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AutoADL: Automatic Detection of Activities of Daily Living and Resident Identification

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A thesis submitted to the faculty of DGIST in partial fulfillment of the requirements for the degree of Master of Science in the Department of Information and Communication Engineering. The study was conducted in accordance with Code of Research Ethics[1]

12. 26. 2014

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[1] Declaration of Ethical Conduct in Research: I, as a graduate student of DGIST, hereby declare that I have not committed any acts that may damage the credibility of my research. These include, but are not limited to: falsification, thesis written by someone else, distortion of research findings or plagiarism. I affirm that my thesis contains honest conclusions based on my own careful research under the guidance of my thesis advisor.

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ABSTRACT

Localization is a basic technique which used by positioning and navigation services in our daily lives. These services typically utilize GPS in outdoor environments. However, they cannot be used in indoor environments because GPS signals are hardly received in indoor environments. By contrast, indoor localization does not utilize GPS as well as has some problems arising from a small space with many obstacles as well as issues of security and privacy. Nevertheless indoor localization is a very important technique for smart homes that can be applied to many indoor services. Therefore, many indoor localization studies have been conducted using sensors such as RF signals, RFID, ultrasonic sensors, smartphones. However, these studies only provide position information or need holding devices to user. There is a problem to be used in indoor localization. So, we propose our system, called AutoADL, which gives position and identification information without using dedicated devices. Existing study [25] has the same advantages as AutoADL. But, this study has some problems such as a limited number of people that can be tracked, and a need for labor intensive installation process. In contrast, AutoADL automatically calculates the number of people it can track and the characteristics of targets using K-means clustering [32], Bayesian Information Criterion (BIC) scoring [33], and error rate checking. In addition, it provides many people's position and identification information with high accuracy using Multi-Hypothesis Tracking (MHT) algorithm. We simulate AutoADL in several environments such as changing the number of residents, home environments, weight-values, and resident's height. In the result, when sensor distribution is smaller than 4cm and the difference of resident height is bigger than 5cm, tracking accuracy became higher than 90%.

Keywords: Indoor Localization, Ultrasonic, Automatic system, Identification

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I. Introduction

Localization is can important service commonly used by, e.g., smartphones. People use many services such as positioning and navigation using a GPS sensor in smartphones. However, GPS cannot be used in indoor environments, because GPS signals are very weak due to the distance between sensors and satellites. So, many services like positioning and navigation for outdoor environments are not available in indoor environments. Typically, indoor localization researches used RFIDs [2]-[4], RF signals [9]-[20], ultrasonic sensors [5]-[8], and smartphones [21]-[24]. But, existing studies have some problems. Studies using RF signals and ultrasonic sensors only offer positioning information and limitation of the number of people it can track. Other studies using RFID and smartphones are inconvenient to use, because a target should be holding dedicated devices such as RFID tags or a smartphone. A study using ultrasonic sensors provide individual positioning and identification information, and does not need to carry any device due to use infrastructures. However, this study has some disadvantages such as difficult usage and limitation of the number of people it can track.

In this thesis, we propose AutoADL to resolve disadvantages of the above-mentioned studies. AutoADL provides practical and easy usage more than existing studies using devices, T. W. Hnat et al [25] proposed. AutoADL installs devices respectively in doorways. When a resident passes through the doorway with the device installed, AutoADL provides resident's position and identification using resident's height, prior position, and direction. In addition, AutoADL is cost-effective because devices consist of ultrasonic sensors. AutoADL automatically performs processes such as calculation of the number of residents and an initialization of for automatic tracking. Therefore, AutoADL reduces a process than an existing study [25]. In addition, AutoADL automatically provides resident's position and identification without holding any devices, and have low computational cost.

The result of this thesis is a simulation using event data. Basic experiment environment is (a) in Figure 8. Using the results of the experiments, it uses the hardware's performance as an indicator because it provides some result about the hardware performance and user's information. Various room arrangements and the number of residents are not affected by these conditions. Also, we will propose optimal sensor for home's environments through experiments results.

The contribution in the thesis is as follows:

- AutoADL provides to track up to 10 people, which makes it practically useful in home environments. In addition, we suggest several results according to constraint such as sensor specification, resident height and so on.
- AutoADL does not only adjust the number of residents it tracks, but also reduces human efforts by automatic calculation of the resident's estimation process.
- AutoADL increases usability by supporting automatic operations for the computation of weight-value.

The rest of the thesis are as follows. First, we introduce related works in Section 2. Next, Sections 3, 4 and 5 discuss the method of estimation of resident's information, resident's height, and weight-values. Section 6 analyzes the results of the experiments. Finally, Section 7 concludes this thesis.

II. Related Work

Indoor environments have a smaller area than outdoor environments, and also have many obstacles like walls, furniture and so on. Therefore, indoor environments are easy to install infrastructure, but is difficult to perform localization like positioning and navigation. In outdoor localization, GPS is used extensively. It is hard to utilize in indoor environments because it is a satellite signal having very low power. An existing study [1] uses GPS in an indoor environment, but it would need an additional antenna and has a high mean distance error of 17.4m. This study has taken into consideration that use for large buildings like supermarkets, department stores, and so on. Therefore, many study of indoor localization use various sensors such as ultrasonic sensors, smart-phone, and RFID exception of GPS. In addition, each studies proposed different localization techniques, positioning methods, and situations of problems. We discuss indoor localization techniques and methods.

2.1 Sensors

RF signals are FM signals, CDMA and WLAN signals. CDMA as code division multiple access is a famous method of cellular networks. WLAN is familiar technology as Wi-Fi. Studies in where users do not to hold any device for receiving signals in infrastructures use RF signal. Studies using RF signals use Fingerprint, and Radio Signal Strength Indicator (RSSI) methods. The fingerprint method determines the receiver's position using databases of pre-measured data, such as RSSI signal, Time Of Arrival (TOA), and so on from different positions. It has a disadvantage whereby it needs to spend much more time to make the database's data. But, its advantage is that it can have higher accuracy than other methods. N. Aloui et al [11] is a study of using the fingerprint method. It saved TOA of CDMA signals from speakers to a receiver. S. Yoon el al [15] proposed ACMI which is indoor localization systems via automatic fingerprint DB construction.

It saved signal strength of each FM stations. This study solved fingerprint method's disadvantage through automatic DB construction.

The RSSI method determines user's position by change of RSSI according to user movement. It has advantage that is less time for installation than fingerprint method. This method's drawback is that has error by target speed's change. X. Zheng et al [12] proposed device-free localization systems using RSS's change. In addition, it implements to deal with target's dynamic speed. Y. Zhao et al [19] proposed Network radio frequency environment sensing (NRSE) system. It supports the position of stationary or moving people.

Ultrasonic-based Studies uses a distance between the sensor and the target. P. Lazik et al [7] challenges a new approach that use adjusted ultrasonic signals that are called chirp signals. Chirp signals have different frequency of each device, so can transmit ultrasonic signals simultaneously. It is big benefit for high precision. E.–E et al [5] proposed rounded ultrasonic sensor sets in a ceiling. It is able to omnidirectional detection. E. A. Wan et al [6] uses signal processing such as band-pass filter, Hilbert transformation, and background subtraction. In addition, it uses Kalman smoother and simultaneous localization and mapping, so detect target's trajectories. Pandhripande et al [8] uses Time Difference of Arrival (TDOA) between each sensors.

RFID systems are similar RF signal systems because utilizes RF signal, so it needs to install infrastructure for transmitting RF signals. Typically, RFID systems have several basic components that are RFID readers and RFID tag. RFID reader read specific information on RFID tag by communication via RF signals. It is a difference, holding a RFID tag, from RF signal's systems. However, this difference became advantage and disadvantage. It can easily find out target's identification. On the other hand, it is an inconvenience point because always holds RFID tag. L.M. Ni et al [3] proposed LANDMARC system. It uses RFID RSS between reference tag and moving/target tag, where reference tags are installed in the target spaces, and moving/target tag is target with holding tag. It calculates target positions from Euclidean distance in RSS between reference tags and moving/target tag. M. Buettner et al [4] proposed activities of daily living detection systems using RFID. It uses RFID tag and WISP with accelerometer. RFID readers detect activities of daily living using location through RFID tag and sensor data via Hidden Markov Model.

Localization systems using smart-phone basically uses IMU sensor such as accelerometer and gyro sensor. It can detect several motions such as walking, stay, running and so on, using sensor data. In addition, it estimates target trajectories using estimations of target motion. For example, if target motion is walking and continues while 10 seconds, the target walks 1.11 meters. Because of human's average walking speed are 4km/h. Smart-phone has many sensors such as Wi-Fi and communication antenna, GPS, microphone, and compass sensor except of IMU sensor. So, it is easy to apply several studies. Like RFID, it has advantage and disadvantage simultaneously about always holding device. K. Liu et al [21] proposed Guoguo systems. It uses processing capability of smartphone in order to calculate distance between smartphone and anchor node using anchor node's signal in target space. In addition, it makes server side for supporting navigation and localization. S. P. Tarzia et al [22] proposed Acoustic Background Spectrum (ABS) technique. It uses acoustic background in target spaces. Most of the spaces have specific acoustic backgrounds according to space's use. It collects ABS of each space and then detects user location using ABS. Luo et al [23] proposed PiLoc system. It uses IMU sensor and Wi-Fi antenna. IMU sensor detects user trajectories and Wi-Fi antenna detects user position in absolute location. So, it supports user positions and floor plan. H. Liu et al [24] proposed Wi-Fi based localization with assisted peers. This system basically uses Wi-Fi fingerprint method. However, it has a specific point that is assisted by peers. Peers send acoustic signals to target, and then the target adjusts the target position using these signal.

2.2 Techniques

Dead-reckoning localization estimates a user's location based on a previously estimated or known position. Recently, this technique basically uses wearable devices or smart-phone using IMU sensor. Smart-phone essentially has IMU sensor and other sub-sensors as well as is held by most of the human. Luo et al [23] and Serra et al [27] are acquired through combination of sensors such as accelerometers, magnetometers, compass, and gyroscope. Dead-reckoning needs to an initial position in order to support navigation service. An initial location is several approaches using typically GPS [28], Wi-Fi signal [23], barcode [27] and so on. Dead-reckoning has a significant challenge that is accumulated error over time. Many studies challenge to solve the problem. A study [23] divide trajectories for short period of time. Other study [29] uses additional sensors and landmark.

Direct sensing localization determines the location of the user through the sensing of identifiers or tags, which have been installed in the environments. It separates two approaches [30]: (1) location information and information on the user's environment is stored in the tag itself or (2) this information is retrieved from a database using the tags unique identifier. These techniques have five different technologies have been identified that being for the tags: (1) RFID, (2) Infrared, (3) Ultrasound identification, (4) Bluetooth, and (5) Barcode.

Triangulation localization uses the location of at least three known points to determine user's location. Typically, triangulation uses lateration method that calculated distance between a target and three nodes. Representatively, GPS use lateration methods in triangulation. Other triangulation method that is called angulation methods using relative angles between a target position and each sensor. Angulation uses the angular measurements from at least three known points to the target to determine the target position.

Pattern recognition localization uses data from one or more sensors carried or worn by the user and compare these perceived data with the set of prior collected raw sensor data that has been coupled with an environment map. It separates two methods: (1) computer vision-based, (2) fingerprint-based. These methods have some disadvantages are required additional hardware for storing patterns, required additional cost for comparing patterns, and required much labor and time for database that storing pattern. However, these methods can have high accuracy, when pattern data is high quality. Generally, computer vision-based methods utilize images using image matching, characteristic analysis, and fingerprint-based methods utilizes RF signal such as Wi-Fi signal [23], FM station signals [15], and cellular signals [31].

III. System Overview

Figure 1 shows the key building blocks of AutoADL, and their connections. We describe the flow of operation here, and expand on the technical details in the next sections.

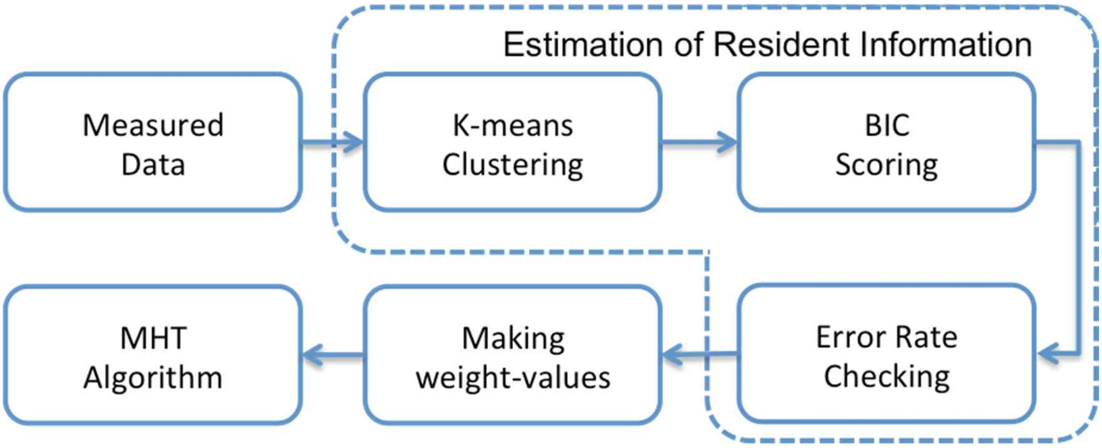


Figure 1. AutoADL system overview

AutoADL has three main processes, which are the estimation of resident information, calculation of weight-values, and tracking. First, the estimation of resident information is to find out the number of residents and resident's height. Measured data includes a space of events, target height, target directions. AutoADL uncovers resident information using those data. K-means clustering indicates the number of groups in the measured data, and BIC scoring verifies the k-means clustering's result. Error rate checking then decides several potential results via the above two processes. Second, making weight-values decides weight-values for using MHT algorithm. In the MHT algorithm, three weight-values for height, direction, and location are used in order to refine the tracking error. Therefore, each resident should set the weight-values, and the resident information is used when weight-values are setting. Finally, the MHT algorithm is a main process to reduce the tracking error. This algorithm resolves tracking error by measuring error, resident motion, and so on.

This thesis has two assumptions. First, residents make sure of closing the door that fires the sensor, when an event occurs. Second, the number of people are zero or one. Those assumptions can be justified as follows. The first assumption is that an ultrasonic sensor using the proposed system is a distance sensor that calculates the distance between the sensor and target. The proposed system uses the change of sensor measurement when residents pass through a door. It indicates movement of the resident. In other words, the target is close to the firing sensor. The second assumption is people who pass through the door, are generally less than one in number.

IV. Estimation of Resident Information

The estimation of resident information is a basic process for system automation. Resident information is environment information, and also is used calculating weight-values. Therefore, this process is a very important process and out main contribution.

Figure 2. Flowchart on the number of resident

4.1 The Number of Resident

Table 1. The result of BIC scoring (three residents)

Bigger sensor error distribution →

Smaller resident's height difference →

	0	1	2	3	4	5	
10	3	3	3	5	6	8	50%
9	3	3	3	3	3	4	83%
8	3	3	3	3	3	5	83%
7	4	3	3	3	4	4	50%
6	3	3	3	3	5	5	67%
5	3	3	3	3	5	5	67%
4	3	3	2	2	2	4	33%
3	3	2	2	2	2	3	33%
2	3	2	2	2	3	2	33%
1	3	2	2	2	2	3	33%
	90%	70%	60%	50%	30%	20%	53%

The estimation of the number of residents is a significant part in this thesis. It is base information that uses the estimation of resident's height and calculation of weight-value in the following section. If compute k-means clustering, Bayesian Information Criterion (BIC) scoring, and comparing error rate as figure 2. This computation method is referenced by X-means algorithm [26]. X-means clustering is based on k-means clustering, and finds out the optimal number of clusters to iterate a

Table 2. The result of checking error rate (three residents)

Bigger sensor error distribution →

Smaller resident's height difference ↓

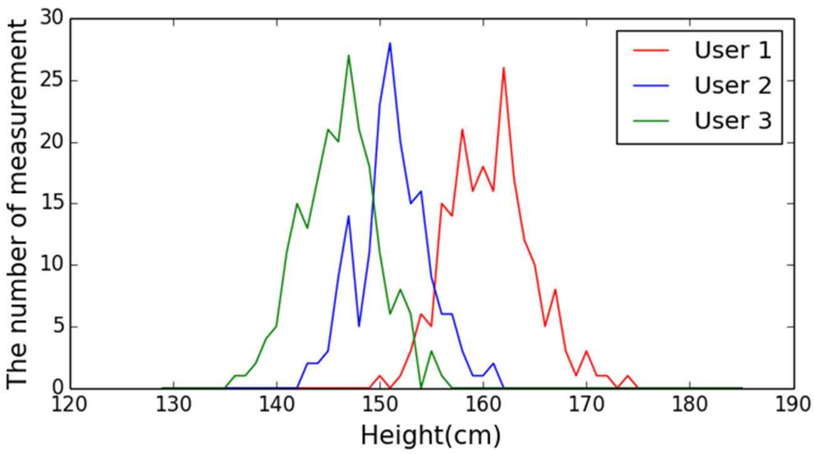
	0	**1**	**2**	**3**	**4**	**5**	
10	**3**	**3**	**3**	**3**	**3**	**3**	**100%**
9	**3**	**3**	**3**	**3**	**3**	**3**	**100%**
8	**3**	**3**	**3**	**3**	**3**	**2**	**83%**
7	**3**	**3**	**3**	**3**	**3**	**3**	**100%**
6	**3**	**4**	**3**	**2**	**3**	**3**	**67%**
5	**3**	**3**	**3**	**3**	**3**	**2**	**83%**
4	**3**	**3**	**3**	**3**	**3**	**2**	**83%**
3	**3**	**3**	**3**	**3**	**3**	**2**	**83%**
2	**3**	**3**	**3**	**3**	**2**	**3**	**83%**
1	**3**	**3**	**3**	**3**	**3**	**2**	**83%**
	100%	**90%**	**100%**	**90%**	**90%**	**90%**	**87%**

work, dividing clusters, using BIC scoring. First, compute k-means clustering. A cluster divides two clusters using k-means clustering. Second, calculate BIC score. The BIC score of each cluster that is divided clusters before, and original cluster is calculated respectively. If BIC score of the divided clusters is lower than the original cluster, the number of clusters is one cluster, otherwise the number of clusters is two clusters. Finally, iterate this works, when the number of clusters is decided. In this thesis, we use only BIC score.

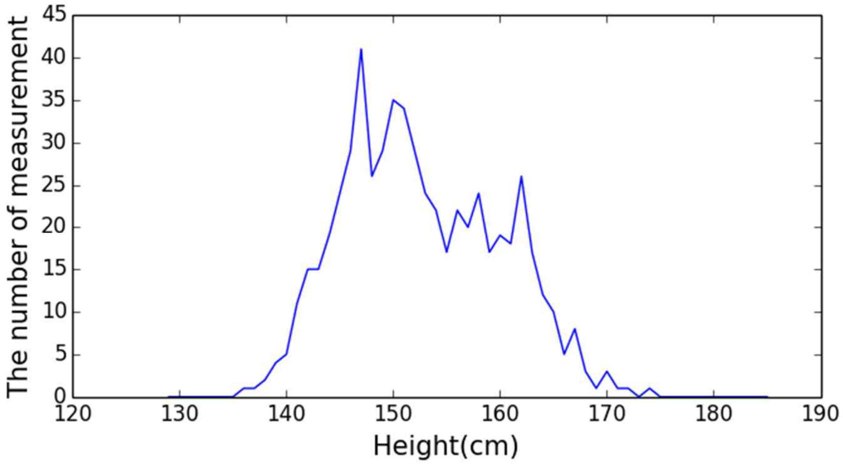
The estimation of the number of residents is following processes, k-means clustering, BIC scoring, and checking error rate in proposed system as figure 2. First, the system operates k-means clustering using event data that obtains in target home. The system does not know the number of residents. So, it operates k-means clustering in all specific ranges (1-10 clusters). Next, BIC score is calculated by result of clustering, and then the system chooses three results of clustering that has higher BIC score than the others. Through k-means clustering, the system gets the base information that estimates the number of residents. In other words, k-means clustering needs an algorithm to obtain the optimal clusters for an estimation of the number of residents, and a solution is BIC scoring. Finally, operating the tracking algorithm using the above three results, and the result of lowest error rates is chosen. Why a final process is needed in the proposed system, because when a difference of each resident's height is small, using only BIC scoring is defeated as show in Table 1. The low height difference of the residents or the bigger sensors error is, the bigger error of BIC scoring is. In order to reduce these errors, the proposed system ranks the clustering result using BIC scoring, and then it operates a tracking algorithm using clusters which are higher than the three ranked. Finally, it chooses one cluster which has the least error rate after checking error rate. Table 2 operates above processes using same data which uses BIC scoring. In this result, we obtain higher accuracy than using BIC scoring.

4.2 Resident’s height

The resident's height is important information that identifies them. Therefore, it is significant that the resident's height is estimated, and decides the systems accuracy. The original Doorjamb uses input data by the user. This method has some problems that need much labor, when the data is inputted, and much data. Therefore, we apply the clustering method, k-means clustering, using measurement data. K-means clustering is when we divide k clusters using given data. It operates using minimize variances of distance between each cluster. Systems get the residents height as clusters mean value, because the resident's height indicates a sensors error. But, in order to utilize k-means clustering, it is necessary to input the number of clusters, k. It is a solution to use the result of above the section.



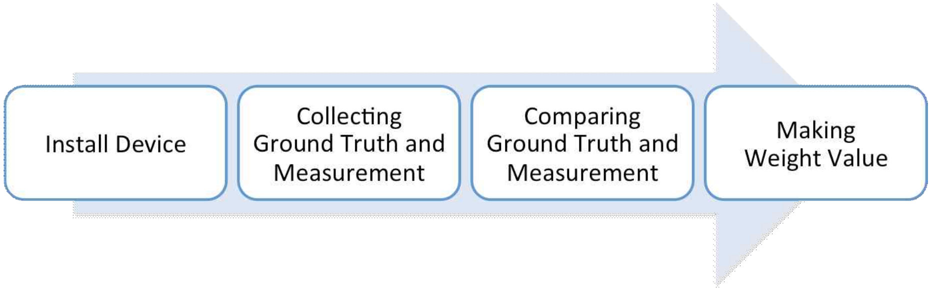
(a) Divided each users



(b) Summated each users.

Figure 3. When User 1=160cm, User 2=150cm, User 3=146cm, and sensor error distribution is 5cm, the distribution of height.

V. Calculating Weight-Values



(a) Flowchart on calculating weight-values of Doorjamb

(b) Flowchart on proposed method

Figure 4. Calculating weight-values flowchart

The measurement data by sensors has some errors such as false positives, false negatives, and measurement faults. These errors can cause a problem to the system. So, AutoADL eliminates this measurement error or adjusts the output. In this thesis, AutoADL uses MHT, adjusting the output. For example in home like figure 5, MHT adjusts the output including all errors, because it considers the probability for all hypotheses. In this thesis, MHT algorithms overview is algorithm 1. State variable in algorithm 1, is stored history of hypothesis and probability. When events occur, stored state variable makes new hypothesis, and verifies them whether they are true or not. The number of hypotheses per an one event is $\leq \mathrm{R}^{\mathrm{U}}$ where the number of rooms is R and the number of residents is U. But, the number of those hypothesis can be reduced to $\leq 3 \times \mathrm{N}$ using the verifying process removes impossible hypothesis after comparing our assumptions. For examples, moving people are more than two people or moving person do not pass through door occurring

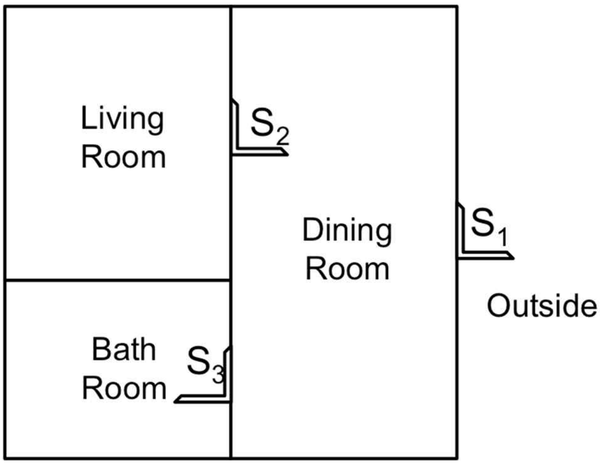


Figure 5. Example room environment.

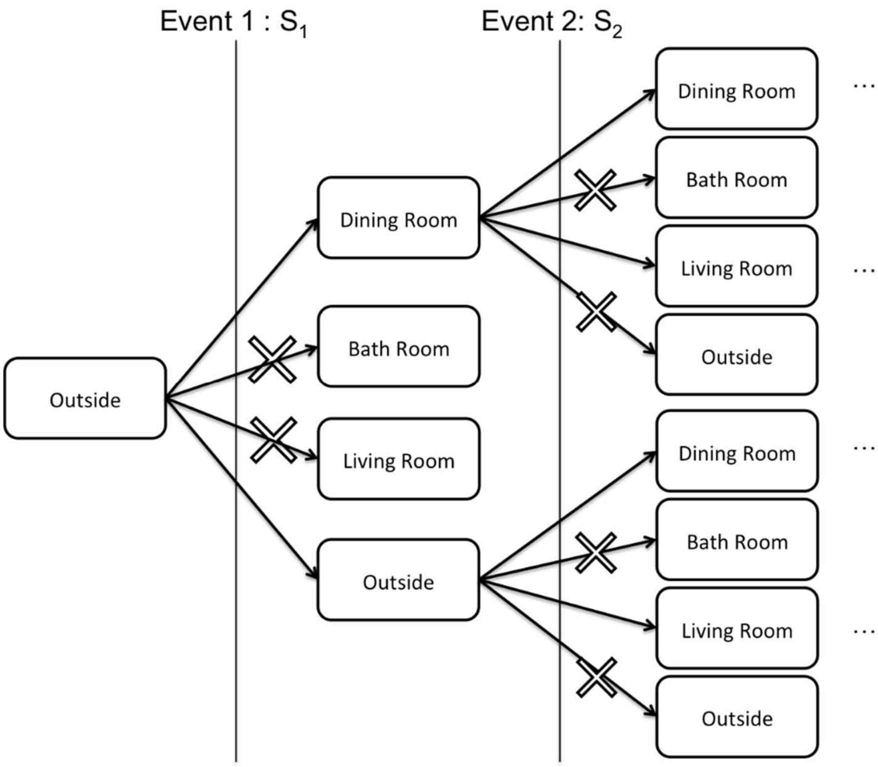


Figure 6. Example of MHT algorithm.

event. Because except impossible hypothesis like break our assumptions. The verifying process gives big advantage that reduces calculating cost. Also, the verifying process for reducing hypothesis aid reducing calculation. Tracking algorithm calculates the probability to exploit new hypothesis and history of state. We discuss the variable for calculating probability in the following

Algorithm 1 MHT algorithm

Input: a number of rooms R, a number of people P

Output: history and probability set Ω

```
while not end of event do
    for history, probability in Ω do
        for s in product (R, P) do
            for i, p in enumerate(P) do
                roomstate[p] = s[i]
            end for
            if validate(Ω[−1], roomstate) then
                newPath = history[:]
                newPath.append(roomstate)
                weight = computeWeight(newPath, probability)
                result.append([newPath, weight])
            end if
        end for
    end for
    result.sort()
    result = result[:given limitation]
    removeRow = determineConsistency()
    if removeRow != null then
        for i in removeRow do
            write state[i]
            delete state[i]
        end for
    end if
end while
```

sections. MHT algorithm is an exponentially increased total hypothesis about the number of occurring events. It is a big problem because it increases calculation, so AutoADL need to reduce calculation or to prevent the increase of hypothesis. There are many methods for solving the problem. It is also caused a calculation increase. Therefore, the system needs to reduce calculation or to prevent the increase of hypothesis. In MHT algorithm methods, it is a popular issue. So, three are many solutions for those problems. In this thesis, it AutoADL uses to limit the number of the total hypothesis. This method is following processes. First, new hypothesis rearrange about to probability. Using weight-values, each hypothesis calculates probability itself. Next, and then remains n hypothesis where limitation value is n. As removing hypothesis having low probability, AutoADL remains the meaningful data. This is that remains the meaningful data as eliminating hypothesis having low probability. This method is able to implement very simple as well as to have high quality. It is possible to easily implement and to reduce calculation. AutoADL initially exploits that the limitation value is 200. For the result that is one of hypothesis, AutoADL needs some time because AutoADL decides the result when all the history of those hypothesis is same history. Also, the decision method of the result is that chooses highest rank hypothesis. This method reduces error by the measurement. We discuss calculating weight-values on a following section.

The verifying hypothesis is that finds out data weight-values from measurement, and then compute the probability multiplying between weight-values. This probability is used to assured the result hypothesis. Therefore, weight-value is a very important component.

5.1 The Height of Residents

Weight-value of the resident's height is based on the difference between residents height. So, it is important to obtain residents real height. We get this data from prior sections, k-means clustering. In this case, estimated height from k-means clustering is more reliable than real height, because it can reduce sensor error about the difference between real value and the measurement. K-means clustering can reduce those sensor errors, distribution and difference between real height and measurement. The weight-values about height are following.

$$\mathrm{U}_1, U_2, U_3 \tag{1}$$

is the resident’s height. Middle value of each resident is

$$\mathrm{C}_1 = \frac{U_1+U_2}{2}, C_2 = \frac{U_2+U_3}{2} \tag{2}$$

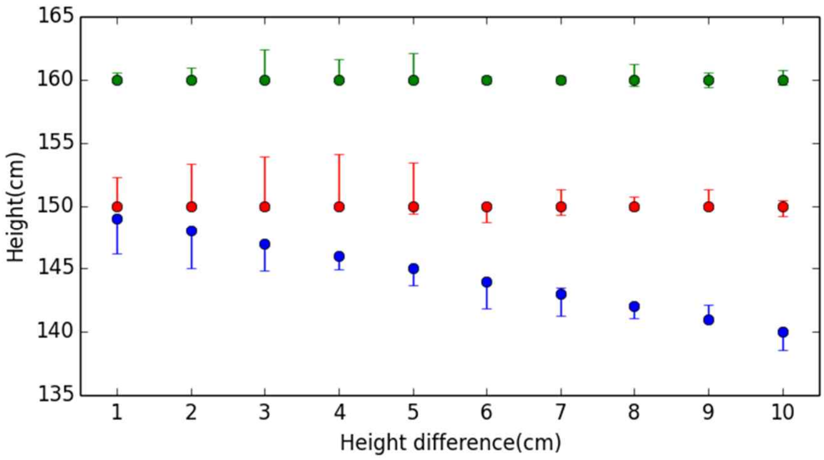


Figure 7. Estimation of resident height while change a resident height.

We calculate the weight-values between U_1 and U_2 using (1) and (2).

$$0.5 + \frac{0.5}{C_1 - U_1}(C_1 - k), \quad U_1 \le k \le C_1 \tag{3}$$

$$\frac{1}{2^{k-C_1}}\left(0.5 + \frac{0.5}{C_1 - U_1}(k - C_1)\right), \quad C_1 \le k \tag{4}$$

(3) and (4) decide weight-values of U_1 and U_2. There is same processes to calculate weight-values between U_2 and U_3. It is easy to understand the difference of the weight-values about the measurement between residents.

5.2 Direction

The weight-values of direction are intuitively calculated. It compares real direction with the measurements. When the real direction is $\mathbf{D_r}$, and the measurement is $\mathbf{D_v}$,

$$D_r = D_v, \quad \text{Correct} \tag{5}$$

$$D_r \neq D_v, \quad \text{Incorrect} \tag{6}$$

Like (5) and (6), it counts whether the measurement is true or not, and then the weight-values of direction are that divides the true count from the all true and false count. The weight-values about direction continually refresh on operating time.

5.3 Location

The weight-values about location compare new positions with prior positions. Moving resident in one event is limited a person by assumptions. A path value is the change between new positions and prior positions, is calculated by Djikstra's shortest path algorithm. The weight-values about location are calculated follow (7),

$$\mathrm{Height}^{sp} \tag{7}$$

where the path values are sp, and Height is estimated height in section 3. The probability multiplies those weight-values about height, direction, and location. It is calculated as a following equation,

$$\mathrm{w_i} = w_{i-1} * w_p * w_d * w_h \tag{8}$$

where $\mathrm{w_i}$ is the probability of i-th event, $\mathrm{w_h}$, $\mathrm{w_d}$, and $\mathrm{w_p}$ are respectively the weight-values of height, direction, and location.

VI.Evaluation

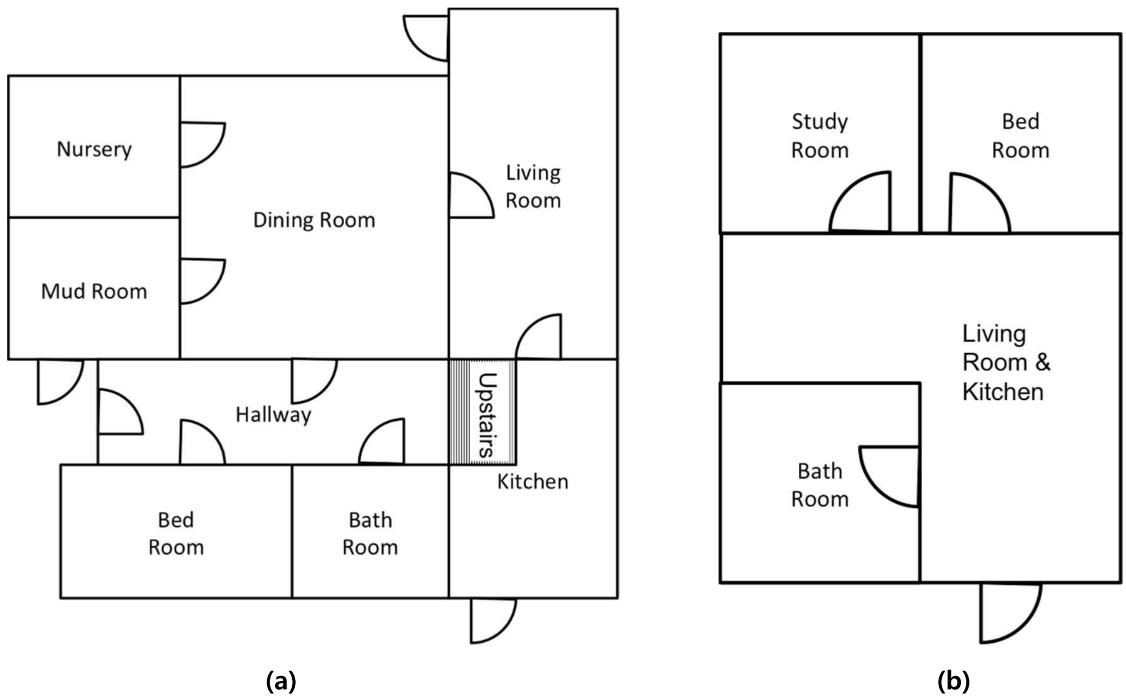


Figure 8. Experiment environments

Evaluation is simulated in two environments on figure 8. Event data is made by following steps. First, making random GT data. Next, adding some error such as distribution of height, and changing direction. Those event data is used in experiments.

6.1 Accuracy about The Distribution of The Height

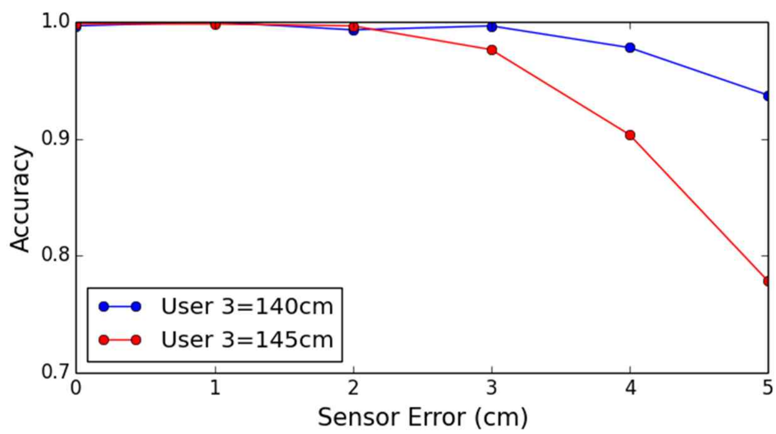


Figure 9. Accuracy of sensor precision

In this section, we check the accuracy about the precision of sensors. Ultrasonic sensor has many variations, and sensors precision is decided by sensor selection. It is helpful to choose a sensor in order to gain the accuracy of what you want. AutoADL accuracy about sensor precision is depicted blue line in figure 9, and add red line that is small a different of the resident's height. Generally, the better sensor precision is, the better systems accuracy is. The difference of the height is an additional point about decreasing accuracy of the system. It is shown by figure 9. Red line is 5cm the difference of height, and blue line is 10cm the difference of height.

6.2 Accuracy about The Difference of The Height

The height of residents in this system is one of important information for identifying residents. Therefore, if it is a perfectly estimated system, it can be easy to track and identify residents as figure 10. In figure 10, blue line is about a situation that has high sensor precision, and red line is about another situation that has low sensor precision. In this results, the difference of height is affected by the sensor precision.

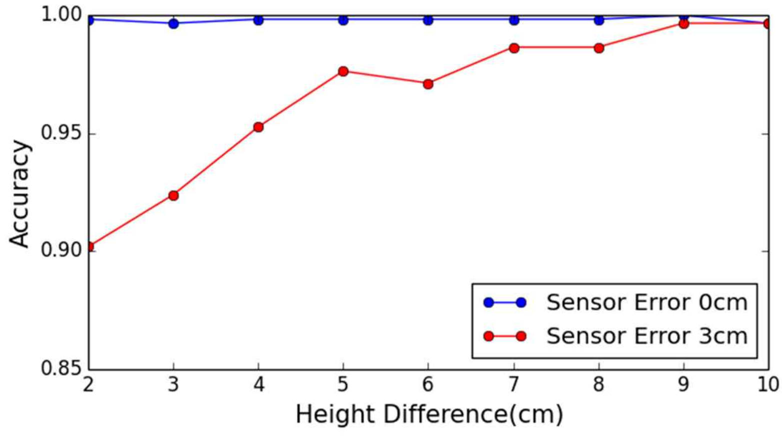
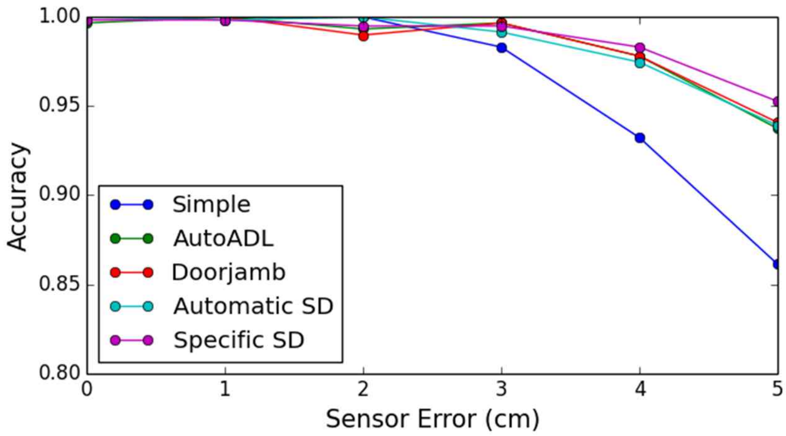


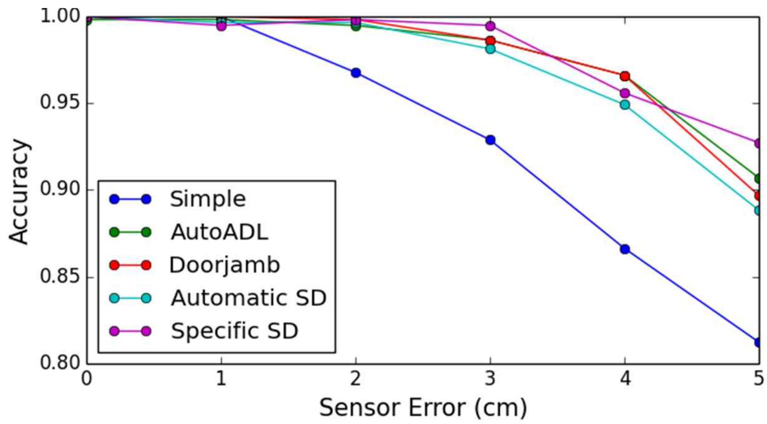
Figure 10. Accuarcy of difference of height

6.3 Accuracy about Weight-Values

MHT algorithm need some weight-values in order to find a hypothesis about more reaching real situations. Therefore, according to weight-values, systems accuracy changes. In this section, several weight-values such as proposed weight-values in section 3-B, original weight-values in Doorjamb, weight-values using standard deviation, and a method without MHT algorithm. In figure 11-(a), all methods have high and similar accuracy's in the difference of the height between residents. But, in figure 11-(b), the methods with MHT algorithm has higher accuracy than the



(a) User 1=160cm, User 2=150cm, User 3=140cm



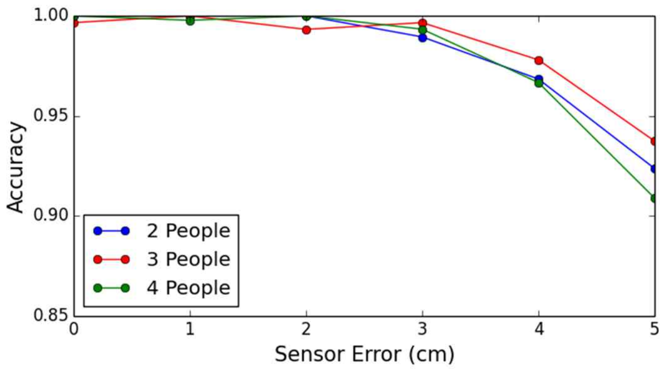
(b) User 1=160cm, User 2=150cm, User 3=143cm

Figure 11. Accuracy when change making weight-values method

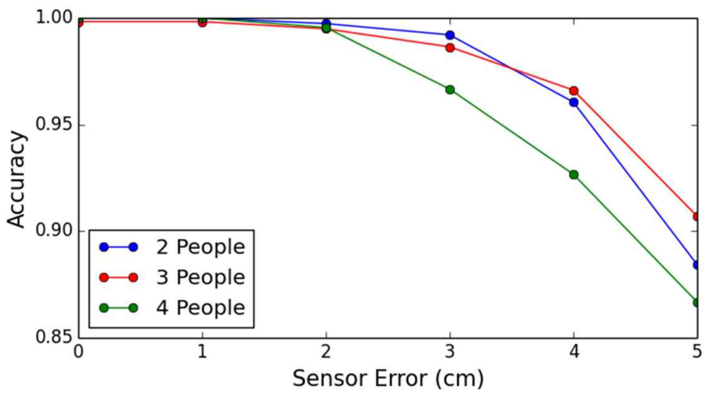
method without MHT algorithm in the difference of the height between residents is high, and sensor precision is low. In this result, MHT algorithm adjusts the effect of those error.

6.4 Accuracy about the Number of Residents

It is a significant challenge to find out the number of residents. Presently, many families consist of 1-2 people. But, most families consist of more than three people. Therefore, AutoADL can track and identify many people in order to make this useful in practical situations. Thus, AutoADL guarantees high accuracy regardless of the number of residents. In figure 12, this thesis proposed system shows the high accuracy regardless of the number of residents.



(a) User 1=160cm, User 2=150cm, User 3=140cm

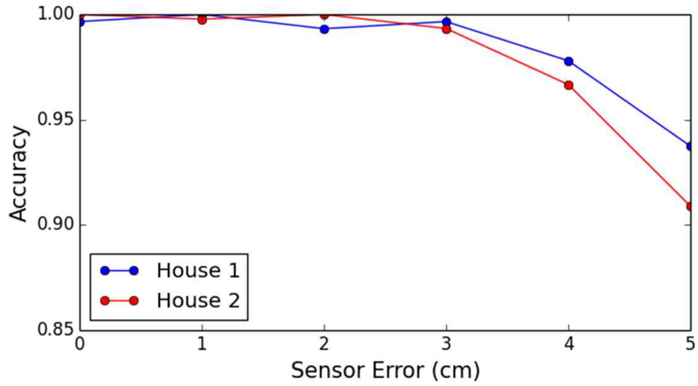


(b) User 1=160cm, User 2=150cm, User 3=143cm

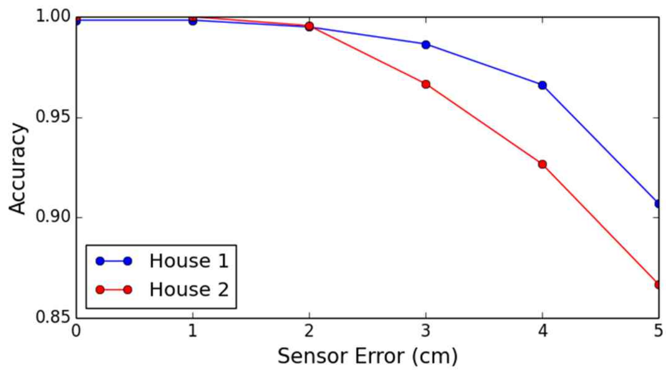
Figure 12. Accuracy about the number of residents

6.4 Accuracy at Different home

Like the above section, home environment is important challenge. Most homes have different home environments with the exception of apartments. Therefore, AutoADL is not affected by the number of rooms, the arrangements of rooms and so on. In figure 13, if the same people live in those homes, the accuracy of the proposed system is calculated. In figure 13, the accuracy of the proposed system is low, about 5%, between those homes. It indicates that the proposed system can be used in several indoor environments.



(a) User 1=160cm, User 2=150cm, User 3=140cm



(b) User 1=160cm, User 2=150cm, User 3=143cm

Figure 13. Accuracy when different environments

VII. Discussion

In this thesis, we proposed AutoADL can be used in practical environment. AutoADL considers easy usage and large coverage. So, AutoADL supports an automatic system through the automatic calculating resident's information and weight-values and sufficient the number of people it can track. In section 5.4 and 5.5, AutoADL satisfies several environments such as structure of home and the number of residents. But, AutoADL has still some problems. It derived from characteristics of AutoADL using ultrasonic sensors. AutoADL utilizes resident's height as resident's identification and tracking. AutoADL need specific condition to properly operate in homes, when the residents are not same height. Resident's height is an important problem in AutoADL, it is shown error in evaluation and calculating resident's information part. In addition, sensor's measurement is important that is equally resident's height, and we deal with these problems in all evaluation part. When a resident pass through doorways, precision of sensors not only occur error of itself, but also occurs resident's motion. So, we need to improve our systems about resident's motion analysis or error compensation.

VIII. Conclusion & Future work

Indoor localization is an important field of research, but most studies such as RF signals, RFIDs, and smartphones have some drawbacks. In this thesis, we propose AutoADL that supports localization and identification without holding any devices. Existing studies have some problems like the limitation of tracking people and spending an abundance of time for installation and usage. So, we proposed an automatic tracking and identification system to resolve those problems. K-means clustering is very popular and sufficient (using our system) algorithm for grouping of height data. BIC scoring has low accuracy for finding the number of resident, but lastly AutoADL has high accuracy through combines BIC scoring and error rate checking processes. In addition, we proposed a new method of calculating weight-values using resident information. So, AutoADL can be used in a practical home from the result of the evaluation. However, AutoADL's tracking accuracy still depends on sensor error and resident height. So, if AutoADL refines those errors, AutoADL can have high accuracy and flexible in various environments. A refining process about resident height is impossible, because resident height is a constant. Therefore, we will adjust sensor error. The sensor error refining process can reduce system's error using resident motion detecting, usage of more precise sensor, or preprocessing measuring data. In order words, our study have potential of development. For example, additional processes such as motion detecting using depth cameras, and using other sensor such as more precise distance sensors. Thus, we will apply the processes and uses the other sensors, so we provide more flexible usage and high accuracy.

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요 약 문

AutoADL: 거주자의 식별 및 Activities of Daily Living 자동 탐지

Localization 는 일상생활에서 많이 사용하는 위치 찾기, 네비게이션 등에 사용되는 기반정보이다. 이와 같은 서비스들은 GPS 를 이용하여 실외환경에서 사용되는 서비스이다. 하지만, GPS 의 사용이 어려운 실내환경에서는 이런 서비스들을 사용하기가 어렵다. Indoor localization 시스템은 outdoor localization 에 사용되는 시스템의 사용이 어렵고, 작은 공간, 많은 장애물 들에 의해, outdoor localization 에 비해 큰 오차를 가지며, 프라이버시, 보안 등의 문제로 인해 외부에서의 간섭을 최소화 해야 하는 문제점이 있다. 하지만, indoor localization 정보는 최근 많이 연구되고 있는 스마트 홈을 구성하는데 기반이 되는 정보이고, indoor localization 정보를 이용하여 제공할 수 있는 서비스가 엄청나므로 꼭 필요한 연구분야이다. 그래서, RF 신호, RFID, 초음파, 스마트홈 등을 이용한 많은 indoor localization 연구가 진행되었고, 진행 중에 있다. 하지만, 기존의 연구들은 개인의 위치정보만을 제공하거나, 개인이 직접 디바이스를 들고 다녀야 하는 등 실내 서비스에 이용하기에는 문제가 있었다. 이에 본 논문에서는 개인의 위치정보뿐만 아니라 인식정보를 제공하고, 개인이 디바이스를 들고 다닐 필요가 없는 시스템 (AutoADL)을 제안하고자 한다. 기존의 연구에서 인프라를 이용하여 AutoADL 의 장점과 동일한 장점을 가지는 연구가 있지만, 제한된 측위 가능 인원, 설치에서 사용까지 많은 노동력과 시간의 필요 등 불편함이 있었다. AutoADL 은 K-means clustering 알고리즘과 Bayesian Information Criterion (BIC) scoring, error rate checking 를 통해 측위 가능 인원의 추정 및 거주자의 특성을 자동으로 계산하고, MHT algorithm 을 이용하여 에러를 보정하여, 다수 인원에 대한 위치 정보와 식별 정보를 높은 정확도로 제공한다. AutoADL 은 측정 인원, 실험환경, weight-values, 거주자의 키의 값과 같은 여러 가지 환경을 변화시키며 시뮬레이션 해보았다. 그 결과, 센서 측정값 분포가 4cm 보다 작고, 거주자 키의 차이가 5cm 보다 클 경우, 측위 정확도가 90%보다 컸다.

핵심어: 실내측위, 초음파, 자동화 시스템, 식별