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Full Paper

Smart bedroom for the elderly with gesture and posture analyses using Kinect

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Abstract: The elderly spend most of their time at home largely due to either physical or financial limitations. Thus, a significant number of them are socially isolated from family members and friends. This situation is more pronounced in an ageing society where people 60 aged years or older make up at least 10% of a country's population. There are some existing systems that equip homes with advanced and expensive sensing devices in order to improve the quality of life of the elderly. However, most people cannot afford access to those so-called smart homes. Therefore, we are motivated to come up with a more affordable, simple but effective system that can work in a smaller-scale setting like a bedroom. Our system leverages the Kinect's infrared sensing capability, which can effectively identify a human skeleton both in daytime and night-time. The skeletal joints are used to perform gestural and postural analyses in order to help the elderly do the following tasks: using a forearm to point and toggle electric devices between on and off modes; using the forearm to wave for a need of assistance; getting a warning of a possible risk of bed falling or of oversleeping past the usual wake-up time; and keeping record of different poses such as sitting, sitting on floor, standing and lying down.

Keywords: smart bedroom, gesture and posture analyses, Kinect, elderly's quality of life

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INTRODUCTION

Based on the definition given by the United Nations [1], when 10% or 7% of a country's population are aged 60 or 65 years or over respectively, that country officially becomes an ageing society. Thailand in particular has been considered an ageing society since 2005 as reported by the National Statistic Office of Thailand [2]. In 2012 the Thai population aged 60 years or over comprised 12.7% of the whole population and it was projected that the number would rise to 15.7% by 2030. In consequence, the quality of life and livelihood of the elderly should be promoted and established for the inevitable ageing society in the oncoming decades.

Human posture and gesture classification has been an active research area because the knowledge can help towards the understanding of human behaviours and the building of artificial intelligent systems. In the past decades, researchers had to work with 2D image processing from video frames [3-5]. Much progress has been made, although with the limitation of hardware capability and the complicated image processing methods. In 2010 Microsoft started selling the Kinect XBOX [6], as shown in Figure 1, as a game controller with a 3D camera operated by human gestures of a player. Currently there are two software libraries for analysing skeletal joints, i.e. Microsoft SDK [7] and the open source OpenNI. The Kinect can capture a 3D human skeleton in real time, both in the daytime and night-time by using its infrared depth sensors. It can detect up to twenty skeletal joints, as shown in Diagram 1. Each joint has three positional coordinates, X, Y and Z. Knowing the spatial locations of those joints, one can readily and effectively use them for gestural and postural analyses as exemplified by our work.

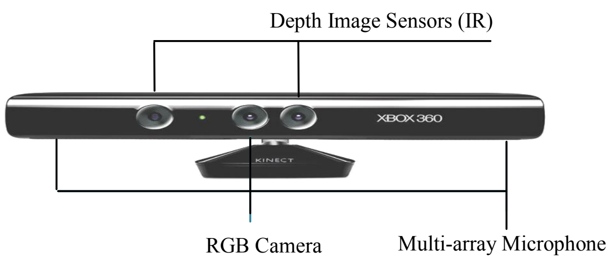

Figure1. Kinect XBOX 360 components [6]

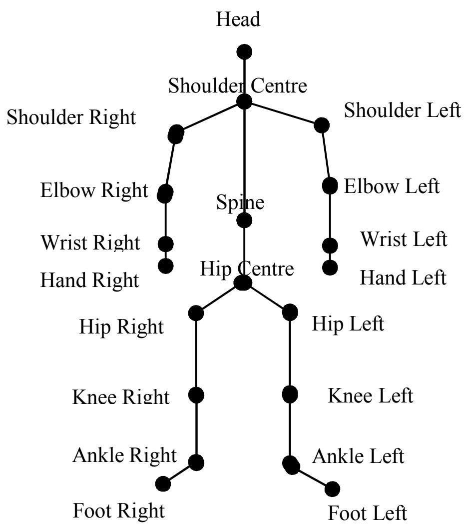

Diagram 1. Twenty joints obtained from Kinect XBOX 360 with Microsoft SDK Library [7]

The following describes some noteworthy work done on detecting and classifying human gestures and postures. First, on detection, Raheja et al. [8] used Kinect to detect fingertips and the centre of the palm in order to detect hand movements. The depth of images was detected without help of any markers; subsequently, the images were segmented into different regions of colours and depths so that each finger and palm could be distinguished. Similarly, Wan et al. [9] used Kinect to collect depth data in order to recognise hand movements. The hand's Cartesian coordinates were tracked and used to detect the motions of 3D movements in real time. Their system could detect many hand movements such as start, stop, leftward or rightward move, and forward or backward move. On the other hand, Ni et al. [10] used Kinect's RGB camera to work on a patient's fall detection in a hospital when getting up from bed. Moving patient's images were tracked, captured and used in multiple kernel learning to analyse the risk of falling. Their system compared historical motion images, histogram of oriented gradients and histogram of optical flows for any irregularities so that caretakers could be notified.

Second, with respect to classification, Cohen and Li [11] presented a human postural classification with support vector machine modelling using a 3D visual-hull constructed from a set of silhouette input data. The system returned the classified human body postures in the form of thumbnail images. Htike and Khalifa [12] used Kinect to capture moving skeletal joints data in order to classify dancing gestures in real time in their gesture classification system. The accuracy was 96.9%. Visutarrom et al. [13] in 2014 proposed a system for simple postural detection and classification of the elderly person while watching television, with key postures such as standing, sitting and lying down. Six classification methods were compared, namely neural network, support vector machine, decision tree, logistic regression, random forest and naïve Bayes. The decision tree with Max-Min normalisation technique gave the best accuracy of postural classification at 97.88%.

The Department of Health [14] in UK produced a report on Research and Development Work Relating to Assistive Technology 2013-2014 to provide a summary of numerous different projects that were done on improving the living quality of the elderly and disabled people. It gave an insight into the benefits, feedback and results of those projects. For example, in telecare and telehealth the European Commission's Integrated Network for Completely Assisted Senior Citizen's Autonomy project [15] used the gathered health and behavioural data from remote monitoring through sensor technologies installed at home to help make decisions if and when the elderly would need a support. Most participants in the project reported receiving better care, more active involvement in care, and a lower number of hospital admissions. Rocker [16] provided an overview of the intelligent environments that had been developed, some being still in a prototype state for the past two decades as solutions to enabling the elderly and disabled people to remain independent at their homes. For instance, the Intelligent Sweet Home developed in South Korea was equipped with many assistive technologies such as an intelligent robotic bed and a health monitoring system. The author suggested that the technologies not only should provide the technical infrastructures but also should support the elderly to maintain an active and socially integrated lifestyle.

We see those imminent problems for the elderly as both a daunting challenge and a promising opportunity and have tried to be part of the bigger solution that many researchers have been pursuing. Our aim is to come up with a simple but effective and affordable bedroom system by extending our previous work on smart bedroom [17], with addition of newly improved functions that would be useful to the elderly person or the carer to perform some simple tasks. These are, for example, turning electric devices on or off without touching the switches or their remote controls, calling for help when needed, being alerted of possible falling out of bed, timely notifying others like family members or caretakers when oversleeping past the normal wake-up time, and keeping a record of poses such as sitting, sitting on floor, standing and lying down. We add a new classification of poses using a multiple-stage classification based on a neural network. The system is intended to help the elderly who may have some difficulty in moving about or seeing at night to be able to live an independent life and to improve their quality of life. Moreover, by knowing the various poses that an elderly person does, we can understand his or her behaviour and accordingly provide health-related services to better suit his or her needs.

METHODS

A number of key methods used in the system can be found in our previous work [17]. However, we have extended them and made some improvements on a handful of functions, using standard vector algebra, such as a newly improved forearm pointing for controlling electric devices, a newly improved forearm waving for help, and a new classification of poses by means of a multiple-stage classification based on neural network. Those improved methods have resulted in better accuracies for both the forearm pointing for controlling devices and the forearm waving for help. The details of each function are given as follows.

Forearm Pointing to Control Electric Devices

To set up a location of each electric device, a person needs to sit on bed or stand in the bedroom where the Kinect can capture a body, and do the forearm pointing to the intended device. The person-to-device distance can be any value within the range of a normal bedroom size. An approximate distance in metres from the person's wrist (W) to the device (D) is required for the initial set-up. The device's location is computed by adding an elbow location (E) to the distance from E to D, along the direction of the unit vector from E to W, as shown in Diagram 2. The location is recorded for later reference.

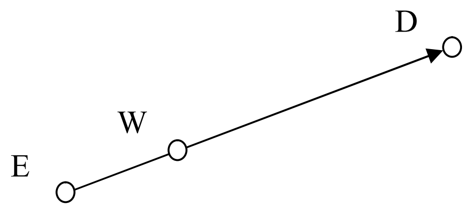

Diagram 2. Calculation of electric device's location

In order to control the electric devices, the person can be anywhere in the room as long as the Kinect still properly detects the skeleton, preferably 0.8-4.0 metres from the camera. During the forearm pointing, another vector is formed from the elbow joint (E) to the wrist joint (W), as shown in Diagram 3. A perpendicular distance from this vector to each recorded device's location (D) is computed. Equation 1 shows how to compute the shortest or perpendicular distance from the vector's extended line to the device. Thereafter, the device that is closest to the vector's extended line can be toggled between on and off. The person is required to do the still pointing for about 3 seconds in order to be certain that the device is intentionally pointed.

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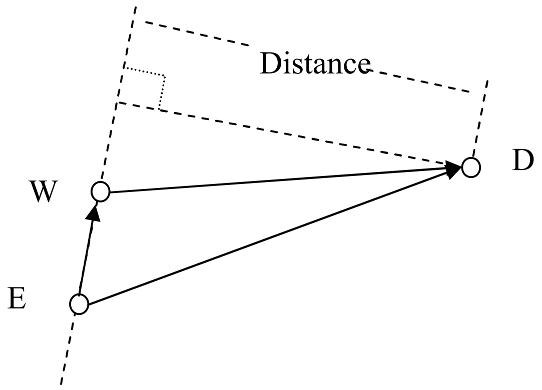

Diagram 3. Vectors and distance involved in forearm pointing to control electric device

$$\text{Distance} = \frac{|(D-E)\times(D-W)|}{|W-E|}, \tag{1}$$

where Distance is the shortest distance from the device to the line of the forearm pointing, $\times$ denotes a cross product, and $|\ |$ denotes the magnitude of a vector. For the perpendicular distance calculation in 3D space, equation 1 is used to get the distance from point D to the line extended from point E to point W. A more comprehensive detail of the calculation can be found in the work of Weisstein [18].

Forearm Waving to Call for Help

To get help or assistance from the system, the elderly person has to wave one of his or her forearms while lying or sitting in bed. The waving done while sitting or lying down will not make any difference as long as the Kinect can capture the joints of elbow and wrist properly. The vector from the elbow to the wrist is computed. When waving, two unit vectors from one end to the other end of the swing that makes the largest angle are used to calculate the scalar dot product value in order to subsequently get the swing's angle. The forearm waving for help is considered a success if the angle is larger than the predefined 50 degrees and the moving forearm's vector crosses the half plane perpendicular to the forearm's swing plane, as shown in Diagram 4, three times in three seconds. Had the elderly happened to fall and lie down on the floor and not been able to move any arm, the system would still have detected that lie-down using the system's postural classification. Currently the system can do the detecting but does not send an alarm. Such alarm feature can be implemented in the future.

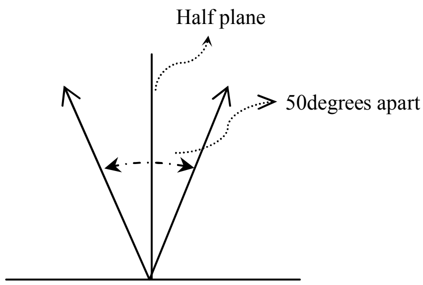

Diagram 4. Waving forearm vectors and their half plane

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Calculated Risk of Bed Falling

The system marks the four corner points of the bed as boundaries, as shown in Figure 2. The four marked points are 2D screen coordinates, X and Y. For each skeletal joint, its 3D coordinates, X, Y and Z, are converted to their corresponding 2D screen coordinates using Windows SDK's *SkeletonPointToScreen* function. Each converted point is then compared to the boundary to check whether it lies within the boundary or not. Even though the Windows SDK provides 20 skeletal joints, only 15 joints are used in the calculation of bed falling risk. The five unused joints are left hand, right hand, left foot, right foot and spine, simply because they are closely located to the more useful joints, namely wrists, ankles and hip. Consequently, we use the 15 joints to contribute to the total risk of bed falling. Each joint simply contributes about 6.66% to the total risk when it is out of the boundary. Currently the elderly person, carer or family members are alerted with a cautiously dangerous orange level when the calculated risk is higher than 30% (i.e. about five joints being out of the boundary). When the risk is higher than 50% (i.e. about eight joints being out), its alert status is at a very dangerous red level. These values are adjustable if needed. The risk of bed falling is considered only when the skeleton's status is lying-down; when the person rises from bed, the status will be changed to sitting or standing, and thus there will be no warning.

Figure 2. Bed boundary setting

Alert for Oversleeping

In order to detect an unusual wake-up time for an elderly person, all the 15 skeletal joints are checked whether all of them are still in the bed's boundary with a lying-down pose when the usual pre-set wake-up time is passed. The system continues monitoring for a certain amount of time and alerts the family members or carer when it appears the elderly is still in bed. In the long run the system can adjust the sleep hours in accordance with the sleep history, although every now and then the elderly person may change his or her sleep pattern. Such feature can be implemented in the future.

Classification of Human Poses

We modified the postural analysis done in our previous work [19] and integrated it with the gestural analysis system done in our smart bedroom [17] in order to have a more efficient and complete system. In the process of building the postural classification model, two main phases, viz. data preparation and data classification, were used. Diagram 5 shows the workflow for building the classification model. Raw data were obtained from the Kinect's streaming 20 skeletal joints. Each joint has three positional coordinates, X, Y and Z. Each coordinate is considered one attribute and hence there is a total of 60 attributes. Thereafter, the raw data are prepared and turned into the attribute transformation, which is the skeletal position transformation training set with transformed data from the skeletal joints captured by Kinect. Out of 20 total joints, 12 skeletal joints are chosen to create 9 attributes in the training set. Those joints are shoulder centre, shoulder left, shoulder right, elbow left, elbow right, wrist left, wrist right, hip centre, hip left, hip right, knee left and knee right. The nine attributes are knee angle left, knee angle right, aspect ratio of height (head to ankle) and width (left shoulder to right shoulder), distance from hip to room floor, back status, differences between the Y coordinates of shoulder and wrist of the left hand side and the right hand side, and differences between the Y coordinates of shoulder and elbow of the left hand side and the right hand side. By using the said attribute transformation, the complexity of attributes in the training set is substantially reduced. Raw data are not used simply because they may make the training set complex and thus affect the learning of the classifier and result in an error accumulation due to redundant attributes.

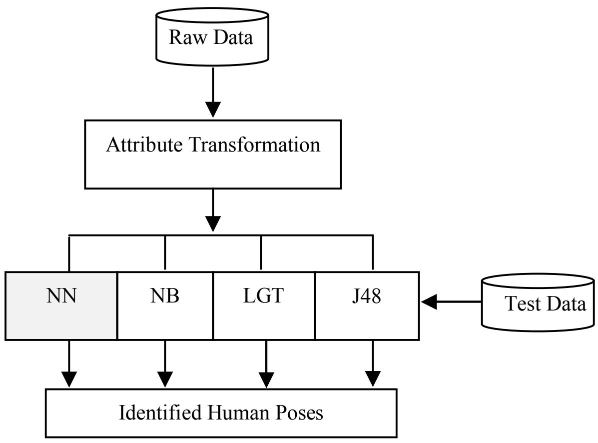

Diagram 5. Workflow for building postural classification model (NN = neural network, NB = naïve Bayes, LGT = logistic regression and J48 = decision tree)

Four learning models based on data mining techniques were used and compared in our experiment, viz. neural network (NN), naïve Bayes (NB), logistic regression (LGT) and decision tree (J48). Those models were implemented with the Weka data mining tool [20]. In this data classification phase we chose a multiple-stage classifier because it can separate the data into multiple training sets, and that helps reduce the time to create the model. Therefore, the multiple-stage classifier requires many models working together in the prediction data. We divide it into two layers. The first layer is used to classify four main postures, viz. standing, sitting, sitting on floor and lying down. The second layer has two classifiers, viz. back status classifier and hand-up classifier. The back status is used to classify 'lean forward', 'straight back' and 'lean backward', while the hand-up classifier is used to classify 'both hands up', 'left hand up' and 'right hand up'. At the end the best model, i.e. NN, was chosen and used as the postural classification model for the system. Diagram 6 shows the final postural classification model based on NN.

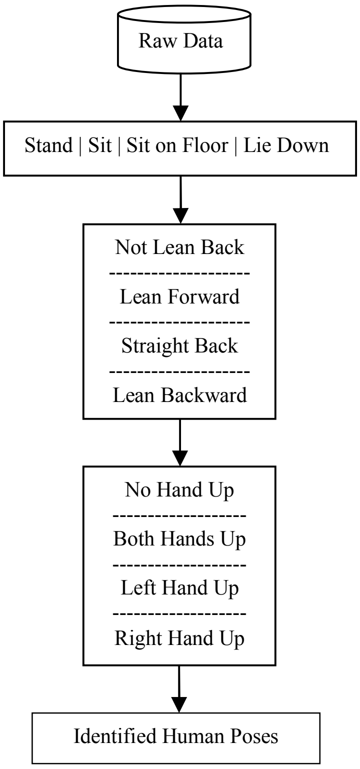

Diagram 6. Multiple-stage postural classification model using NN

RESULTS AND DISCUSSION

We ran several experiments to find out the performance ofthe system's features. These were, for example, forearm pointing to toggle the electric devices such as lights, television, fan and air conditioner between on and off, forearm waving to call for help, calculating a risk of bed falling, giving an abnormal wake-up time alert, and classifying different poses such as sitting, sitting on floor, standing and lying down. The test results are very promising and satisfactory. The best accuracies of the forearm pointing to control the electric devices are 96.67% for fixed locations (i.e. test subjects stay at the same place both when doing the forearm pointing set-up and when pointing to control the devices) and 95.83% for moving locations (i.e. test subjects move around when doing the forearm pointing set-up and when pointing to control the devices). The accuracy of the forearm waving for help is 95%. The method for calculating the risk of bed falling is proposed and the corresponding warning system is implemented. The alert for oversleeping is tested with a 100% accuracy. For the classifications of various poses, the average accuracy is 87.68%. The details are given as follows.

Using Forearm Pointing to Control Electric Devices

We compared the newly improved method to our previous one [17], using 12 test volunteers. Each volunteer performed both of the method settings to register the accuracies of locating and controlling electric devices using the forearm pointing. The devices were positioned about 0.5 metre apart horizontally, from device no.1 to device no. 7, as shown in Diagram 7. The success of operation as a function of device separation was evaluated. Each volunteer performed the forearm pointing 10 times for each of the 6 pairs of devices, e.g. devices no. 1 and 2. The accuracy of turning those devices on and off was recorded. Similar tests were done for the devices no. 1 and 3, devices no. 1 and 4, and so on.

The tests were repeated for both fixed positions and moving positions. In the fixed positions the volunteers stayed at the same position when doing the pointing, while in the moving position when pointing they could be at any positions different from the ones used when doing the forearm pointing set-up. Figure 3 shows a slight improvement in general of the new method over the previous method for the forearm pointing at fixed positions. Figure 4, however, shows a substantial improvement of the new method in all 6 cases in which the forearm pointing was done while moving. Nevertheless, both methods perform poorly when the two electric devices are located about 0.5 metre apart. This is attributed to an imprecise location calculation when the devices are placed close to each other.

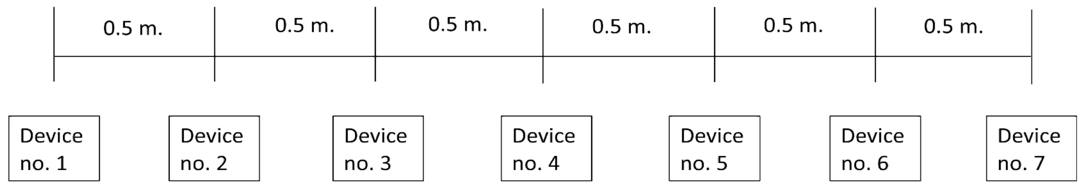

Diagram 7. Arrangement of devices' positions

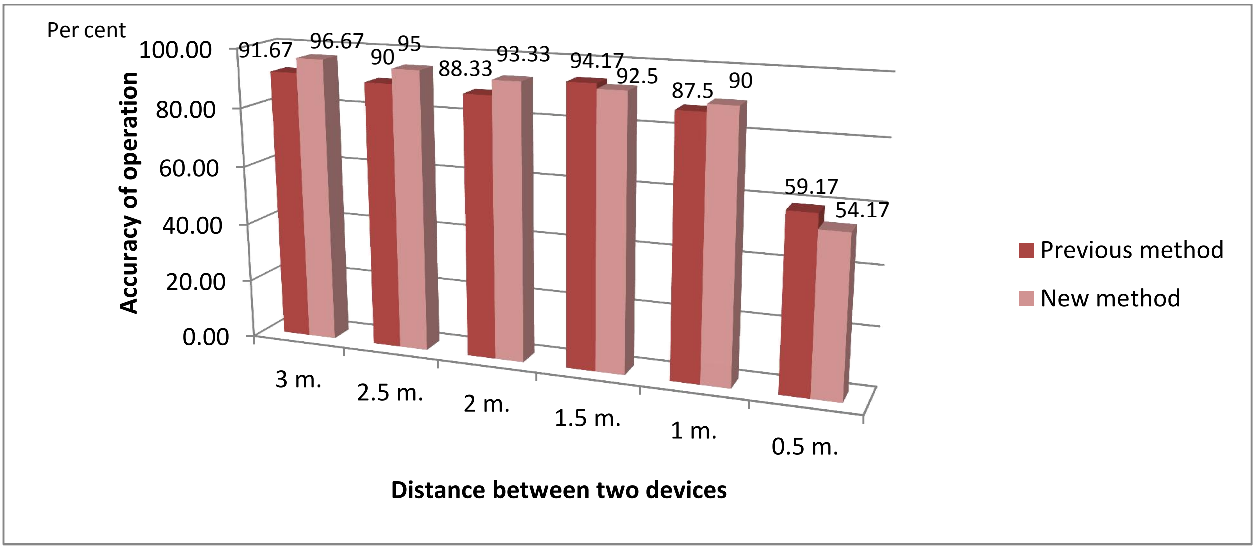

Figure 3. Accuracy (%) of forearm pointing at fixed positions

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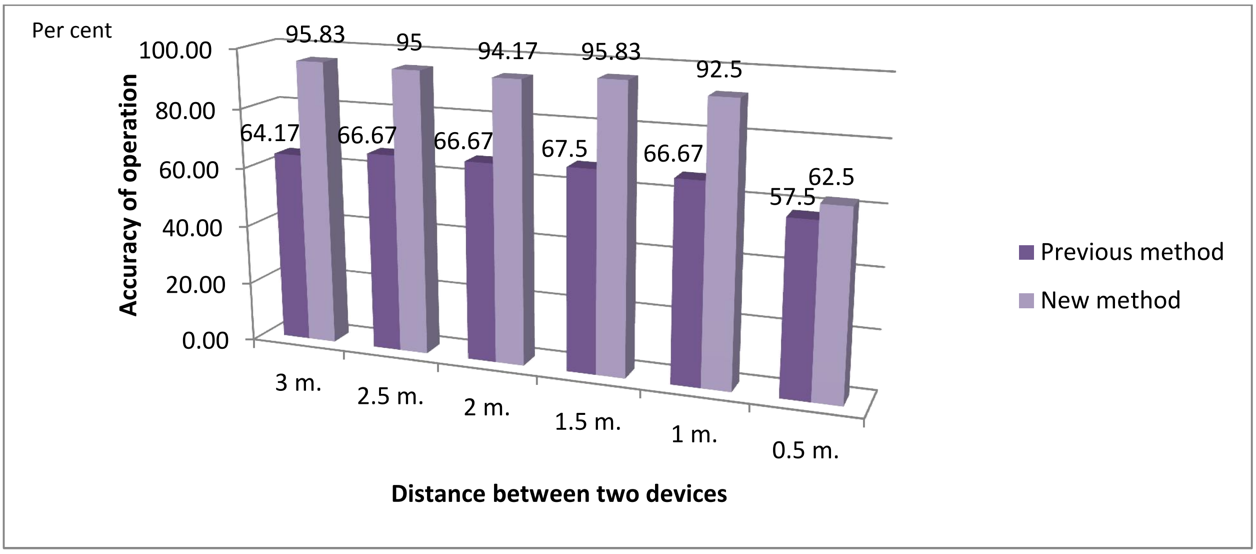

Figure 4. Accuracy (%) of forearm pointing while moving

Using Forearm Waving to Call for Help

We asked 5 test volunteers to perform forearm waving. Each person repeated the experiment 20 times. We then recorded the accuracy of detecting the call-for-help forearm waves. The system could detect the waves correctly with an accuracy of 95%. Out of the total of 100 intended waving trials, two volunteers had all forearm waves detected, one had one undetected wave, and each of the other two had two undetected waves. There were no false alarms found in the test cases. Out of those 100 trials, 5 were undetected and 95 were detected. So the false positive was 0 and the false negative was 5. Figure 5 shows the screen capture of the system which can correctly detect the forearm waving for help. Consequently, a carer or family member can be notified quickly of needed assistance.

Calculated Risk of Bed Falling

We tested how well the system can calculate the risk of bed falling by asking one volunteer to rise while still sitting in the bed, as shown in Figure 6. The status of the person is correctly shown as sitting (getting up from bed). Even when the upper part of the body rises from the lying-down position, the system still correctly registers no bed falling risk. As shown in Figure 7, while the person lies in bed, he rolls to his right side with some parts of the body being out of the bed boundary, when the system indicates that there is about 20% chance of falling out of bed. Based on our previous work [17], the test for bed falling was done100 times, and the system gave 97 accurate risk calculations or an accuracy of 97%.

Alert for Oversleeping

The system could correctly detect and give an alert when the person oversleeps past his or her usual wake-up time. As shown in Figures 6 and 7, the normal status is shown in light blue colour. However, as the person oversleeps past the normal wake-up time, the colour of the status changes to amber, orange and red when the overdue time is 15, 30 and 45 minutes respectively, as shown in Figure 8.

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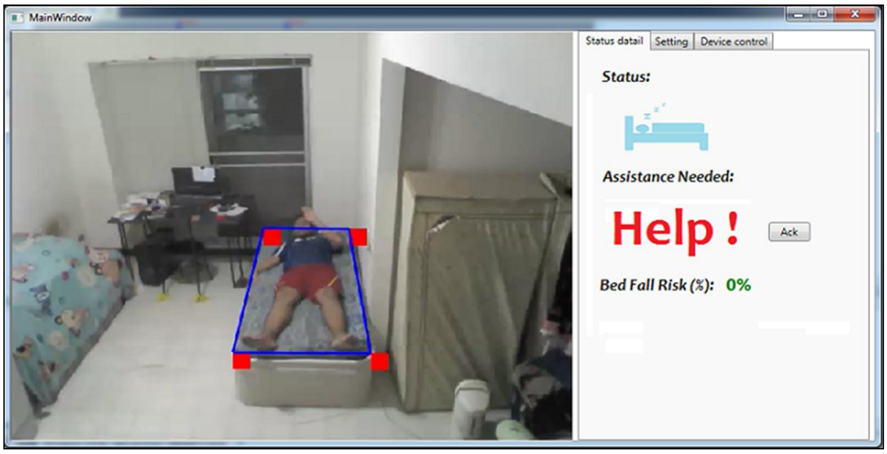

Figure 5. Forearm waving to call for help

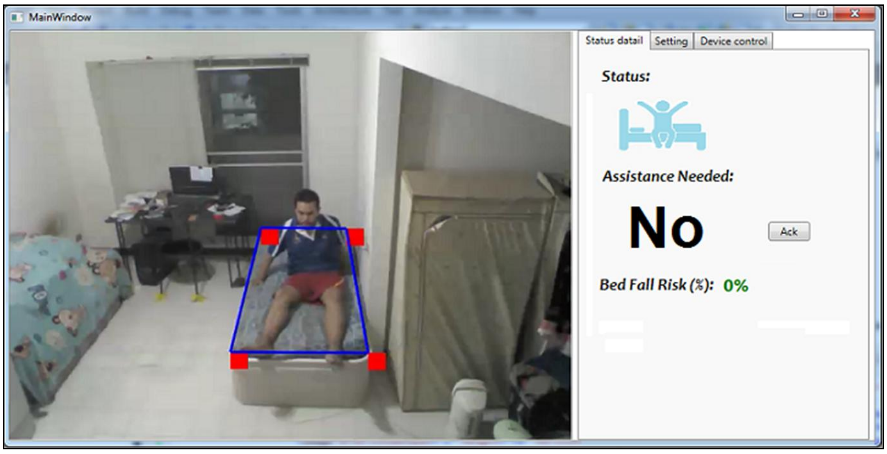

Figure 6. Sitting in bed with no risk of bed falling found

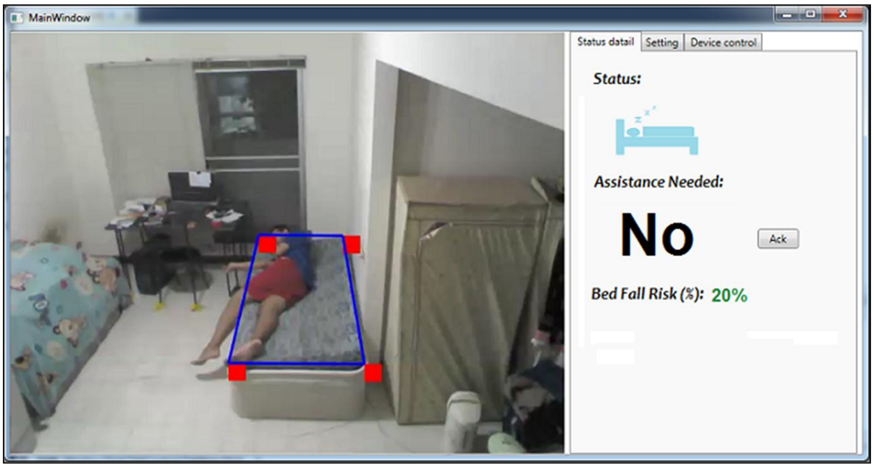

Figure 7. Lying in bed with some parts of body being outside bed's boundary (20% risk of bed falling)

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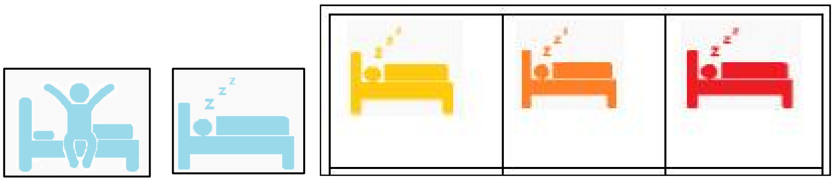

Figure 8. Normal sleep status in blue icons and different warning levels (amber, orange and red) of oversleeping

Classification of Poses

The system can capture four key postures, namely sitting, sitting on floor, standing and lying down. Figures 9 and 10 respectively show the sitting and lying-down icons after the pose of the test subject has been analysed and classified. In the steps of building the postural classification seven volunteers (four males and three females) were asked to perform 18 different postures, as shown in Table 1, for the training sets. The obtained training sets comprised 110,751 instances. Another three volunteers provided 20,868 instances for the testing data. The learning model which gave the best results was the NN with the skeletal position transformation, and thus it is chosen for our system. The NN is the simple multilayer perceptron that uses a back propagation algorithm. Its structure comprises 3 layers, namely input, hidden and output layers, the hidden layer values being the default values from Weka [20]. Its average classification accuracy for those 18 postures is 87.68%, while the other three models (i.e. NB, LGT and J48) have slightly lower average accuracies, as shown in Table 1.The console version of Weka was used for building the classifiers and testing with a separate data set. By default the Weka console uses 10-fold cross-validation to build the classification model when both the training and testing data sets are provided. In addition, we have separate training sets and testing sets obtained from different groups of people and enough data to fit the models.

Figure 9. Sitting pose obtained from postural analysis

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Figure 10. Lying-down pose obtained from postural analysis

Table 1. Accuracies of each posture using transformed attributes

Pose	Accuracy (%) of each learning model			
	NN	NB	LGT	J48
Normal standing up	89.36	83.26	88.65	86.56
Standing, both hands up	89.56	83.25	88.58	86.45
Standing, left hand up	89.53	83.14	88.56	85.14
Standing, right hand up	89.66	82.36	87.48	85.36
Standing and leaning forward	89.79	82.34	86.32	85.47
Sitting, straight back	88.69	80.24	86.64	85.36
Sitting and leaning forward	88.89	80.53	86.32	85.69
Sitting and leaning backward	87.96	81.56	86.95	85.36
Sitting, both hands up	87.21	79.45	85.36	85.32
Sitting, left hand up	87.45	79.36	85.99	85.15
Sitting, right hand up	86.35	79.85	85.86	84.26
Sitting on floor, straight back	87.69	79.45	85.36	84.89
Sitting on floor and leaning forward	87.65	79.25	84.26	84.56
Sitting on floor and leaning backward	87.36	78.54	84.38	84.36
Sitting on floor, both hands up	87.45	78.56	84.35	84.57
Sitting on floor, left hand up	87.35	78.98	84.15	83.53
Sitting on floor, right hand up	87.39	78.36	84.28	83.63
Lying down in various manners	78.98	69.58	78.64	78.79
Average	87.68	79.89	85.67	84.69

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CONCLUSIONS

We have proposed a smart bedroom system for the elderly who tend to live alone, especially in an ageing society whose number has been increasing worldwide. The system uses two Microsoft Kinect devices to capture the movements of an elderly person in a variety of gestures and postures in the bedroom. The skeleton from one Kinect is used for detecting the forearm pointing to turn the electric devices such as lights, television, fan or air conditioner on and off, the forearm waving to call for help, the risk of bed falling and for making an alert for oversleeping. The other Kinect analyses the skeleton and classifies different poses that the elderly person makes. The system can classify key poses such as sitting, sitting on floor, standing up and lying down. The proposed system is simple in terms of technicality and implementation, yet very effective, practical and affordable, and does not require any expensive and advanced sensing devices like those found in some existing smart home systems. This makes our system fairly practical and accessible to many potential elderly users.

For a future improvement, the risk calculation for bed falling detection may be made more effective. In the long term, a sleep pattern can also be adjusted automatically to improve oversleeping detection. Moreover, we plan to implement the system using just one Kinect and integrate it with a stay-in-touch system [21], which is the system that can deliver the multimedia to an Internet-connected television, as most elderly spend a lot of time in front of televisions. Once completely integrated, the system will be a realisation of the conceptual framework developed to assist the elderly to practice 'active ageing' in order to improve the quality of life as proposed by Chan [22].

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