Chapter 11

Object and Human Localization with ZigBee-Based Sensor Devices in a Living Environment

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1. Introduction

Radio frequency identification (RFID) systems are currently widespread in business applications such as inventory management and supply chain management. In particular, the active type of system is often used for total management over a large area because of its long communication range. With the increasing miniaturization and price reduction of RFID tags, the applicable area is expanding from business to consumer. One of the most promising areas is the home environment. In the home environment, object management is as important as that in business areas such as warehouses, because there are many pieces of equipment in daily use. While many objects are accessed often in a warehouse environment, only a few objects are replaced in the home environment. The management of massive objects is thus unnecessary for the home. Another application is in the understanding of the environmental situation. In warehouses, tags with temperature and humidity sensors are often used for quality management. These tags realize not only object identification but also understanding of the object's situation. The next step in situation understanding is behavior recognition for home occupants. Behavior recognition is useful for intelligent home automation, healthcare based on life patterns, and monitoring of people living in remote locations.

To capture human behavior using an active RFID system, the system must measure various information related to human behavior. A typical example of human behavior measurement using a wireless sensing system, which is regarded as a kind of active RFID system, is MITes [1]. MITes can capture home environmental information (e.g. lighting changes and passing people) using wireless sensor devices attached to each of the rooms. MITes can also measure details of human behavior using wearable sensors. Traditional active RFID systems can capture large segments of human behavior, even without the use of a complicated system like MITes. Environmental information can be measured using sensors in the tags. With the addition of the environmental information, the RFID system can easily identify the object with the attached tags. However, while identification alone is suitable for object management, information about object handling and object locations is required to measure human behavior. For object handling, the work of Philipose et al. [2] indicates that the object handling sequence assists with the estimation of human behavior. This information can be captured easily with sensors included in the tags. For the location, as an example of the use of location information for human behavior recognition, the information that a cup exists on a sink indicates that someone is washing the cup. The presence of the cup on a table suggests that someone is drinking from it. Also, if it is known that one specific person uses the cup, this information also identifies the person who is drinking. Although direct information about humans is desirable for behavior recognition, direct measurement is difficult with active RFID systems. If the inhabitants wear tags, some information can be captured. However, wearing the tags constricts the natural behavior. Intille et al. [3] suggested that a rough human location is useful for human behavior recognition. Based on their work, we decided that our measurement target for humans using active RFID systems is sub-room-level human localization without the humans wearing tags. Therefore, our research goal is object and human localization using an active RFID system.

Popular approaches for tag position estimation use radio signal strength indicators (RSSIs) for communication between tags and readers, because RSSI depends on the distance between the tag and the reader [4-6]. The simplest approach uses a triangulation algorithm. However, in the home environment, which contains many obstacles for RFID systems such as furniture and electrical appliances, localization is more difficult because the strength of the radio wave can change easily with the room situation. One solution is the deployment of multiple reference tags, which indicate true position [5] [6]. However, this approach is impractical in a living environment because of the cost and difficulty. Distortion of the radio waves by the occupant's presence decreases the localization performance. When we consider the above applications, accurate position (i.e. x-y-z position) estimation is not necessary, but rough location (e.g., on a table, in a drawer, or in a cabinet) is required. Based on this idea, we have already proposed a method for localization of tag-attached objects [7]. The method uses a machine learning technique and a rule-based algorithm to combine RSSI data and sensor data captured by externally distributed sensors across the room. This combination improves the performance in the presence of humans. However, this method has some disadvantages, including the cost of a commercial RFID system, the necessity for the tag readers to have a local area network (LAN) connection, the additional introduction of distributed sensors and the limitations of the estimation locations (e.g. the system cannot distinguish any drawers that do not contain switch sensors).

To overcome these problems, we must use a new active RFID system instead of the current commercial active RFID systems. We have focused on ZigBee technology for wire-

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less communications. ZigBee has advantages for accurate localization. RSSIs in ZigBee are sensitive to distance because of its high frequency radio wave. Another advantage is that ZigBee provides protocols for sensor devices, which leads to easy transmission of the sensor data from the tags. However, because the ZigBee-based RSSI is more sensitive than a low-frequency RFID system, the presence of humans disturbs the RSSI more severely. The use of sensor data on tags would improve the object localization performance. Rowe et al. [8] have already reported that limitation of the location candidates improves the localization performance. We have expanded the previous algorithm to prevent performance degradation. The algorithm uses the RSSI data, the environmental sensor data, and data from the sensors on the tag to prevent degradation of the performance by human interference.

On the other hand, the sensitivity of ZigBee-based RSSIs to the presence of humans is effective for human localization. Wilson and Patwari developed a human tracking method based on RSSI values from reference nodes at the outside of the walls [9]. Their approach requires many wireless devices to generate tomography data for tracking, and no obstacles exist in the room. For our application, we do not need high-resolution human positioning but require only rough location using a few devices. If human interference with the radio waves is stable, the pattern of the RSSI values among the nodes specifies the human location. Our challenge is therefore to estimate a sub-room-level human location based on this RSSI distortion using a fingerprinting approach, which is the same as object localization.

In this paper, we constructed a prototype active RFID system using ZigBee devices. We also proposed an object localization method using RSSIs among tags and data from sensors attached to the tags. Our experimental results demonstrated the feasibility of our localization approach for both objects and persons in a realistic home environment. The results also show that our approach reduces the performance degradation caused by the presence of humans.

2. ZigBee-based sensor device

To avoid limitations in the sensor variety and the communication protocols, we developed a new ZigBee-based prototype system. The system consists of the target nodes, which are tags in the RFID system, and the reference nodes, which are readers in the RFID system. The difference between this system and the traditional RFID system is that our system enables communication among the readers and can gather RSSI data because the reference nodes are also regarded as a kind of target node. The devices consist of the XBee, which is a commercial ZigBee communication module, and the Arduino or Arduino Fio microcontroller, which is commonly used in prototype device construction because of its compactness and ease of programming. The antenna used for wireless transmission and reception is non-directional to reduce the system performance dependence on device direction. The developed sensors and deployment examples are shown in Fig. 1.

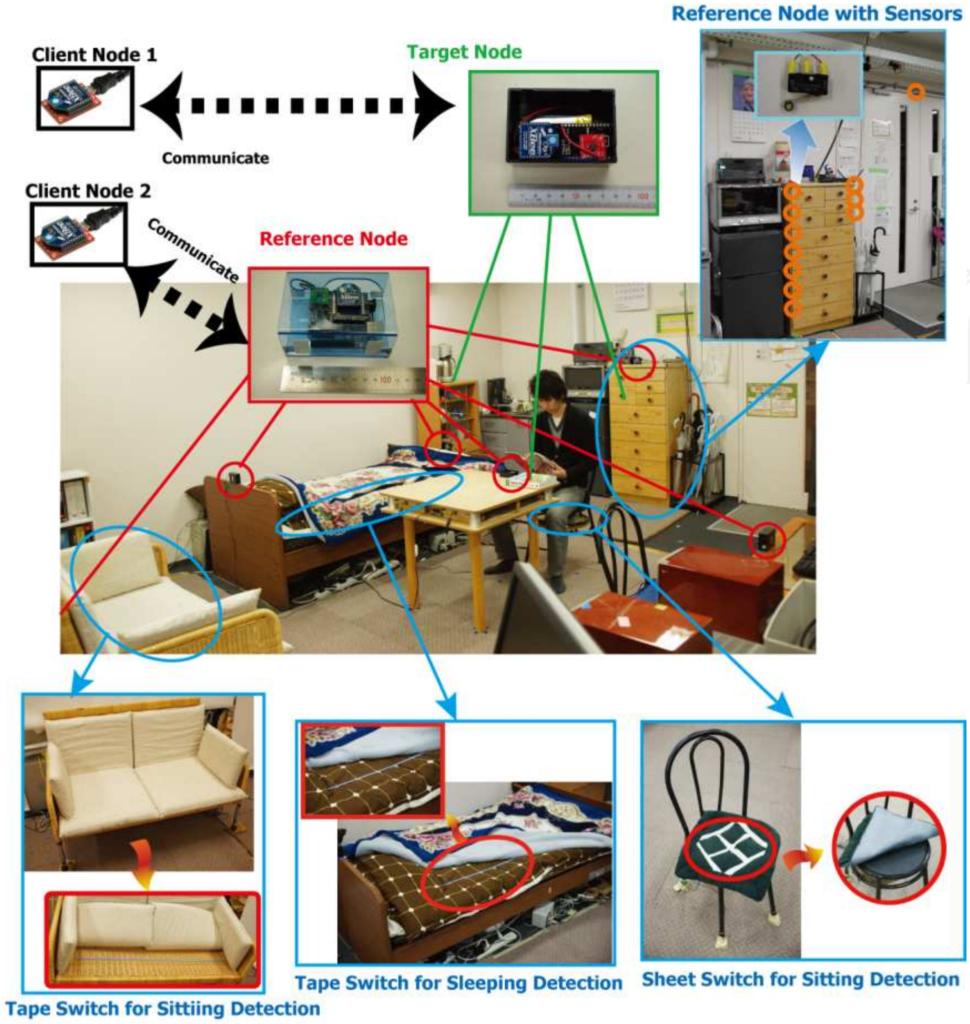

Figure 1. Developed devices and deployment examples.

2.1. Target node

The target node is used for object identification and localization. The node is attached to an object in a room. The node consists of the Arduino Fio and the XBee. The node contains an acceleration sensor (ADXL355) for detection of object handling, along with a luminosity sensor (CdS cell), a humidity sensor (HIH-4030), and a temperature sensor (TEMP6000) for environmental status measurement near the object. The node is battery powered. However, the current device has a battery life of only 3 days, and provision of longer battery life will be part of our future work.

The target node detects the object handling state by using an acceleration sensor, which acts as a trigger to localize the object position. In our research, we estimate the following five motion states by analysis of the acceleration changes:

i. Stable: object is in a stable state;

ii. Start Moving: object begins to move;

iii. Keep Moving: object continues to move;

iv. Ambiguous: object is either in "Moving" state or in "Stable" state;

v. Stop Moving: object stops moving.

To be specific, when a node shows noticeable changes in acceleration beyond a set threshold after a long time in the "Stable" state, our system judges this change to be to the "Start Moving" state. Then, as long as the acceleration sensor continues to respond, the state is regarded as being the "Keep Moving" state. However, in the real case, even if an object is moving, the acceleration sensor attached to the node sometimes does not show any noticeable response because of the way it moves. To avoid mistaken estimation in such cases, where even changes in acceleration cannot be detected, the system does not instantly determine the state to be "Stop Moving". Instead, the system regards such a state as "Ambiguous", which means that the node is either in the "Keep Moving" state or the "Stop Moving" state. If the acceleration sensor does not output any noticeable changes after a fixed period of time, the system decides that the first moment where the acceleration sensor's response disappears is the "Stop Moving" state, and the subsequent moments are the "Stable" state. Typical detection results using this algorithm are shown in Fig. 2.

To examine the validity of this algorithm, we performed some preliminary experiments. Because it is difficult to generalize all possible patterns of object motion, in the preliminary experiments, we simply raise an object with a node and move it for a time, and then set it down somewhere. However, despite the simplicity of the algorithm, the system can distinguish the state of object motion from the other states quite well, with a success rate of more than 90% according to our experimental results.

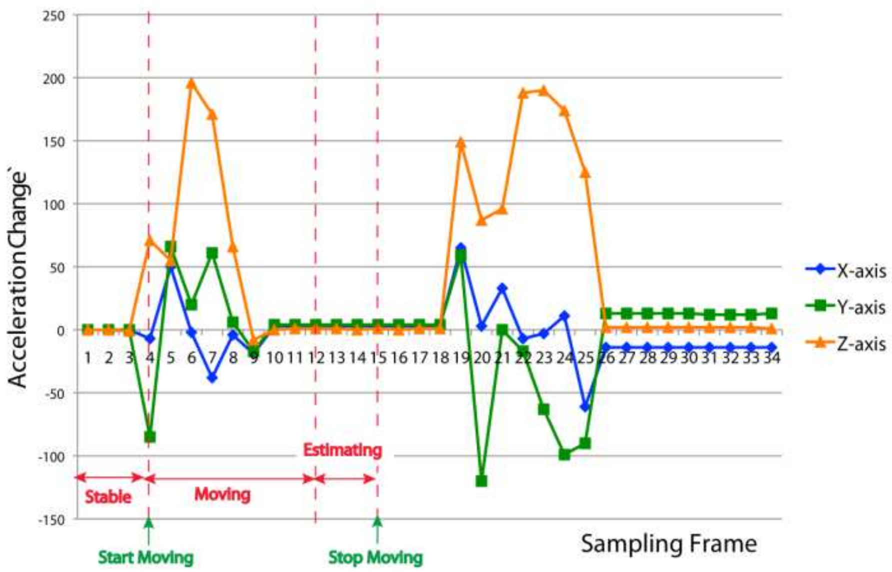

Figure 2. Motion sensing example results with acceleration sensor.

2.2. Reference nodes

A reference node is used for communication with the target nodes and for collection of the environmental sensor data. The node consists of an Arduino and an XBee. The node is capable of connecting to various sensors for environmental data collection. In our experiment, the node contains the same sensors as the target nodes and switch sensors to detect human behavior such as sitting and sleeping. Because the reference nodes cannot move if they are to provide localization reference data, the nodes are attached to fixed objects such as furniture and electrical appliances. The electric power is supplied to these nodes by a power line, because they do not move.

2.3. Communication protocol

The computer for object and human localization collects and controls all the sensor data and the RSSI values. For synchronization and simultaneous data collection, the computer controls the targets and the reference nodes separately with two gateway nodes, which are called client nodes. A typical communication example is shown in Fig. 3. In the figure case, the target nodes and reference nodes transmit sensor data periodically. The reference nodes also regularly gather RSSI values between the reference nodes to estimate human presence and human location based on the algorithm given in section 5 of this paper. When the target node detects object handling using the acceleration sensor, the node transmits a signal to indicate the handling of the object by the occupant. After transmission, the node sends the state of the target node periodically. When the node detects that the object has been put down somewhere, the node broadcasts the putting down action to all reference nodes. Finally, the target node receives each reference node's data with RSSI values and transmits all data to the client node. The computer calculates the object location from the collected RSSIs.

3. Object localization using only RSSI

3.1. Object localization method

While RSSI has a dependence on the distance between the nodes, the RSSI values do not change linearly with the distance. Although the RSSI is sensitive to some types of environmental noise, an RSSI from a fixed location almost always indicates the same value, regardless of the time. Therefore, our main idea is to reduce the environmental effects on the RSSI by not using just a single RSSI, but by using a pattern extracted from several RSSIs. To realize this idea, we must introduce three kinds of pattern recognition method.

The three kinds of pattern recognition method used in our work are the k-nearest neighbor (KNN), the distance-weighted k-nearest neighbor (DKNN) [10], and the three-layered neural network (NN) algorithms. KNN is a method for classification of objects based on the closest training examples in the feature space. The nearest neighbor algorithm, which means that K equals 1, has strong consistency results. As the amount of data approaches infinity, the algorithm is guaranteed to yield an error rate that is no worse than twice the Bayes error

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rate, which is the minimum achievable error rate given the distribution of the data. KNN is guaranteed to approach the Bayes error rate, for some value of K. DKNN is an extension of KNN, which weights the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant neighbors. We use the inverse of the squared Euclidean distance as a weight function. NN is a kind of classification technique. It is known that NN can demonstrate high discrimination ability for data that has multiple dimensions and is linearly inseparable. We therefore adopted these three methods in our work for object location estimation with RSSIs.

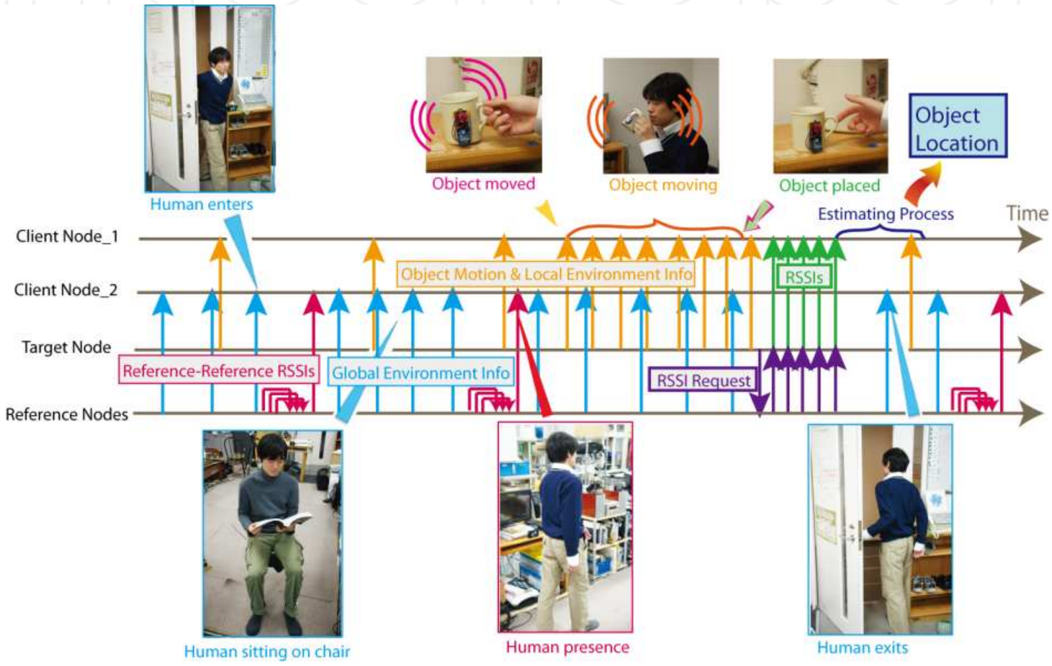


Figure 3. Communication protocol overview.

3.2. Experimental conditions

To investigate the basic object localization performance of the ZigBee-based RFID system, we conducted three experiments. Generally speaking, the classification performance depends heavily on the parameters used in the pattern recognition algorithm. For example, the performance of KNN or DKNN is dependent on the parameters such as the value of k, whereas the performance of the NN depends on parameters such as the number of nodes in the hidden layer. In our experiments, we tried various cases by varying the parameter values and chose the best combination of the parameters according to the estimation performance.

The experimental environment and conditions are shown in Fig. 4. The room contains various articles of furniture. Generally speaking, the largest contributors to reduced localization accuracy are environmental obstacles such as furniture made of metal. This environment provides extreme conditions for localization. However, the difficulty in localization using RSSIs in this environment helps to show that our proposed method is valid in actual living spaces.

To evaluate our estimation algorithm based on pattern recognition methods, we conducted experiments under different conditions: 1) estimation with different numbers of learning data; 2) estimation of different numbers and types of locations; and 3) estimation using different numbers of reference nodes. We collected the same number of RSSI data sets (about 50 to 150) from each of the 17 labeled locations as data sets. The parameters for each of the pattern recognition methods were tuned in advance with the data sets. For performance evaluation, we calculated the estimation accuracy, which is the rate of true positives among the total number of data sets. Ten-fold cross-validation was performed to eliminate any data bias.

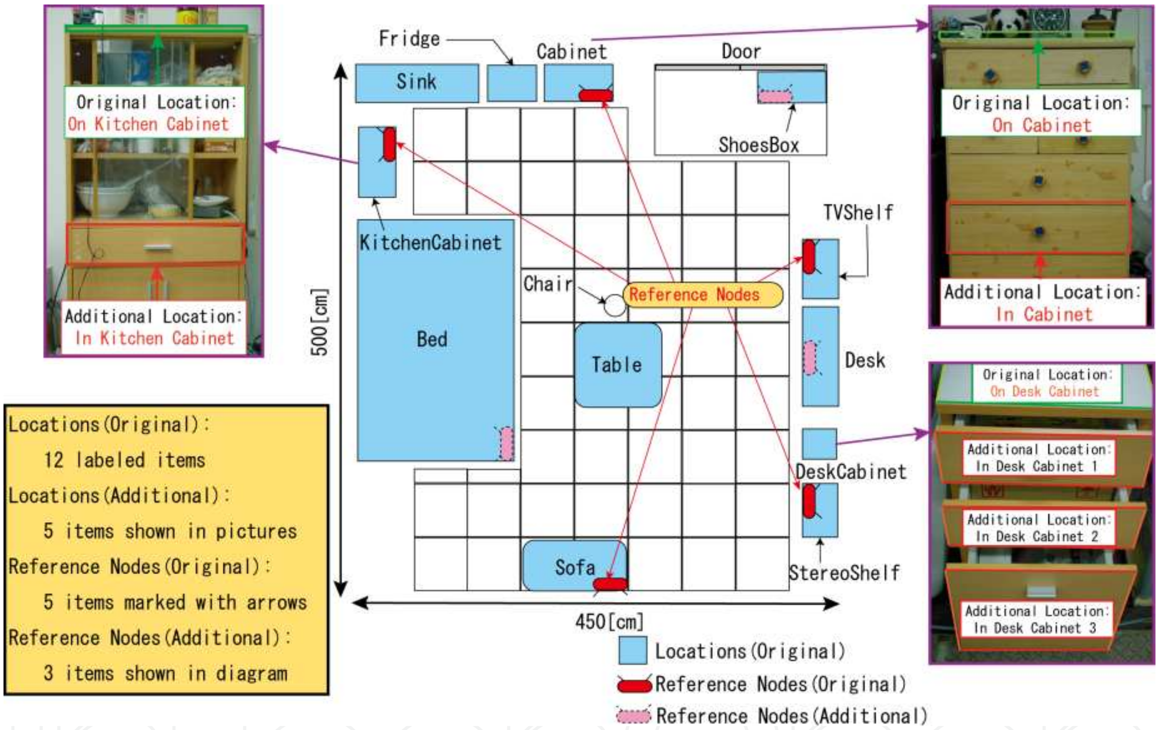


Figure 4. Experimental conditions for object localization using only RSSI.

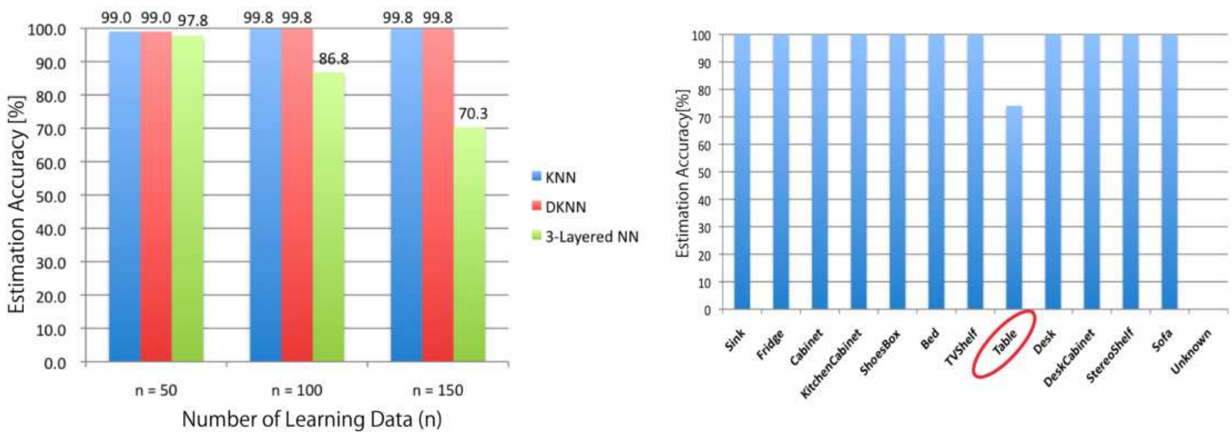
3.3. Experimental results

3.3.1. Estimation with different numbers of learning data

As mentioned above, we collected RSSI data at each location in the environment and used these data sets to classify objects into particular locations. In Fig. 5a), "n" indicates the number of RSSI data sets collected at each location.

The graph of the results suggests two things to us. The first is that 50 learning data sets per location are sufficient for localization. Therefore, in the following experiments, we used a learning database that contains 50 data sets per location. The other is that as long as the system uses KNN or DKNN as the pattern recognition method, the estimation accuracy is not so heavily dependent on the number of learning data. However, 3-layered NN has increasing difficulty in estimating the object location as the number of learning data increases.

The estimation accuracy at each location with the 3-layered NN is shown in Fig. 5b). The graph demonstrated that the "Table" seems difficult to estimate with the NN. This is because the table is located right in the middle of all of the reference nodes, which means that the table is far from every reference node.



a) Relationship between the number of learning data and estimation accuracy

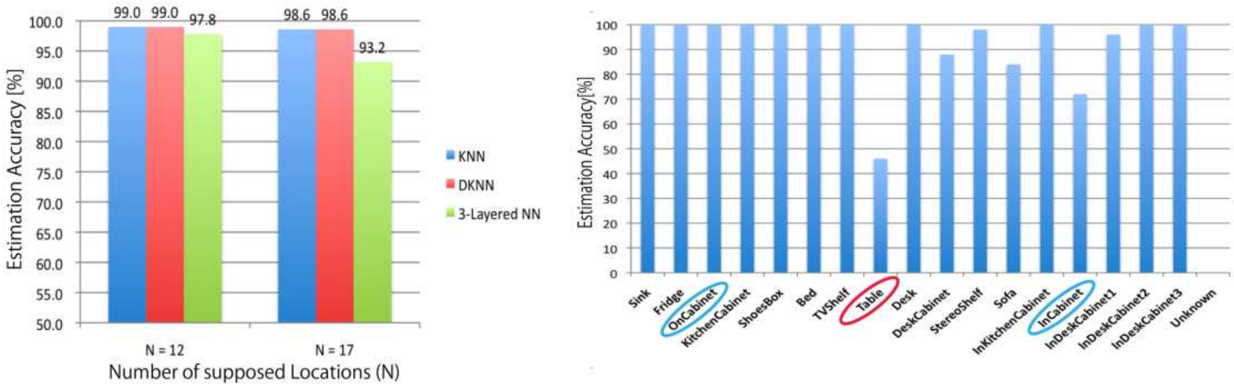
b) performance of NN at n = 50 per location

Figure 5. Experimental results with regard to the number of learning data.

3.3.2. Estimation with different numbers and types of locations

We conducted another experiment to investigate how well our proposed method can accommodate an increase in the number of locations. In this experiment, we added 5 new locations, shown in Fig. 4, to the existing 12 locations. We used a learning database consisting of 50 training data sets for each location and 5 reference nodes to measure the RSSIs with the target node.

Figure 6a) shows that our proposed method can estimate object location effectively even when the number of locations increases. In particular, it has been proved that estimation with KNN and DKNN is hardly affected by an increase in the number of locations, whereas estimation with the 3-layered NN becomes worse when the variety of locations increases. In Fig. 6b), we can see a similar tendency to that which appears in Fig. 5b). However, in this case, the estimation accuracy of the "InCabinet" state also drops seriously along with that of the "Table" state. The reason for this phenomenon is thought to be that it is becoming increasingly difficult to distinguish the "OnCabinet" state from the "InCabinet" state.



a) Relationship between the number of supported locations and estimation accuracy

b) Performance of NN at n = 17 per location

Figure 6. Experimental results with regard to the number of estimation locations.

3.3.3. Estimation by different numbers of reference nodes

We conducted another experiment to investigate the influence of the number of reference nodes on the estimation accuracy. All the experiments above used the 5 reference nodes illustrated in Fig. 4. In this experiment, however, we changed the total number of reference nodes in two ways: one was to subtract two reference nodes from the existing nodes, and the other was to add three nodes to the existing nodes. In the former case, we only used the reference nodes installed at the kitchen cabinet, the TV shelf, and the sofa, while in the latter case we attached reference nodes to the bed, the shoebox, and the desk.

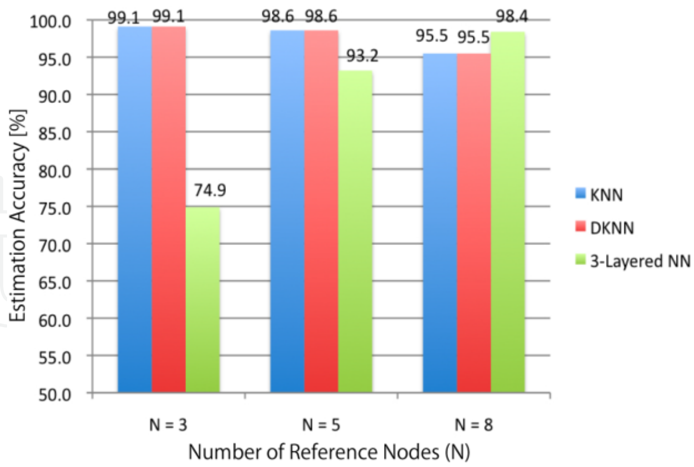


Figure 7. Experimental results with regard to the number of reference nodes.

The graph of the results shown in Fig. 7 suggests two things to us in particular. The first is that there is little difference in the best estimation accuracy with the different numbers of reference nodes. The other is that KNN and DKNN perform strongly with fewer reference nodes, whereas the 3-layered NN has trouble in estimating object locations with fewer reference nodes, although it demonstrates better ability than KNN and DKNN when the number of reference nodes increases.

These results indicate that the ZigBee-based RFID system has the capability for object localization using pattern recognition methods under human-absent conditions.

4. Object localization under human presence conditions

4.1. Object localization using sensor data on target node

The conditions for previous experiments are far from realistic. In a living environment, humans are present and handle the tagged objects. The existence of a human degrades the localization performance because the human body disturbs the radio waves. Our system can measure not only the environmental sensor data but also the sensor data on the target nodes. We extended our previous method [7] to be able to handle the sensor data on the target nodes. Because the previous method limits the location candidates based on estimated human behavior, location candidates are also limited in the new method based on sensor data on target nodes.

In the following algorithm, we use DKNN for RSSI-based localization. Because the sensor data on the target nodes indicates the node location well, the algorithm merges the sensor data on the target nodes into the RSSI-based localization results before combination of the sensor data on the reference nodes.

4.1.1. Integration of target-attached sensor data and rssi-based estimation results

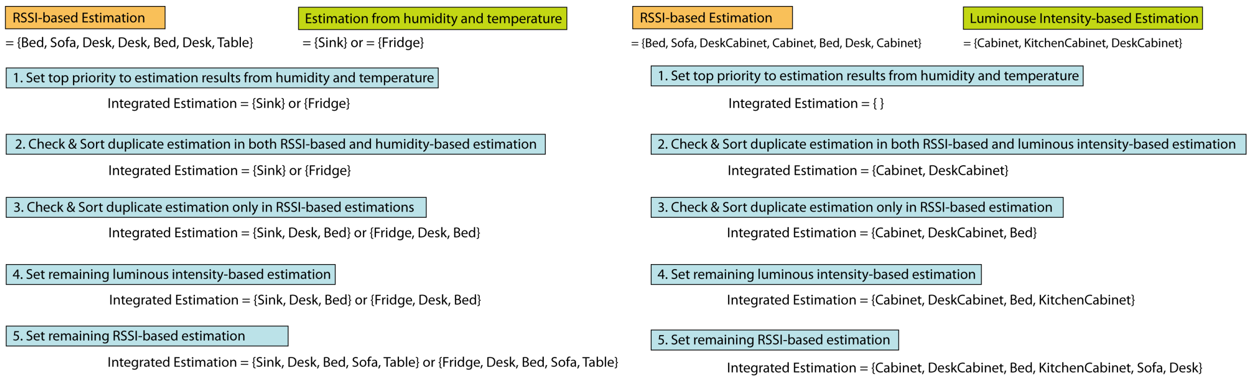
In our system, each target node contains a humidity sensor, a temperature sensor, and a luminous intensity sensor. The humidity and temperature sensors show changes only at specific locations, whereas the luminous intensity sensor is highly sensitive to the environment. This is why the system changes the estimation priority relative to the sensors that have reacted. First, the system integrates the estimation based on humidity or temperature sensors into the RSSI-based estimation. Then, the system integrates the estimation based on the luminous intensity sensor into the results.

- Integration of Humidity and Temperature Sensor Data

Because both the humidity sensor and the temperature sensor change dramatically only at specific locations, the system gives top priority to estimations based on these sensors. For example, because the system can detect object motion through the acceleration sensor, if the humidity rises around the time when an object is set down, it probably indicates that the object has been placed near the sink, because the sink is the only place that can cause a dramatic change in humidity. In the same way, if the temperature drops around the time when an object is set down, it suggests that the object has probably been placed inside the refrigerator, because the preliminary experiments indicate that the temperature only changes dramatically in the refrigerator. The system places its highest level of trust in these sensor reactions because they limit the object location candidates to one in each case. A localization example based on this policy is shown in Fig 8a).

- Integration of Luminous Intensity Sensor Data

The luminous intensity sensor does not limit the object location candidates to only one. This sensor can provide the system with several candidates for the object location. For example, if the luminous intensity drops dramatically around the time when an object is set down, it suggests to the system that the object has been placed in a dark place, such as the inside of a drawer or underneath the bed. Because the luminous intensity changes sensitively depending on the location, the system may even be able to tell the difference between the inside of a drawer and underneath the bed by comparing the sensor's outputs. A localization example based on this policy is illustrated in Fig. 8b).



a) Example where humidity and temperature data limits location candidates

b) Example where luminous intensity data limits location candidates

Figure 8. Typical examples of sensor data integration on target nodes.

4.1.2. Integration of sensor data on reference nodes into the results

Because the reference-attached sensor data provide the system with information about human behavior and locations, the system can limit the object location candidates. For example, if a sensor embedded on a sofa continuously reacts around the time when an object is set down, it is easy for the system to guess that the object location is not far from the sofa. In our experimental room, the reference-attached sensors consist of pressure-type switch sensors and microswitch sensors. Pressure-type sensors are installed in the chairs, the sofa, and the bed, whereas the microswitch sensor is installed in the drawer of a cabinet. Each time that an object is set down, the system refers to the reactions of all types of reference-attached sensors around that moment, and keeps track of them. The pressure-type switch sensors, such as those in the chair modules, usually continue to react, not only at the moment when the object is placed, but also during the periods before and after placement, so there is little possibility that the system will fail to detect them. For the microswitch switch sensors such as the drawer modules, however, the sensor reactions usually occur ahead of the moment when the object is placed. If the system only refers to the sensor data within a particular period, it might fail to detect them. However, by tracking the sensor reactions over longer periods, the possibility of missed detection decreases. Thus, the system can use the reference-attached sensors to provide several location candidates, and with the following integration algorithm, shown in Fig. 9, the system integrates reference-based estimation into target-based estimation.

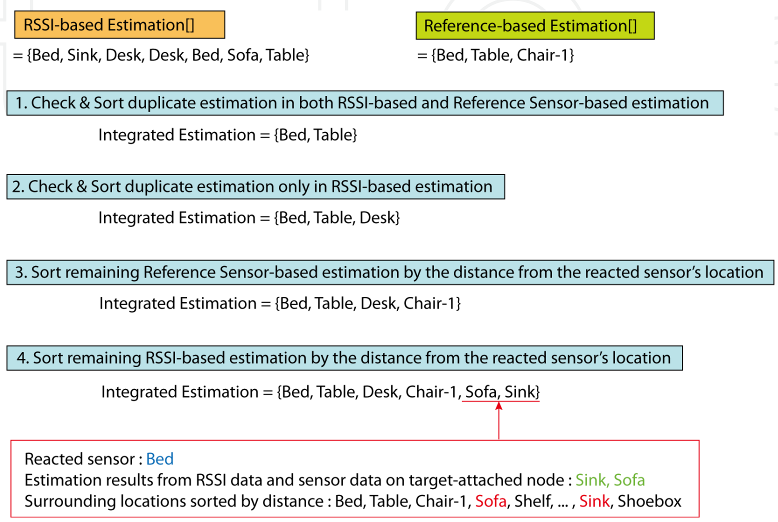


Figure 9. Typical example of sensor data integration on reference nodes.

4.2. Experiment

To evaluate the performance of our system, an experiment was conducted. The experimental room, the sensors for the reference nodes and the deployment locations are the same as those in Fig. 1. The target locations are illustrated in Fig. 10. The total number of target locations is 19. For the training data sets, we collected 400 samples per target location in advance under human absent conditions. For the evaluation, the subject puts down and picks up the object at all of the target locations 5 times, which means 19×5=95 location test data were collected. Strictly speaking, in a single trial, one subject conveyed a target node from location to location in the following order: OnDeskCabinet, InDeskCabinet, StereoShelf, Sofa, Shelf, BedHead, BedBottom, OnKitchenCabinet, InKitchenCabinet, InCabinet, Table, Desk, Chair1, Chair2, TVShelf, ShoeBox, OnCabinet, Fridge, and Sink. For the performance evaluation, we calculated the estimation accuracy in the same way as in the previous experiments. We compared the following five conditions.

1. **RSSI Only:** Estimation based on RSSI data between target node and reference nodes only;

2. **RSSI & Target Sensors:** Estimation directly based on RSSI and target sensor data;

3. **Integration of RSSI and Target Sensor Data:** Estimation based on proposed integration algorithm using the RSSI and target sensor data;

4. **Integration of RSSI and Reference Sensor Data:** Estimation based on proposed integration algorithm using the RSSI and reference sensor data;

5. **Integration of RSSI and All Sensor Data:** Estimation based on proposed integration algorithm using the RSSI and all sensor data (our system performance).

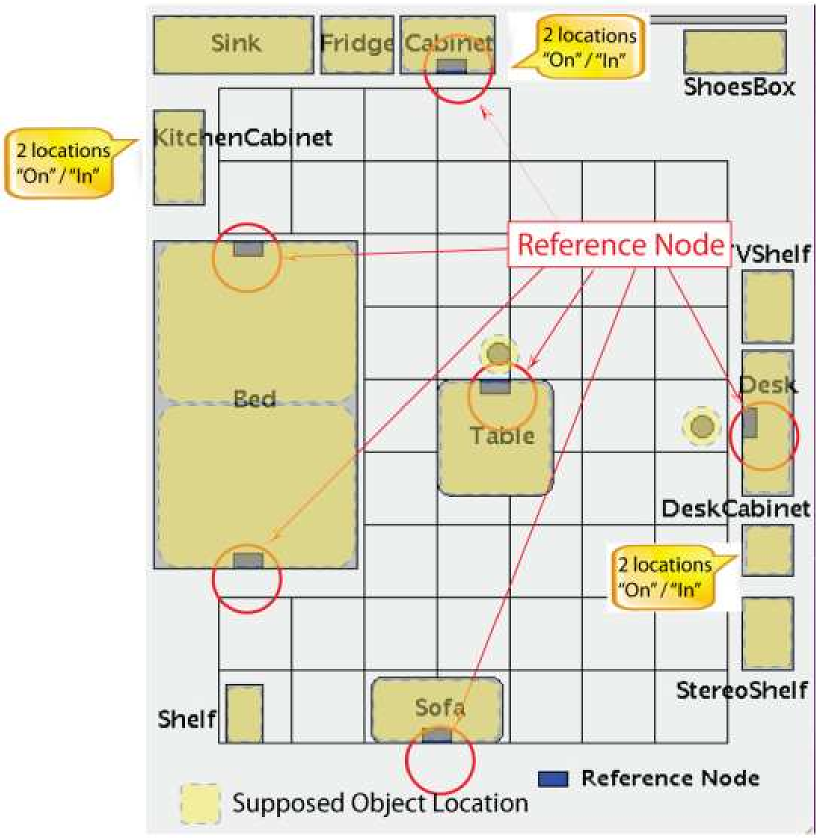


Figure 10. Experimental conditions for object localization with human presence.

The estimation results are shown in Fig. 11. Dynamic interference sources such as a human being had a serious effect on the RSSI-based estimation results. When we use the datasets in our learning database to conduct cross validation, the estimation accuracy is more than 90%. However, in this case, estimation based only on RSSI produced a poor performance.

Estimation based on the RSSI and target sensor data shows lower performance than that of RSSI-only based estimation. In this evaluation, we added another two dimensions (humidity and luminous intensity) to the original RSSI datasets. Because the luminous intensity changes are quite sensitive to the surroundings and to how the target node is placed, they might mislead the estimation to the wrong locations. However, this approach has one point of focus. In the RSSI-based approach, the sink is one of the most difficult places to estimate because it is surrounded by metal. However, by introducing the humidity data, the system estimated the sink correctly through all the scenario tests. This fact indicates that if we integrate target sensor data into RSSI more effectively, then the performance will become higher than that of this simple combination of RSSI and target sensor data.

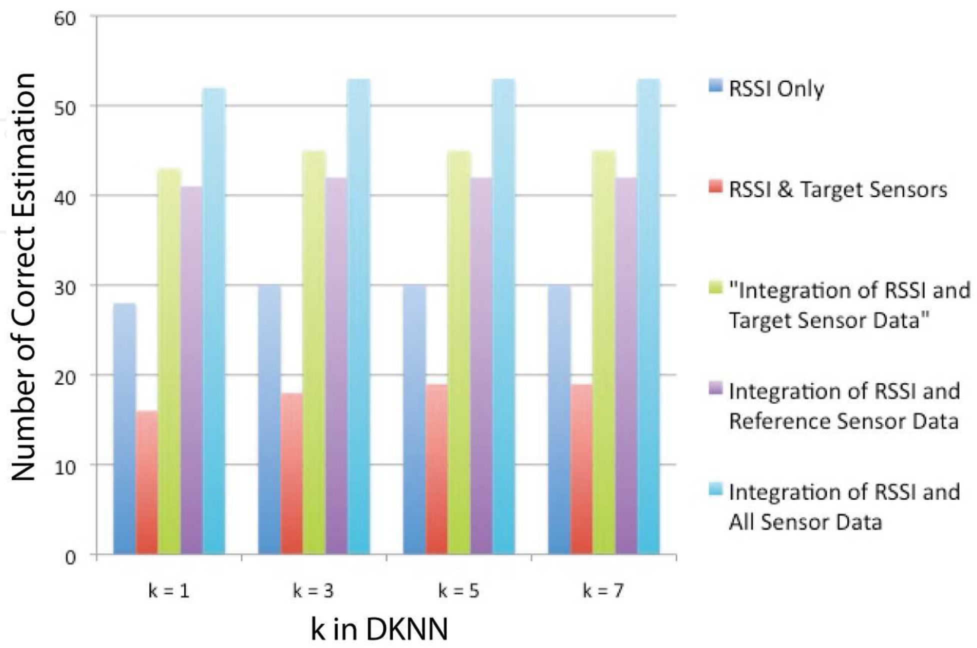


Figure 11. Results for the object localization algorithm at each K in DKNN.

Our proposed integration algorithm based on the RSSI and target sensor data shows much higher performance than the previous two algorithms. It clearly shows the effectiveness of our integration algorithm, which can correct the estimation even if the RSSI-based estimation provides a wrong result. Our proposed integration algorithm based on the RSSI and reference sensor data also shows high performance, similar to that of the RSSI and target sensor data approach. To investigate this in more detail, the contribution of the integration of the reference sensor data is seen to be different from that of the integration of the target sensor data. This therefore indicates that our system should produce a higher performance than these two integration algorithms. The system that integrates RSSI with all kinds of sensor data actually shows the highest performance.

The details of the estimation based on each approach are shown in Fig. 12. These results demonstrate that the use of sensors and limitation of the candidates improves the object localization. The locations where the performance improved are the sinks, the drawers, the bed and the sofa, i.e. locations where the sensor can easily localize the object. These improved locations indicate the effectiveness of the sensor data use. The results also showed that there are several locations that could not be correctly estimated by any of the five algorithms. Any of the five algorithms can estimate an object location based on the results of RSSI-based estimation, but if the RSSIs are heavily distorted by the presence of a human being, even the integration algorithm can hardly correct the mistaken estimation.

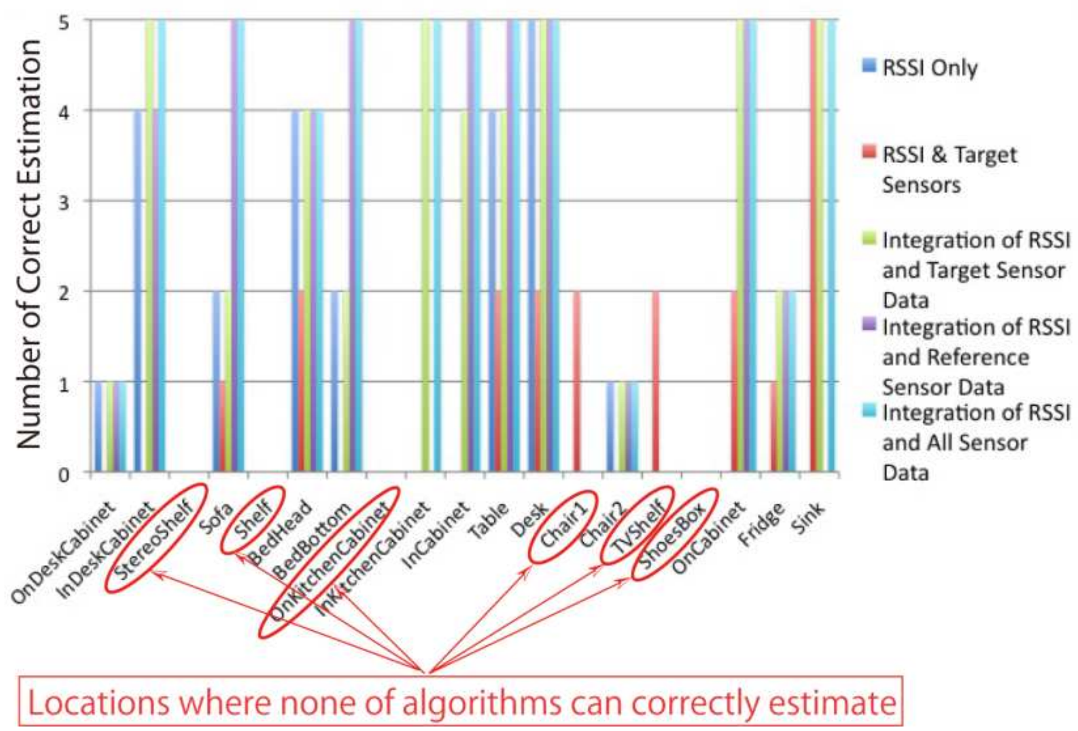


Figure 12. Performance results for each location.

5. Human localization with RSSIs between reference nodes

The human interference with the RSSI values degrades the localization performance. However, because human distortion of the RSSI values is stable, this distortion may be used to indicate the human's location. The human location is estimated by the same approach as that for object localization, using the pattern recognition technique. This is our idea for sub-room-level human localization. While the object location is estimated at the application request time, the human position is always required. Because the continuous use of a target node reduces the battery life, only the reference nodes are used for human localization.

5.1. Experiment on human localization in four areas

To confirm that the distorted RSSI can be used for human localization, we conducted a simple experiment. In this experiment, we make one person stand or sit to cut off the RF signals between two reference nodes. Because this situation drastically disturbs the RSSIs, estimation of the human's location should be easy.

The conditions for the evaluation experiment are described in Fig. 13. The datasets were gathered from 4 reference nodes. When one node is selected to be the base node, as shown in Fig. 13, the node collects RSSI from the three surrounding nodes. In total, 12 (=4×3) RSSIs were used for human localization. In the experiments, the subject sat or stood at the four locations illustrated. Data for the human absence case were also collected. This problem is regarded as 5-class classification. Direct human interference means that the RSSIs between two particular reference nodes are frequently missed, which means that the RF signals could not be received successfully. This data deficit may lead to human location estimation failure. We therefore compensated the part with the data deficit using the average of the successfully collected RSSIs. We evaluated the ratio of the true positive value in all data. Each pattern recognition method adopted the most suitable parameters for the estimation. Ten-fold cross-validation was also used for the evaluation.

The estimation results are shown in Table 1. These results indicate the possibility of estimating the four assumed human locations using the RSSIs among the reference nodes. Estimation with the 3-layered NN algorithm appears to be a little difficult, but estimations based on KNN and DKNN showed high accuracies.

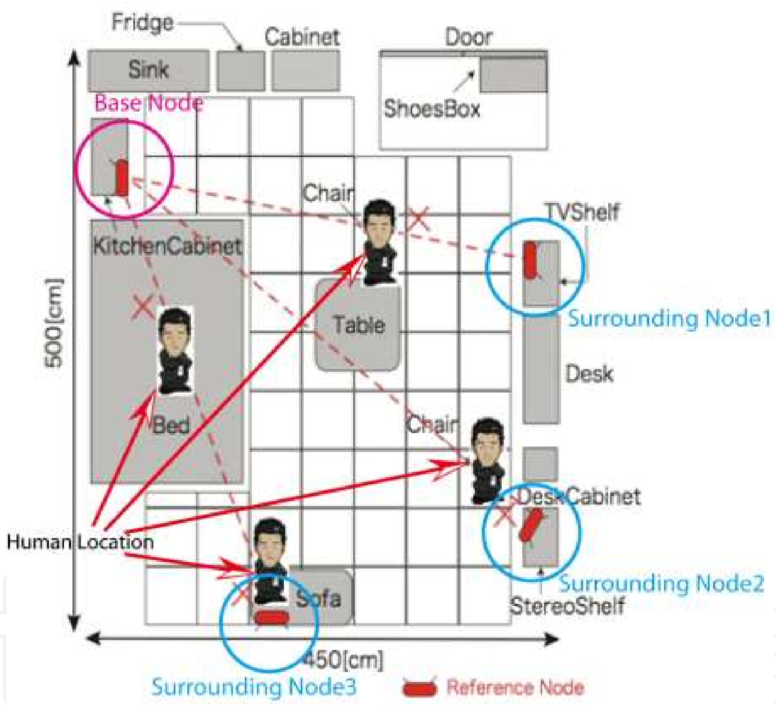


Figure 13. Conditions for experiments on human localization in four areas.

The estimation results suggest two points in particular. The first is that the 3-layered NN algorithm is poor at distinguishing the human presence case from the human absence case. It is also weak at human location estimation when compared with the other two pattern recognition methods. The other point is that KNN and DKNN can not only tell the difference between the human presence case and human absence case, but can also estimate human locations with high accuracy even under the condition where the human presence is unknown.

	Absence	Sofa	Bed	Table	Desk	Total
KNN	96.7%	96.7% (98.3%)	93.3% (88.8%)	91.7% (100.0%)	93.3% (96.7%)	94.3% (95.8%)
DKNN	98.3%	96.7% (98.3%)	93.3% (93.3%)	93.3% (100.0%)	96.7% (95.0%)	95.7% (96.7%)
NN	36.7%	90.0% (98.3%)	95.0% (98.3%)	51.7% (68.3%)	86.7% (95.0%)	72.0% (90.0%)

*Upper selection: Estimation including human absence data.

Lower selection: Estimation excluding human absence data.

Table 1. Results for human localization in four areas with RSSIs among the reference nodes.

5.2. Experiments on sub-room-level human localization

The previous experimental results showed that the direct human interference in communication between two reference nodes contained rich information for human localization. We now address a more complicated case.

The conditions for the evaluation experiment are shown in Fig. 14a). The reference node installed at the table is regarded as the center node, which then receives 14 RSSIs from the remaining surrounding nodes. For human location estimation, we took measurements with each node acting as the center node in turn to cover the whole environment. However, in this case, the same approach will increase the dimensions of the input RSSI data dramatically, which definitely results in the estimation time being too long. Therefore, we only use the reference node on the table as the center node because it is located at the center of the environment and, as Fig. 14a) illustrates, the RSSIs between this center node and other surrounding nodes can cover the majority of the environment.

We divided the environment into 49 grids (0.5 m×0.5 m) as shown in the left part of Fig. 4. We asked a subject to stand or sit on each grid to collect data sets for human localization. Also, human absence was appended to the data sets as one of the conditions. Thus, the problem is regarded as 50 (49+1) class discrimination from 14-dimensional vector data. For the experiment, 50 data sets were collected per location.

In this experiment, we assume an "Unknown" class in the output classes, which is the class to be used when the estimated result is less probable. This means that when the similarity between an input dataset and the most likely dataset in the learning database is smaller than a certain threshold, the system regards the estimated result as wrong and classifies it into the unknown class.

The estimation results are shown in Fig. 14b). The estimation accuracy as a whole is 86.2%, and the discrimination between the human presence case and the human absence case can be discriminated completely, with an accuracy of 100%. The percentage that was estimated as being in the unknown class was 1.3%, which means that almost all of the data is correctly classified.

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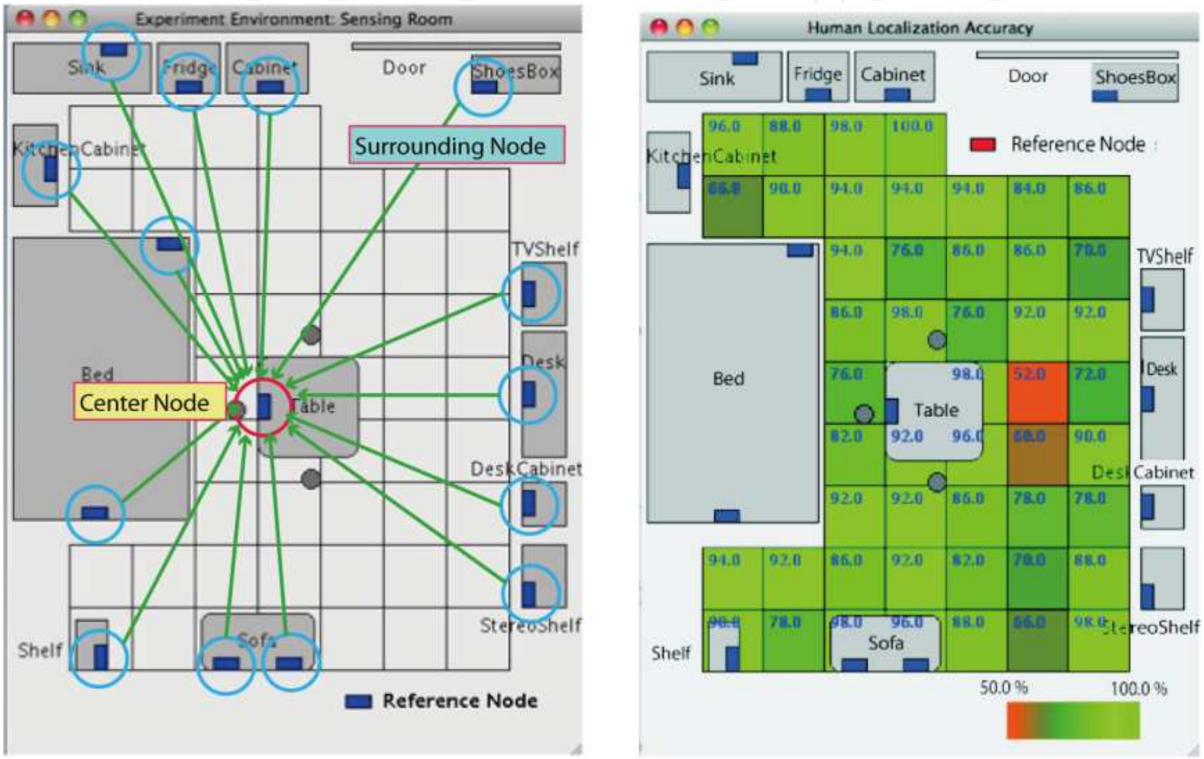
The results show that RSSIs among the reference nodes can be used as good indicators to localize a human in the environment. It is interesting that although a human standing at the right lower corner of the room does not disturb the radio wave directly, the method estimates the location accurately, which may indicate that the pattern recognition method is sensitive to slight differences caused by human interference.



a) Condition for Human Localization b) Human Localization Results

Figure 14. Conditions and results for the human localization experiment

There are some positions that are difficult to estimate with our approach. The worst two estimations are illustrated in Fig. 15. These scattered estimation candidates are the minority of the estimation as a whole and the majority of the mistaken estimation candidates are quite close to the correct location. This result means that loose conditions such as large grid size may improve the localization performance. Human localization using only RSSIs may contain some trade off between spatial resolution and localization accuracy.

These results demonstrated that the system could localize human positions in indoor environments with RSSIs only.

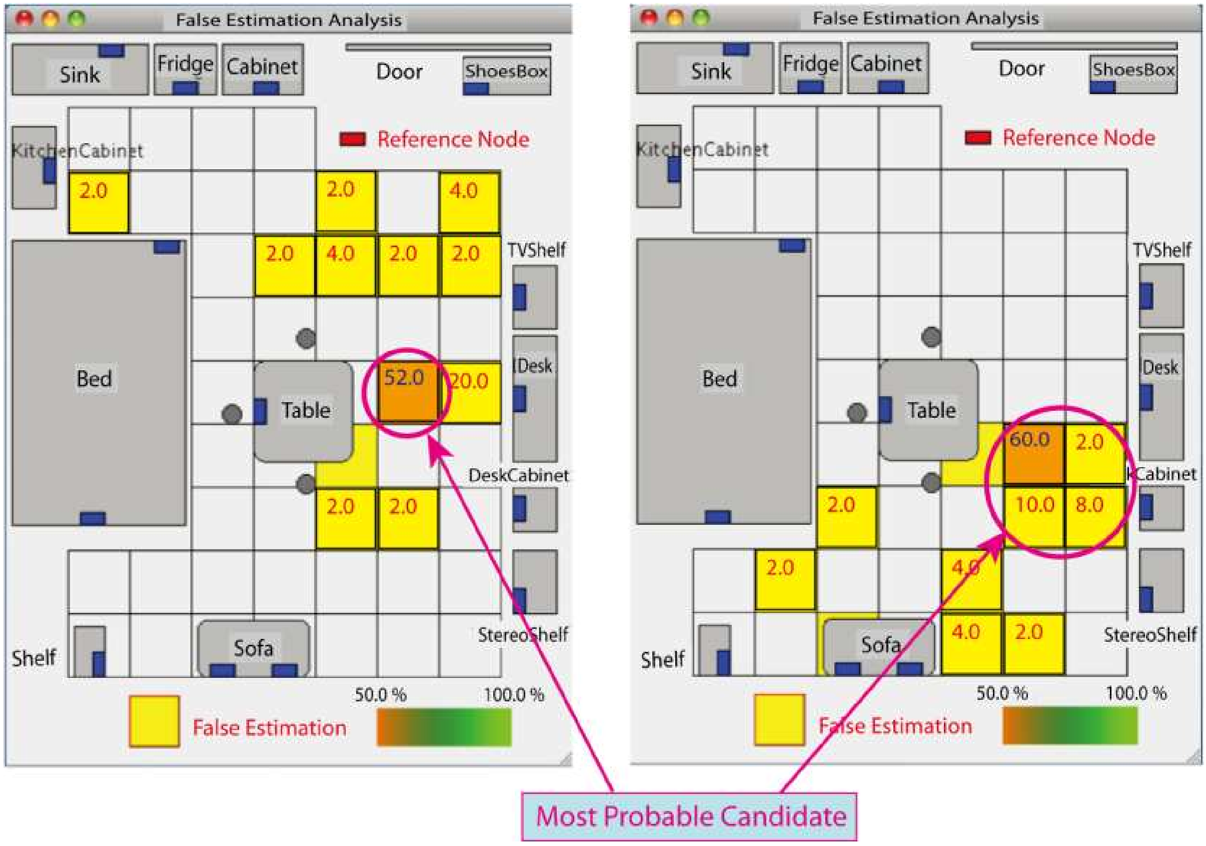


Figure 15. Estimation results at the worst estimation score areas.

6. Conclusion

We proposed methods for object and human localization using a ZigBee-based RFID system. Our method estimates the node locations using a pattern recognition technique from RSSI data among the nodes, environmental sensor data and estimated human behavior to reduce performance deterioration caused by human interference with radio waves. The experiments demonstrated that our method increases object localization accuracy by about 20% under human presence conditions. Considering the fact that human interference with the RSSI is stable, we also performed human localization using pattern recognition based on the RSSI values. Our experimental results showed that our approach is feasible for sub-room-level human localization.

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