Non-Restrictive Continuous Health Monitoring by Integration of RFID and Microwave Sensor

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Abstract

Continuous non-intrusive health monitoring system is designed for watching residents in nursing homes. RFID and microwave sensor are integrated to monitor the behavior and vital data of the residents, and to detect the critical event such as falls and strokes. In welfare center, hospital rooms are sometimes quadruple and double, more than one person is staying a room. Not only patients, but also staffs, helpers, nurses, and doctors are getting in/out of the room, thus it is difficult for normal sensors to identify from which subject it receives the vital signals.

RFID is introduced to resolve this. UHF gen2 RFID tags are attached to the resident's pajama or staff's uniform, which identifies who are in the room now and what they are doing. And, for vital data monitoring, 24GHz microwave sensor is introduced because of its remote sensing capability of target person's heart rate, respiratory rate, and body motion with similar precision as the piezoelectric sensor. By integrating RFID and remote sensors, we can get the information of "who is in what condition", where "who" is identified by RFID tag and "what condition" is vital data sensed by the microwave sensor.

In this paper, the architecture of watching system is presented. The UML diagrams are used for modeling the S/W system and its target person and his/her living environment. Activity and health status are defined and the sensing model is designed to interpret the sensors' primitive data as activity/health status. RFID sensing model is also proposed to interpret the RSSI signals as position/posture of the subject. Online recognition system is developed and its experimental results are evaluated.

1. Introduction

Many types of sensors are used for monitoring and checking health status of the elderly in welfare center. Among them, wearable type sensors such as wrist watch type or pendant type are popular, but elderly person often puts off these sensors at bedtime, when the most accidents occur such as heart strokes or brain strokes. Also wearable sensor often suffers from dead battery. It is therefore not trustful as a continuous monitoring for critical event. In-house installation type sensors are more reliable than wearable ones. For vital data sensing, mat-type sensors are popular. It can detect small vibration of the subject by piezoelectric sensor and it can detect the heart rate and respiration rate after signal processing such as FFT. By integrating these vital data, it can monitor the sleep condition of the subject such as REM and Non-REM sleep (Takadama 2012). Different types of sleep monitor are available from vendors such as Omron. Some sensors use 24GHz microwave (Heide 1999) (Suzuki 2011). It is completely contact-less and it can detect almost the same vital data as the mattress type sensors. The sensing range is about 5 m. It would be preferable if all wearable sensors would be replaced by the installation type remote sensors, but major demerit is the interference of signals which disturbs the subject identification: if more than one person is staying in a room, a remote sensor might receive the signal not only from the target subject, but also from the others nearby. It is difficult to distinguish the subject person from others. RFID, on the other hand, sends nothing but the subject's ID as a message, which compensates the demerit of remote sensing sensors.

UHF-band RFID specifications are standardized internationally by EPCglobal (EPCglobal 2016). Generation-2 specification (Gen2) supports multi-antenna/Multi-tag read function, where 1 reader can read about 1000 different tags in 1 second. The sensing distance depends on the radio power and the size of tag, in normal case it is within 7 meter, which is good for in-room sensing. An RFID tag is a battery-free passive device that consists of a microchip and an antenna. A linen type RFID tag is also available. Thus, in our application, linen type RFID tags are attached to the resident's pajama or staff's uniform, which identifies who are

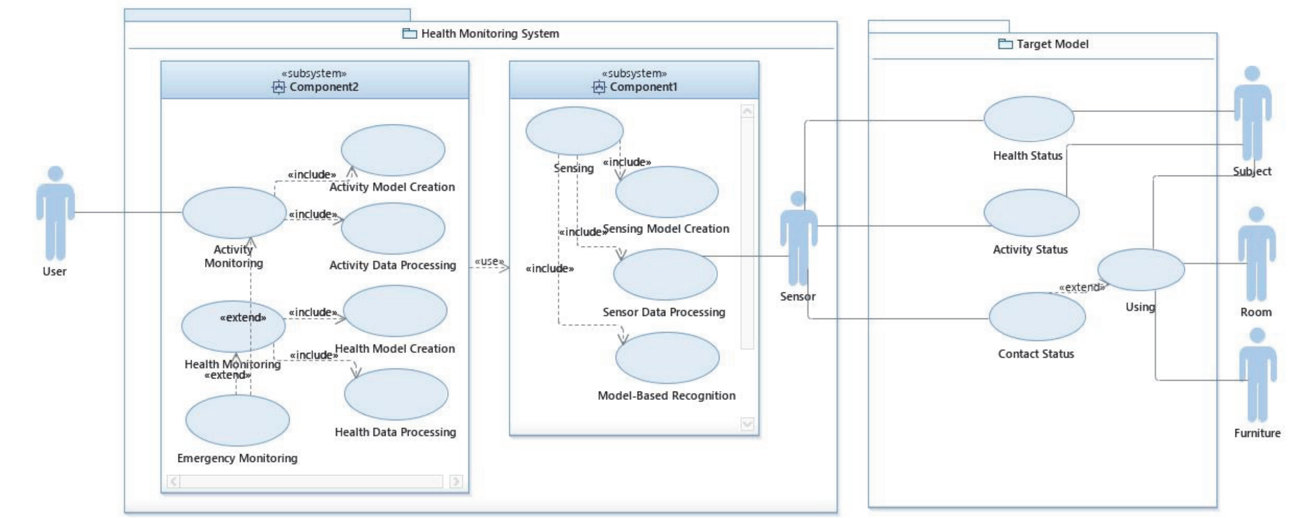


Fig.1 Use Case Diagram of Health Monitoring System and Target Model

in the room now and what they are doing (Agrawal 2006) (Foester 1999).

By integrating RFID and remote sensors, we can get the information of "who is in what condition", where "who" is identified by RFID tag and "what condition" is vital data sensed by the microwave sensor.

Life watching system as end product is a real time system that consists of the sensors, database, and S/W application that processes data, recognizes the subject's activity and health status, and visualizes the results. To design S/W application, it is important to define the external view: the boundary of target system and surrounding systems, and the interaction between them. Here, we adopt a model-based approach to design the system with its surrounding environment.

The remainder of the paper is organized as follows: Section 2 defines the health monitoring system with its relationship with other systems by using UML. Section 3 proposes RFID sensing model, by which the posture of target object can be decided from the RSSI. Section 4 shows the experimental results of RFID-based posture/position recognition. Section 5 shows the life watching system by integrating with the microwave sensor. Section 6 concludes.

2. Life Watching System Architecture

Context Model

In order to design the life watching system as a S/W system, it is important to identify the contexts and boundaries. A system and its environment are modeled by using the UML Use Case diagram. Fig. 1 shows use case diagram of the monitoring system (S/W system) and its target model that is monitored by the S/W system. There, 2 contexts are defined as follows:

- *Health monitoring system* is a S/W system we need to develop as life watching system. It consists of 2 subsystems: monitoring system and sensing system.
- *Target model* models activity and health of the subject observed by the monitoring system.

5 actors are defined as follows:

- *User* is a user of the S/W system.
- *Sensor* is a component of the S/W system, and also it receives the activity/health status of the subject.
- *Subject* is a person whose activity/health status is monitored by the S/W system.
- *Room* and *furniture* configure the living environment for the subject.

These actors are considered as external systems, which are independent from the S/W system. Sensor acts a bridge between the two contexts: the monitoring system and the monitored subject.

The monitoring system consists of a monitoring subsystem and a sensing subsystem. Sensing subsystem receives the data from Sensor and interprets the data as the subject's activity. Monitoring subsystem receives the activity data from the sensing subsystem and reconstructs the subject's health and activity status.

The target model consists of the person and his/her living environment. The target model models the person's activity and health status by observing his/her activity in the room or the use of furniture, which is modeled as the contact status.

Activity/Health Status Model

Fig. 2 shows the class diagram of the subject class and its associative classes at the top, and the monitoring system class and its associative classes at the bottom.

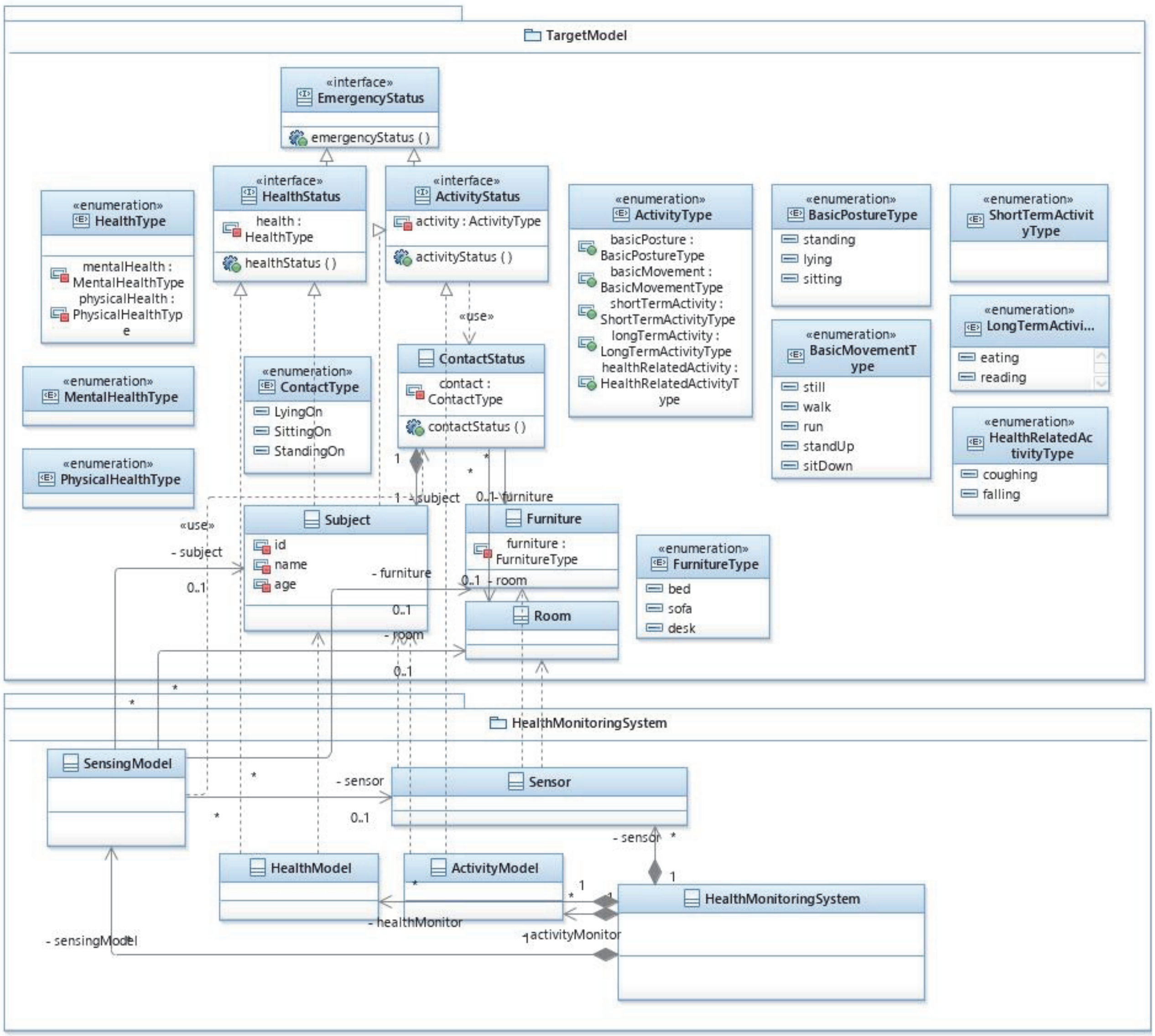


Fig.2 Target Model and Health Monitoring System Model

The target model consists of classes and interfaces as follows:

- *Subject* class
- *Room* and *Furniture* classes
- *ContactStatus* class
- *HealthStatus*, *ActivityStatus*, and *EmergencyStatus* interfaces

Health/activity status is represented by interface; abstract superclass of the subject class, which means that the subject must have the health/activity status. The type of health status is defined as follows:

- *MentalHealthType*
- *PhysicalHealthType*

The type and value of the activity status is defined as follows:

- *BasicPostureType: {standing, lying, sitting}*
- *BasicMovementType:{still, walk, run, standup, sitDown}*
- *ShortTermActivityType*
- *LongTermActivityType: {eating, reading}*
- *HealthRelatedActivityType:{coughing, falling}*

Activity status is determined not only by the person's single movement, but also by the interaction of how the person uses the furniture in the room (Patterson 2003) (Ravi 2005). Contact status captures this interaction, and its type and value are as follows:

- *ContactType*: *{lyingOn, sittingOn, StandingOn}*

The monitoring system consists of the classes as follows:

- *HealthMonitoringSystem* class
- *HealthModel* and *ActivityModel* classes
- *Sensor* class

● *SensingModel* class

Sensor has the physical relationship with Subject, Furniture, and Room. SensingModel translates the data to the subject activity data by using the setting status of sensors and the interaction between the subject and furniture in ContactStatus. HealthModel and ActivityModel inherit the same HealthType and ActivityType respectively, thus they will reconstruct the status defined by HealthStatus and ActivityStatus.

This model-based approach gives a good perspective to design the activity/health recognition system (Hido 2009) (Murthy 2008) (Robson 2007), because unless the subject and his/her environment can be modeled within the recognition module, it cannot interpret the subject behavior.

3. RFID Sensing Model

Coordinate by Multiple RFID Antennas and Tags

One of the most advanced features of UHF RFID generation 2 (gen2) specification (EPCglobal 2016) is that the reader can read multiple tags at once, about 800 tags/second. Many gen2 compliant RFID readers such as Mitsubishi UHF RFID Reader can get Receive Signal Strength Indication (RSSI) with each tag read. The RSSI values changes based on the distance and direction between tag and antenna. Here we are interested in the direction of tag: if tag is parallel to the antenna, the RSSI value is maximum, and if tag is vertical to the antenna, it is minimum. The RSSI value is approximated by the inner product of the normal vectors of antenna and tag.

By using this RSSI directivity, we construct a RFID tag coordinate system for a room shown in Fig.3. 3 antennas are placed at the ceiling and two adjacent walls that construct xyz coordinate. For example, the antenna placed on the ceiling measures the z-value of the tags. For subject's posture

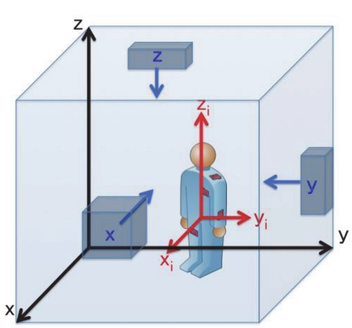


Fig.3 RFID Coordinate

recognition, three tags are placed at top, front, and left side of the subject that represent (x,y,z) position in the coordinate.

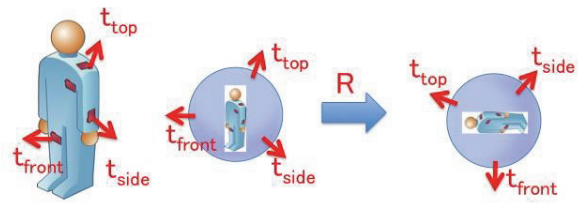


Fig.4 RFID Sphere Imaging and Rotation Matrix

The number of antennas is not necessarily limited by 3, so as the number of tags. If the number is more than 3, the excessive antennas and tags contribute to the accuracy of the position recognition. Also the position and direction of the antennas and tags are not necessary perpendicular each other. We will use machine-learning technology to calibrate them.

RFID Tag Imaging

Assume that the antennas placed on ceiling, front wall, and side wall are named Ant-z, Ant-x, Ant-y, respectively, and that the tags placed at top, front, and side of the subject are named Tag-z, Tag-x, Tag-y, respectively. When the subject is standing and faced to front wall, Ant-x detects Tag-x, Ant-y detects Tag-y, and Ant-z detects Tag-z. When the subject moves to the different direction, the antennas detect the different tags, and thus they can detect the subject's movement and direction.

This can be modeled by the sphere image shown in Fig.4. For each tag, Ant-x, Ant-y, Ant-z get the different RSSI values based on the direction of the tag, it is considered as the position of the tag: (x,y,z). Thus, each tag placed at the subject has the point ti= (xi,yi,zi), and if the tags are placed almost the same distance from the antenna and only the direction is different, the tags' position as a whole forms a image that the tags are placed on the sphere.

Since the tags placed on the subject form a 3D sphere image in the coordinate system, change of subject's posture can be detected by the rotation of the sphere. In actual living environment, the critical events can be detected by subject's movement, such as fall. In our model, change of posture is reflected by the rotation matrix.

Let $T_i=(x_i,y_i,z_i)^T$ be i-th tag's position in the coordinate, and $T'_i=(x'_i,y'_i,z'_i)^T$ be the same tag's position after some time Δt. The rotation matrix is defined as $T'_i=RT_i$.

Assume that the subject is rigid, then the same rotation matrix R can be applied to all tags T_i (i=1,..,m), where the m is the number of tags on the subject. In that case, the R can be determined to minimize the objective function:

$$\min_R \Sigma_i \|t'_i - Rt_i\|^2 \quad (1)$$

It is rewritten by using (3,m) matrix $T=(t_1\ t_2\ ..\ t_m)$ and $T'=(t'_1\ t'_2\ ..\ t'_m)$

$$\min_R \|T'-RT\|_F^2 \quad (2)$$

$\|A\|^2_F$ is Frobenius norm. If $A=(a_{ij})$, then $\|A\|^2_F = \Sigma_{ij}(a_{ij})^2$.

This problem is well known in computer vision as a object pose estimation (Rosenhahn 2008). Several approaches are proposed to determine the matrix. The classic approach uses the matrix's singular value decomposition (SVD).

4. Experimental Evaluation

Fingerprint-Based Recognition

We conducted several experiments to evaluate the RFID-based posture/position recognition. First, fingerprint-based recognition is evaluated in the following conditions:

- Number of tags per person: 8
- Number of antenna in room: 4
- Number of person in room: 1 or 2

Fingerprinting-based method uses a machine-learning technology that consists of 2 phases: learning and recognition. Random forest algorithm is used and the accuracy is evaluated by 2-fold cross validation. The results are shown in Table.1. The accuracy is about 90% in single person environment, and about 58% in 4-person environment. From these results, it is important to develop number-of-person invariant posture recognition system.

	Lying	Sitting	Standing	Accuracy (%)
Lying	72 (212)	5 (25)	19 (7)	75.0 (87.6)
Sitting	39 (35)	41 (210)	20 (4)	41.0 (84.3)
Stand-ing	21 (5)	21 (2)	58 (242)	60.0 (97.2)

Table.1 Confusion Matrix of RFID Recognition
Multiple persons and single person (in parenthesis)

Online Learning

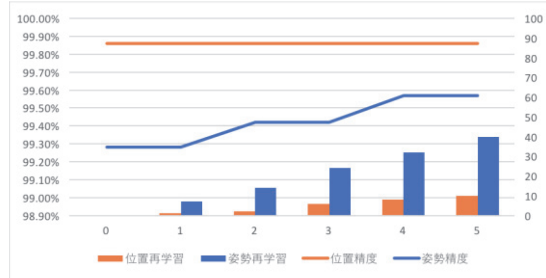
Online learning feature is necessary for a real-time system. Online machine learning can update the predictor sequentially while the batch-type learning fixes the predictor after learning phase finishes with the training data.

For the life watching system, we developed the online learning system where the predictor is first constructed by the training data and it is updated whenever the wrong decision is found. The system is evaluated in the following conditions:

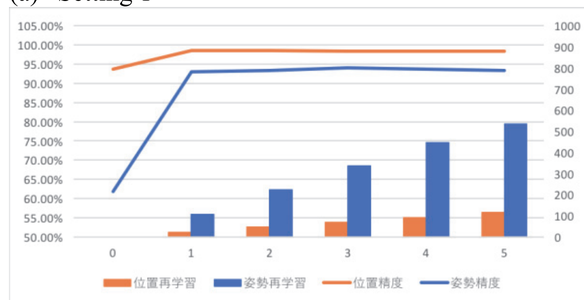
- Number of tags per person: 8
- Number of antenna in room: 8
- Number of person in room: 1 or 2

4 different settings of selecting the training data set and the test data are evaluated as follows:

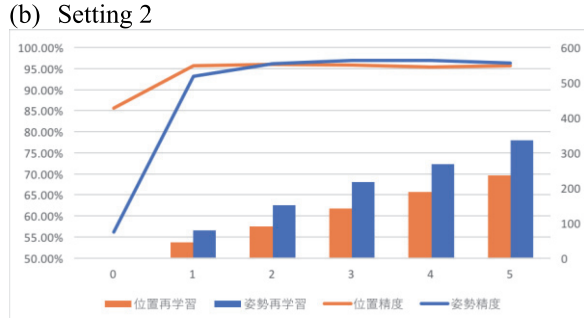
- Setting 1: Training data set is collected for a single subject over single day, test data set is chosen from the training data set.



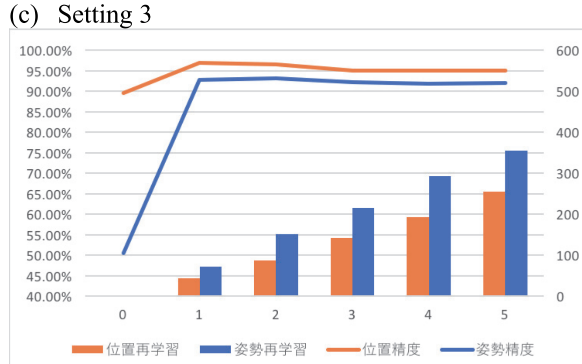
(a) Setting 1



(b) Setting 2



(c) Setting 3



(d) Setting 4

Fig. 6 Accuracy of online classification

- Setting 2: Training data set is collected for a single subject over single day, test data set is collected for the same subject over the different day.
- Setting 3: Training data set is collected for a single subject over single day, test data set is collected for the different subject over the same day.
- Setting 4: Training data set is collected for a single subject over single day, test data set is collected for the different subject over the different day.

Fig. 6 shows the evaluation results. The red and blue lines show the accuracy of position and posture recognition improvement over the number of online update. The red and blue bars show the cumulative number of wrong decisions. The results show that the online leaning capability is essential for actual environment, where multiple people are using the same room.

5. Integration with Microwave Sensor

Vital Data Sensing by Microwave Sensor

Microwave Doppler sensor sends 24MHz radio wave to the target object and receives the reflected wave, and the differences of Doppler frequency is calculated to get the target's movement. The Doppler frequency is processed by FFT and divided into 3 frequency bands, which reflect the target's heart rate, respiratory rate, and body motion, respectively from high frequency to low frequency. Fig. 7 shows the vital data obtained by the microwave sensor.
The sensor's range is about 6m, and the vital data is almost the same quality as the piezoelectric sensor which must be contacted to the subject.

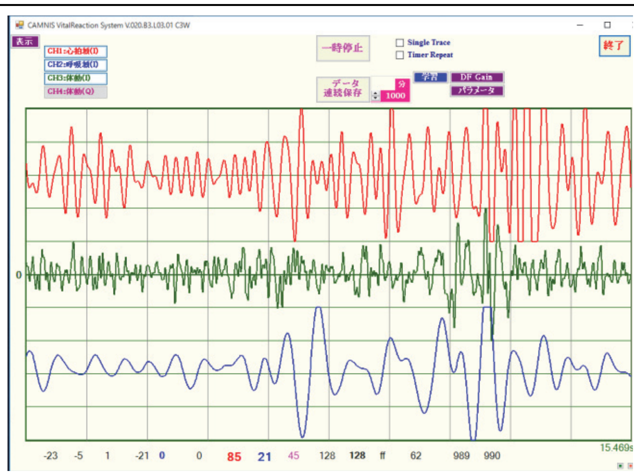


Fig. 7 Vital Data by Microwave Sensor:
(from the top) heart rate, body motion, respiratory rate

Life Watching System

The final image of the life watching system is shown in Fig.8. Different types of sensor are installed in the hospital room, and S/W system recognizes the activity/health status of the subject, and visualizes the status. Alert is given whenever the emergency occurs such as fall and strokes.

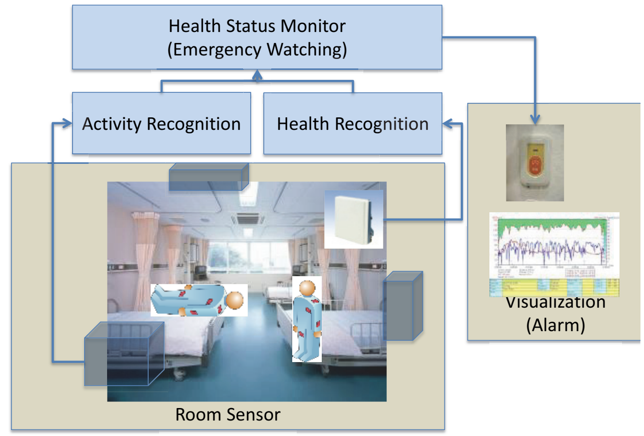


Fig. 8 Life Watching System for Nursing Home

6. Conclusion

This paper proposed a model-based approach to develop a watching system for nursing homes. Both of the monitoring system and the target subject environment are modeled to define the health/activity status. RFID sensing model is proposed to recognize the position/posture of subject by using multi-tag/multi-antenna setting.
Detailed health status is recognized by considering the vital data and the activity type when the vital data is obtained, which is useful for deciding the emergency call such as fall and strokes, also for controlling the long-term health exercise. For that purpose, the rule based decision logic should be developed where medical expert needs to be involved.
Now, we plan to install the watching system in actual nursing home and evaluate the performance and effect.

Acknowledgement

24GHz microwave sensor toolkit is provided by Wireless Communication Lab, Inc.

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