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Activity and Emotion Recognition for Elderly Health Monitoring

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Abstract: The problems facing elderly who are living independently, are considered to be one of the most important motivations of the activity recognition research. The advances in sensing technologies allow collecting several types of data and communicate it wirelessly. However, most existing activity recognition systems requires pre-calculated pattern recognition models. This paper lays the theoretical foundations of a real-time methodology for activity and emotional recognition based on body and environment sensors simultaneously, then tackles one aspect of the method which is the path estimation using chest-mounted IMU sensor, for which a zero velocity update criteria is proposed. Finally path estimation results for sitting down, laying down, falling down and standing up are discussed.

Keywords: *Elderly, Activity recognition, Path estimation, IMU sensors*

1. INTRODUCTION

The global population of older persons (aged 60 years or over) is expected to increase from 841 million people in 2013 to more than 2 billion in 2050 [1], which is more and more seen as a problem especially by economists and care services, they predict that the available resources are not sufficient enough to maintain the independent living [2].

Intelligent house care researches have considered as an objective the resolution of this problem, through what is called Human Activity Recognition (HAR), which can help supporting elderly independent living and reducing the burden of their caregivers. Automatic recognition of Activities of Daily Living (ADL) in the context in which elderly care is conducted, such as detection of person falling down [3], Detecting gait freezing [4] and more complicated activities [5-9].

HAR researches employs physical sensors, which are often deployed in environments, attached on the objects or worn on human bodies to continuously collect sensor readings. They can be divided into three categories related on the type of data they are based on:

i) Motion-sensor-based methods [7, 10-13], attached or wearable, they utilize on body sensors like the accelerometer and gyroscope, to sense the movements of body parts.
ii) Radio-based methods [14, 15], the wireless radio types include: ZigBee; which build a small network of sensors on the body. WiFi; passive activity recognition system, RFID which is practically based on the gesture recognition system that employs signal fluctuations in a limited area.
iii) Vision-based methods [16-18], which employs cameras to record the video, than recognize the activities using computer vision algorithms. According to the camera type, the video may be RGB video, which use no compression and impose no real limit on color depth or resolution, depth video, which are used for the 3D depth capture, and RGB-D which is the combination with of RGB cameras with depth video sensors.

For the elderly health monitoring system, it is thought that some researches from the first category attaches too many sensors to different parts of the observed person's body, and that the second category may mandatory not have the ability to make a difference between the observed person and other sources of wave disturbance like pets, the third type of researches can be criticized for their big amount of calculation and data compared to the earlier methods.

Although the mentioned activity recognition methods obtain are widely accepted, they require pre-calculated pattern recognition models, on which the results of the recognition depends strongly, this is considered to be the biggest difficulty for elderly health monitoring research, as the variation between elderly subjects has far more data divergence compared to standard models, which may be impractical if it would require to build a model for every individual.

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In following sections a review of ADL in elderly health monitoring is presented, then the methodology for activity and emotion recognition for elderly health monitoring will be discussed. The last section is dedicated to solving one major aspect of the proposed methodology which the human body path estimation is using single IMU sensor mounted at the chest.

2. "ADL" IN ELDERLY HEALTH MONITORING

Elderly health monitoring is a research topic that interest a lot of researchers, where ADL is central, Wearable sensors and smartphone sensors data are often employed [19], we can mention some works, like [20] that used a wearable device for collecting acceleration data obtaining a 94% of recognition accuracy. Also one of the earliest works [21], employed five biaxial accelerometers are worn on the user's right hip, dominant wrist, dominant ankle, non-dominant upper arm, and non-dominant thigh to monitor 20 types of activities, the models were trained with 20 users using instance-based learning, C4.5 and Naive Bayes classifiers; Their results indicate that the accelerometer placed on the thigh was the most powerful for distinguishing between activities.

Also a relatively early work by [12] a single triaxial accelerometer is worn near the pelvic region in order to recognize 8 different activities: Standing, Walking, Running, Stairs-Up, Stairs-Down, Sit-Ups, Vacuuming, Brushing Teeth, different settings are considered for the dataset. Their experimental results difficulty to distinguish Stairs-Up from Stairs-Down or Running, and impossible to distinguish Teeth Brushing versus Stairs-Down activities.

A more recent research have been presented in [22], where the authors have single and multiple for recognition of 8 related activities like sitting down and standing up from toilet seat and sitting down and standing up from armchair, also other activities like walking for getting out of car seat and walking for 10 meters. They collected data from dwelling older adults ranging in age from 70 to 83 years, capable of walking and having various conditions such as osteoporosis, COPD, with leg, ulcer and knee replacement. Different classifiers were investigated. Results shown that one scenario of single sensor have obtained high accuracy level of 92.8% compared to maximum accuracy 96.4% obtained by multiple sensors. The results also have shown that there are more confusions levels in the case of single sensor cases, especially in the transition between activities.

The search presented in [23], shown that activity recognition can be achievable with only one triaxial accelerometer sensor, the authors applied two different classifiers (k-NN, Naïve Bayes) to recognize some basic activities like running, jumping, sitting. The training data was collected from healthy young persons with sensor positioned at the wrist.

The physical activity recognition in [10, 24] utilized a single triaxial accelerometer to distinguish between the different ADL of relatively old persons (six males, two females, age: mean = 65, SD = 3 years old). The a triaxial accelerometer was attached to 5 different places of the body, the position of chest, a particular orientation, was found to be very practical and was able to classify fifteen activities with an average accuracy of 97.9%.

3. PROPOSED PLAN

This methodology is based on two sources of data. The first source is the observed person and the second is the environment in which the subject live and the everyday devices used.

3.1 Body sensors

The idea is to equip the subject with a sensor that can help detect its position in the three dimensional space. Intuitionally the sensor should be positioned in the center of the chest of the observed person, in that configuration, we can estimate that the subject lying down if the sensor indicate its position to be the closest to the ground, if the sensor's position is in a medium distance the subjects most likely to be sitting, if the sensor indicate its highest distance compared to the ground the subject must be standing.

By initiating the calculation in known position, we can track the sensors path. Therefore the state of the subject; if we detect motion toward up, it means the subject is standing if the motion is toward the ground, the subject is sitting or lying down (depends where the motion stops), same principle will let us know the location of the subject and estimate the activity, for example, if the sensor indicate motion toward the area identified as the kitchen and stopped there, the subject is more likely to be cooking or doing kitchen related activities.

Tracing everyday path will provide important information, first by giving access to history/development of activities, second by giving a strong indicator of sudden change which may mean change in the subject's health or emotions.

Localization using accelerometer data, by integrating the acceleration is not reliable, as the error is very large due to the big amount of noise, also posing the sensor at the chest will endure more noise due to breathing. In other hand, Inertial Measurement Unit (IMU) [25-28], which consisting of accelerometers, gyroscopes and magnetometers has been widely used for localization purposes, mainly for Indoor localization and motion capture, by calculating the velocity and location of the tacked person, through acceleration tuning algorithm, the acceleration data is refined and combined with the velocity calculated from body kinematics to get a drift-free and accurate 3D velocity result. The location of the person is tracked based on this velocity estimation.

A different type of data can be achieved with the heart beat monitor, which combined with localization and path tracing, can confirm the state information (rest, active, making effort…) and lead to more accurate activity estimation.

In our project, we plan to use wearable heart beat rate monitor which can track heart beat rate continuously and hands-free using smartphone with Bluetooth live data transmission. Besides we plan to take wireless heart rate monitor in the near future.

3.2 House sensors

This kind of sensors is very important for determining precisely the activity of the subject [29, 30]. But there are some technical difficulties, like the short battery life [29], also here could be some devices where it is hard to install a sensor that can indicate precisely the state of the device, like the television for example.

In other hand, almost every device in the standard house has some kind of indication of its activeness, like for example in the refrigerator a light ill turn on when its door is open, the washing machine, microwave, air-conditioned, television, IH cookers… they contain a small diodes that will light up when these tools are active. Also the bath, the toilet seat can be seen that way.

To make use of the already existing sensors, signal emitters can be introduced to these devises, connected with the light diodes directly. This can not only indicate precisely the activeness of the devices, but also the exact time of use, plus the problem of short battery life will be avoided.

In our project, we plan to use sensor which has 2-meter range and 1 year battery life to detect motion, temperature, and humidity. The sensor connects to web service and easy to export data to conventional application such as Google drive.

4. EMOTION RECOGNITION

Emotion recognition is based on two kinds of sensor, one is wearable or wireless sensor to monitor heart beat rate and breathing, the other is thermography that is body surface heat distribution.

4.1 Heart beat rate and breathing

Heart beat rate is a very strong indicator of emotions [31], another source of data is the breath rate. The combination of both information is used in several researches of emotion recognition. It is thought that the techniques used in emotional recognition researches are hard to be employed in elderly health monitoring system, like the radio based researches which have area limitation in order to obtain accurate breathe rate measurements [32, 33].

In the breathing process, the chest enlarges when inhaling air and decreases when exhaling, this can be considered as source of data, by positioning sensors in both sides of the human chest, two sensors, one in each side is probably optimal. This type of sensors should provide only one information, which is the distance between sensor's positions relative to the human body, it is estimated that one dimensional distance could be enough.

The distance between sensors will vary in a cyclic manner according to the breathing process, it can probably be considered as it is (distance value), or also a mode can be built to describe the relation between this distance and the volume of air being breath. This will provide a cheapest breath rate indicator and more applicable approach to the elderly health monitoring system. Combined with heart rate monitor data, emotional recognition research can be conducted. Knowing the exact effect of breathing on sensors positioned in the chest, will help clarify the data of localization by deleting the noise due to breathing.

4.2 Thermography

Thermography is well-known as condition monitoring such as energy leaking behind wall, or health monitoring such as detection of suspected bird flu cases just before passport control at airport. Recently, there are several trials to detect emotion from facial thermal image [34, 35]. They mentioned that emotion recognition research by face thermal image is ongoing challenge. In our project, we plan to merge heart beat rate, breathing, and thermography for emotion recognition.

5. MOTION PATH ESTIMATION BASED ON CHEST-MOUNTED IMU SENSOR

Several studies employs IMU sensors, along with other sensors like the magnetometer sensor in some cases, to track position of the sensor by calculation the velocity and orientation [36, 37] , or by counting steps [38].

Method based on step counting is thought to be unfitting for elderly HAR, since they require pre-knowledge of the user's physical dimensions also their accuracy require regular walking style.

In other hand, integral based method are more fitting for HAR but they suffer small amount of errors when estimating the distance due to hardware limitations, and more importantly the signal noise, which when used in double integration for estimating the distance, these errors will be accumulated.

To solve this problem, the commonly used method Kalman Filter (KF), the adopter algorithm suppose that the velocity errors and position errors are correlated, therefore if the estimated speed is incorrect, the estimated position error can is predicted. In other words, when the sensor has stopped moving, this phase is called Zero velocity (ZV), but the estimated speed isn't zero, it can be predicted that the estimated position will likely to be incorrect.

Zero Velocity Update (ZUPT) is proposed to reduce the velocity and position estimates, the Kalman filter estimates their error covariances and cross-covariances. The cross-covariances let the filter correct the position (and not only the velocity) during a ZUPT. At the end of each ZUPT, the estimated errors in velocity and position are subtracted from the estimates. Figure 1 describes the algorithm [39].

The initial position and velocity are set equal to zero, and initial orientation matrix is used to estimate the transformation from the sensor frame to the navigation frame, and calculated based on acceleration data as follows:

$$C = \begin{pmatrix} \cos(Pitch) & \sin(Roll) sin(Pitch) & \cos(Roll) sin(Pitch) \\ 0 & \cos(Roll) & -sin(Pitch) \\ -\sin(Pitch) & \sin(Roll) cos(Pitch) & \cos(Roll) cos(Pitch) \end{pmatrix} \quad (1)$$

$$Roll = arctan\left({}^{a_y}\!/_{a_z}\right) \quad (2)$$

$$Pitch = a - rctsin\left({}^{a_x}\!/_{g}\right) \quad (3)$$

$$Yaw = 0 \quad (4)$$

g is the gravity value 9,8. The Kalman filter parameters are the followings; Accelerometer noise σ_a, gyroscope noise σ_ω and zero-velocity measurement noise σ_v.

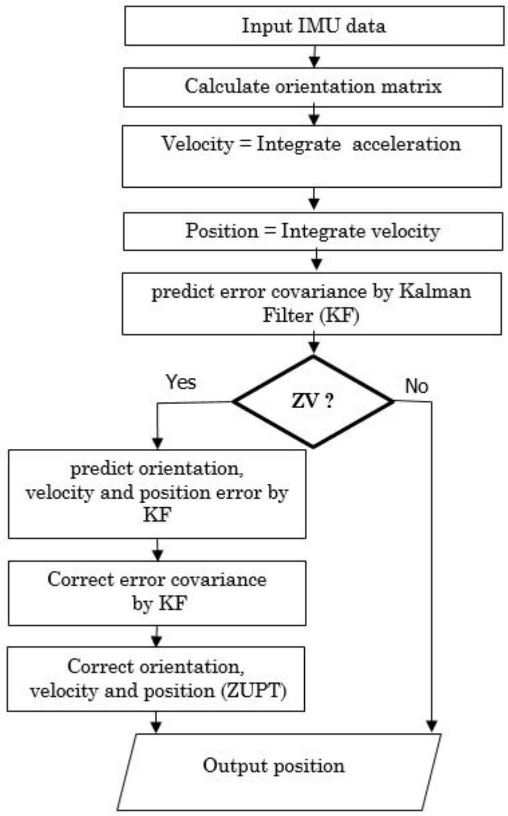

Figure 1: Position, velocity and orientation estimation corrected by Kalman filer ZUPT

5.1 Zero velocity detection

Detecting ZV phases is commonly detected using the norm of gyroscope data, by setting a threshold under which the body is considered in a stationary phase.

It is much easier to recognize ZV when the sensor is mounted on the foot than when it is mounted on the chest, as when the foot start contact with the floor it totally stop movement until the other foot finishes the step, while the chest is moving almost at all moment in a much slower rate, meanwhile, in order to achieve elderly health monitoring, it is very important to position the sensor at the chest to be able to make difference between standing up, sitting down and laying down.

When observing the human walking style, we can see that the body is slightly leaning from side to side as is progress in walking. From the chest perspective, the center of the chest reach the most far position in the left side when the body is depending on the left foot and the same applies for the opposite side as shown in Figure 2.

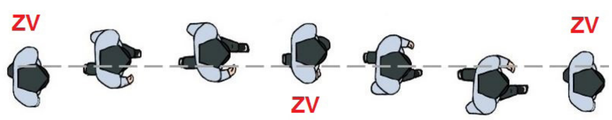

Figure 2: Walking trajectory from an above view

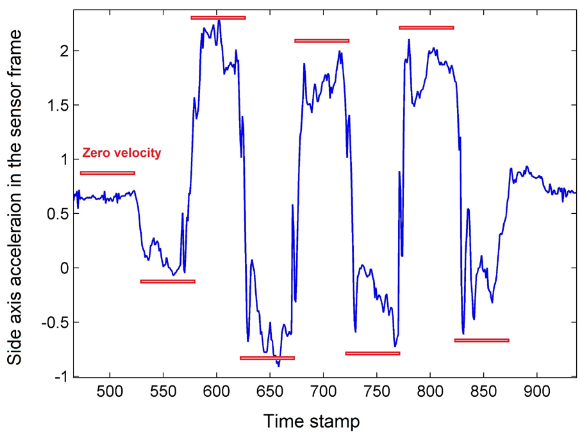

Figure 3: Side axis acceleration from chest-mounted sensor (Sensor frame)

This can be observed in the side axis acceleration data, presented in Figure 3, resulted from walking seven steps in a straight path.

By overlapping the graph of side axis acceleration with other acceleration and gyroscope graphs, it was found that there is correlation with the navigation frame vertical acceleration data; noticed that when the side acceleration is in a zero velocity phase, the vertical acceleration value is every time below a value close to g. Figure 4 describe the implication of this criteria.

The suggested criteria for chest mounted ZV detection is formulated as:

$$na_z(t) < A \tag{5}$$

na_z is the vertical acceleration in the navigation frame, and A is the threshold. Where in the navigation frame, X axis correspond to the side axis (from the human body perspective), the Y axis correspond to the front/back axis that cross and the Z axis correspond to the vertical axis.

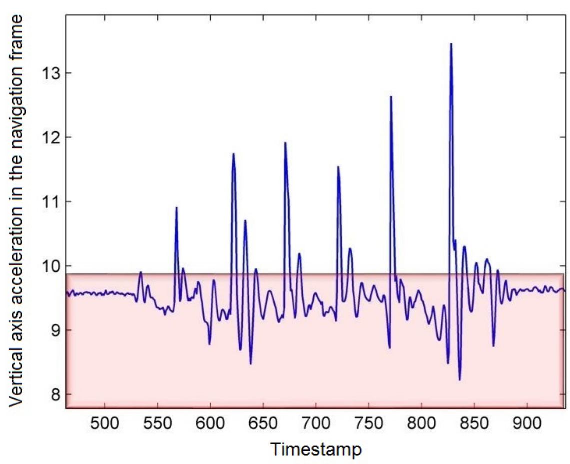

Figure 4: Vertical axis acceleration from chest-mounted sensor (Navigation frame)

Figure 5: Chest-mounted IMU sensor (smart phone)

5.2 Sit down-stand up estimation

An experiment is set to examine the ability of the chest-mounted IMU tracking method in estimating motion paths of basic actions, namely laying down, standing up and falling down. The experiment in conducted on 8 persons of different heights, using an Android smart phone accelerometer and gyroscope sensors, the phone is mounted as shown in Figure 5.

The chosen algorithm parameters are: $\sigma_a = 0.007\ \mathrm{m/s^2}$, $\sigma_\omega = 0.01$ rad/s, $\sigma_v = 0.01$ m/s and $A = 9.8\ \mathrm{m/s^2}$

The error of the estimated distance in the case of sitting down varied between participants from 0.06 % to 59% with a standard deviation equal to 20%.

While in the case of estimating the of standing up from a sitting down state, there was a difficulty in estimating the distance due to the nature of this motion from the chest perspective, in which the chest moves in three phases namely: downward, forward than upward in a different speeds.

Results showed that the estimation outcome of all participants have similar path shapes, but the total estimated distances varies from one to another. Also participants tend to maintain a certain level of distance despite the different motions; in other words if a participant had a large total distance in one motion, all the distances of the other actions tend to have large values, and the opposite is true. This might be due to speed in which the preformed the motions.

Figures 6 and 7 depicts the estimated motion paths of the same participant, in the case of standing up (from a sitting state) and the case of sitting down respectively.

Figure 6 shows the estimated standing up (from a sitting state) path, where the phase in which the chest moves downward dominate the estimation, the motion forward can be seen clearly, but the motion upward is very small

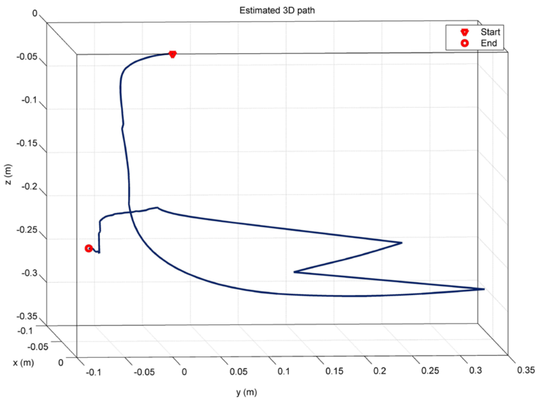

Figure 6: Best estimated path of standing up motion from sitting state

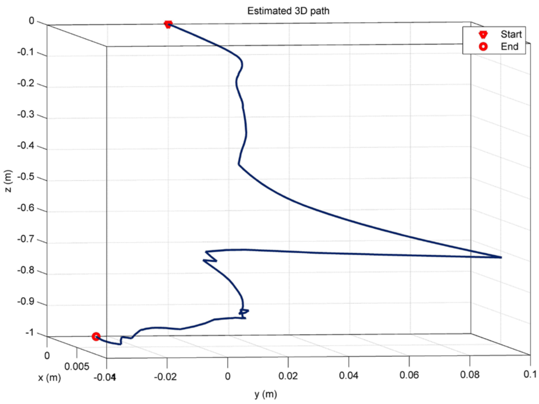

Figure 7: Best estimated path of sitting down motion

compared to the first two phases. While Figure 7, that discuss siting down path, estimate the path shape accurately, with motion toward down is dominating with sleight motion to backward and forward respectively.

5.3 Lay down-stand up estimation

Estimation in this kind of motion have shown significant path shapes, while the errors of estimation in the case of laying down motion varied between participants from 4.25 % to 64% with a standard deviation equal to 21%, and in the case of standing up from a laying state, the error varied between 48% and 82%, with standard deviation equal to 13.41%, with most estimations are around half the real distances.

Figures 8 and 9 depicts the estimated best motion paths of standing up (from a laying state) and laying down respectively.

Figure 8 showed good estimation of motion toward up with sleight motion to backward and forward respectively, which is a result of the standing up process. Figure 9 showed also good estimation of motion toward down with a disturbed motion to backward, resulted of the careful laying down on the floor.

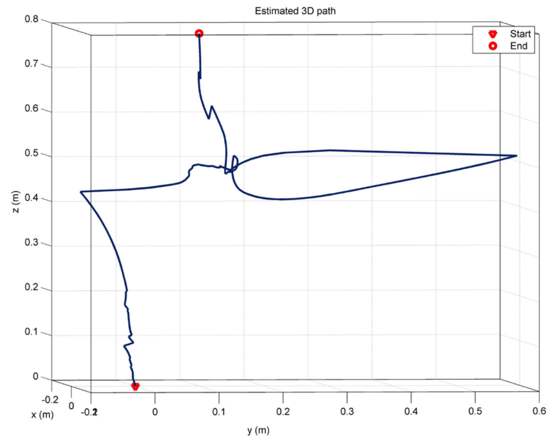

Figure 8: Best estimated path of standing up motion from laying state

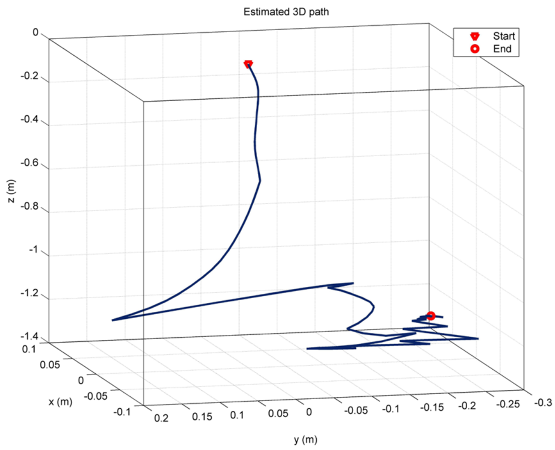

Figure 9: Best estimated path of laying down motion

5.4 Falling down estimation

Falling down is an important motion that activity recognition approach should be able to estimate due the fact that an elderly falling down is a strong indicator of danger. Figure 10 shows the estimated path of falling down motion.

Figure 10 shows good estimation of motion toward down than backward, with a shape that is significantly different that the one of laying down. The transition between downward

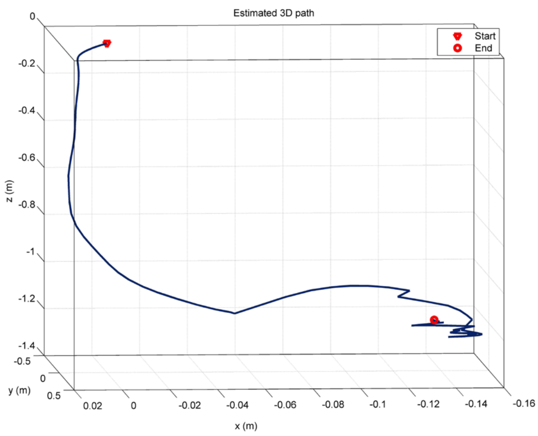

Figure 10: Estimated path of falling down motion

and backward is much smoother than the laying down shape, also the in the phase of downward motion, the body appear to be in free fall compared the laying down path shape (Figure 9).

6. CONCLUSION

The proposed theory provides the possibility to conduct activity and emotion recognition research based on different types of sensors, where all sensors can be assembled in a strap around the chest of the observed person (heart monitor, localization sensor, breath rate sensors). It is imagined that the strap will not be necessary and can be replaced usual wear.

Estimation of the motion path is a very important feature of this methodology, the results shows that the proposed ZV criterias could help estimating sitting down, laying down and falling down, despite the fact that chest undergo large levels of noise and its ZV phase is very small compared to the foot-mounted observation.

The estimated distances are smaller than the real ones due to the fact that the ZV criteria in chest mounted sensor requires elimination of large amount of data. Standing up estimated distance is small compared to downward motions distances. Farther studies will tackle correction of distance estimation error.

Future plan consider tackling emotional recognition and fusion of sensor information in order to construct a model capable of identifying elderly user, estimating the location inside the house, and determining the sort of activity and emotion.

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