Abstract - Elderly people living by themselves or at a senior living community may not have the infrastructure for emergency response in case of discomfort while in bed at night or day. Often, they have to call for help themselves in case of an emergency situation. This problem is resolved by using a new Motion Recognition-Based Emergency Alarm System (MR-BEAS) that alerts emergency responders in case of an illness or discomfort based on motion recognition under any ambient lighting conditions. A depth sensor is employed that can provide a heat map of the subject that will be used to derive a skeletal frame, which will be analyzed for any gesture of interest. In addition, a novel predictable matching algorithm is designed and implemented to identify pre-determined gesture for triggering an alarm using a low-cost platform. This system can alert responders within the same building or remotely over the internet for added flexibility.

Keywords: senior living, motion recognition, predictable matching algorithm, emergency response, sleep discomfort

1 Introduction

The population above 65 years is a rapidly growing segment of the United States population. The growth rate of this population is 15.1% as opposed to 9.7% of the general population between the year 2000 and 2010 [1]. This demands a need for more assisted living facilities. Eighteen states already made statutory, regulatory, or policy changes in 2010 and 2011 impacting assisted living/residential care communities. The focal points of state assisted living policy development include life safety, disclosure of information, Alzheimer’s/dementia standards, medication management, background checks, and regulatory enforcement. The fast growing 65 or older population demands more and more caregivers working at assisted living facilities round the clock. This demands automated systems to substitute certain monitoring activities.

Alwan et. al. conducted a study to assess the acceptance and some psychosocial impacts of monitoring technology in assisted living [2]. They installed Monitoring systems in 22 assisted living units to track the activities of daily living (ADLs) and key alert conditions of residents (15 of who were non–memory care residents). The Activity reports and alert notifications were sent to professional caregivers who provided care to residents participating in the study. They assessed the diagnostic use of the monitoring data. Non–memory care residents were surveyed and assessed using the Satisfaction With Life Scale (SWLS) instrument. They compared the pre- and post-installation SWLS scores. The older adult participants accepted the monitoring. The results showed that monitoring technologies provided care coordination tools that are accepted by residents and positively impacted their quality of life. The SWLS is very broad in nature and hence a more directed questionnaire would unearth privacy concerns while being monitored.

Hou et. al. presented Personal Assistance System (PAS) open architecture for assisted living, which allowed independently developed third party components to collaborate [3]. They also discussed the key technological issues in assisted living systems, such as tracking, fall detection, security and privacy. They conducted the pilot study in a real assisted living facility. In their system they used a handheld blood oximeter and an IBM Thinkpad T43 (with Windows XP Home Edition, Java Runtime Environment Standard Edition 1.5.0 06, Bluetooth stack: Avetana) placed in the resident’s room. The two residents received alert messages on a flat computer screen twice a day that reminded them to take an oximeter reading. The alert times were collaboratively set by the residents and the staff. The resident after taking the oximeter reading had to tap the computer to acknowledge the alert message. The oximeter reading was then sent wirelessly (and transparently to the resident) to an IBM Thinkpad T41 (with Windows XP Professional, Java Runtime Environment Standard Edition 1.5.0 09, MySQL Server 5.0, WebServer: Apache-Tomcat version 5.5.20) in the nurse’s station. The monitoring interface, installed at the nurse’s station, provided a history of alert adherences and oximeter readings. Albeit the PAS was quite well-received by the residents, they suggested several technical directions for future research. This includes suggestions for incorporating robustness in the impasse with a wide range of failure scenarios and enforces reliability in diverse operating conditions. In addition, they suggested having a secure communication interface with third party service providers, respecting the privacy of its users, and providing Quality of Service (QoS) even in the presence of wireless interference and other environmental effects.

Doulkas and Maglogiannis presented the implementation details of a patient status awareness system that has human activity interpretation capability and emergency detection of patient collapses [4]. This system utilized video, audio, and motion data captured from the patient’s body using appropriate body sensors and the surrounding environment using overhead cameras and microphone arrays. The limitation of this system is that all the equipment needs to be installed within the monitored area, and sensors have to be
worn by the subject. The body sensor network implemented in this solution is considered as an invasive technology, and requires special treatment by users with respect to proper body placements, battery replacement, etc.

Stroiescu, Daly, and Kuris presented the design for wireless event detection and in building location awareness system [5]. This system used a body worn sensor to detect events such as falls when they occur in an assisted living environment. Event detection algorithms were developed and used an in-house wireless network to transmit the information to the assisted living facility and to an off-site monitoring facility. The project did not provide enough data to validate the system or associated algorithms. Few of the limitations are low battery life and the need for frequent charging, incapability to integrate the sensor into a garment, and not being water resistant.

Fleck and Staber presented a distributed and automated smart camera based approach to analyze the real world and identify only relevant information that could be used for geo-referenced person tracking and activity recognition in case of a fall [6]. The performance of the system relied on the performance of the automated video analysis algorithms. These would not complement the human operators but replace them from sensor level all the way up to a level where the information is not directly privacy-related anymore. Park, et al. suggested a method that detects abnormal behavior using wireless sensor networks in an assisted living environment. They modeled an episode that is a series of events, which includes spatial and temporal information about the subject being monitored. An abnormal behavior that has similar sequence of events and does not differ from each other for duration could be identified as a normal event.

In this research, a novel method is proposed to recognize an emergency situation in an assisted living facility using motion recognition while the subject is in bed. Senior citizens may not have the infrastructure for emergency response in case of discomfort especially while in bed at night. This research focuses on alerting emergency response in case of an illness or discomfort based on motion recognition.

2 Motion Recognition based Emergency Alarm System (MR-BEAS)

The proposed research on “Motion Recognition-Based Emergency Alarm System (MR-BEAS)” focuses on detecting discomfort/illness in real time without invasion of privacy automatically during sleep for senior citizens. The automatic detection is done by the system using a pre-defined gesture performed by the subject in the event of a discomfort or illness. This system will work irrespective of the ambient lighting conditions. The staff/care takers will need to respond only when an alarm signal is generated by this system.

An expandable platform having a software development kit manufactured by Microsoft called Kinect is used to identify and detect an emergency condition. Kinect sensor bar was released by Microsoft for use with their Xbox 360 video game system [7]. The sensor bar consists of a VGA camera, two 3D depth sensors, multi-array microphones, and a motorized tilt mechanism. The sensing range for Kinect is 3.9 – 11 feet. The Software Development Kit (SDK) was released for the Windows 7 operating system. It enables the development of applications with C++, C#, or Visual Basic by using Microsoft Visual Studio 2010. The SDK will let the programmer have access to low level sensor streams from the depth sensor, color camera sensor, and four-element microphone array. The depth sensor that is primarily utilized for this system consists of an infrared laser projector combined with a monochrome CMOS sensor, which captures video data in 3D under any ambient light conditions. The 320x240 depth stream has an 11 bit depth. The Kinect has received interest from the academic and research world as a tool for various research areas including security, medical, archeology (i.e., 3D scanning of digging sites), Natural User Interface (NUI), etc. Researchers at the University of Missouri have been using the depth sensor in Kinect to detect early signs for fall indication for senior citizens [8].

Figure 1. Architecture of the Motion Recognition-Based Emergency Alarm System (MR-BEAS)

An architecture is presented for the MR-BEAS, and is shown in Figure 1. The architecture consists of modules for “Capture Depth Stream”, “Derive Skeleton Object”, “Predictable Matching Algorithm”, and “Generate Alarm”. An NUI Application Programming Interface (API) is used for capturing the raw depth stream from the depth sensors. The NUI API is part of the SDK for Kinect. This API allows the retrieval of sensor streams, and also controls the Kinect device. The depth data stream delivers frames in which each pixel represents the Cartesian distance, in millimeters, from the camera plane to the nearest object at that particular x and y coordinates in the depth sensor’s field of view. Applications can process data from a depth stream to provision various custom features, such as tracking users’ motions or identifying background objects to ignore during application play. A depth data value of “0” indicates that no depth data is available at that position, because all the objects may be too close to the camera or too far away from it.
Application code acquires the latest frame of the image data using a frame retrieval method, and passes on to a buffer. If the application requests frames of data before the new frames are available, then there is an option to choose whether to wait for the next frame or to return immediately and try again later. The NUI API never provides the same frame of data more than once. The NUI Skeleton API provides information on the location of the subject in front of Kinect sensor bar with detailed position and orientation information. This information is provided to application code as a set of points, called skeleton positions, that composes a skeleton [9]. This skeleton represents a subject’s current position and pose. This system utilizes this feature by enabling skeletal tracking technique during the initialization phase of the system. The process flow of the system is shown in Figure 2.

Once the co-ordinates are retrieved, a predictable matching algorithm is implemented to see if there is a match between the gesture performed by the subject and the one that is stored in the system to indicate a danger situation. The skeletal data can be retrieved irrespective of the ambient lighting conditions inside the room that the subject is residing. The flow of the predictable matching process is shown in Figure 3. Once the skeletal data is obtained for each frame, it will be stored in a buffer to perform the predictable matching algorithm. The algorithm will determine whether the subject is having a discomfort/illness while in bed. Initially, the joint co-ordinates are extracted from each frame of interest. The distance between the joints being analyzed and the angles between them are used to check each frame against the danger situation. If successive frames meet the condition for danger situation, then an alarm is generated by posting a danger message. If the subject shows the danger gesture by accident, the system will not mistake it as a danger situation since the gesture has to be performed for a predefined duration. It is highly unlikely to have this situation emulated by mistake.

3 Evaluation of the MR-BEAS

The Kinect device was connected to a PC. The program was running in the .NET environment for capturing and analyzing the image of the subject. For simulation purposes, the subject was allowed to stand at a distance of 6 feet from the Kinect sensor bar. This would simulate a person lying on a bed and the sensor mounted on the ceiling. The first scenario involves monitoring a person in a well lit room (~800 lumens), the second is a poorly lit room (~10 lumens) and the third is a dark room (~0 lumens). The simulation windows for each case are shown in Figures 4a, 4b, and 4c respectively.

The top left corner of the window shows the 3D depth map and the top right portion shows the skeletal frame. The color video stream from the RGB camera is displayed on the right bottom to show the ambient lighting in the room. The text display shows whether there is a danger condition or not, and the frame rate of the captured data at the bottom left. Figure 4a shows the simulation window in a well lit room (~800 lumens) and Figure 4b shows the simulation window in a poorly lit room (~10 lumens). In Figure 4c, the simulation is shown in a dark room (~0 lumens). It can be seen that the skeleton of the subject is tracked despite the absence of ambient lighting in the room.
For simulation purposes, the pre-determined gesture that the system was programmed to recognize was raising both arms up and holding it perpendicular to the body. This gesture was chosen as it is a highly unlikely event when someone lies down in bed. The subject will have to hold that position for a set amount of time for the gesture to be recognized. The time required for testing purposes was set to 3 seconds. If the position is not held for 3 seconds, the predictable matching algorithm will re-analyze the frames from the following frame onwards.

Figure 5a shows a danger scenario recognized by the MR-BEAS. Recognition of the danger condition by this system in a dark room is shown in Figure 5b. The performance of the system was same as observed in the well-lit room with ~800 lumens. Since the “Danger” message is displayed for both scenarios, it can be concluded that the performance is not affected by the ambient lighting conditions. As is evident from Figure 5(b), the color video stream window is dark showing that the room had no ambient lighting.
The experiment was performed while holding both arms not perfectly perpendicular to the body. The borderline conditions where the system stops to recognize the gesture is shown in Figures 6a and 6b respectively.

The system was made more robust by incorporating a tolerance that was determined experimentally. The tracking of angular positions lies between 27 degrees +/- 90 degrees for the current experimental setup. This constitutes a 30 percent tolerance. The implementation results are summarized in Table 1. The outstretched arm held approximately at 90 degrees from the body is considered as normal position. The frames were captured in three different lighting conditions. The first scenario involved the simulation is a well lit room that has approximately 800 lumens. The second scenario was a poorly lit room with about 10 lumens. Finally, the third situation was a totally dark room (~0 lumens). The MR-BEAS successfully tracked and identified the “danger” situation irrespective of the ambient lighting conditions within the tolerance (< 28 degrees angle between arms and body).

<table>
<thead>
<tr>
<th>Postures</th>
<th>Lighting (Lumens)</th>
<th>Angle between arms &amp; body</th>
<th>Detection</th>
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<tr>
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<td>0, 10, 800</td>
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<tr>
<td>Normal + 15 degrees</td>
<td>0, 10, 800</td>
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<tr>
<td>Normal - 30 degrees</td>
<td>0, 10, 800</td>
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<td>No</td>
</tr>
</tbody>
</table>

4 Conclusions and Future Work

The MR-BEAS was designed, implemented, and analyzed for senior living that alerts emergency responders in case of an illness or discomfort based on motion recognition regardless of ambient lighting conditions. This system was evaluated under different ambient lighting conditions. The implemented predictable matching algorithm sensed the subject’s movements and accurately identified emergency situations automatically. Unlike traditional motion recognition systems, the MR-BEAS system requires only two frames of depth data for performing the emergency alert. This results in significant reduction of hardware complexity and resources to achieve the low-cost objective. The proposed predictable matching algorithm accurately analyzes the skeletal data derived from the depth map. A low end computer with 2 GB RAM on a 2.66 GHz or faster processor will be capable of accommodating MR-BEAS without heavy video processing that required in prior arts. In addition, MR-BEAS offers a platform for extending this to a more robust and intelligent system. The predictable matching algorithm is incapable of monitoring dual subjects simultaneously, but can be implemented by building upon the present algorithm. Furthermore, MR-BEAS is expandable to utilize voice recognition technology by integrating to the microphone array sensor for confirming an emergency situation if necessary. This algorithm can incorporate more artificial intelligence to track and identify candid emergency situations without the subject having to perform a gesture.

5 References


[8] News Bureau, University of Missouri, Using Kinect to Identify fall risk in seniors; Craven, Samantha