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Mining User Activity Patterns from Time-Series Data Obtained from UWB Sensors in Indoor Environments

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SUMMARY In recent years, location-based technologies for ubiquitous environments have aimed to realize services tailored to each purpose based on information about an individual's current location. To establish such advanced location-based services, an estimation technology that can accurately recognize and predict the movements of people and objects is necessary. Although global positioning system (GPS) has already been used as a standard for outdoor positioning technology and many services have been realized, several techniques using conventional wireless sensors such as Wi-Fi, RFID, and Bluetooth have been considered for indoor positioning technology. However, conventional wireless indoor positioning is prone to the effects of noise, and the large range of estimated indoor locations makes it difficult to identify human activities precisely. We propose a method to mine user activity patterns from time-series data of user's locationss in an indoor environment using ultra-wideband (UWB) sensors. An UWB sensor is useful for indoor positioning due to its high noise immunity and measurement accuracy, however, to our knowledge, estimation and prediction of human indoor activities using UWB sensors have not yet been addressed. The proposed method consists of three steps: 1) obtaining time-series data of the user's location using a UWB sensor attached to the user, and then estimating the areas where the user has stayed; 2) associating each area of the user's stay with a nearby landmark of activity and assigning indoor activities; and 3) mining the user's activity patterns based on the user's indoor activities and their transitions. We conducted experiments to evaluate the proposed method by investigating the accuracy of estimating the user's area of stay using a UWB sensor and observing the results of activity pattern mining applied to actual laboratory members over 30-days. The results showed that the proposed method is superior to a comparison method, Time-based clustering algorithm, in estimating the stay areas precisely, and that it is possible to reveal the user's activity patterns appropriately in the actual environment.

key words: *human activity recognition, indoor location-based system, human bahavior analysis, wireless sensor network*

1. Introduction

In recent years, location-based technologies in the ubiquitous environment have aimed to realize services tailored to each individual's purpose based on his or her current location information. For example, such location-based services include not only inventory monitoring in warehouses and route navigation considering real-time traffic information, but also analysis of activities within organizations such as factories and hospitals and optimization for improving productivity based on the analysis results. In terms of location technology for the outdoor environment, the Global Positioning System (GPS) has already been in standard use, providing a large number of services [1]. On the other hand, for indoor environment location technology, several methods using conventional wireless sensors, such as Wi-Fi, RFID, and Bluetooth, have been investigated, however, each of them has its own disadvantages in precisely analyzing human behavior in a practical indoor environment [2]–[4]. For example, although Wi-Fi is easy to install in indoor facilities and has a small detection error of 230 mm on average, it is susceptible to noise [6]. Since RFID and Bluetooth have a large detection error of more than 3000 mm on average [7], [8], their sensors can be used to detect the location of objects on a room-by-room. Thus, their wireless sensors are not suitable for accurately estimating the location of a human and his or her behaviors indoors.

In order to establish advanced indoor location-based services, highly accurate location technology is required to recognize and predict the movements and activities of people and objects in the indoor environment. By constantly acquiring accurate location information of those and mining their significant behaviors according to the purpose from a massive amount of time-series data of location information, it is possible to detect and predict interactions among people and between people and objects, as well as the human behaviors and their behavior patterns. It allows for the development of indoor location-based and context-based services which are more appropriate to the user's situation than conventional services, such as improvements of user's life style, team activities, and social interactions.

In recent years, indoor location estimation using ultra-wideband (UWB) sensors has also been explored. UWB sensors can provide highly accurate location estimation with errors of 100–200 mm [9], further improvements are required for practical indoor environments to reduce the effects of measurement errors in indoor environments due to the problems of Non-Line-of-Sight (NLOS) and reflection caused by metallic objects and obstacles. So, high-precision target tracking systems using UWB sensors have yet to be addressed in indoor location estimation. Conversely, target recognition technology using cameras [10], [11], Internet of Things devices [5], [13]–[16], and accelerometers (wearable sensors) [17]–[19] has been adopted as a realistic solution; however, there are still issues such as privacy for indoor behavior [13], [20], scalability of device settings, and accuracy to identify daily indoor activities. Therefore, location-based behavior recognition technology with high-precision wireless sensors is required for real-world applications.

Hence, we propose a method to mine activity patterns

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of a user from time-series data of user's locations in an indoor environment using a Ultra-Wideband (UWB) sensor. The proposed method consists of three steps: 1) obtaining time-series data of the user's location using a UWB sensor attached to the user, and then estimating the areas where the user has stayed; 2) associating each area of the user's stay with a nearby landmark of activity and assigning indoor activities; and 3) mining the user's activity patterns based on the user's indoor activities and their transitions. We conducted experiments to evaluate the proposed method by investigating the accuracy of estimating the user's stay-areas using a UWB sensor and observing the results of activity pattern mining applied to actual laboratory members over 30-days. The results showed that the proposed method is superior to a comparison method, Time-based clustering algorithm, in estimating the stay areas precisely, and that it is possible to reveal the user's activity patterns appropriately in the actual environment. To the best of our knowledge, this is the first effort to mine human's activity patterns using a UWB sensor.

2. System Implementation

2.1 Overview

We have implemented a system to sequentially acquire the locations of UWB sensors installed indoors and extract meaningful behavior patterns from the time-series data of the location information of those UWB sensors. The system is capable of discovering the behavior patterns of a person who is attached to a UWB sensor in case that the person engages in activities in the system environment.

The implemented system consists of UWB anchors installed at the four corners of a room and a location database server, as shown in Fig. 1. The location database server includes a location information table, an indoor landmark mapping table, and two data processing modules which are a stay-area extraction and an activity pattern mining. The location information table contains the location information of each UWB sensor along with a timestamp. The indoor landmark mapping table registers the area coordinates where indoor landmarks are located, as shown in Table 1. The present system manually registered indoor landmarks that typically represent the user's activities. The examples of the landmark are each member's work desk, refrigerator, coffee maker, whiteboard, printer, bookshelf, etc., which are registered together with indoor coordinates of their location. The stay-area extraction is a clustering algorithm that extracts the coordinates of the area where the UWB sensor stayed for a certain period of time in order to exclude errors or meaningless motions of the UWB sensor. The activity pattern mining is an algorithm that generates a graph representing the areas where UWB sensors stayed and their transitions from the time-series data of the extracted stay-areas, and extracts meaningful behavior rules through association rule analysis. The details of these modules are described in Sect. 2.2, respectively.

During the system's operation, UWB sensors in the system environment communicate with each UWB anchor at regular time intervals, and calculate the distance to each UWB anchor and its quality factor (QF) [12], which is confidence degree in ranges from 0 to 100, based on the communication time and signal strength. Then, using the distances to the three UWB anchors that are closest to the UWB sensor, the two-dimensional location of the UWB sensor in the room is calculated by trilateration [21] and sent along with its confidence level to the server via Bluetooth communication. Then, it is stored in the location information table. In the present system, the UWB sensor obtains the distance to each UWB anchor and sends the data in 0.1 s intervals.

On the other hand, the server asynchronously retrieves the location information of a specific UWB sensor and time period from the location information table to mine it's behavior patterns, and extracts time-series data of the stay-area and stay-time using the stay-area extraction. Then, each stay-area is replaced by an user's activity assigned with the one of indoor landmarks within a certain distance to each

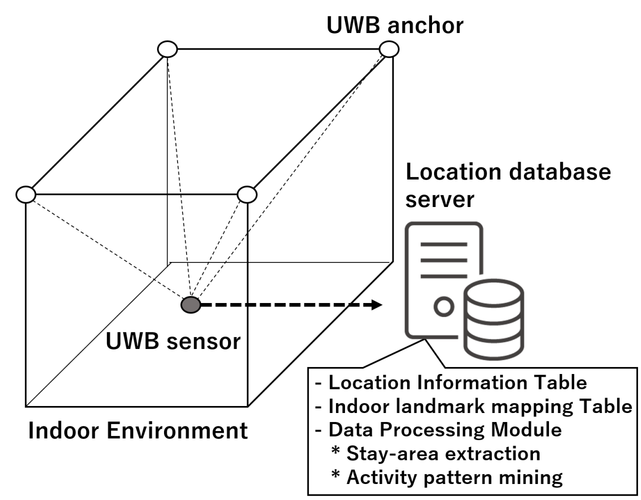


Fig. 1 System composition.

Table 1 Table structures of the database contained in the location database server

Location Information Table

Event ID	UWB tag (MAC address)	X	Y	Timestamp
1	DD:0B:1F:73:91:0D	750	750	MM/DD/YYYY 12:43:00 PM

Indoor Landmark Mapping Table

ID	Indoor landmark	X	Y	Width	Depth
1	AAA's Desk	500	500	500	1000
2	Coffee Maker	6000	6000	200	1000

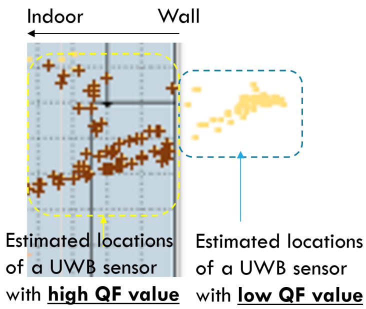


Fig. 2 An example of the effectiveness of QF filtering.

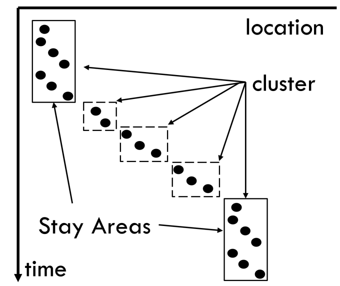


Fig. 3 Illustration of time-based clustering algorithm.

stay-area using the indoor landmark mapping table. Finally, from the time-series data of the user's activities, the activity pattern mining generates a graph representing the user's activities and their transitions, and it also extracts the user's characteristic activity patterns.

2.2 Data Processing Modules

2.2.1 Stay-Area Extraction

To reduce the effects of NLOS and metallic reflections [22], the stay-are extraction takes as input the time-series data of locations of a UWB sensor and performs three processing steps:

1) The input data is filtered by the QF value of the UWB sensor,
2) Stay areas of the UWB sensor are identified from the time-series data of filtered locations of the UWB sensor using a time-based clustering algorithm [23], [24],
3) Each stay area is assigned to one of the indoor landmark.

It is expected that the QF filtering reduces the effect of NLOS on the UWB sensor, and the time-based clustering algorithm removes large location errors caused by metallic reflection and locations which the UWB sensor generated when the user was moving to the other place.

In the QF filtering, location information with a QF value less than 60 in the range between 0 and 100 is removed. This setting is based on our results of investigating the relationship between the location error of the UWB sensor and the QF value. Figure 2 shows an example of the effectiveness of QF filtering; it shows that the QF filtering removed the location information outside the room of the UWB sensor.

In the time-based clustering algorithm [23], the time-series of the location data is clustered along a time axis; if a new location is further away from the previous location, the new location is considered to belong to a different cluster from the cluster of the prior location, as depicted in Fig. 3. The algorithm starts with the input of a time-series of location information with timestamps, a time parameter, and a distance parameter, then creates clusters of the location data, and identifies stay areas using the clustering data. In the clustering process, the location is called up sequentially from the time-series of location data, and if the location is closer to the prior location, i.e., smaller than the distance parameter, the location is involved in the same cluster as the prior. Even if the location is far from the prior location, it may be in the same cluster as the prior location if the location is an outlier. After clustering all locations in the location data, if the total time to pass locations in a cluster is longer than the time parameter, the cluster is identified as a stay area. The time and distance parameters are set to optimal values throughout the experiment.

To assign each stay area to one of the indoor landmarks, the distances between the center location of each stay area and each indoor landmark registered in the indoor landmark mapping table are calculated, and then, each stay area is assigned to the closest indoor landmark to it with a distance less than the threshold value. If a stay area isn't assigned to any indoor landmark, the stay area is assigned to an unknown indoor landmark.

2.2.2 Activity Pattern Mining

Activity pattern mining is an algorithm for discovering frequent activity patterns and episode rules [26]. Activity patterns are a subset of frequent activities and their transitions in the history of activities, and are represented by a directed graph. An episode rule is represented by a meaningful relationship between two episodes in episodes contained in the activity patterns. In this study, we implemented a data processing module for activity pattern mining based on time-series data of location information of a user attached with a UWB sensor.

The activity pattern mining consists of four steps. First, it starts with an input data which is an ordered set of activities generated from the time-series data of the stay areas. Next, from the ordered set of activities, the frequent episode candidates are generated, and the frequent episodes are recognized among them. Then, the frequent episodes are pruned to exclude episodes that are low significant, and the episode rules are discovered by applying association analysis to the frequent episodes. Each step of the process is described in detail as follows.

1. Generating frequent episode candidates: Frequent episode candidates are generated from an ordered set of activities by using transitive reduction of partially ordered directed acyclic graphs. To achieve this, an episode is generated as a directed graph in which an

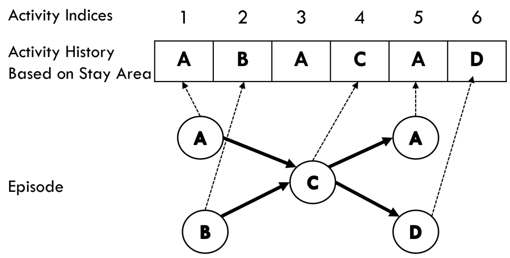


Fig. 4 Example of mapping an episode to an activity history of stay areas.

activity and the activities at its input and output and their transitions are represented by nodes and links, respectively. If a projective mapping exists between two episodes, the two episodes are merged into an episode.

2. Recognizing frequent episodes: The frequency of occurrence of each episode can be calculated using Eq. (1). Each episode is mapped to the activity history of the stay area as shown in Fig. 4. If the frequency of occurrence of an episode in the activity history is higher than a threshold value, the episode is recognized as a frequent episode.

$$freq(\alpha) = \frac{|[T_i | T_i \in L \wedge \alpha \subset T_i]|}{|L|}. \quad (1)$$

Here, α, T_i, i, and L represent an episode, an activity history of user i' stay area, and activity histories of all users' stay areas, respectively.

3. Pruning: A frequent episode is excluded if its number of activities and trace distance defined by Eqs. (2) and (3), respectively, are smaller than the set parameters.

$$ActFreq(A) == \frac{|[T_i | T_i \in L \wedge A \subset T_i]|}{|L|}. \quad (2)$$

Here, A indicates a frequent episode.

$$traceDist(\alpha, T) = \max\{h(v) | v \in V\} - \min\{h(v) | v \in V\}. \quad (3)$$

Here, $\max\{h(v)|v \in V\}$ and $\min\{h(v)|v \in V\}$ denote the maximum and minimum values of the activity index in mapping the stay areas in the episode to the activity history, respectively.

4. Discovering episode rules: These are the association rules for episodes. Rules with low episode confidence and magnitude ratings, as defined in Eqs. (4) and (5), are excluded.

$$conf(\beta \Rightarrow \alpha) = \frac{frec(\alpha)}{frec(\beta)}. \quad (4)$$

Here, $\beta \Rightarrow \alpha$ indicates an association rule with $\beta \prec \alpha$ stating that after seeing β.

$$mag(\beta \Rightarrow \alpha) = \frac{size(\alpha)}{size(\beta)}. \quad (5)$$

Here, $size(\alpha)$ denotes the number of stay areas in an episode α.

2.3 Expected Effects

The following two effects are expected from the use of the implemented system by a user who engage in activities indoors.

- By taking into account the signal strength of a UWB sensor and user's indoor movement speed, the indoor positioning error of the UWB sensor can be reduced so that the detected stay-areas of the user can be properly extracted in terms of the number of stays indoor, the proximity between a stay area and it's targetted indoor landmark, and the blurriness of the stay areas.
- By gathering time-series data of stay areas based on precise indoor location information, the user's activity patterns and characteristic behavior can be extracted at a granularity level to enable human indoor activity recognition.

3. Evaluation

3.1 Settings

To evaluate the effectiveness of the implemented system, we conducted evaluation experiments in terms of the accuracy of the stay-area extraction of a UWB sensor and the usefulness of activity pattern mining in the authors' laboratory, as depicted in Fig. 5. The size of the lab room is 5840 mm wide and 10440 mm long. The room is equipped with the below.

- 17 pairs of desks and chairs,
- personal computers on each desk,
- four metalic bookshelves,
- four whiteboards,
- a printer,
- a coffee maker,
- two refrigerators, and
- an accessory box.

The UWB anchors are installed at the four corners of the room at a height of 2700 mm. We checked the measurement errors of a UWB sensor at nine points in the room, and, as listed in Table 2, the total average error of a UWB sensor is 251.6 mm on the X-axis and 201.3 mm on the Y-axis, whereas the errors at Position IDs (1,3,7-9) near the hallway side and metallic bookshelves are larger than the average.

First, to confirm the effectiveness of stay-area extraction, we compared it with a simple time-based clustering method in terms of the detection accuracy and size of stay areas. The detection accuracy is defined as the distance from the center of the extracted stay-area to the measuring location, and the detection size for each stay area is defined as the distance between the center of the extracted stay-area and the farthest location of the stay area. Thus, the higher the detected accuracy and the smaller the detected size of the stay

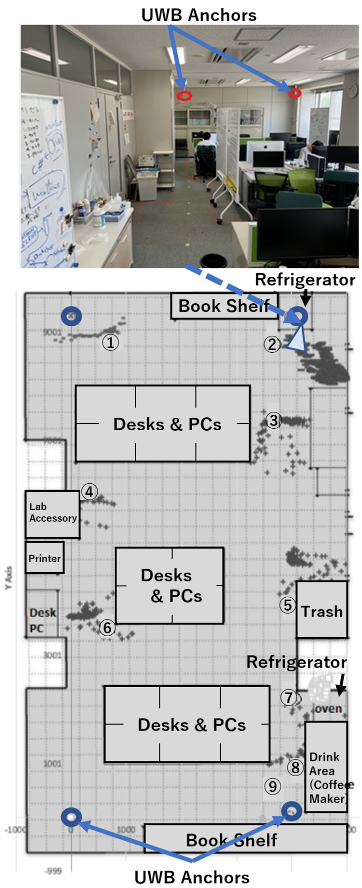


Fig. 5 Experiment environment (the authors' laboratory); the dots indicate the estimated locations of a UWB sensor, and each circled number indicates the location to investigate the errors of a UWB sensor.

Table 2 Results on location error (mm) measured for each location ID.

	X-axis error			Y-axis error		
Location ID	Ave.	S.D.	Max.	Ave.	S.D.	Max.
1	235.7	209.6	1254.0	611.0	216.8	977.0
2	13.3	275.4	2003.0	24.7	185.2	279.0
3	385.0	509.0	2307.0	74.0	198.7	220.0
4	71.0	453.8	1478.0	15.7	186.1	82.0
5	58.7	387.7	797.0	25.5	257.3	276.0
6	196.0	365.0	1896.0	9.8	113.3	39.0
7	459.3	117.2	1607.0	253.9	114.9	746.0
8	479.8	691.2	2264.0	357.5	348.4	47.0
9	365.8	480.0	2071.0	440.1	306.5	1340.0
Total	251.6	387.7	2307.0	201.3	214.1	1340.0

area, the more effective the extraction is since the measurement error is smaller. The location information of a UWB sensor was obtained while a user wearing the UWB sensor moved around the room according to a predefined schedule. In the schedule, a user wearing a UWB sensor stayed at Location IDs from 1 to 9 for 2 seconds each, as shown in Fig. 5, and then moved in order, repeating the schedule 10 times. The user's staying locations includes three points with large positioning errors, three points with approximately average errors, and three points with smaller-than-average errors.

Next, to confirm the usefulness of activity pattern mining, we collected the location data of four laboratory members in the laboratory for 30 days. Then, by applying the activity pattern mining to the time-series data of collected locations, we confirmed the validity of the results along with the members. After the experiment, the members were asked to check their own activity pattern graphs and episode rules. There were no restrictions on the laboratory members' activities during the experiment, except wearing the UWB sensor around their necks in the laboratory. Some members refrained from laboratory activities during the experiment period due to concerns about the spread of the coronavirus.

Table 3 The distance (mm) to the measuring location and size (mm) of stay areas extracted by the stay-area extraction method with/ without QF filtering.

	With QF filtering		Without QF filtering	
Location ID	Distance to measuring location	Size of stay area	Distance to measuring location	Size of stay area
1	858.0	3.0	1026.0	128.0
2	690.0	277.0	647.1	317.0
3	547.8	154.0	455.0	137.0
4	162.1	122.0	140.0	131.0
5	547.8	154.0	547.8	154.0
6	278.5	139.0	222.5	139.0
7	133.2	264.0	133.2	264.0
8	140.4	66.0	117.4	66.0
9	196.0	335.0	196.0	335.0
Total	394.9	168.2	387.2	185.7

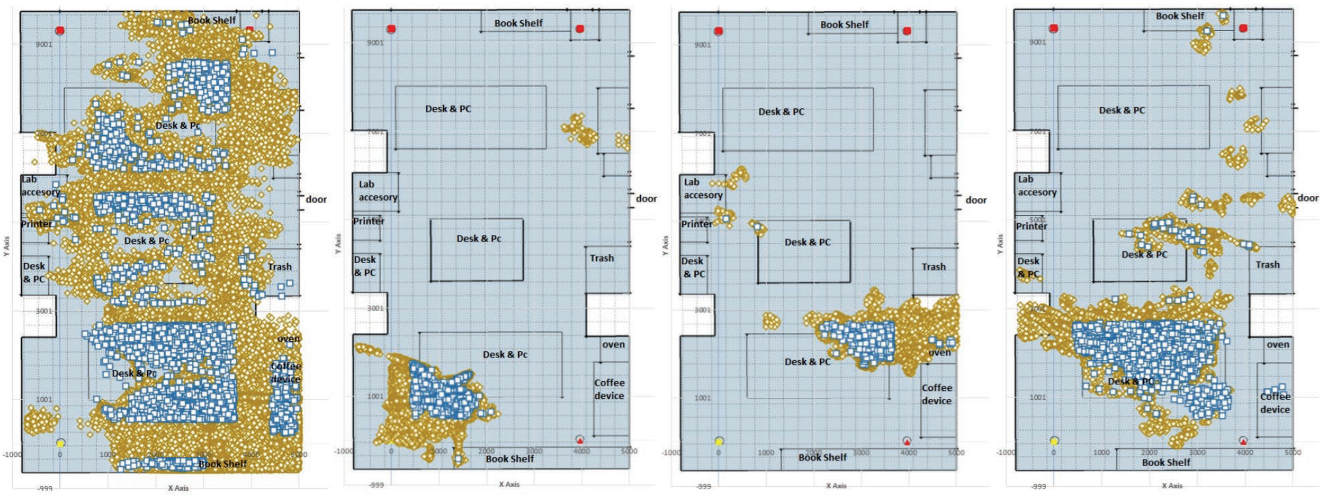
3.2 Results

The evaluation results of stay-area extraction and activity pattern mining are described in Sects. 3.2.1 and 3.2.2, respectively.

3.2.1 Stay-Area Extraction

Table 3 shows the detection accuracy and size of stay areas which were extracted by a stay-area extraction method with/ without QF filtering from the time-series data of a UWB sensor. Figure 6 shows the graphs of the precision, recall, and F-score for each stay-area extraction.

As shown in Table 3, the average size of the stay-areas extracted by the stay-area extraction with QF filtering was smaller than the one extracted by the stay-area extraction without QF filtering. In particularly, the sizes of the stay areas detected by the stay-area extraction with QF filtering were improved at the Location IDs 1 and 2 by more than 50 mm. Conversely, the average distance to the measuring location in case of using the stay-area extraction with QF filtering was larger than the one in case of using the stay-area extraction without QF filtering. In particularly, the distances at Location IDs 2, 3, and 6 in case of using the stay-area extraction with QF filtering were worsen by more than 40 mm. One of the reasons for such errors is the influence of the NLOS environment due to metal obstacles; at Location IDs 2, 3, and 6, two of the four anchors were hidden by metallic desks, resulting in the detected locations with smaller QF



(1) Use A (2) Use B (3) User C (4) User D

Fig. 7 Illustrations of the locations of stay areas of 30 days for each user during 30 Days. The yellow and blue dots indicate the stay areas extracted by the stay-area extraction and the center locations of stay-areas, respectively.

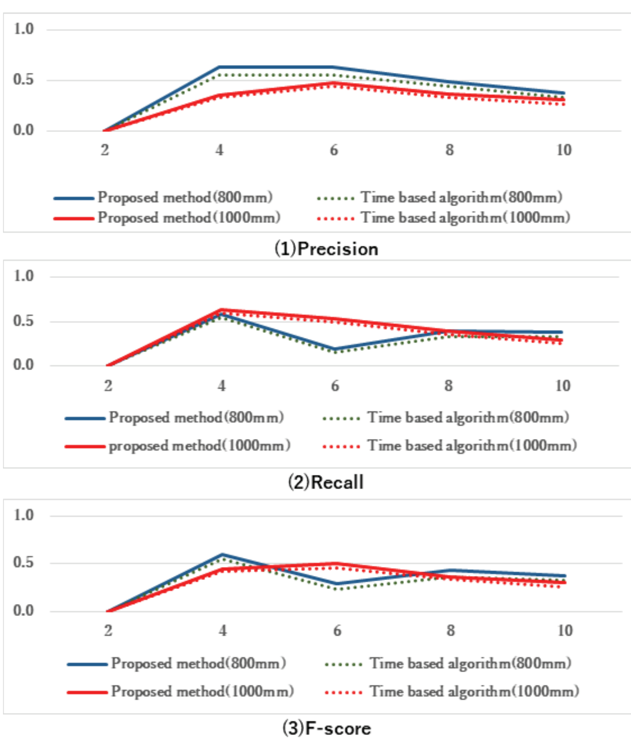


Fig. 6 Precision, recall, and F-score of the proposed stay-area extraction and the time-based clustering algorithm for each time parameter (second).

values closer to the measuring locations. So that the locations detected by the stay-area extraction with QF filtering were removed. To address this issue, countermeasures such as installation of new UWB anchors should be considered.

As depicted in Fig. 6, the stay-area extraction with QF filtering provided better accuracy than the time-based clustering algorithm in terms of precision, recall, and F-score. For the time parameter, the proposed method showed the best results when set to 4 s, with precision of 0.63 and recall of 0.64, respectively. For the distance parameter, the proposed method showed the best results for precision and F-score when set to 800 mm. Therefore, the proposed method with QF filtering and time and distance parameter settings of 4 s and 800 mm, respectively, is effective.

In the experiment, the proposed method obtained precision of 0.64 and recall of 0.60, which indicates that the proposed method cannot extract the same number of stay-areas as the one of user-visited locations. One of the reasons for this is largely due to the large detection error of a UWB sensor, causing that the stay areas generated far from the measuring locations. To address the issue, the installation of UWB anchors would be designed for each indoor environment to avoid too large NLOS locations, so that the performance of the proposed method could be improved.

3.2.2 Activity Pattern Mining

Figures 7, 8, and 9 show the locations of stay areas of 30 days for each user, the activity pattern graph of 30 days for each user, and the episode rules of 30 days for each user, respectively.

As depicted in Fig. 7, the stay areas extracted by the stay-area extraction represent the characteristics of each user's activities during 30 days. For example, user A frequently visited the entire room and engaged in various activities, followed by user D, who also engaged in various activities. Conversely, users B and C had a smaller range of indoor activities, and their activities were mostly around their desks. The figures representing the stay areas of users B and C show that the stay-area extraction removed their locations while the users were moving around.

As depicted in Fig. 8, the activities and their transitions for each user are understandable concretely from the stay areas which were extracted from the locations of a UWB

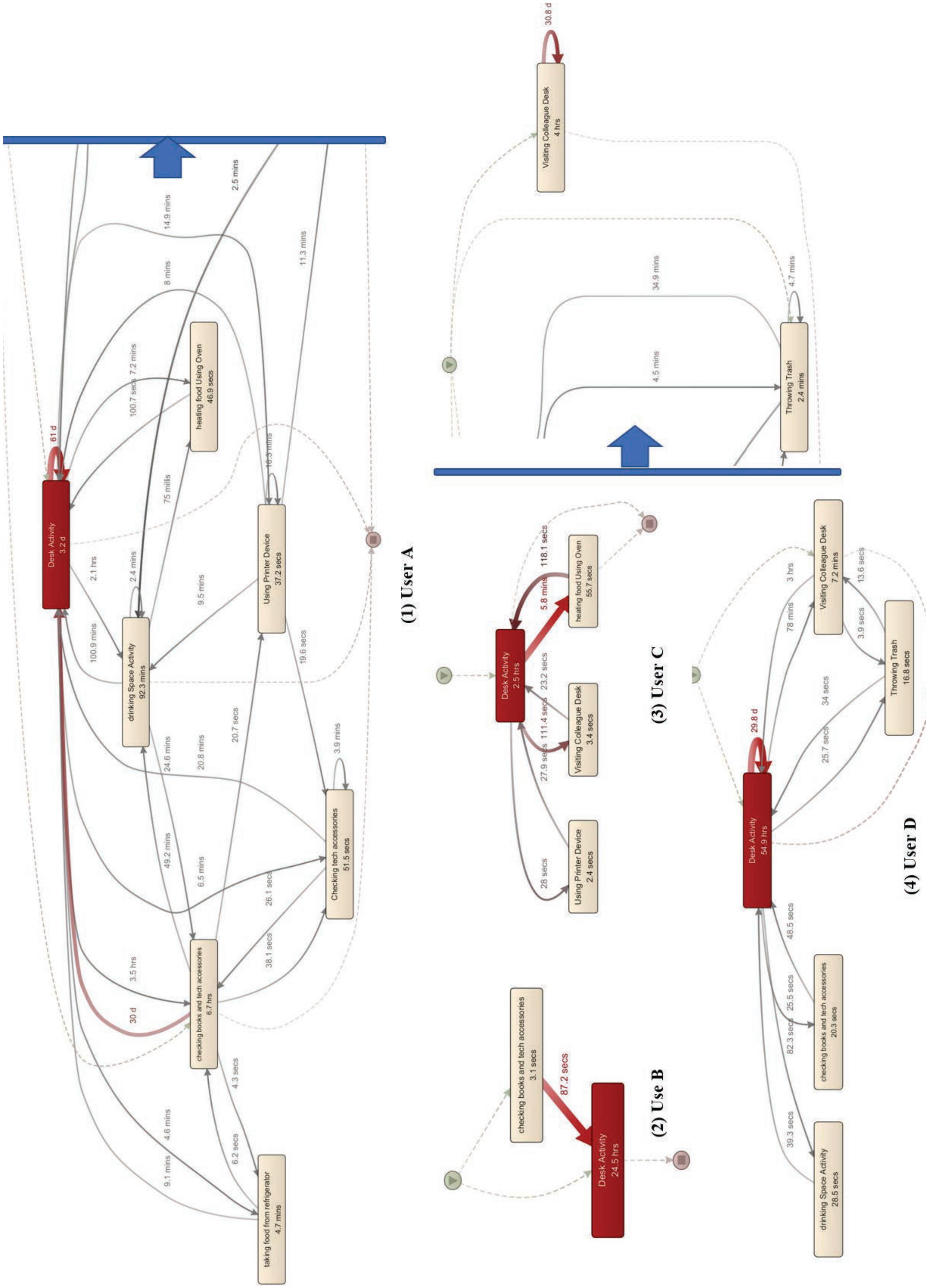


Fig. 8 Activity pattern graph of 30 days for each user generated by the activity pattern mining. The red arrow and rectangle indicate the most frequent transition and activity of each user, respectively.

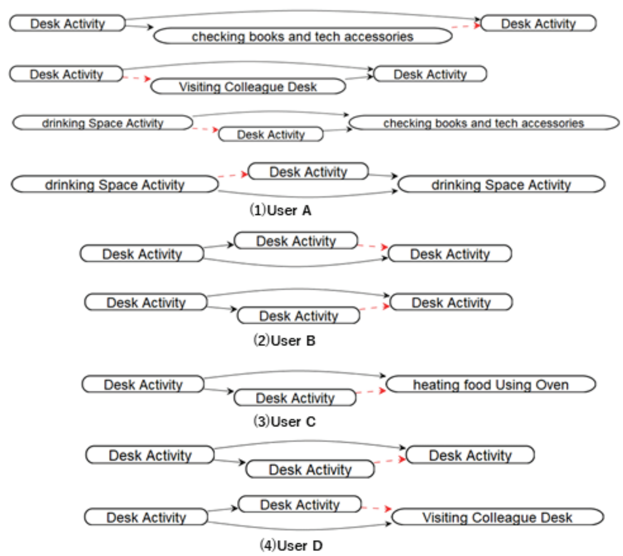


Fig. 9 Examples of the episode rules for each user. The red dotted line indicates the association rule.

sensor. For example, users A, D, C, and B engaged in 9, 5, 4, and 2 activities during the experiment period, respectively. All users spent the majority of their time at their own desks, and each user also made short stops at some locations, such as their colleagues' desks, bookshelves, an accessory box, drink space, a microwave oven, a printer device, trashes, and refrigerators.

As depicted in Fig. 9, the episode rules for each user were extracted by association analysis from the frequent episodes included in the activity pattern graph of each user as shown in Fig. 8. The episode rules indicate the relationships among the characteristic episodes of each user. For example, the users A and D were frequently observed visiting colleagues' desks, whereas the users B and C were rarely observed visiting others' desks. Furthermore, the user A frequently utilized the drink corner, whereas the user C frequently used the microwave oven.

We confirmed that the activity pattern graph and episode rules of each user were acceptable to each user, based on their understanding of their activities in the laboratory and their interactions with other laboratory members. Therefore, the proposed method of mining user activity patterns from time-series data of location information using a UWB sensor is useful for recognizing human behavior indoors.

As a limitation of the proposed technique, it is necessary to consider the activities to be assigned based on the measurement error of a UWB sensor. As shown in Table 2, the average error of the UWB sensor radius was approximately 250 mm in this indoor environment, and the distance to each indoor landmark for assigning activities was set to be within 500 mm. However, if a user's activity needs to be recognized within a narrower range, it is difficult to do so using only location measurements with a UWB sensor. To address this issue, it is considered to incorporate environmental installation type sensors such as IoT or Wearable type sensors into the implemented system, however, it is a future issue since further technological development is required.

4. Conclusion

In recent years, location-based technologies for ubiquitous environments have aimed to realize services for different purposes based on an individual's location information. Although estimation technology that accurately recognizes and predicts the movements of people and objects is necessary to realize advanced indoor location-based services, conventional wireless indoor positioning is susceptible to noise and has a wide range of indoor location estimation, making it difficult to accurately identify human activities. Therefore, in this study, we developed a system using UWB sensors to estimate user activity patterns from time-series data of user location in an indoor environment. The developed system extracts indoor stay areas using a QF filter from time-series data of location information of a UWB sensor attached to a user, and extracts a user's frequent activity pattern graph and characteristic episode rules based on the stay areas and their transitions by the activity pattern mining. To evaluate the developed system, we conducted experiments to investigate the accuracy of estimating the user's stay areas using a UWB sensor and to monitor the results of the activity pattern mining applied to actual laboratory members for 30 days. The results showed that the proposed method is superior to the comparative method, Time-based clustering algorithm, in the accuracy of estimating the stay areas and can appropriately reveal the users' activity patterns and their characteristics in the real environment.

In our future works, we will obtain many case studies in which human interactions are analyzed for indoor activities using the developed system. In particular, we will investigate how new members develop their indoor behavior over time. In addition, based on indoor behavior patterns, we will develop indoor services to improve users' life style, team activities, and social interactions.

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