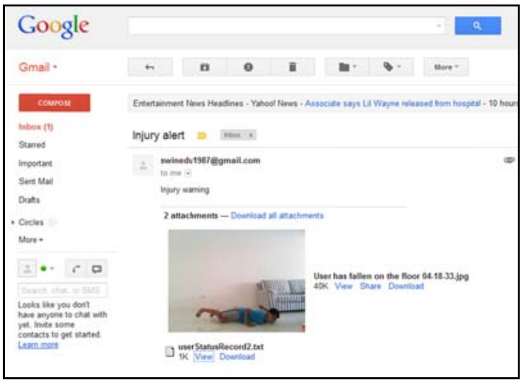

Figure 7. Example of fall snapshot and activity log send to guardian email (Gmail).

Figure 7 shows a snapshot of fall detection scene being sent to guardian's email in real time. The log file containing the recent activities is also attached in the email. This enables the guardian to verify the events happen prior to the fall such as the subject was running before he fell down.

For sending SMS, we use an external GSM modem (Figure 8) as the gateway to deliver short message. The device comes with a SMS Gateway Development Kit [18] allowing our prototype to send SMS to pre-set mobile phone number. The SMS contains type of critical event and time the event being detected. In addition, personalization allows email addresses and mobile phone contacts to be stored (refer Section 4.8).

Figure 8. The external GSM modem

4.7 Motorization of the sensor

The occurrence of blind spot in any surveillance system is always an issue. This is crucial for successful real time recognition of moving subject without using multiple sensors. To reduce the blind spot on the left and right of our system, we rotate the sensor with a custom made motorized stand as shown in Figure 9 and Figure 10. The motorization includes a microchip being programmed to interface with the sensor for a rotation up to 90^o on the left or right.

Figure 9. Infrared sensor on the custom made stand.

The range of 150 pixels from each side (left and right) of the sensor view is taken as the reference, the range has been chosen based on the experiments conducted. This optimum range allows the sensor to rotate and detect the subject within the sensor view range.

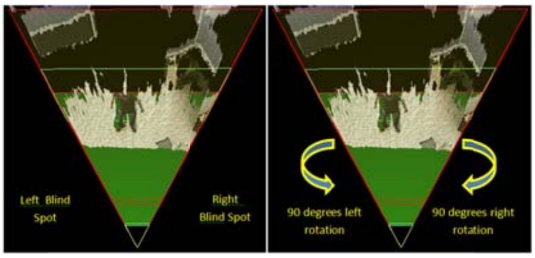

Figure 10. Blind spot (left) and rotatable area (right)

This optimum range avoids unnecessary rotation whenever a subject moves, which consumes more computational resources. The system instructs the stand to rotate when the hip center joint of the subject fall within the range to ensure the subject is always in the center of the view.

4.8 User Interface

Our prototype system promotes affordability design concept by adopting a simple user interface to suit the guardians. Figure 11 shows the main GUI which consists of menu bar and a screen to display human skeletal representation.

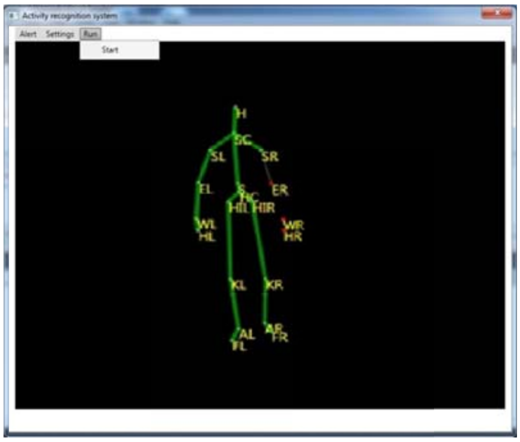
Figure 11. System main GUI

Guardian can start using the system easily by just click Run > Start.

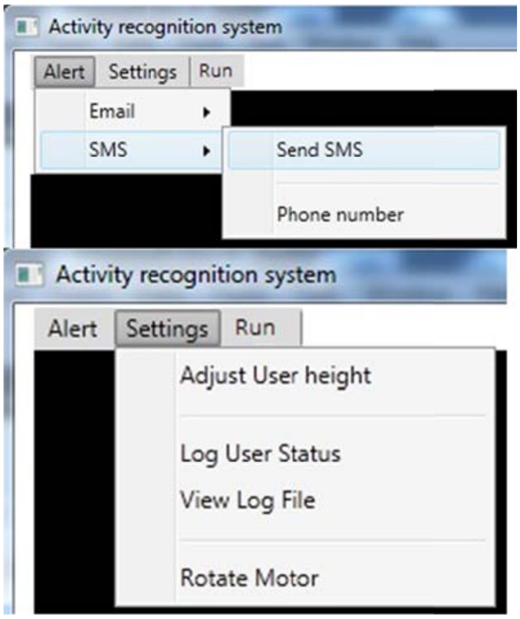

Figure 12. System user interface with features controller at the menubar

Figure 12 shows other features available within the system. Guardian can configure the system by inserting his/her contact information i.e. email address, mobile phone number and enabling alert to receive notification through email or/and SMS when a critical event is being recognized.

They also can browse through setting to adjust subject height to calibrate our system, enable user activity log keeping and view user activity log file to check what the subject did previously.

5 EXPERIMENTAL RESULTS

We invited 10 volunteers to evaluate the efficiency of our system. The volunteers were given some scenarios (Figure 13) to perform various ways of fall, inactivity, seeking for help as well as activity recognition.

Figure 13. 14 Injury recognition test cases.

Table 1 shows the results obtained for fall recognition under three scenarios, 1) faint and fall, 2) walk and kick something on the floor then fall, 3) fall from sitting on a chair. In this experiment, we obtained an overall of 83.33% of fall recognition accuracy.

Table 1. Fall recognition

Scenario	Recognition Accuracy
Faint and fall	80.00%
Walk and kick something then fall	90.00%
Fall from sitting on a chair	80.00%
Overall Accuracy	**83.33%**

As for inactivity recognition, we examined our volunteers in two scenarios, 1) sit still for more than 30 seconds and 2) sit still with the head on the desk for more than 30 seconds. Our system only recognized an overall of 40% inactivity as shown in Table 2. The recognition rate was low because the sensor failed to detect the subjects when the views of their joints were blocked by the desk.

Table 2. Inactivity recognition

Scenario	Recognition Accuracy
Sit still	60.00%
Sit still with the head on the desk	20.00%
Overall Accuracy	**40.00%**

For the recognition of seeking help, the volunteers were given three scenarios, 1) Seek for help while sitting on the floor, 2) Seek for help while sitting on the chair, and 3) Seek for help while standing. Our volunteers waved either one or both hands in all the help scenarios. In this experiment, we obtained an overall of 80% recognition accuracy (Table 3).

Table 3. Help recognition

Scenario	Recognition Accuracy
Seek for help while sitting on the floor	100.00%
Seek for help while sitting on the chair	40.00%
Seek for help while standing	100.00%
Overall Accuracy	**80.00%**

We also conducted an experiment to evaluate the recognition of false events. Our volunteers were instructed to perform actions that could lead to false recognition, 1) walk for two minutes, 2) stand still and look around, 3) draw something while sitting on the floor, 4) bend down and pick up an object, and 5) look for a piece of paper under a cabinet.

The system achieved an overall of 100% false events recognition which no alarm were triggered. The results are shown in Table 4.

Table 4. False event recognition

Scenario	Recognition Accuracy
Walk for 2 minutes	100.00%
Stand still and look around	100.00%
Draw something while sitting on the floor	100.00%
Bend down and pick up an object	100.00%
Look for a piece of paper under a cabinet	100.00%
Overall Accuracy	**100.00%**

We also evaluated the activity recognition module. Throughout the evaluation, we obtained an overall accuracy result of 83.57% in activities recognition as shown in Table 5. Activities like drinking with a cup/mug/glass and writing with a pen/pencil had lower accuracy due to the visual occlusions.

Table 5. Activities Recognition

Activity	Recognition Accuracy
Standing	100.00%
Walking	100.00%
Running	100.00%
Sitting	100.00%
Bending	90.00%
Waving left hand	100.00%
Waving right hand	100.00%
Brushing	80.00%
Drinking	40.00%
Eating	80.00%
Writing	60.00%
Reading	70.00%
Combing	70.00%
Shaking head	80.00%
Overall Accuracy	**83.57%**

5 DISCUSSIONS

Throughout a series of experimental processes with 10 volunteers, we evaluated the efficiency of our proposed system in detecting fall (83.33%), detecting inactivity state of a person i.e. unconscious (40.00%), detecting help request by hand wave (80.00%) and identifying activity (83.57%) . We found that our system detect falls, help requests and activity patterns precisely when the subject is visible and traceable from its view. When the subject is occluded by other object i.e. furniture from view, our system face difficulty in tracing human skeletal as well as their joints. Hence, our system couldn't detect whether the subject is fall, inactive or seeking for help precisely.

We found a few scenarios produced lower recognition accuracy rate such as unconscious in sitting position while forehead lay on desk (20%) which happened in inactivity recognition experiment and ask for help while seated on a chair (40%) which happened in help recognition experiment. This happened due occlusion problem which is encountered in most of visual based monitoring or surveillance system. However, many papers are now discussing and figure out methodologies and ways how occlusion problem can be resolved as long as computer vision is concern.

Table 6. Overall results

Scenario	Recognition Accuracy
Fall	83.33%
Inactivity	40.00%
Seek for help	80.00%
False negative event	100.00%
Activity recognition	83.57%
Overall Accuracy	**77.38%**

Table 6 shows the overall recognition accuracy of 77.38% which indicates the potential of our system in minimizing injuries of people with multiple disabilities.

6 CONCLUSION AND FUTURE WORKS

This paper proposed an injury recognition system with single 180 degree rotatable infrared sensor to overcome blind spot issue and allow wider view as well as coverage. Our system manages to recognize fall with 83.33% accuracy, inactivity at 40.00% accuracy, and seeking for help at 80.00% accuracy. The system also exhibits its capability to avoid false event as we obtained 100% of recognition accuracy in various scenarios. In addition to above mentioned features, our system also equips with additional capability to recognize 14 human activities. We obtained 83.57% of recognition accuracy through a series of evaluation. Overall, the system achieved 77.38% recognition accuracy throughout the whole experiments. In this research, we encountered a challenge when human subject is blocked by objects i.e. visual occlusion as in most of the vision based recognitions. The recognition lost track on body joints when the human subject is blocked by other object such as a desk. In future, we will investigate on the ways to overcome occlusions of body joints to improve the recognition accuracy.

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