

AtHoCare: An Intelligent Elder Care at Home System

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Abstract. In recent years, the shortage of nursing home and the demand from elders have made the balance inclined. Additionally, the increased numbers of elders per year have not deemed fit to wait for growth rate of nursing home. Therefore, more and more elders have to stay at home and live alone, which easily leads them to be in danger, especially when unexpected emergency occurring like falling. To investigate this issue, we have designed AtHoCare, an intelligent elder care at home system, which employs Microsoft depth camera sensor Kinect to detect fall and an intelligent server to send alarms to nurses' smart phones. In this way, medical staffs could easily monitor several elders at the same time, which greatly increases work efficiency. It is worth stressing that AtHoCare also proposes an algorithm of fall detection based on skeleton data of elders only. It protects elders' privacy much more than other vision based algorithm of fall detection. Results from our preliminary lab-environment test showed that AtHoCare has a well-done performance on detection.

Keywords: Healthcare · Fall detection · Intelligent system

1 Introduction

Nowadays, population ageing has become a worldwide serious problem and drawn public attention. Limited resources and labor force of nursing home and a huge requirement from elders made this issue acute that all countries have to face. The data from Ministry of Civil Affairs of P. R. China indicates that every one thousand elders in China have only 25 beds in nursing house. With no choice, many elders have to stay at home. However, these elders may not get an in-time treatment when some health emergencies happen, such as stroke, heartache, and especially fall. Falls of elderly people are the main cause of admission and extended period of stay in a hospital.

It is also the sixth cause of death for people over the age of 65, the second for people between 65 and 75, and the first for people over 75 [1]. A number of studies have been carried out to detect falls. These investigations can be classified into three main types: wearable device based approaches, ambience sensor based approaches, and camera based approach. Camera based approaches have been increasingly adopted in home assistive/care system recently, since these approaches can be used to detect multiple events simultaneously with less intrusion [2]. Bevilacqua et al. [3] proposed a fall-detection tool based on commercial RGB-D camera that was capable of accurately detecting several types of falls. Stone et al. [4] presented a two-stage fall detection system detecting falls in the houses of old adults using the Microsoft Kinect. Miaou and his colleagues [5] designed a fall detection system that used a MapCam (omni-camera) to capture images and performed image processing over the images. The personal information of each individual has been also considered in the processing tasks. Wu [6] used the velocity profile for detection of normal and abnormal (i.e., fall) activities, which made the automatic detection of falls during the descending phase of a fall. Williams et al. [7] designed a system based on distributed network of smart cameras, whose function was to detect and localize falls. In this work, they designed and implemented an important application in elderly living environment. However, these studies usually lacked strategies to protect data privacy [8].

To crack this hard nut, we design an intelligent elder care system, which can help medical staffs to monitor elders' falls and other activities in door at home and protect their sensitive data. The model of system consists of three main components: sensors (Kinect), intelligent server and clients. This system only employs Kinect to get elders' skeleton data for monitoring elders' activities, without gathering other biometrics data like facial expression. Through computing body's centroid changing and the recovery time, we can detect the status of elder, that is, falling or not. When falls happen, the medical staffs will be informed at different urgent levels. This paper is organized as follows. It starts with describing the intelligent elder care at home system structure at first. Then a fall detection algorithm based on center of mass (COM) is proposed. Finally, results and discussion are stated based on a preliminary lab study.

2 AtHoCare: The Intelligent Elder Care at Home System

2.1 System Structure

AtHoCare is designed to help elders take care themselves in their homes. It consists of three main parts: intelligent server, clients and sensors (Kinect). The system structure is shown in Fig. 1.

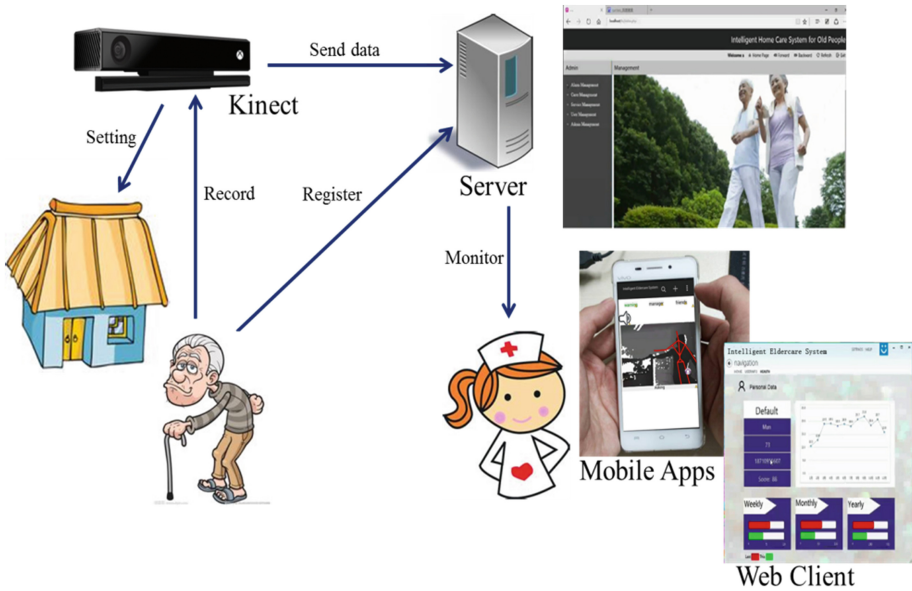


Fig. 1. Intelligent elder care system

Intelligent server has two main functions. One is responsible for storage personal information for elders, including: name, gender, age, telephone number and medical record. Elders can easy to sign it up via internet. Another one is to collect elders’ activity information, which can be used to analyze elders’ body movements, habit and health status. When a fall or other abnormal activities occur, the data relating to these activities will be sent to the server. Also, it employs web service to provide access to PC and mobile.

The client is designed to help medical staffs to easily find elders in emergency situation anywhere at any time. It has two methods to access to intelligent server: web client and mobile application (with regard to testing version, we develop an app running on Android OS). When elders falling in their homes, client will receive an alarm from intelligent sever.

The core part of AtHoCare is to monitor elders’ daily activity and to detect elders’ abnormal activity: fall when it taking place. We employ Kinect to trace elders’ daily activities; it is a line of motion sensing input devices by Microsoft for Xbox 360 and Xbox One video game consoles, as well as Windows PCs. Based on an IR depth-finding camera and a RGB camera, Kinect enables advanced gesture recognition, facial recognition and voice recognition [9]. Besides this, Kinect is capable of simultaneously tracking up to six people, including two active players for motion analysis with a feature extraction of 20 joints per person. We set Kinect in the high corner of room to monitor elders’ daily activities. With regard to privacy concerns, we block the RGB data and leverage skeleton joint data to detect elders’ accidental fall and other abnormal activity. It can not only get elders’ precise behavior information in a small data quantity but also protect their privacy to maximum extent.

2.2 Fall Detection Algorithm

Based on AtHoCare as described above, we propose an algorithm of fall detection based on COM. We use the acceleration of COM, the distance changed of COM, and the recovery time as three key features to detect a fall. Then we combine the fall type and contextual information to evaluate the danger level.

De la Leva's work [10] segments human (female and male) into eight parts: head, trunk, upper arm, forearm, hand, thigh, shank, and foot. The Kinect can get 3D position data of 20 joints' of human body, which cannot match Leva's work directly. Thus, we consider dividing the human body into six parts anew: head, trunk, two arms, and two legs to match the motion of people with the segment of body mass. The segment mass is the weight ratio of body part to the whole body. As shown in Table 1, we listed these common ratios or percentages from Leva's work. Since Kinect cannot identify the gender from skeleton data, we compute the average percentage based on female's and male's percentage. The last column in Table 1 shows the calculated average. Finally, we also use the average body mass as 67.45 kg, based on Leva's work (male, 73.0 kg; female, 61.9 kg).

Table 1. Human's Segment Weight data

Segment	Quantity	Female's percentage (%)	Male's percentage (%)	Average percentage (%)
Head	1	6.68	6.94	6.810
Trunk	1	42.57	43.46	43.015
Total arm	2	4.49	4.92	4.715
Total leg	2	20.88	19.86	20.370

Based on the position information and the average body mass, we convert 20 joints into six parts to represent human body, as shown in Fig. 2. The whole body's COM data can be computed as the weighted sum of the whole body [11].

We get the real-time vertical acceleration of COM from each interval two frames based on function (1):

$$a_{COM} = P_{frame\ n} - P_{frame\ n-1} / \Delta t \quad (1)$$

Based on Li's work [12], we define threshold value as: 2.5 g ($g = 9.8m/s^2$). When a_{COM} is bigger than the threshold value, we consider it as a fall-prone action.

In order to obtain the distance changed of COM, we measure the angle between the Kinect and the vertical wall, as shown in Fig. 3. Through the calculation of the coordinate system of Kinect, we then infer and obtain the actual distance changed of COM.

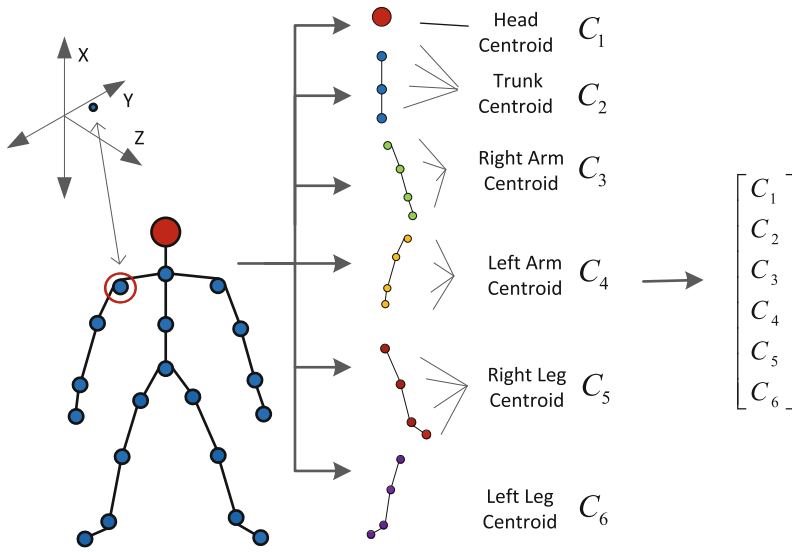


Fig. 2. The model of activities based on skeleton joints' centroid

With respect to the recovery time, we define it as the interval lasting from a fall-prone action occurring to the COM that is higher than that of the sitting posture on the ground. We detect the fall-prone action by using the rule set method, which is based on the acceleration of COM and distance changed of COM. The fall type is determined by the recovery time. We classify the falls into three main categories: non-risk falls, low-risk falls and high-risk falls.

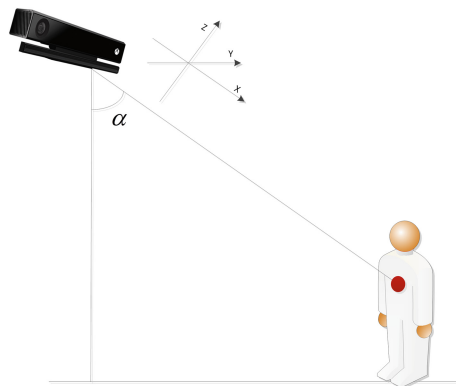


Fig. 3. The framework to obtain the distance changed of COM

Finally, we get the danger level of the fall based on fall type and elder's context at that time, as shown in Fig. 4. This level helps the system to distinguish the fall is danger or not. For instance, some elders in Asian countries are accustomed to take a nap after lunch, sleeping directly on the ground.

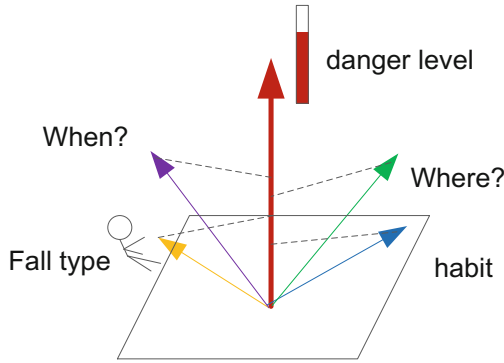


Fig. 4. The danger level (Color figure online)

3 Results and Discussion

We test AtHoCare in a lab environment. The AtHoCare is built based on a PC, with Intel(R) Core(TM) i7-3520 @2.9 GHz, 12.0 GB RAM, Windows 8.1 Operation System, a Kinect, a smart phone on Android, and five volunteer participants. The Kinect is fixed at the high corner in the test room to record users' activities. The intelligent server is developed in Java, which provides web service based on AXIS2.

We select and define three common activities in daily life: walking, sitting and jumping, to make a comparison with falling.

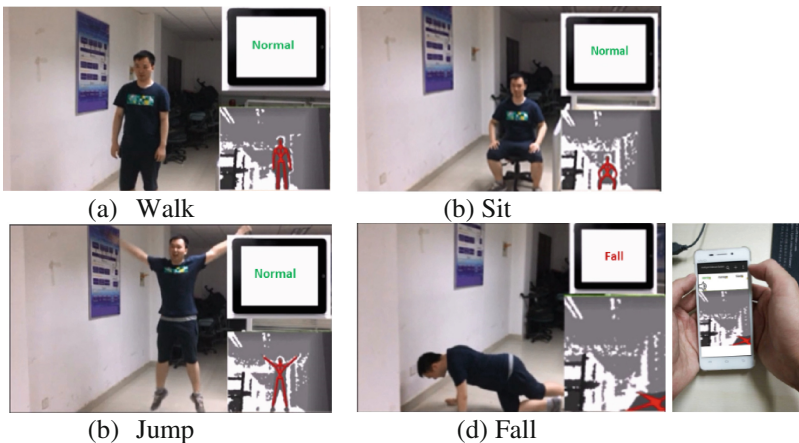


Fig. 5. The test in a lab-environment

The results are shown in Fig. 5. From results, the system can easily detect falls from other normal activities. Due to the use of the skeleton data as source data, we could ensure the protection of users' privacy and make the data small enough to be easily and quickly transferred. The client end can be alarmed immediately while the volunteer falling, even in cellular networks.

4 Conclusion

In this paper, we present the AtHoCare, which is the intelligent elder care at home system and can help medical staffs to monitor elders' health situation distantly. In this system, the intelligent server can estimate the danger level of activities based on fall type and users' situation, including the contextual information, elder's behavior habits, etc. Medical staffs can check the status of elders through the mobile app and web client. Based on the in-time information, they could provide medical services immediately. Finally, the system is evaluated in a lab-based environment. In our future work, we will set our intelligent elder care system on real house to test its performance in the real environment.

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