We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

6,900
Open access books available

185,000
International authors and editors

200M
Downloads

Our authors are among the

154
Countries delivered to

TOP 1%
most cited scientists

12.2%
Contributors from top 500 universities



WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com



12

Use of Active RFID and Environment-Embedded Sensors for Indoor Object Location Estimation

Hiroaki Fukada, Taketoshi Mori, Hiroshi Noguchi and Tomomasa Sato
The University of Tokyo
Japan

1. Introduction

Indoor object localization system has become more and more important in various fields these days. For example, people not only feel stress but also waste precious time when they cannot find what they want in the expected place. If we can provide people with information about the object location, people will save lots of time and lead a comfortable daily life. Furthermore, if we can detect object movement and estimate object location online, we will be able to know life patterns of people by analyzing the behavior of objects in everyday life. Efficient online object localization system should be able to identify the object a user wants and to determine its location. In our work, we focus on object's "location" in the environment (e.g. Table, Bed, Sofa, etc.) instead of object's 3-dimensional "position", because we think the only object location is sufficient to achieve our application. Various technologies have been used to construct such systems up-to-date, but most of them have difficulty in recognition of the objects.

Against this problem, many studies have focused on radio frequency identification (RFID) technology due to its strong identification ability(Hightower et al., 2000; Mori et al., 2007; 2005; Ni et al., 2004; Shih et al., 2006). In general, RFID system is composed of two devices: 1) RF readers and 2) RFID tags. Data including RFID tags' identification information are communicated between RF readers and RFID tags via RF signals, which can be transmitted even if obstacles stand between RF readers and RFID tags. At this point, RFID technology is superior to other technologies such as camera vision in identifying objects. Another important characteristic of RFID technology is that signal strength indicator received by RF readers, which we call RSSI, has a certain dependency on the distance between RFID tags and RF readers. This relationship can suggest us an effective clue to estimate the distance from each RF reader to the target RFID tag(Hightower et al., 2000).

RFID technology can be divided into two types depending on the mechanism of data transmission: 1) Passive RFID and 2) Active RFID. The main difference of these two RFID systems is the way of data transmission. Because passive RFID tags do not contain any batteries inside them, they utilize the power of passive readers to activate themselves. As a result, the data transmission range is short, 1 meter at best. In contrast, because active RFID tags contain batteries inside themselves, they utilize their own power for data transmission. Consequently, the data transmission range of active RFID is much longer than that of passive one, some active RFID systems can achieve data transmission range up to 100 meters.

We adopt active RFID instead of passive one as our key technology for the following reasons. One reason is its long transmission range. Since we aim to develop an indoor object localization method, long transmission range is more convenient than short one. Another reason is the number of RF readers required for object localization. As the transmission range of active RFID is much longer than that of passive RFID, the required number of RF readers is much less than that of passive ones. This advantage of active RFID plays a great role in reducing the total introduction cost of the system. The other reason is for the potential of active RFID tag. One remarkable characteristic of active RFID tag compared with passive one is that active RFID tag can attach sensors inside. In fact, every active RFID tag, which we used in our work, contains a vibration sensor to detect object motion. It is certain that users have to exchange battery of active RFID tags regularly in about one year or so. However, the battery itself is inexpensive and the benefits provided by the system are much greater than the exertion spared for the exchange. Also, rapid technology progress will definitely expand the battery life in the near future.

Several researchers have focused on developing indoor localization methods based on active RFID up-to-date(Hightower et al., 2000; Ni et al., 2004; Shih et al., 2006; yao Jin et al., 2006; Zhao et al., 2007). For example, Hightower et al. (2000) applied triangulation algorithm to the SSIs received by several RF readers to estimate the 3-dimensional position of tag indoors. This estimation method works well under the condition that few obstacles exist in the environment, however it fails to localize objects once too often in the environment where various obstacles exist like actual human living space. The main reason for the failures is that received SSI, which we call RSSI, is quite sensitive to environmental factors such as the presence and the location of people and furniture because the radio waves are weak against those factors. To reduce the environmental influences on RSSI, some researches introduced the concept of reference tags as an indicator of object position(Ni et al., 2004; Shih et al., 2006). It is certain that reference tags are useful for reducing the influences on RSSI to a certain extent, still it cannot be evaluated as the perfect solution to indoor object localization. In those researches, the authors also conducted some experiments in the environment where obstacles exist to show the robustness of their methods. However, the complexity of their experimental environment is far from that of our target environment. Human living space is full of various obstacles not only static ones such as furniture, but also dynamic ones such as human beings. To estimate object location robustly in such an environment, we have to confront with more difficult problems than those researches.

To improve the robustness of object localization, our previous work(Mori et al., 2007) focused on the idea that any objects' movements were connected with human behavior. In other words, human position in the environment would be an important clue in estimating object location. Therefore, we introduced a kind of position sensors underneath the floor in the previous work, which we call floor sensors, so as to detect human position in the environment. As a result, floor sensors played an effective role in detecting human position, however, some challenges still remained unsolved, such as the number of sensors required for human localization. To achieve high-resolution human localization, the position sensors need to cover the whole area of the environment. As a matter of fact, 356 position sensors were embedded in the environment. Because each position sensor is not cheap, to cover the whole area costs a great deal. In addition, it is troublesome to repair those position sensors in case of breakdown. To reduce the cost and maintenance burden caused by floor sensors, we have combined active RFID technology with various types of switch sensors. The main advantage of these

sensors against floor sensors is that they are inexpensive and easy to install into any kinds of environment. In addition, because these sensors are generally used for human monitoring and crime prevention nowadays, it is quite natural to have these sensors embedded in human living space. Substitution of simple sensors for floor sensors makes it difficult to detect human position accurately in the environment, which will cause a decline in estimation accuracy of object location. To solve this problem, we use an integrated algorithm in compensation for the lack of human position information. By taking this approach, we have proposed a method for indoor object location estimation based on active RFID and simple environment-embedded sensors, which achieves sufficient accuracy even without using any costly sensors designed for detecting human position.

2. Hardware composition

In this section, we introduce our active RFID system and various sensors embedded in our experiment environment.

2.1 Active RFIS system

In our research, we adopted *Spider V Active RFID System* (Fig. 1) produced by RF Code as the key technology for the following two reasons.

- Capability of measuring received signal strength indicator (RSSI) between a tag and reader
- Vibration sensor attachment on each Active RFID tag



(a) RF Reader (b) RFID Tag

Fig. 1. Spider V Active RFID System

The specifications of the RF reader and the RFID tag are summarized in Table 1 and Table 2.

Item	Specification
Operating Temperature	−20 °C to +70 °C
Read Range	Over 10m
Dimensions	127mm × 130mm × 40mm
Operating frequency	303.8MHz

Table 1. Specifications of Spider V Active RFID Reader

2.2 Environment-embedded sensors

Sensing Room(Mori et al., 2006) is a typical residential environment embedded with various types of sensors in different spots such as high resolution pressure sensors under the floor,

Item	Specification
Battery type	Replaceable coin cell (CR2032)
Battery life	Up to 3 years
Operating Temperature	−20 °C to +70 °C
Weight	20g
Dimensions	60mm × 30mm × 10mm
Operating frequency	303.8MHz
Group code & tag ID code	Over 1 trillion IDs
Signal transmission period	1 sec

Table 2. Specifications of Spider V Active RFID Tag

and micro switch sensors in a cabinet and a refrigerator. Retrieved from these sensors, the data are accumulated into the database system and then used to learn users' behavior pattern in a daily life to provide them with appropriate supports. Figure 2 shows the overview picture of *Sensing Room* and its sensor modules. The following sections will describe each sensor module's structure in details.

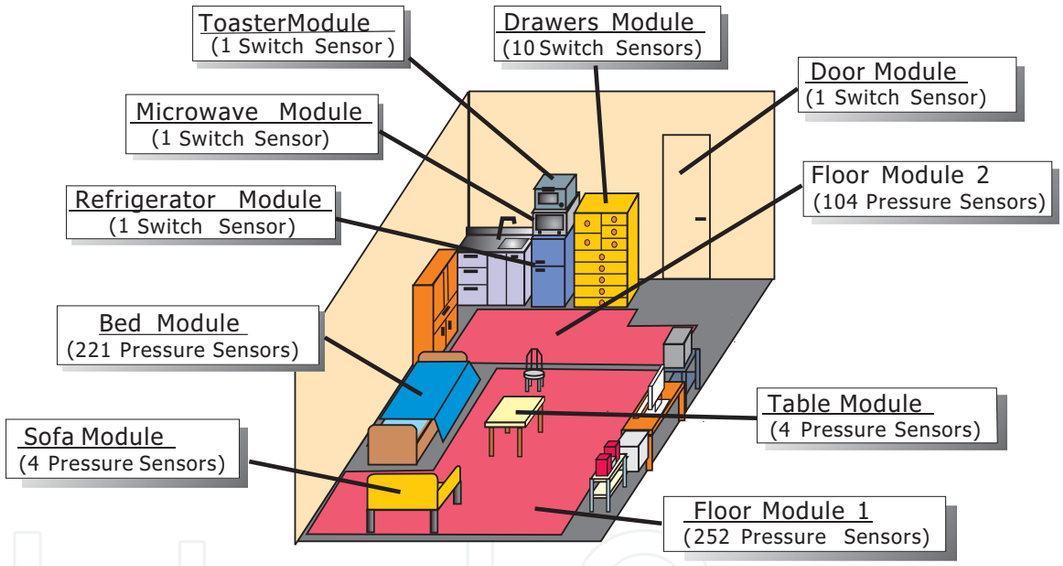


Fig. 2. Experiment Environment (Sensing Room)

- **Floor Sensor Module**

  Sensing Room's floor is embedded with a number of high resolution pressure sensors underneath. By analyzing the pressure values obtained from these sensors, the locations of persons in the room can be estimated. The arrangement of pressure sensing units and screenshots taken during the execution time of floor sensor monitor program are illustrated in Fig. 3.

  In floor sensor module, a Force Sensing Register (FSR) manufactured by INTERLINK co. is used as a basic pressure sensing element. FSR is a pressure-sensitive resistor that has a characteristic of changing its resistance value when a load is charged on its surface. This characteristic is utilized to detect person's weight charging on the floor. Floor sensor

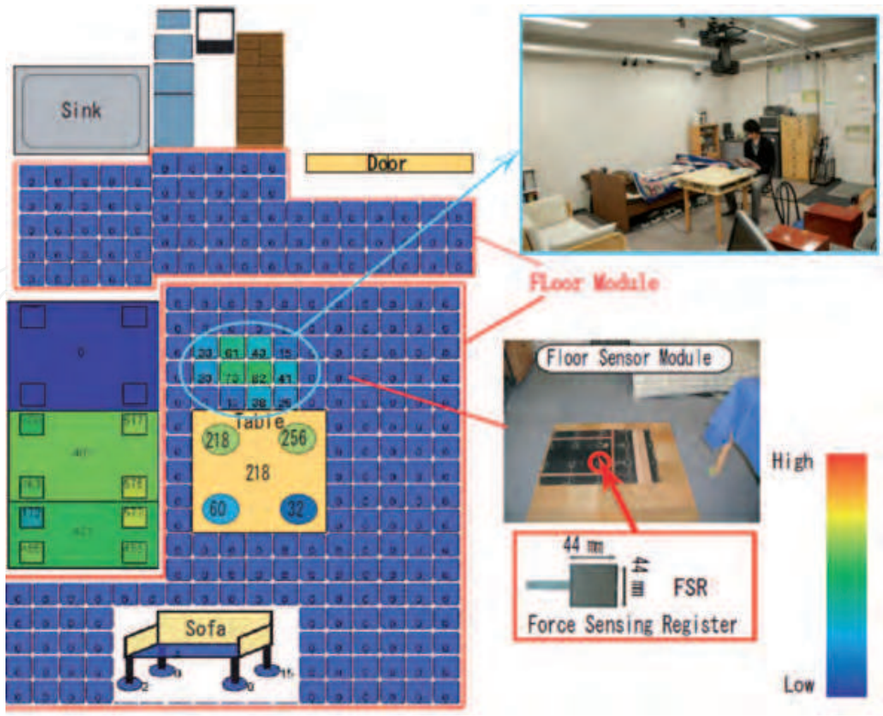


Fig. 3. Floor Sensor Module

module has 356 pieces of FSR in total embedded under a large number of 200mm x 200mm veneer tiles spread thorough the floor.

Firstly all pressure values are retrieved from each FSR; these data are analyzed to derive a pressure load distribution on the floor. Next, a labeling process will be taken on the retrieved pressure value data that exceed a determined threshold value to compute approximate weight and the CG (Center of Gravity) point of a load distribution corresponding to each labeling area. This process will produce the output as pairs of (x, y) coordinates corresponding to estimation result of a user's location in the room. Because the interval between FSRs is 200mm, the resolution of location estimation is also 200mm at best. Sensor data sampling rate of floor module is 10 Hz, a sufficient speed to track a person's location smoothly in a daily situation.

- **Switch Sensor Module**

  Our switch sensor module utilizes a number of micro typed switch sensors equipped to a cabinet, a toaster, a microwave, and a refrigerator to detect a cabinet drawers', a toaster door's, a microwave door's, and a refrigerator doors' open-closed state. Ten micro switches are embedded to each drawer of a cabinet, while two are equipped to the refrigerator, one to the toaster, and one to the microwave oven. Same as floor sensor module, the switch sensor data's sampling rate is 10 Hz. Although we did not target those locations in the evaluation experiment, switch sensor module can be used for locating objects in the locations where RFID signal is not accessible such as "in the cabinet drawer" or "in the refrigerator".

- **Table Sensor Module**

Table sensor module measures weight on it with pressure sensors embedded at its four corners. As well as floor sensor module and switch sensor module, the sampling rate of table sensor module is also 10 Hz. By analyzing the reaction of the acquired sensor data, the system can detect the moment smoothly that an object is placed on the table or the moment that an object is taken from the table.

- **Sofa Sensor Module**
  Sofa sensor module has the same structure as table sensor, which has four pressure sensors embedded at its four corners. The sampling rate of sofa sensor module is also the same as other sensors, which is 10 Hz. Analyzing the reaction of the acquired sensor data provides the system with the information such as human is sitting on the sofa or human moves from the sofa.

3. Location estimation methods

To provide a robust object localization method in residential environment, we integrate the following two approaches in our research: 1) RSSI-based Localization and 2) Sensor-based Localization. RSSI-based Localization regards plural received signal strength indicators (RSSIs) as a unique RSSI pattern to classify into particular object location. Whereas, sensor-based localization estimates possible location candidates based on the information about human behavior and location detected with various sensors. We describe each estimation approach in the following part, and then we demonstrate how to integrate these two approaches into one localization method.

3.1 Location estimation based on RSSI

As mentioned above, RSSI has a certain dependency on the distance between RF readers and RFID tags, which is shown in Fig. 4. According to Fig. 4 however, the dependency does not demonstrate linear relationship due to the nature of RSSI and environmental noises such as furniture. Still, RSSI does not change dramatic unless the layout of the environment changes dramatically. In other words, RSSI shows rather constant value under static environmental condition. Therefore, we attempt to use plural RSSIs instead of single RSSI in order to provide a reliable location indicator.

Based on the idea described above, several RF readers are installed at different spots in the environment. Because active RFID shows long data transmission range, only five RF readers are sufficient to cover the whole area of the environment. By attaching an RFID tag to each object, these RF readers can receive RF signals from RFID tags, which means there are the same number of clues to estimate the distance between the object and the surrounded RF readers. Pattern recognition approach regards these location clues as one pattern and determines the object's location by comparing the acquired pattern with typical patterns of each supposed object location.

In our work, we adopted three kinds of pattern recognition methods such as k-nearest neighbor (KNN)(Cover & Hart, 1967), distance-weighted k-nearest neighbor (DKNN)(Pao et al., 2008), and three-layered neural network (NN)(Shimodaira, 1994) algorithms. The main reason for these choices is the high flexibility in dealing with multidimensional data. In addition, KNN and DKNN algorithms in particular are strong at pattern discrimination of high dimensional data within short processing time.

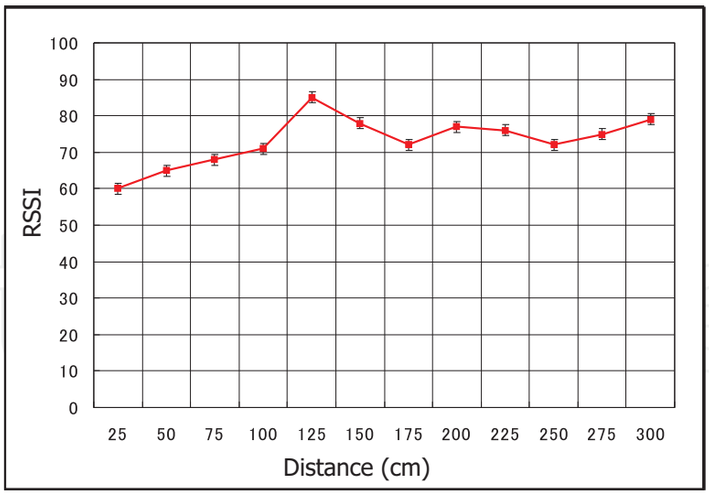


Fig. 4. Dependency of RSSI on Distance

In general, pattern recognition process can be divided into three phases: 1) Preparation Phase, 2) Learning Phase, and 3) Classification Phase. In preparation phase, the system needs a learning database including representative training datasets of each class. Then, in learning phase, the system determines some parameters required to discriminate each class from others. Lastly, in classification phase, the system compares input data with training datasets in the learning database and determines the most similar class according to the defined degree of similarity.

In KNN algorithm, for example, the pattern recognition process is demonstrated as Fig. 5. The first step when the target object is placed at unknown place, is to collect SSIs transmitted from the tag attached with target object and received by several RF readers. In the Fig. 5, we supposed five RF readers in the environment. We can regard this five SSIs, which we call data set, as one pattern of SSI. Next step is to compare the pattern with training data set stored in learning database. In learning database, we have sufficient data sets, which store both SSI pattern and object location, which is called class, as one set. What we explained so far is common process about pattern recognition. The unique process to KNN is called voting process which we will mention below. In KNN algorithm, we used euclid distance as an indicator represents the similarity between one data set pattern and another. In other words, the smaller the euclid distance is, the more similar the data sets are. We calculated the euclid distance between the new data set and every data set stored in learning database and sorted the training data set in increasing order. Then we choose 'k' data sets from the top of the sorted learning database. What we call voting process is to determine object location by counting the number of locations contained in the selected data sets and choosing the most one as estimated result.

Our learning database is constructed as follows. RFID tags are placed at each supposed object location to acquire RSSIs between surrounding RF readers with themselves. The typical scene of RSSI calibration is shown in Fig. 6. Thus, RSSI calibration is conducted at 13 locations with five RF readers installed in the environment, which is shown in Fig. 7. As 1420 datasets are acquired at each object location, the total number of datasets saves into the learning database is;

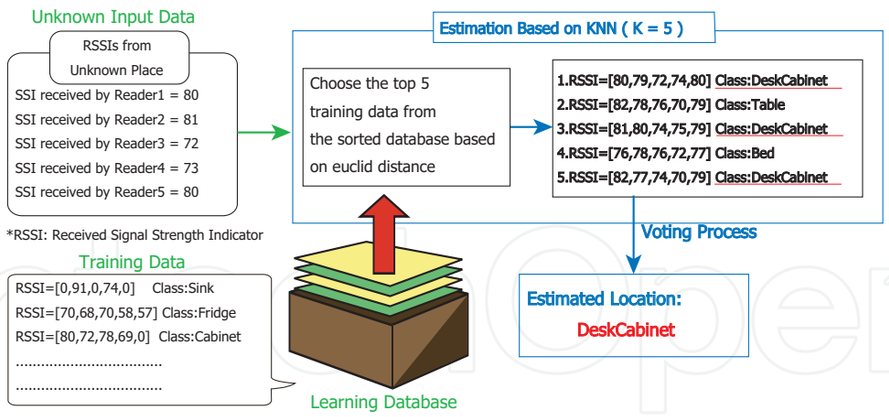


Fig. 5. Location Estimation Based on KNN

$$13(locations) \times 1420(datasets/location) = 18460(datasets) \quad (1)$$

The time required for conducting the whole RSSI calibration is about 13 minutes since our system can collect RSSIs from 24 RFID tags at the same time in one second.

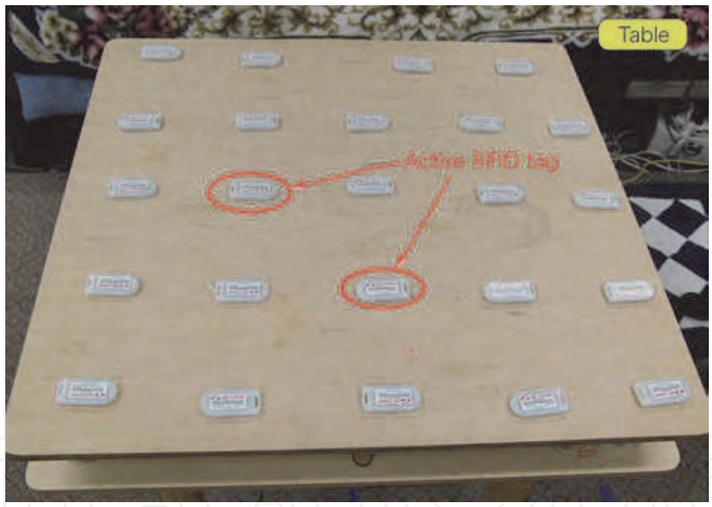


Fig. 6. RSSI Calibration at Table

Based on this learning database, we conducted a cross validation to evaluate the effectiveness of our pattern recognition approach. In the cross validation, the whole learning database is divided into two parts, one is called testing dataset, and the other is called training dataset. A testing dataset consists of one RSSI dataset from every object location in the environment, whereas, a training dataset consists of the rest part of the learning database. After the first evaluation, another testing dataset composed of the next 13 RSSI datasets from every object location will be chose for evaluation. Thus, 1420 times of evaluation are conducted in total. The estimation performance based on KNN algorithm is demonstrated in Fig. 8.

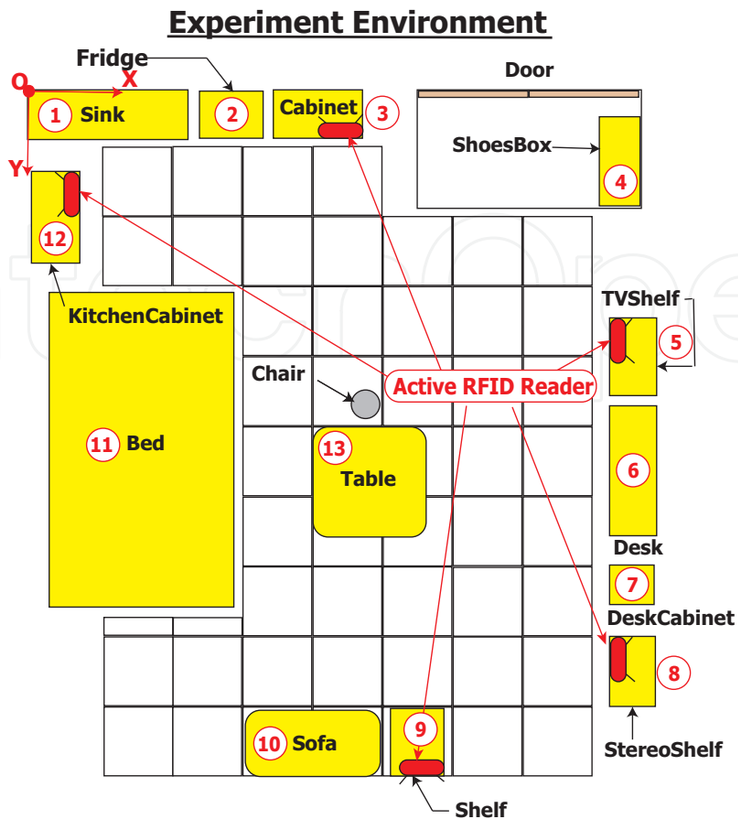


Fig. 7. Supposed Object Locations and RF Readers

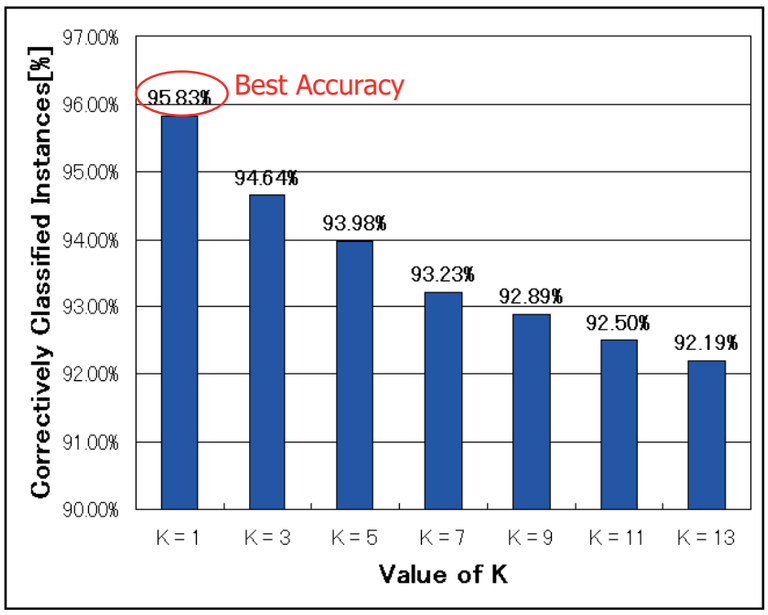


Fig. 8. Location Estimation Performance by KNN Algorithm

According to Fig. 8, the pattern recognition approach works effectively in discriminating each class from others, although there is slight dispersion in estimation performance between different k values.

3.2 Location estimation based on object motion and human behavior

Another approach to improve object localization performance is to make the best use of sensing information. As mentioned before, several kinds of sensors are used in our work. Vibration sensors attached inside RFID tags are supposed to provide the system with the information about object motion state, whereas, sensors embedded in the environment are supposed to provide the information about human behavior and location.

It is important to perceive the moment that an object is placed for estimating its location with sensors in the environment effectively. The vibration sensor on each RFID tag offers a great solution to meet this requirement by detecting object motion state. However, to integrate the vibration sensors into our system needs another problem to be solved.

Generally, active RFID tags are produced under the following policies, 1) saving the battery, 2) miniaturizing the size, and 3) cutting down the cost. To follow these policies, the frequency of data transmission and the performance of vibration sensor inside are set up to be low. These restrictions cause some significant problems. For example, the system cannot detect the moment that object motion state changes in real-time because vibration sensor data requires a moment, which is the sampling rate, to convey its reaction to the system. In addition, vibration sensor often fails to detect object motion in the case that the movement is faint. However, object motion detected with vibration sensor is considered as the most important information in our system because the system uses vibration information to determine the timing to estimate object location. To deal with the time delay between actual object movement and vibration detection, we stagger a few seconds in our algorithm to estimate the exact moment that an object starts to move.

The concrete location estimation algorithm based on environment-embedded sensors and vibration sensor is constructed as follows. Our system can estimate the following three cases individually online by combining detected reaction of each sensor. a) Object is put on and taken away from a table. b) Object is put on and taken away from a sofa. c) Object is put into and taken out of a drawer. That is to say, as long as the movement of object is concerned about the area where we installed embedded sensors, we can estimate its behavior. To be concrete, our system can detect not only the final location where object is placed, but also the state of object in starting and quitting movement. The system estimates the two kinds of object state as follows.

3.2.1 Estimation of movement start

In this section, we describe an algorithm to detect the start of object movement and to estimate the original location from which object begins to move. On the occasion of estimation, we assume that target object is in a still state before the system receives any change of sensor state.

1. **Check the state of environment-embedded sensors**

   According to the embedded sensors. if an object starts to move from a place where sensors are installed, the system can detect the exact moment with the related sensors. Even if the object moves from a place where no sensors are installed, the system can also recognize the moment by referring to the reaction of the vibration sensor and other embedded sensors.

2. **Check the state of vibration sensor**
   If a vibration sensor also reacts soon after the embedded sensor reaction, the system estimates that object movement should have something to do with the sensor-embedded place. In other words, the object is very likely to be moved from that place.
3. **Recheck the state of environment-embedded sensors**
   After the vibration sensor reaction, if the system receives the reaction of the same embedded sensor, it indicates that the object must be moved from the place.

To make the general rules mentioned above clearer, we pick up a typical scene to demonstrate the estimation rules in Fig. 9. Figure 9 shows the scene that an object is moved from the table. Firstly, the system can detect the state that something is on the table by checking the reaction existence of the table sensor. Secondary, when the object moves, the vibration sensor reaction will inform us of the timing of motion start. If the object does move from the table, the change of table sensor data will indicate the strong relativity of the object and the table. Thus, the system can estimate the object has been moved from the table in good possibility.

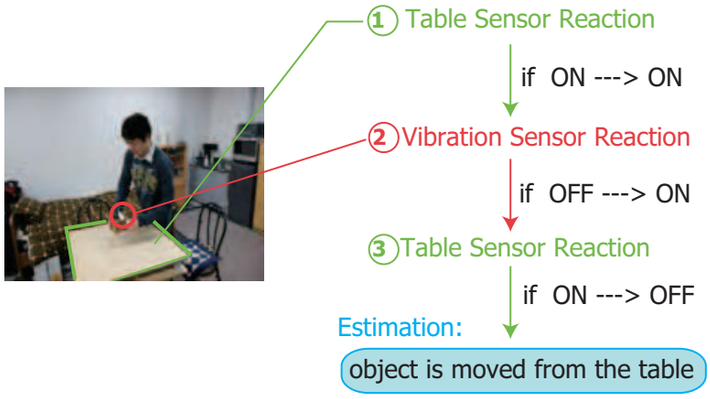


Fig. 9. Sample of Movement Start Estimation

Whereas, the process of object location estimation based on sensors is described as follows.

3.2.2 Estimation of movement end

In this process, we describe an algorithm to detect the end of object movement and to estimate the final location where the object is placed. The system estimates the object location on the assumption that target object has been moving until the vibration sensor reaction disappears.

1. **Receive the change of state of environment-embedded sensors**
   If the system receives the reaction of environment-embedded sensor on the condition that the object is in the moving state, it will suggest that the object is close to the place where the sensor is embedded because of the presupposition that only one user is in the environment.
2. **Check the change of state in vibration sensor**
   The phenomenon that vibration sensor's reaction vanishes under the condition of the embedded sensor being active indicates the high relativity between the object and the place where the sensor is embedded.

3. **Recheck the state of environment-embedded sensors**
   The second time reaction after the vibration sensor becomes inactive allows us to determine that the object is placed on the place.

To make the general rules mentioned above clearer, we pick up a typical scene to demonstrate the estimation rules in Fig. 10. Figure 10 shows the scene that an object is placed in a drawer of a cabinet. Firstly, the system will receive a reaction from the related switch sensor in addition to the continuous reaction from the vibration sensor on the RFID tag, which means the user opens the drawer with the object gripped in his or her hand. Soon after that, if the reaction of the vibration sensor disappears, the possibility of the object being put into the drawer suddenly increases. However, this does not give the confirmation because the location where the object is placed might have no relationship with the drawer at all. Still, if the system receives another reaction from the same switch sensor before long the vibration sensor's reaction vanishes, the connection between the object's location and the drawer becomes even deeper than ever.

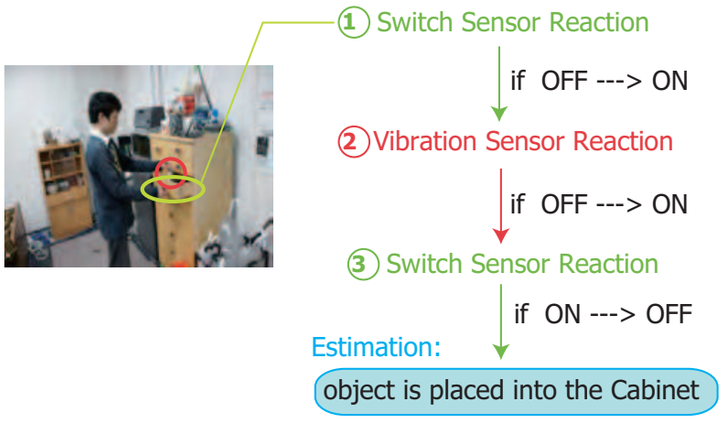


Fig. 10. Sample of Movement End Estimation

In this way, the system estimates the motion and the location of the object by combining the information from vibration sensor and environment-embedded sensors. The concept of the algorithm is easy to follow, but we have to overcome some difficulties to make the estimation algorithm work well. One of the difficulties is to deal with the time delay caused by limited sampling rate, which we used to collect sensor data. For example, an object must have moved before the reaction of the vibration sensor and must have been placed before the reaction disappeared from the system. We estimate the length of time delay from actual experiments and conquer the difficulty by taking the time lag into consideration in estimating object motion.

Another difficulty about the vibration sensor is that sometimes it does not work well. For example, if an object is moved roughly, vibration sensor will keep reacting throughout the movement, however, if an object is moved silently, the vibration reaction will sometimes disappear. This means that the system should not expect continuous vibration reaction during the object movement. Therefore, we defined a time interval to estimate the state of object movement more accurately. If the period from the last reaction of vibration sensor is within that interval, the system still regards the object as moving. Because the length of that

time interval depends on the way a user moves object, we decide the parameter from actual experiments.

Although the solution mentioned above works well in estimating object motion, it also has a problem in other aspect. That solution makes it difficult to decide the timing when an object is moved or when an object is placed in real-time because the system has to wait for the time interval to make the decision. It matters when we combine the reaction of a vibration sensor with those of environment-embedded sensors to estimate where the object is placed. According to the estimation algorithm mentioned above, the real-time detection of the object being placed is essential in determining the final location of the object. However, the information that object is placed will be clarified for the first time a few seconds later after the actual point in time. Toward this problem, the system saves a series of sensor reactions into a temporary buffer and applies the proposed estimation rules to those data after the state of object motion fixes. The weakness of this solution is that the system cannot estimate object location in real-time. However, we can know the correct time about the object being placed from the object movement history into which the system stores the object estimation results every sampling rate. In case that the system cannot estimate object location in real-time, it saves the estimated result until the state of object is settled.

3.3 Integration method

So far we explained two estimation algorithms, one is based on pattern recognition, the other is based on sensing technology. Each approach has its own strength and weakness. In our work, as we have mentioned, we integrated these two approaches into one estimation method as shown in Fig. 11. First, the algorithm processes the data from the vibration sensor and embedded sensors to decide whether the target object is in the sensor-embedded area or not(Case 1 in Fig. 11). If the object is in the area, the system uses the data from the vibration sensor and embedded sensors (except for the floor sensor) for the estimation. If the object is not in the area, the algorithm estimates the candidates for object location by using the human position and object motion detected with floor and vibration sensors. In this case, the system determines the most probable object location by integrating the locations estimated on the basis of the RSSI data with those estimated on the basis of the human position data.

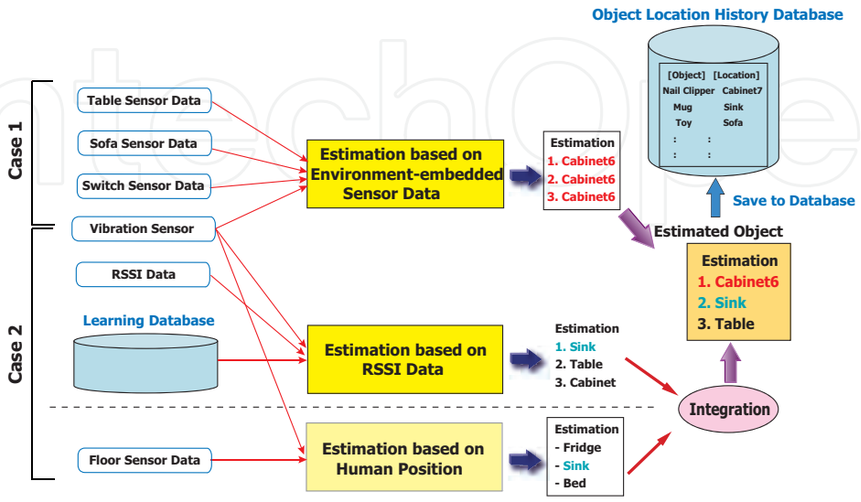


Fig. 11. Object Localization Algorithm

4. Experiments

In this section, we describe the design of our experiments to evaluate the proposed system effectively and the conditions which we used throughout the experiments.

4.1 Experimental design

To evaluate our estimation algorithm from different aspects, various experiments were conducted based on different conditions. First, we conducted exactly the same experiment as many times as the number of pattern recognition methods used in our research, which are k-nearest neighbor (KNN), distance-weighted k-nearest neighbor (DKNN), and three-layered neural network (NN). The purpose is to examine the effect of each method on the estimation performance. In general, classification performance highly depends on the parameters used in each pattern recognition algorithm. For example, the performance of KNN or DKNN is dependent on parameters such as the value of k, whereas the performance of neural network depends on parameters such as the number of nodes in hidden layer. In our experiments, various combination of parameters were examined to find out the best one that presents the highest estimation performance.
Besides, we divided experiment conditions into three types, 1) Estimation only based on RSSI data, 2) Estimation based on RSSI data and sensor data that contains floor sensor data, and 3) Estimation based on RSSI data and sensor data except for floor sensor data. This division enables us to evaluate not only the efficiency of estimation based on RSSI, but the effectiveness of our proposed integration of estimation algorithm.

4.2 Experimental conditions

Our experimental conditions are listed in Fig. 12. As introduced before, *Sensing Room*, shown at the left part of Fig. 12, was our test environment. Throughout the experiments, four objects, shown at the top left part of Fig. 12, were selected as typical daily objects, which were a nail clipper, a mug, a coffee mill, and a stuffed animal. On each object, an active RFID tag including a vibration sensor was attached. Also we assumed 13 locations where objects would be placed and five readers installed at different places. For pattern recognition, we constructed a learning database with about 18,000 data sets stored in it. In more detail, the same amount of RSSI datasets of each location of the labeled 13 locations were stored as training datasets.
In the experiment, a participant leaded a typical daily life using four objects with active RFID tags attached shown in Fig. 13. The system was supposed to estimate the location of each object every sampling frame. The total number of targeted frames was 2520. To provide the localization performance through a sequence of daily activity, we defined the ratio of the number of correctly estimated frames to the total number of targeted frames as the performance metric (Eq.2). In this case, "correct frame" means the frame that both identification and localization succeeded. Furthermore, throughout the experiment, we only adopted first location candidate and ignored the second and third location candidates in order to provide a more reliable indicator of object localization.

$$Accuracy[\%] = \frac{CorrectNumberofFrames}{TotalNumberofFrames} \tag{2}$$

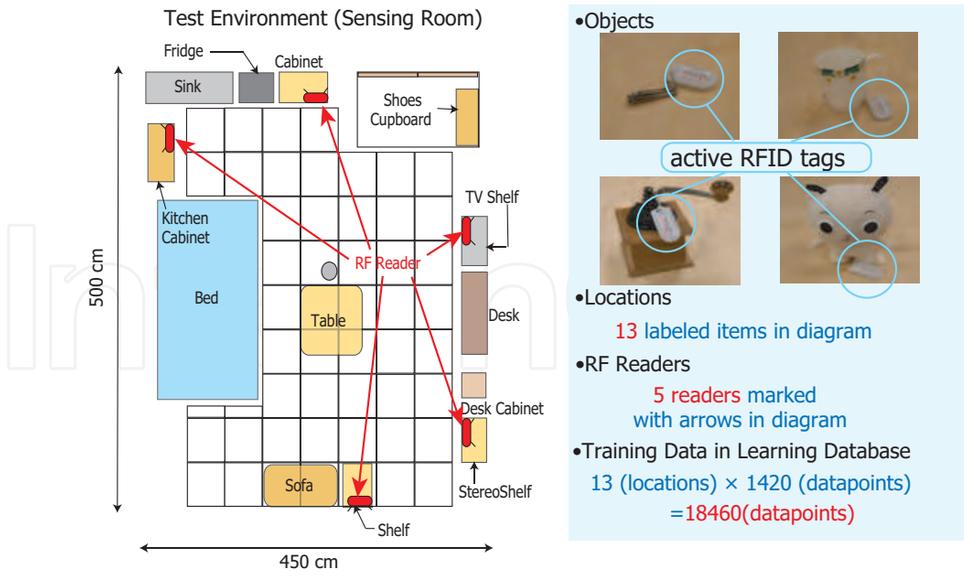


Fig. 12. Experiment Conditions

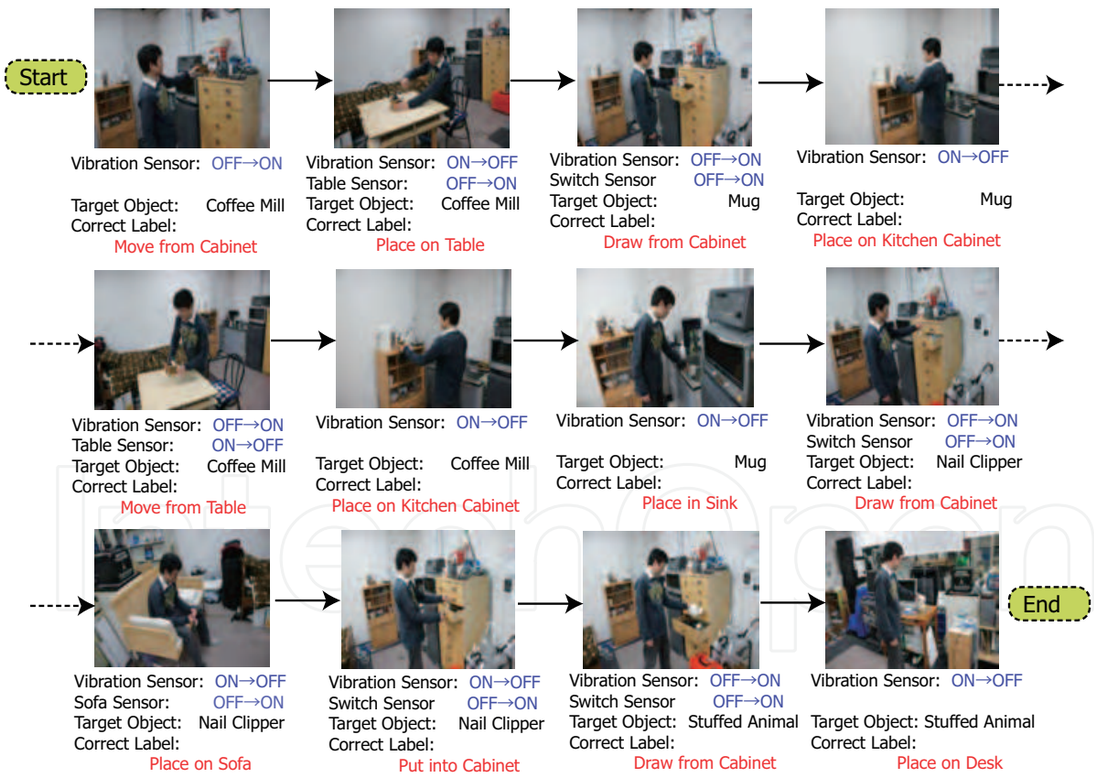


Fig. 13. Experiment Scenes

4.3 Results and discussion

We classified the estimation results by the pattern recognition method used for the localization and by the types of information used for the estimation, as shown in Table 3. There was

(Data from floor, table, sofa, switch, and vibration sensors)

	RSSI Data Only	RSSI and Sensor Data	RSSI and Sensor Data (w/o Floor Sensor)
KNN	50.2%	97.0%	95.3%
DKNN	49.6%	97.0%	95.3%
3-layered NN	22.0%	98.6%	90.6%

Table 3. Location Estimation Results (Only first location candidate is allowed)

(Data from floor, table, sofa, switch, and vibration sensors)

	RSSI Data Only	RSSI and Sensor Data	RSSI and Sensor Data (w/o Floor Sensor)
KNN	60.3%	100.0%	95.3%
DKNN	61.2%	100.0%	95.3%
3-layered NN	36.5%	100.0%	92.6%

Table 4. Location Estimation Results (Up to third location candidate is allowed)

little difference in the results among the pattern recognition method used: KNN, DKNN, and three-layered NN algorithm. There was a substantial difference in the results among the pattern recognition methods used for the estimation. Localization accuracy with only RSSI of the active RFID was 50% at best, whereas when we combined these two approaches followed our proposed estimation algorithm, the accuracy reached 97.0% regardless of the pattern recognition method. With the three-layered NN algorithm, it reached 98.6% at best. Although we used floor sensors for the estimation in the best case, the system still recorded 95.3% even without floor sensors as shown in the table.

The results shown in Table.3 suggest two things in particular. One is that the pattern recognition method used has little effect on the location estimation accuracy. Although we used three kinds of methods such as k-nearest neighbor (KNN), distance-weighted k-nearest neighbor (DKNN), and three-layered neural network (NN), none of them achieved sufficient accuracy in object localization. The main cause of estimation mistakes we suppose is that the object location is far from all the RF readers. As the radio wave is sensitive to environmental noises, the further the distance between tag and reader is, the more unreliable RSSI becomes.

The other thing which we noticed from the results is that the lack of estimation accuracy caused by not using floor sensor data can be approximately compensated for by using the proposed algorithms and other simple sensors instead of floor sensors. Although floor sensors can detect human position accurately, they are costly and require complicated maintenance. To reduce the cost and maintenance burden, we estimated object location by using only the RSSI data and data from other simple sensors (table, sofa, and switch sensors). The results indicate that data from a combination of these sensors can achieve accuracy almost equal to that of using floor sensors.

To make a comparison, we conducted another experiment using exactly the same data as the previous experiment. In this case, not only the first location candidate but also the second and the third location candidates were counted. The result is shown in Table 4.

The result shown in Table 4 indicates that the estimation performance does not make a big difference between single location candidate and plural location candidates. Of course, when we allow the second and the third location candidates, the estimation performance improves to some extent. However the improvement is too slight to make a significant impact on the estimation performance of our system.

Although we conducted all the experiments in *Sensing Room*, our object location estimation method does not rely on either the experimental environment or the kinds of sensors. That is

to say, our method can work well in any houses as long as the sensors embedded in the house can detect the same kinds of human behavior.

5. Conclusion

In conclusion, we have developed an indoor object localizing method by using active RFID tags and simple switch sensors embedded in the environment. Our system uses 1) a pattern recognition approach to classify the RSSIs collected from several RF readers into a particular location, and 2) the information detected by vibration sensors and environment-embedded sensors to improve the robustness of the method. Although position sensors used in our previous work can detect accurate human position in the environment, we attempted to eliminate them because of their disadvantages by combining simple switch sensors. The results show that our method can be used to estimate the location of daily objects with sufficient accuracy without the use of the position sensors.

One of future work is to reduce the number of RF readers. In our work, we use five active RFID readers placed at different locations so as to cover the whole environment. However, because the unit cost of RF readers is quite expensive, we have to reduce the number of RF readers to ease the economical burden on introducing our system without lowering the performance of object location estimation.

6. References

Cover, T. & Hart, P. (1967). Nearest neighbor pattern classification, *Information Theory, IEEE Transactions on* 13(1): 21 – 27.

Hightower, J., Borriello, G. & Want, R. (2000). SpotON: An indoor 3d location sensing technology based on rf signal strength, *Technical Report UW CSE 2000-02-02*, University of Washington.

Mori, T., Noguchi, H., Takada, A. & Sato, T. (2006). Sensing room environment: Distributed sensor space for measurement of human dialy behavior, *Transaction of the Society of Instrument and Control Engineers* E-S-1(1): 97–103.

Mori, T., Siridanupath, C., Noguchi, H. & Sato, T. (2007). Active rfid-based object management system in sensor-embedded environment, *FGCN2007Workshop: International Symposium on Smart Home (SH'07)*, Jeju Island, Korea, pp. 25–30.

Mori, T., Takada, A., Noguchi, H., Harada, T. & Sato, T. (2005). Behavior prediction based on daily-life record database in distributed sensing space, *International Conference on Intelligent Robots and Systems*, pp. 1833–1839.

Ni, L. M., Liu, Y., Lau, Y. C. & Patil, A. P. (2004). Landmarc: Indoor location sensing using active rfid, *Wireless Networks* 10(6): 701–710.

Pao, T.-L., Cheng, Y.-M., Yeh, J.-H., Chen, Y.-T., Pai, C.-Y. & Tsai, Y.-W. (2008). Comparison between weighted d-knn and other classifiers for music emotion recognition, *International Conference on Innovative Computing Information and Control(ICICIC'08)*, pp. 530–530.

Shih, S.-T., Hsieh, K. & Chen, P.-Y. (2006). An improvement approach of indoor location sensing using active rfid, *the First International Conference on Innovative Computing, Information and Control(ICICIC'06)*, pp. 453–456.

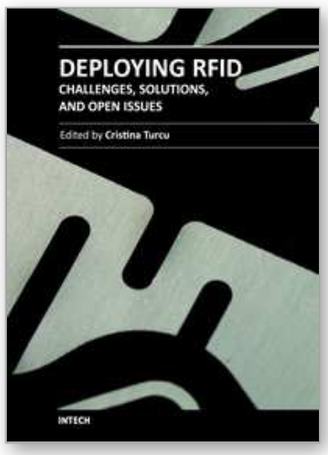
Shimodaira, H. (1994). A weight value initialization method for improving learning performance of the backpropagation algorithm in neural networks, *International Conference on Tools for Artificial Intelligence (ICTAI)*, pp. 672–675.

yao Jin, G., yi Lu, X. & Park, M.-S. (2006). An indoor localization mechanism using active rfid tag, *IEEE International Conference on Sensor Networks, Ubiquitous, and Trustworthy Computing(SUTC'06)*, pp. 40–43.

Zhao, Y., Liu, Y. & Ni, L. M. (2007). Vire: Active rfid-based localization using virtual reference elimination, *International Conference on Parallel Processing (ICPP'07)*, pp. 56–63.

IntechOpen

IntechOpen



Deploying RFID - Challenges, Solutions, and Open Issues
Edited by Dr. Cristina Turcu

ISBN 978-953-307-380-4
Hard cover, 382 pages
Publisher InTech
Published online 17, August, 2011
Published in print edition August, 2011

Radio frequency identification (RFID) is a technology that is rapidly gaining popularity due to its several benefits in a wide area of applications like inventory tracking, supply chain management, automated manufacturing, healthcare, etc. The benefits of implementing RFID technologies can be seen in terms of efficiency (increased speed in production, reduced shrinkage, lower error rates, improved asset tracking etc.) or effectiveness (services that companies provide to the customers). Leading to considerable operational and strategic benefits, RFID technology continues to bring new levels of intelligence and information, strengthening the experience of all participants in this research domain, and serving as a valuable authentication technology. We hope this book will be useful for engineers, researchers and industry personnel, and provide them with some new ideas to address current and future issues they might be facing.

How to reference
In order to correctly reference this scholarly work, feel free to copy and paste the following:

Hiroaki Fukada, Taketoshi Mori, Hiroshi Noguchi and Tomomasa Sato (2011). Use of Active RFID and Environment-Embedded Sensors for Indoor Object Location Estimation, Deploying RFID - Challenges, Solutions, and Open Issues, Dr. Cristina Turcu (Ed.), ISBN: 978-953-307-380-4, InTech, Available from: http://www.intechopen.com/books/deploying-rfid-challenges-solutions-and-open-issues/use-of-active-rfid-and-environment-embedded-sensors-for-indoor-object-location-estimation

INTECH
open science | open minds

InTech Europe
University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China
Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821

© 2011 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike-3.0 License, which permits use, distribution and reproduction for non-commercial purposes, provided the original is properly cited and derivative works building on this content are distributed under the same license.

IntechOpen

IntechOpen