Object Location Estimation with ZigBee Module in Actual Living Environment

Ming Li, Taketoshi Mori, Hiroshi Noguchi, Masamichi Shimosaka, and Tomomasa Sato
Graduate School of Information Science and Technology, The University of Tokyo
7-3-1 Hongo Bunkyo-ku, Tokyo, JAPAN
Email:{fukada, tmori, noguchi, simosaka, tomo}@ics.t.u-tokyo.ac.jp

***Abstract*—This paper describes a method for estimating object location in a real living environment. We have developed this method with ZigBee module, which is a kind of wireless communication module based on low-cost, low-power, wireless mesh networking proprietary standard. In addition, to grasp the motion state of object, we attached a three-axis acceleration sensor to the module as a motion detector of objects. Regarding how ZigBee module is used, we adopt a pattern recognition method to choose features appeared in the signal strength indicators (SSIs) received by several reference modules at different places. Then, we classify the selected characteristics into a particular location through the comparison of input RSSIs with learning data, which contain RSSIs collected at every location in the environment in advance. In our work, we regard the estimated location as the most probable location where the object is placed. As for the acceleration sensor, we analyze the change of acceleration of each axis to detect the information about when the object is moved or placed, which decides the timing to estimate object location. Experiment results showed that the proposed method can estimate object location accurately more than 95% in a real living environment without human existence. Moreover, our method was proved to be able to distinguish some confusing locations such as drawers of cabinet. In addition, the results also suggested that our proposed method is valid even in the situation that plural persons exist in the environment.**

I. Introduction

Indoor object localization system has become more and more significant in various fields recently. For example, people not only feel stress but also waste their 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 residents' life patterns 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 not 3-dimensional "position" of the object, but its "location" in living environment such as "on cabinet" or "on table", because we think the only object location is sufficient to achieve our application. Various technologies have been used to construct such kind of systems so far [1], but most of them have difficulty in identification of the objects.

Against this problem, many studies have focused on using radio frequency identification (RFID) due to its strong identification ability[2][3]. Because RFID tag has a property to communicate with RF reader by RF signals, it is superior to other technologies for identifying objects. RFID can be divided into two types, one is called passive RFID, and the other is called active RFID. Passive RFID is widely used in many fields nowadays. Suica, a rechargeable contactless smart card used as a fare card on train lines in Japan, is the best example of passive RFID. When people hold Suica up over the prescribed place, RF reader embedded at the place will energize and activate the passive RFID tag by electromagnetic waves. Then the reader receives traffic information of users from the activated RFID tag. The main characteristic of passive one is that it uses reader's energy to transmit its information. For this reason, the transmission range of passive RFID is short, 1 meter at best. In contrast, because active RFID has a battery inside, it can use its own energy to communicate with RF reader. This characteristic enables active RFID to have longer transmission range than passive one. Active RFID has another significant characteristic that deserves our attention. Signal strength indicator (SSI) received by RF reader depends on the distance between a tag and reader. This dependency can be used as a clue about object location[4][5].

We choose active RFID rather than passive RFID as our key technology for the following reasons. The first one is for the long transmission range. Because our purpose is to develop an indoor object localization method, long transmission range is more convenient than short one. Another reason is for the number of RF readers required in object location estimation. As the transmission range of active RFID is much longer than that of passive RFID, the necessary number of active RFID 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. 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.

A great number of researchers have focused on developing indoor localization methods based on active RFID up-to-date. For example, Hightower[4] 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[5][6]. 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 location estimation, related work[3] focused on the idea that any kinds of motion of objects must be caused by human. Therefore in the previous work, we introduced floor sensors to detect human position in the environment. Floor sensors are pretty effective for the detection of human position, however they also have some serious problems. One is that accurate human position detection requires quite a lot of floor sensors embedded in the environment. Actually, we installed 356 pressure sensors to cover the whole environment. Because the unit price of a floor sensor is not cheap, the total cost for installing all the floor sensors is highly expensive. Besides, because floor sensors are supposed to be buried under the floor, they need not only heavy labor but also long time to install. It must be troublesome to repair those floor sensors when some of them go out of order.

Toward this problem, our previous work[7] tried eliminating floor sensors in location estimation. According to the experiment results, it was proved that even without floor sensors, which means that even without using the accurate human position information in the environment, the method can also estimate object location in high accuracy. However, it still requires external sensors such as table sensor, sofa sensor, and switch sensors for the estimation.

To reduce the installation cost and maintenance burden caused by external sensors, we intend to use only active RFID tag and sensors which are small enough to attach to it for indoor object localization. In our previous work[3][7], we used active RFID of SpiderV series, whose transmission range if 303MHz. Such kind of low frequency band has a characteristic that signal reflects easily and even an obstacle stands between a tag and reader, the signal will be diffracted to accommodate. However, as the signal reflection will occur easily, the signal strength indicator (SSI) received by a reader not necessarily equals to the SSI received through minimum distance. As mentioned above, because we use the dependency of received SSI (RSSI) with distance between a tag and reader as a significant clue for estimating object location, this kind of characteristic of SpiderV gives a fatal influence on estimation accuracy.

For this reason, we use ZigBee module, which follows a low-cost, low-power, wireless mesh networking proprietary standard. Its frequency band is 2.4GHz, which means that it goes straight on rather than diffraction. Therefore the RSSI between two nodes mostly indicates the SSI received through minimum distance. Regarding ZigBee module, MOTE and Sun Small Programmable Object Technology (Sun SPOT) also have the same characteristic. However, because we intend to attach various types of sensors to ZigBee module according to the necessity for object localization, and because we have a plan to minimize the size of each sensor node in the near future, we try making a trial product which contains ZigBee module and a microcomputer because of its extension possibility for sensor attachment. We choose to attach three-axis acceleration sensor to the prototype for the detection of object motion. As for the microcomputer chip, it is used to control transmission with ZigBee module and determine the format of transmitting data.

Thus, we did some experiments in the real living space and the results indicate that our proposed method can achieve sufficient accuracy in non-human existed environment. Our experiment results also proved that even human exists in the environment, although the estimation accuracy will drop a little, it is also valid for object location estimation.

II. Materials

In this section, we will introduce the prototype device for object localization and explain how we set up the protocol for collecting RSSI data and for estimating object location.

A. Requirements Specification

To estimate object location in daily life, the active RFID tag should meet some requirements both in appearance and in function. We decide the following elements as the requirements for the device.

1) small enough to attach to object
2) easy to acquire the components
3) able to measure the received signal strength indicator (RSSI)
4) long enough transmission range
5) easy to control the transmission
6) able to attach various sensors depends on necessity

According to the above requirements, we selected XBee module, and Arduino Diecimila or Funnel I/O as the components of our prototype. In the following subsection, we will explain each characteristic and how it function in estimating object location.

B. Active RFID Tag Components

- **XBee**
  XBee is a wireless communication module, which follows ZigBee standard.1 ZigBee is a specification for a suite of high level communication protocols using small, low-power digital radios based on the IEEE 802.15.4-2003

standard. The advantages of active RFID with XBee can be summarize as the following.

1) easy to purchase because of its high saturatino level
2) able to measure the received signal strength (RSSI) between nodes
3) long transmission range
4) easy to change or set up transmission protocol

- **ADXL355**
ADXL355 is a kind of acceleration sensors, which can detect three axes' accelerations.2 With this sensor attached with XBee module, we can know whether the object moves or not. Furthermore, we can also estimate object motion state accurately by focusing on the change of each axis' acceleration. Information about object motion state is important because it helps system determine when to estimate object location. In other words, system does not estimate object location while the object are moving. System estimates object location only when it knows that the object is placed somewhere.

Fig. 1. XBee Module

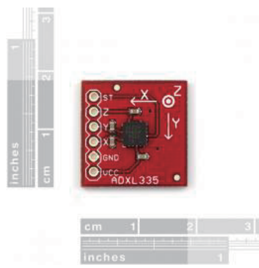

Fig. 2. ADXL355 Acceleration Sensor

- **Arduino Diecimila or Funnel I/O**
Both Arduino Diecimila(Fig.3) and Funnel I/O(Fig.4) are the tools for the design and development of embedded computer systems, consisting of a simple open hardware design for a single-board microcontroller, with embedded I/O support and a standard programming language. As the following figures illustrate, we use Arduino Diecimila as reference nodes, which are mainly attached to rather fixed objects such as furniture. Whereas, because of its small size, we use Funnel I/O as target nodes, which are chiefly attached to objects that resident intends to manage.

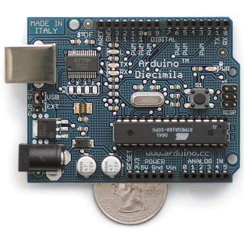

Fig. 3. Arduino Diecimila

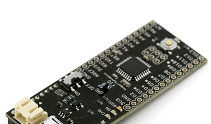

Fig. 4. Funnel I/O

We use these components to assemble our active RFID. For the reference tag, which behaves as a reader, we uses XBee module, Arduino Diecimila as the components(Fig.5). Whereas, for the target tag, we attach not only XBee module but also ADXL355 acceleration sensor to Funnel I/O(Fig.6). Because Arduino Diecimila is used as a reference tag and does not move as often as a target tag, we supply power to it through a wired cable. Whereas, because Funnel I/O plays a role as a target tag and moves much more frequently than Arduino Diecimila, we have to supply power to it from a battery whose life approximates 2 or 3 days. Of course, from the practical point of view, it will be quite troublesome to exchange batteries of Funnel I/O modules every 3 days. However, because what we think as the most important is to examine the possibility of indoor object localization by SSI, the devices we introduce here do not come up with any ideas for saving batteries. In short, we place Funnel I/O just as a trial module. As for the problem of device's batteries, we think technology improvement can resolve it, that is to say, device for data communication will be smaller and more energy-saving than now, and the capacity of battery will also become larger in the future, which means the span for battery exchange will be extended. Besides, if we make target tags stop or reduce transmitting data when they are not activated, for example, the life of battery will be longer than ever.

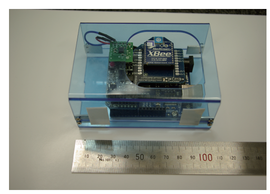

Fig. 5. Reference Node

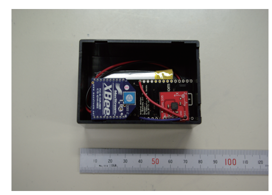

Fig. 6. Target Node

In the following subsection, we explain how to collect RSSIs for pattern recognition and how to detect object motion and estimate its location during daily life.

C. Protocol Establishment

For the following reasons, we divide the transmission mode with XBee module into two modes, "Motion Detecting Mode" and "RSSI Collecting Mode". The first reason is that system has to know what kind of data it requires because it does not intend to estimate object location while the object is moving. And the second reason is that to guarantee the quality of RSSI transmitted between XBee modules, system should stop all other communications in RSSI Collecting Mode. XBee module is normally in Motion Detecting Mode, which allows wireless communication between the target node and itself. We can use one XBee module to communicate with just one node or all the nodes available in the environment, however, the destination address has to be set up in RSSI Collecting Mode. To get into RSSI Collecting Mode, system has to send a especial string to the node that it intends to control during Motion Detecting Mode. Once the target node changes to RSSI Collecting Mode, it cannot communicate with other nodes until it gets out of the mode. Therefore, to detect object motion in daily life and measure the RSSIs between the target node and reference nodes, we have to handle XBee's transmission modes in the following way.

In the first step, the system keeps receiving three axes' acceleration from every node. Then, if a remarkable change in any axis' acceleration occurs, the system makes that node get into RSSI Collecting Mode, which means that the system can control that node and make that node send commands to others. After the target node gets into RSSI Collecting Mode successfully, the system has the node send a command to get the RSSIs between the target node and every reference node. Here, as the characteristic of RSSI Collecting Mode, the target node cannot send those RSSI data back to the system because all of the communication with the target node is stopped. Therefore the target node stores those collected RSSIs and send back to the system after the system allows it to escape from the RSSI Collecting Mode. All the process is illustrated in the following Fig.7～Fig.9.

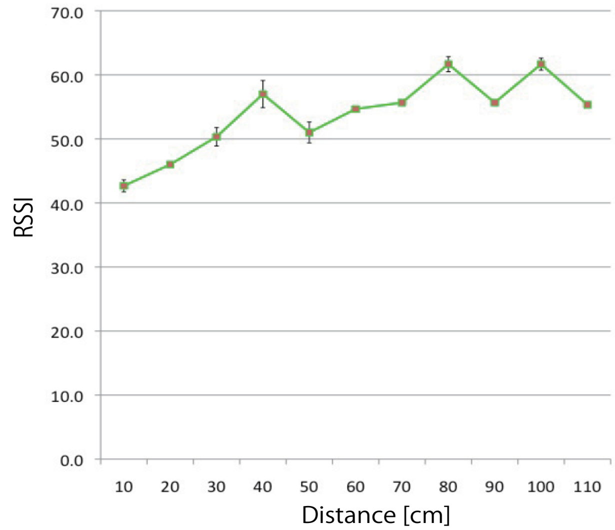

Fig. 10. Dependency of RSSI on Distance

III. Methodology

This section introduces the proposed algorithm used for indoor object location estimation in a real living environment. The algorithm can be divided into two parts, one is about how to detect object motion state, and the other is about how to estimate object location in the actual environment.

A. Object Motion Detection

As mentioned above, ADXL355 acceleration sensor can provide us with accelerations of three axes. Because the acceleration of each axis changes quite sensitively according to its posture, we consider this change of acceleration of each axis can be an important clue to know object motion state. It is possible to estimate object motion states just based on the change of accelerations. In our research, we estimate the following five types of motion states by analyzing acceleration changes.

1) **Stable** object is in stable state
2) **Start Moving** object starts moving
3) **Keep Moving** object keeps moving
4) **Ambiguous** object is either in ”Moving” state or in ”Stable” state
5) **Stop Moving** object stops moving

To be concrete, when a node shows noticeable changes in acceleration beyond thresholds after a long time of ”Stable” state, our system judges it tobe ”Start Moving”. Then, as long as the acceleration sensor responds, the state is thought of ”Keep Moving” state. However, in the actual case, even an object is moving, sometimes the acceleration sensor attached to the node does not show any remarkable response up to the way it moves. To avoid mistaken estimation in such cases, even the changes of accelerations cannot be detected, the system does not determine the state as ”Stop Moving” instantly. Instead, the system regards such a state as ”Ambiguous”, which means that the node is either in the state of ”Keep Moving” or ”Stop Moving”. If the acceleration sensor does not show any noticeable changes after a fixed period of time, the system judges the first moment that the acceleration sensor' response disappears as ”Stop Moving”, and the following moments as ”Stable” state.

To examine the validity of this algorithm, we made some preliminary experiments. Because it is difficult to generalize all the patterns of object motion, in the preliminary experiments, we just raise an object and move it for a while, then place it somewhere. However, in spite of the simple algorithm, system can distinguish the state of object motion from others quite well more than 90% according to our experiment results.

B. Object Location Estimation

As we mentioned above, one of the most important characteristics for object location estimation is that RSSI, which stands for Received Signal Strength Indicator, has a dependency on the distance between nodes. Against our expectation however, as shown in Fig.10, RSSI does not have linear relativity with the distance between XBee nodes, as well as show in a one-to-one ratio with the interval due to environmental factors such as human and furniture. That is to say, although the relativity between RSSI and the distance can be used as a clue to determine object location, it is difficult to use the dependency without processing.

The approach that we tried to improve the accuracy of object location estimation is to use pattern recognition method. Although the RSSI is sensitive to some environmental noises, it still has dependency on the distance to a certain extent. According to some pilot experiments, we found that the RSSI from a fixed location indicated almost the same value regardless of time as shown in TABLE.I. Therefore, the main idea is that we may reduce the environmental influences on RSSI not by using just one RSSI, but by using the pattern extracted from several RSSIs. In order to realize this idea, we placed several reference nodes at different places so that each reference node can receive the SSI from the target node.

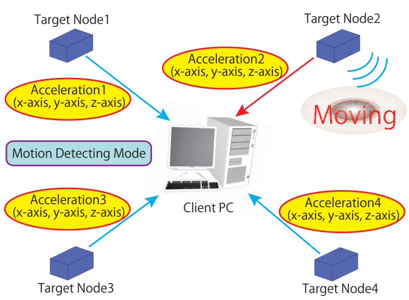

Fig. 7. Detecting Object Motion

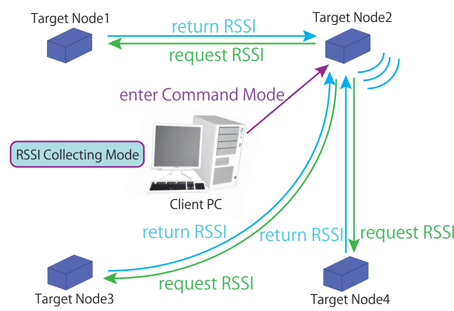

Fig. 8. Collecting RSSIs

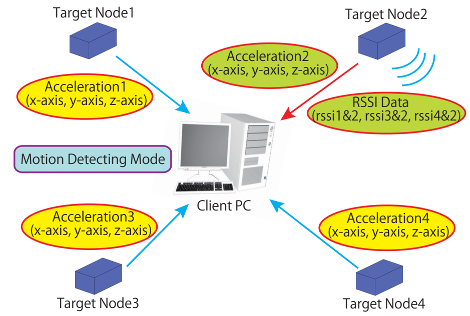

Fig. 9. Sending RSSIs and Detecting Object Motion

TABLE I
ESTIMATION PERFORMANCE DEPENDENCY ON TIME

Number of Data (N)	2 months ago	present
N = 50	94.7%	99.0%
N = 100	93.3%	99.8%
N = 150	94.6%	99.8%

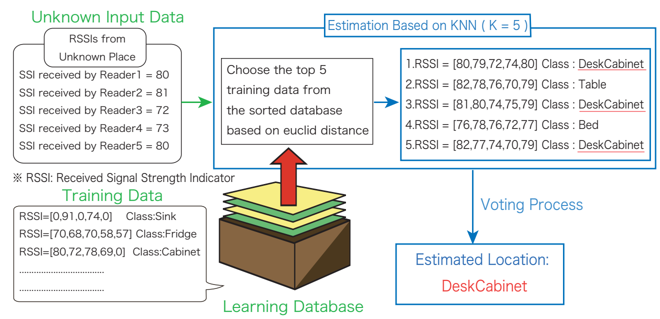

Fig. 11. Location Estimation Based on KNN

In our work, we used three kinds of pattern recognition methods such as k-nearest neighbor (KNN), distance-weighted k-nearest neighbor (DKNN)[8], and three-layered neural network (NN) algorithms. KNN is a method for classifying objects based on closest training examples in the feature space. The nearest neighbor algorithm, which means that K equals to 1, has strong consistency results. As the amount of data approaches infinity, the algorithm is guaranteed to yield an error rate no worse than twice the Bayes error 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. As for DKNN, it is a extension of KNN, which weights the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. When it comes to 3-Layered NN, in many cases it can demonstrate high discrimination ability toward data of multiple dimensions and linearly inseparable. Therefore, in our work, we intend to adopt these three methods for object location estimation with RSSIs.

Let's take an example of KNN algorithm to explain the recognition process in Fig.11 The first step when the target object is placed at unknown place, is to collect RSSIs between the target node attached with the object and reference nodes placed at different spots in the environment. In the Fig.11, we supposed five reference nodes 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.

IV. 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.

A. Experiment Design

To evaluate our estimation algorithm from different aspects, we made various experiments based on different conditions.

We conducted the same experiments as many times as the number of pattern recognition methods we used. In our work, we tried three kinds of pattern recognition methods such as KNN, DKNN, and 3-Layered NN, to evaluate the effect of each method on the performance of estimation. Generally speaking, the performance of classification highly depends on the parameters used in 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, we tried various cases by varying parameters from one to another and chose the best combination of parameters according to the estimation performance.

Besides, we divided experiment conditions into five types, 1) Estimation with different number of learning data, 2) Estimation of different number and type of locations, 3) Estimation by different number of reference nodes, and 4) Estimation under the condition of human existence. According to 1), we expect to know the proper number of learning data, and the locations that each pattern recognition method has difficulty in estimation. From 2), we hope to know how well our proposed estimation method can accommodate to the increase of supposed locations. Moreover, we intentionally add some confusing places to estimate such as the different drawers of the same cabinet to examine distinction ability of our estimation method. Regarding 3), as the total cost of each node is not inexpensive, we would like to know the sufficient number of reference nodes for object location estimation. Lastly, as for 4), because RSSI is thought to be influenced greatly by human existence, we intend to prove this knowledge and see how well our method can accommodate to it.

B. Experimental Conditions

As our work aims to estimate object location in real living environment, we made all the experiments in a room shown in Fig.12. As Fig.12 demonstrates, the room contains various kinds of furniture. Generally speaking, one of the most serious factors to drop localization accuracy is environmental obstacles such as furniture made of metal. However, to prove our proposed method is valid in actual living space, we appear ready to make experiments under this condition.

Besides that, we determined several experimental conditions listed in Fig.13. At the first step, we assumed 12 locations where objects would be placed and 5 reference nodes installed at different places. Regarding human existence, we did not allow human in the room at the first step. However, to add more difficulties to experiments, we increased the number of supposed locations from 12 to 17 shown in Fig.13, and also changed the number of reference nodes to see the influence on estimation accuracy. As for the number of supposed locations, we chose 12 as a standard number because 12 locations can cover almost all the areas inside the environment, under the precondition that objects will not be placed on the ground. The 5 additional places are composed of drawers that are difficult to distinguish from others because they located quite closely. On the other hand, as for the number of reference nodes, we chose 5 as a standard number. That is because, from the experimental point of view, it is the smallest number to cover all the areas inside the environment geometrically. Afterwards, we added or reduced some reference nodes to examine how much the estimation performance would depend on the number of reference nodes. For pattern recognition, we constructed a learning database with about more than 2,500 data sets stored in it. In more detail, we saved the same amount of RSSI data

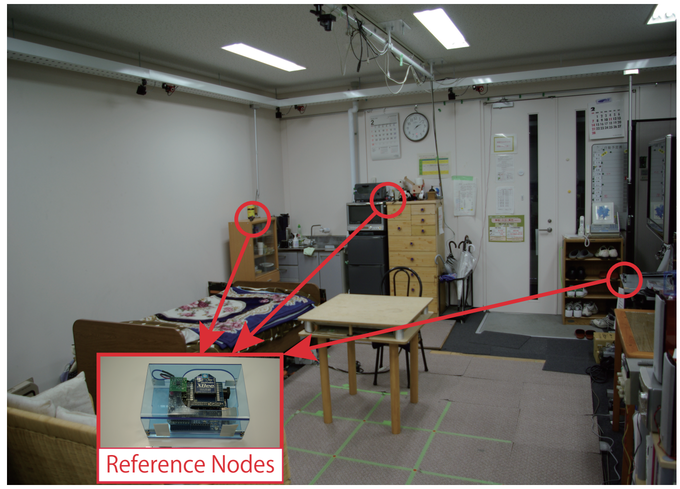

Fig. 12. Experiment Environment

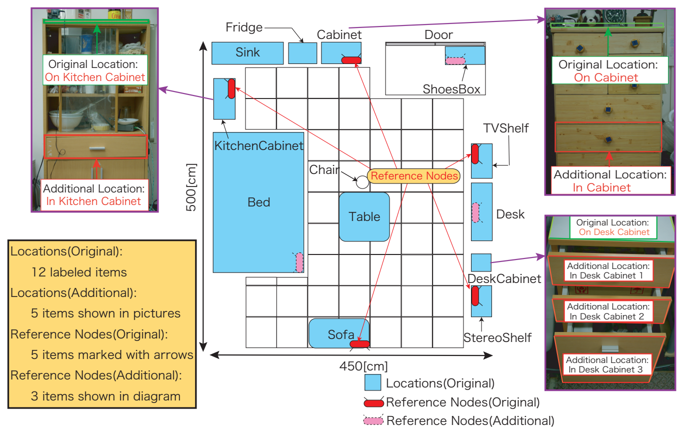

Fig. 13. Experimental Conditions

sets (about 50〜150) from every location of the labeled 17 locations as training data.

In the evaluation part, we applied cross validation to the learning database. To be concrete, we divided the learning database into two parts. One is called testing data, which contains one set of RSSIs of every location, and the rest is called training data, which is used for pattern learning. Then, we took the next set of RSSIs as testing data to estimate location. Thus, the estimation performance of our proposed method is defined as the following equation(1).

$$EstimationAccuracy[\%] = \frac{\sum_{i=1}^{N} EA_i}{N} \qquad (1)$$

EA: Estimation Accuracy of Testing Data
N: Total Number of Testing Data

C. Results and Discussion

In this subsection, we demonstrate experiment results corresponded to our experiment design.IV-A Then, we give our discussion about each experiment.

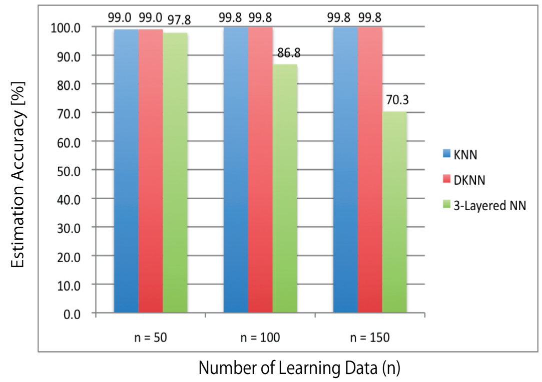

Fig. 14. Estimation by Different Number of Learning Data

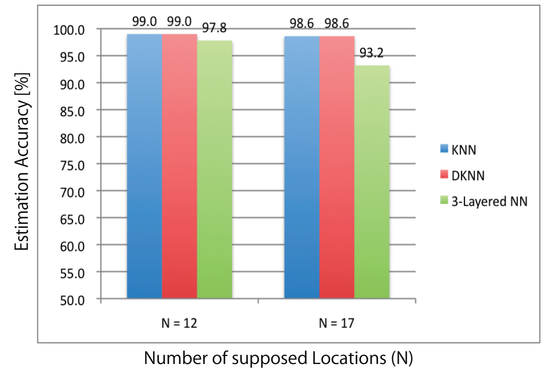

Fig. 16. Estimation by Different Number and Type of Locations

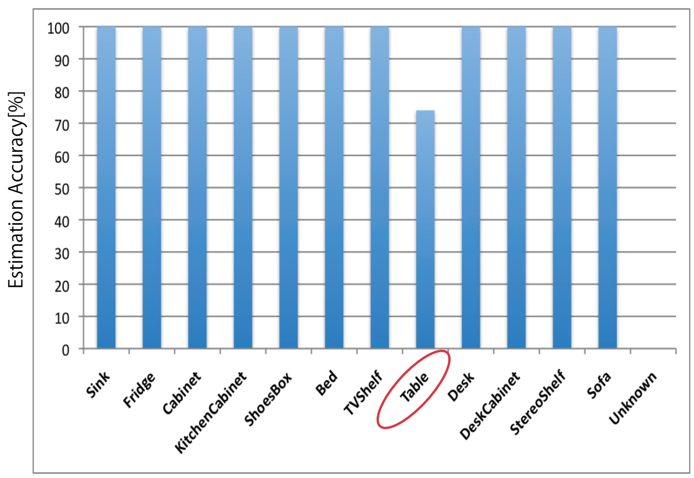

Fig. 15. Estimation with 3-Layered Neural Network

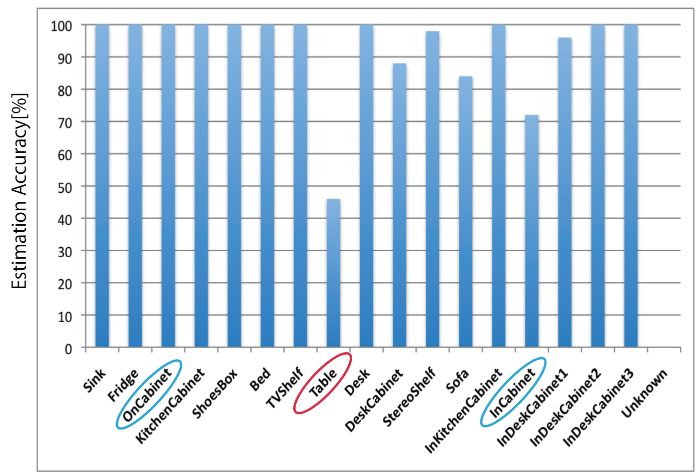

Fig. 17. Estimation with 3-Layered Neural Network

1) Estimation with different number of learning data: As mentioned above, we collected RSSI data at each location in the environment and used those data sets to classify object into particular location. In Fig.14, "n" means the number of RSSI data sets collected at each location. The result graph suggests us two things. One is that 50 learning data sets per each location are enough for localization. Therefore, in the following experiments, we use the learning database that contains 50 data sets for each location. Another is that as long as the system adopts KNN or DKNN as the pattern recognition method, the estimation accuracy does not depend on the number of learning data so remarkably. On the other hand, 3-Layered NN has more difficulties in estimating object location as the number of learning data increases.

To make this difference clear, we will show the estimation accuracy by each location with 3-Layered Neural Network (NN) in Fig.15. According to this graph, we can notice that "Table" seems difficult to estimate with NN. That is because table is located just in the middle of all reference nodes, which means that table is far from every reference node. As Fig.10 demonstrates, the farther the distance between nodes becomes, the more difficult object localization with RSSI will be.

2) Estimation of different number and type of locations: In the next step, we intend to see how well our proposed method can accommodate to the increase of locations. In this experiment, we add 5 new locations shown in Fig.13 to the existing 12 locations. We used learning database consisted of 50 training data sets for each location and 5 reference nodes to measure the RSSIs with the target node.

In the following Fig.16, we can notice that our proposed method can effectively estimate object location even the number of locations increase. Particularly, it has been proved that estimation with KNN and DKNN are little affected by the increase of locations, whereas, estimation with 3-Layered NN becomes worse when the variety of locations increases. In Fig.17, we can see the similar tendency that appears in Fig.15. However, in this case, "InCabinet" also drops its estimation accuracy seriously other than "Table". The reason for this phenomenon is thought to be that it becomes more difficult to distinguish "OnCabinet" from "InCabinet".

3) Estimation by different number of reference nodes: In the third step, we intend to see the influence of the number of reference nodes on estimation accuracy. All the experiments above use 5 reference nodes illustrated in the Fig.13. In this experiment, however, we change the total number of reference

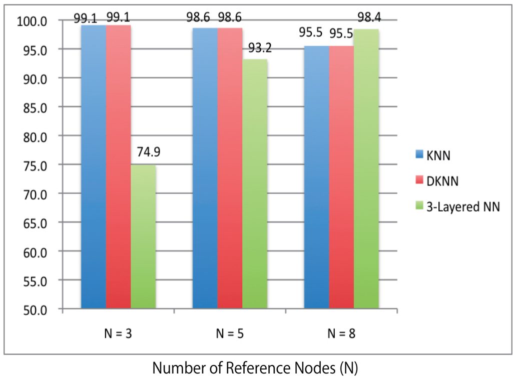

Fig. 18. Estimation by Different Number of Reference Nodes

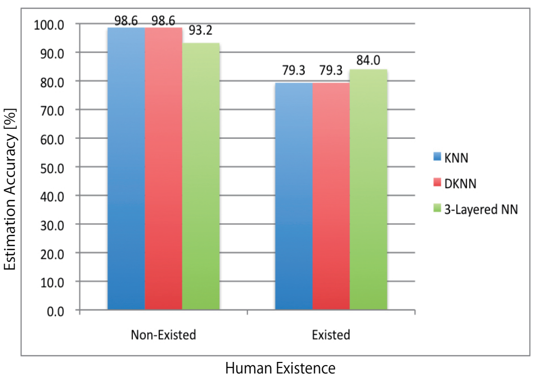

Fig. 19. Estimation against Human Existence

nodes in two ways, one is to reduce two reference nodes from the existing nodes, and the other is to add three nodes to the existing nodes. In the former case, we only used the reference nodes installed at kitchen cabinet, TV shelf, and sofa. Whereas, in the latter case, we attached reference nodes to bed, shoes box, and desk.

The result graph shown in Fig.18 suggests us two things in particular. One is that the best estimation accuracy has little difference among each number of reference nodes. The other is that KNN and DKNN are strong under the condition of few number of reference nodes, whereas, although 3-Layered NN has trouble in estimating object location when reference nodes are few, but it demonstrates its ability better than KNN and DKNN when the number of reference nodes increases. That is to say, we should chose the proper pattern recognition method according to environmental conditions.

4) Estimation under the condition of human existence: In the last step, as we indicate that environmental noises such as the presence of human has serious influence on RSSI, we must examine how well our proposed approach can estimate object location even under the human existed condition. In this experiment, we used 5 reference nodes and supposed 17 locations to estimate. As for pattern recognition, we use learning database that contains 50 training data sets for each location.

As Fig.19 shows, the estimation accuracy does drop when human exists in the environment. However, when we use 3-Layered NN as pattern recognition method, the estimation accuracy is sufficient even under the human existed condition. Furthermore, as the above experiments show, when human does not exist in the environment, KNN and DKNN demonstrate its classification ability well, however, when human exists in the environment, 3-Layered NN can estimate object location more effectively than those two methods. This conclusion suggests us that we can change the pattern recognition methods used in the system according to situations.

V. Conclusion

In conclusion, we have constructed a wireless communication device with ZigBee module and an acceleration sensor attached with it, and used that to develop an indoor object localization method, which shows sufficient estimation accuracy even under human existed condition. Besides, we made various experiments to find that our proposed method can accommodate both the increase of locations and decrease of reference nodes. This result indicates that we can use less references nodes to estimate more locations without dropping localization accuracy seriously, which contributes to the reduction of expenses. In addition, those experiment results prove that it is possible to estimate quite ambiguous locations such as drawers of cabinet with the high accuracy more than 70%.

One of the future work is to reduce the locations that are difficult to estimate accurately because of various environmental influences. To achieve this goal, we intend to attach some new types of sensors that can tell us richer information about surroundings such as temperature sensor or humidity sensor.

References

[1] S.Park, K.Kim, S.K.Park, and M.Park. ”Object Entity-based Global Localization in Indoor Environment with Stereo Camera”, In Proceedings of SIC-ICASE Intl. Joint Conference 2006, pages 2681-2686, October 2006.

[2] T.Mori, A. Takada, H.Noguchi, and T.Sato. ”Behavior Prediction System Based on Environment Sensor Records”, International Conference on Network Sensing Systems 2005 (INSS 2005), pages 40-43, 2005.

[3] T.Mori et al. ”Active RFID-based Object Management System in Sensor-Embedded Environment”. FGCN2007 Workshop. International Symposium on Smart Home 2007 (SH 2007), pages 25-30, 2007.

[4] J.Hightower, G.Borriello, and R.Want. ”SpotON: An Indoor 3D Location Sensing Technology Based on RF Signal Strength”, In Technical Report UW-CSE 2002-02-02, The University of Washington, February 2000.

[5] L.M.Ni, Yunhao Liu, Yiu Cho Lau, and A.P.Patil. ”LANDMARC: Indoor Location Sensing Using Active RFID”. Pervasive Computing and Communications 2003 (PerCom 2003). Proceedings of the First IEEE International Conference on. pages 407-415, 2003.

[6] Sung-Tsun Shih, Kunta Hsieh, and Pei-Yuan Chen. ”An Improvement Approach of Indoor Location Sensing Using Active RFID”. International Conference on Innovative Computing Information and Control 2006 (ICICIC 2006), Vol.2:pages 453-456, August 2006.

[7] Ming Li, Taketoshi Mori, Hiroshi Noguchi, Masamichi Shimosaka, and Tomomasa Sato. ”Use of Active RFID and Environment-Embedded Sensors for Indoor Object Location Estimation”, International Universal Communication Symposium 2009 (IUCS 2009), December 2009.

[8] Tsang-Long Pao, Yun-Maw Cheng, Jun-Heng Yeh, Yu-Te Chen, Chen-Yu Pai, and Yao-Wei Tsai. ”Comparison Between Weighted D-KNN and Other Classifiers for Music Emotion Recognition”. International Conference on Innovative Computing Information and Control 2008 (ICICIC 2008), pages 530, June 2008