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Situation Recognition from Behavior Logs in Caregiving Services

By Kaoru Sato

A thesis submitted to
School of Information Science,
Japan Advanced Institute of Science and Technology,
in partial fulfillment of the requirements
for the degree of
Master of Information Science
Graduate Program in Information Science

Written under the direction of
Professor Kunihiko Hiraishi

September, 2015

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Professor Kunihiko Hiraishi
Professor Ryuhei Uehara
Professor Kazuhiro Ogata

August, 2015 (Submitted)

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Chapter 1

Introduction

1.1 Background and Motivation

In Japan, age-population ratio has been shifted to more elderly one, and the ratio of young people decreases rapidly in the population. In such aging society, while demands for caregiving services are increased, the number of employees who provide the services is insufficient. Thus, improvement of both efficiency and quality of the services are a critical issue for the society.

Recently, introduction of ICT systems is considered by many researchers for the purpose of improving the operation efficiency. As one of such research trends, Smart Voice Messaging System is proposed by our research group [1]. In the system, as shown in the Figure 1.1 care staffs ware ICT devices, like smart watch, and whenever a care staff needs help from other staffs, she tweet a message to her ICT device. The tweeted message is sent to proper staffs at proper time by analyzing the place, the time stamp, the keyword of the tweeted message. As a consequence of introducing the system to caregiving field, communication efficiency among care staffs is highly improved compared to no help of ICT devices, which is shown by some field experiments [1]. Moreover, introduction of that system brings another benefit that use logs of ICT devices are automatically collected into database. Because the use logs in database contain operation information of the caregiving service, proper analysis of the use logs might further improve efficiency and quality of caregiving services.

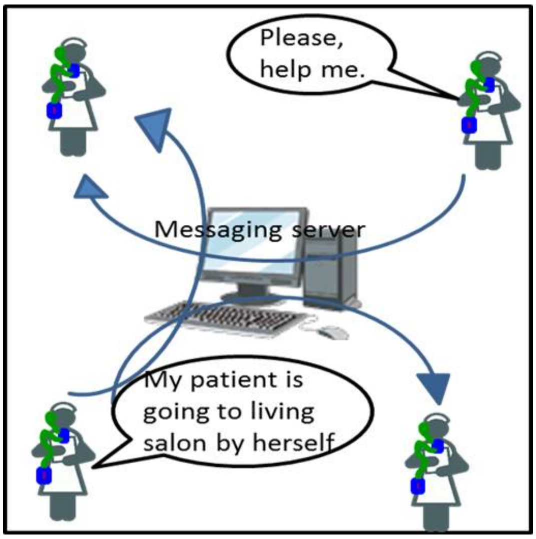

Figure 1.1: Smart Voice Messaging System

Previously, there are two studies that utilize the use logs for improving their operation efficiency. In [2], the use logs are used to visualize changes of operation areas of each care staffs by animation. This reproduction of the past operations is used during conferences for improving work operations. However, it takes quite a lot of time to manually find out information valuable for the improvement from the animation. Thus, applying some data mining techniques, so as to automatically extract the valuable information, may contribute to improving their user experience. In [3], on the other hand, an automatic information extraction technique is applied to the use logs. The authors of [3] mainly focus on individual behaviors of care staffs, and suspicious activities in these behaviors are extracted from the use logs by constructing a probabilistic model. This type of techniques that unusual events are extracted from a large amount of event logs is eagerly studied in the research field of Outlier detection [4]. However, although caregiving service is partitioned into multiple operation time zones such as meal care time, recreation time, etc., and whether or not a behavior of a care staff can be regarded as a suspicious activity highly depends on that operation time zone, the latter research does not consider so much about the entire operation situation.

When utilizing information extracted from any ICT devices, considering about the process that a human make a decision based on the extracted information might be beneficial for proposing an effective utilization of the use logs because, in most case, purpose of inventing new function on an ICT system is to help a human to make decisions on their business. Situation Awareness (SA) is the cognitive process in human decision making . According to Endsley [5], SA is defined by the following three levels: Perception, Comprehension, and Projection. In this research, we focus on not only individual behaviors of each care staffs but also the entire caregiving service space, and apply the concept of SA to analysis of the use logs. In other words, operation situations as the entire service space are extracted from the use logs of ICT devices in caregiving services. The research of this paper might correspond to solving the problem in [3], which the previous research do not consider about the entire operation situations. Also, we assume two applications of the research of this paper. The first one is an automatic extraction of anomaly operation situations. This technique might be used during conferences of the past work operations together with the system proposed in [2]. Another one is a human decision making support system. In the system, an operation situation is estimated during their real time operations. This real time estimation might help care staffs to keep track of their proper decision making in their operations.

1.2 Organization of the Thesis

The reminder of the thesis is organized as follows.

- In Chapter 2, background knowledge for the proposed method is described.
- Chapter 3 mentions about the field experiments previously conducted, and observation during the experiments
- In Chapter 4, the proposed method is discussed.
- In Chapter 5, the results that the proposed method is applied to the use logs obtained in the field experiments are shown. Also, in the latter half of this chapter, we have discussion based on the results.
- Chapter 6 describes about two of assumed applications.
- In Chapter 7, we conclude the thesis.

Chapter 2

Background knowledge

2.1 Situation awareness

Broadly speaking, Situation Awareness (SA) [5] is a cognitive process which is aware of what kind of information is around your environment, what means that information for your task or goal, and what is expected to happen in near future from that understanding. This concept is originally developed from the world of military pilots, and nowadays SA is applied to various types of operation fields such as driving a car, treating a patient, etc., in addition to military aviation. When people make a decision in these listed fields, usually they set goals or objectives to complete their operation tasks, and what kind of information they need varies the set goals or objectives. Therefore, required information for SA in decision making highly depends on operation field and goals or objectives in it.

There are some definitions of SA process. According to [6], for example, SA consists of two stages. However, the most commonly used definition is Endsley's one. According to [5], SA is defined by the following three different levels: (1) Perception of the elements in the environment. (2) Comprehension of the current situation. (3) Projection of future status. In the rest of this paper, Endsley's definition is used for SA. Figure 2.1 shows roles of each different level in SA and their relationship.

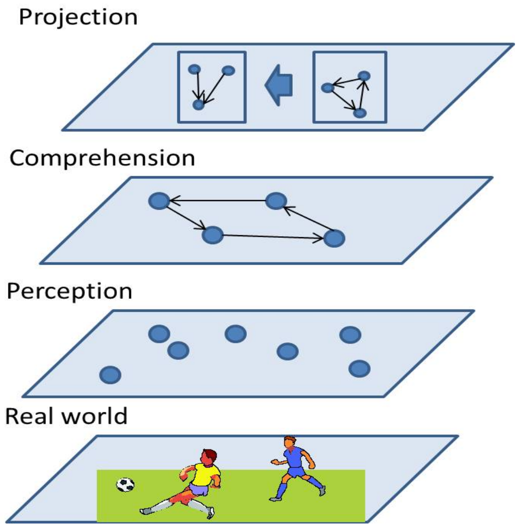

Figure 2.1: Roles of each different level in SA

Perception of the elements in the environment.

At the first step for SA, perception stage, a person perceive the states, attributes, and dynamics of elements in environment surrounding him or her as shown in the bottom and the second from the bottom planes in Figure 2.1. This perception process is achieved through all human sensory organs such as visual, auditory, tactile, etc., whereas human is not able to detect all needed information for them because of the limitation of their sensing ability. In military aviation, for example, the pilot never perceives the altitude of the aircraft through his or her sensory organs directory though the awareness of that altitude is critical for safety. In such case, altitude sensors extract the needed information, altitude, instead of him or her, and just show the numerical value or the graph. Therefore, in the perception stage, although basically a person perceives elements in the environment through their sensory organs directory, electronic sensors certainly help a person perceive the needed information.

Comprehension of the current situation.

The second step for SA is comprehension of the current situation. In this stage, a person understands what the data perceived in the first stage of SA mean for their goals or objectives as shown in the second and third from the bottom planes in Figure 2.1. This comprehension stage can be seen in the following example. When you are watching a game, like soccer, you may understand which team has a chance for scoring and another team is defending against that attack by perceiving the team possessing the ball, distribution of players in the field. What you can understand from the perceived information highly depends on your own knowledge for soccer in this case. While you may barely understand which team is in offense if you are novice for watching soccer, you can even understand basic formation of each team, like 4-4-2, 3-5-2, etc. if you have much experience to play soccer.

Projection of future status.

In the last stage for SA, once the person understands what the data means for their goals or objects, he predicts what will happen in the environment in near future as shown in the top plane in the Figure 2.1. In the real world, this projection stage corresponds to the following case. For example, when you are driving a car, occasionally a pedestrian rushes out of the sidewalk. In this case, as soon as you get aware of the pedestrian, you must step on the brake pedal of the car because you predict that the pedestrian is likely attacked by your car if you do not take any actions. This prediction comes from your understanding about the status of the pedestrian.

In the projection stage, failure of SA comes from insufficient mental resources or insufficient knowledge of the domain.

2.2 Data mining techniques

2.2.1 Hierarchical clustering

Hierarchical clustering algorithms output a graph representation of data [7]. Based on analysis of the produced graph, a number of clusters is determined in contrast with that many of other clustering algorithms require a pre-specified number of clusters. There are two types of hierarchical clustering algorithms: top-down and bottom-up. In the bottom-up known as an agglomerative approach, at first each input element is treated as a singleton cluster. Then, iteratively, the closest pair of clusters are merged until all clusters have been merged into a single cluster which contains all input elements. On the other hand, the top-down, known as a divisive approach, starts from a single cluster containing all input elements, and iterate splitting a cluster into smaller ones until individual input elements are reached.

The result of hierarchical clustering is visualized in the form of dendrograms as shown Figure 2.2. Each marge is represented by a horizontal line connecting two vertical lines, and the y-coordinate of the horizontal line shows the similarity of the merged two clusters. Based on the dendrogram, we can determine the number of clusters, as 3, by cutting the dendrogram at a certain threshold value of the similarity as shown by the dotted line in the dendrogram.

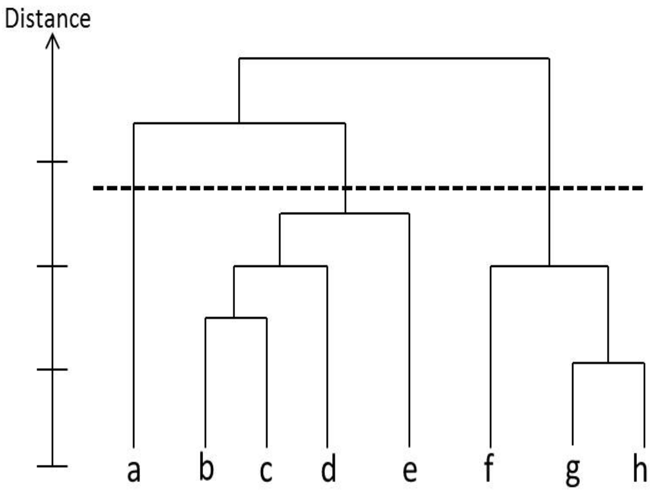

Figure 2.2: Dendrogram example

Similarity metrics between two clusters are roughly divided into 4 types: Group-average method, Single-link method, Complete-link method, Ward method. Assume two clusters A and B. Then, each similarity metric defines the distance between the two clusters, represented by $d(A, B)$, as the followings.

(1) Single-link method

In the Single-link method, the nearest data pair is selected as the minimum distance between two clusters. This data selection as the distance between two clusters is represented by the following equation.

$$d(A, B) = \min_{\boldsymbol{x} \in A, \boldsymbol{y} \in B} d(\boldsymbol{x}, \boldsymbol{y}) \tag{2.1}$$

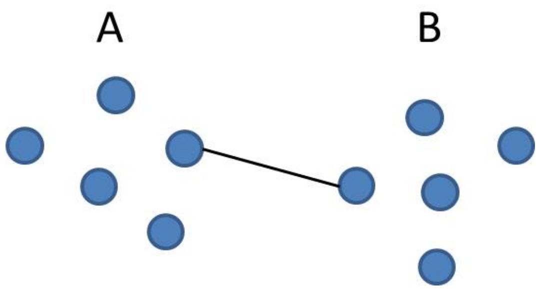

Figure 2.3: Single-link method

(2) Complete-link method

In the Complete-link method, the farthest data pair is selected as the maximum distance between two clusters. This data selection as the distance between two clusters is represented by the following equation.

$$d(A, B) = \max_{\boldsymbol{x} \in A, \boldsymbol{y} \in B} d(\boldsymbol{x}, \boldsymbol{y}) \tag{2.2}$$

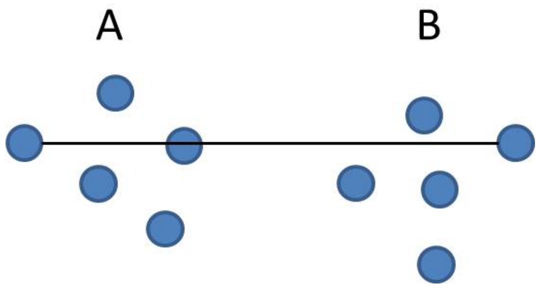

Figure 2.4: Complete-link method

(3) Group-average method

In the Group-average method, all possible data pairs across two clusters are summed up, and the sum gives the distance between the clusters. This construction of the distance is represented by the following equation.

$$d(A, B) = \frac{1}{n_A n_B} \sum_{\boldsymbol{x} \in A} \sum_{\boldsymbol{y} \in B} d(\boldsymbol{x}, \boldsymbol{y}) \tag{2.3}$$

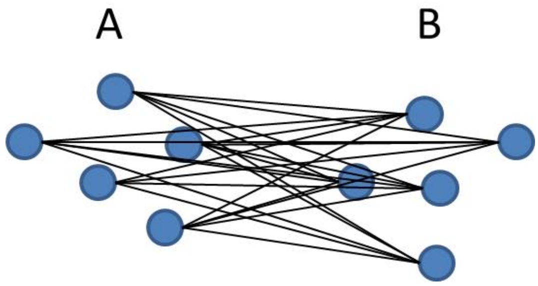

Figure 2.5: Group average method

(4) Ward method

According to [8], in the Ward method, arbitrary two clusters are merged so as to minimize the increase of the sum of squares as shown in the Figure 2.6. The increase as the distance between two clusters is represented by the following equation.

$$d(A, B) = \sum_{x \in A \cup B} |\boldsymbol{x} - Center(A \cup B)|^2 - \sum_{x \in A} |\boldsymbol{x} - Center(A)|^2 - \sum_{x \in B} |\boldsymbol{x} - Center(B)|^2 \quad (2.4)$$

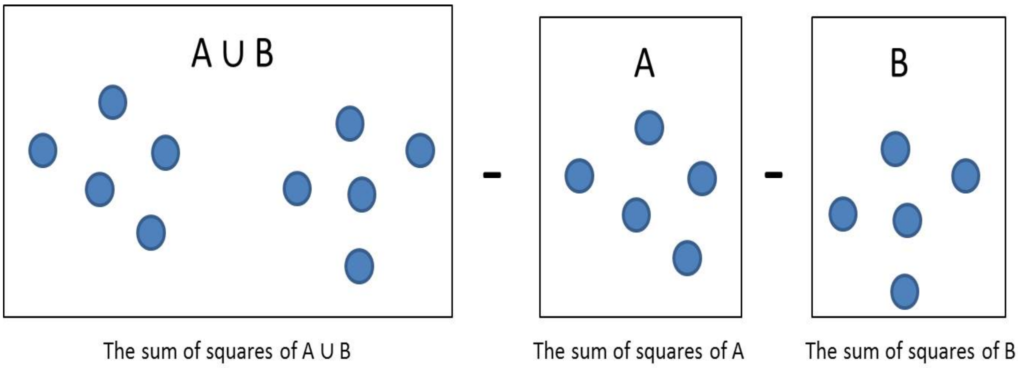

Figure 2.6: Ward method

In the Hierarchical clustering, there is a general expression of above mentioned similarity metrics known as the Lance-Williams dissimilarity update formula [9]. When clusters A and B are merged, the distance between the merging result of the two clusters and other arbitrary cluster C is represented by the following form.

$$d_{A \cup B, C} = \alpha_A d_{A,C} + \alpha_B d_{B,C} + \beta d_{A,B} + \gamma |d_{A,C} - d_{B,C}| \quad (2.5)$$

In this equation, the parameters α_A, α_B, β, and γ are the setting values depending on types of similarity metrics. The selection of these values is summarized in the Table 2.1

Table 2.1: Values of the parameters in the Lance-Williams dissimilarity update formula

Similarity metric	α_A	α_B	β	γ
Single-link	$1/2$	$1/2$	0	$-1/2$
Complete-link	$1/2$	$1/2$	0	$1/2$
Group-average	$1/n_B$	$1/n_A$	0	0
Ward	$\frac{n_A+n_C}{n_A+n_B+n_C}$	$\frac{n_B+n_C}{n_A+n_B+n_C}$	$-\frac{n_C}{n_A+n_B+n_C}$	0

2.2.2 Graph similarity

Graph structure is suited for representing relationship features among elements. Because of this characteristic, graph structure is used for various types of data mining applications that require extracting knowledge about relationship features. Especially when extracting temporal knowledge from time varying graphs, measuring similarities among graphs is an ideal method for extracting temporal knowledge. Such method is actively studied in the field of Graph Similarity. According to Koutra [10], the research field of Graph Similarity is divided into two categories depending on their problem definitions: Known node correspondence and Unknown node correspondence.

Broadly speaking, known node correspondence problems require comparing two graphs which have the same nodes sets, and the difference in between their graph structures is only their edge sets, as shown in Figure 2.7. In this problem, similarity score of the comparing two graphs is produced as an output of the problem. Problem definition of known node correspondence is summarized as follows.

Known node correspondence problem

- Given
  - 2 graphs with the same nodes and different edges sets
- Find
  - Similarity score of the comparing 2 graphs

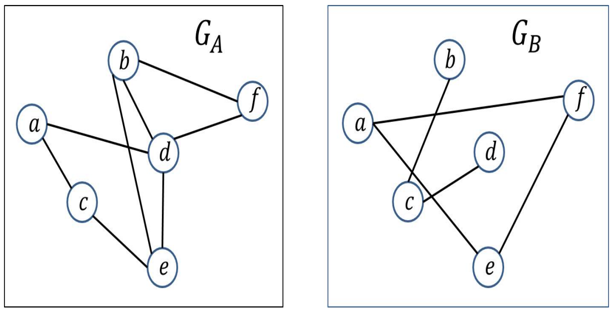

Figure 2.7: Known node correspondence problem

On the other hand, unknown node correspondence is a kind of emerging research field, derived from the field of Social Network Analysis. Originally unknown node correspondence aims to identify users across different social network services. This identification is done by comparing network structures around them. Therefore, in unknown node correspondence problems, nodes sets of comparing two graphs are not necessary same, and only node IDs are given. Problem definition of unknown node correspondence is summarized as follows.

Unknown node correspondence problem

- Given
  - 2 graphs with different nodes and different edges sets
  - Only nodes IDs are given
- Find

- Structural score around different nodes
- Mapping nodes over the 2 given graphs

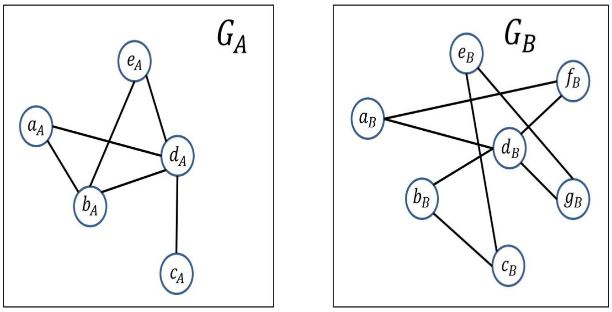

Figure 2.8: Unknown node correspondence problem

Although unknown node correspondence can be applied to many modern research areas, like social network analysis, chemical compound composition, etc., main focus of the research field is a kind of big data application. Thus, we focus on explanations about known node correspondence.

As a similarity metric of graphs in known node correspondence problem, there are broadly 4 types of the metric as described in the followings.

(1) Vertex / Edge overlap

According to [11], this similarity metric is represented by the following equation. The idea comes from that two graphs are similar if they share many vertex and edges.

$$sim(G_A, G_B) = \frac{|V_{G_A \cap G_B}| + |E_{G_A \cap G_B}|}{|V_{G_A}| + |V_{G_B}| + |E_{G_A}| + |E_{G_B}|} \tag{2.6}$$

(3) Vector similarity

In [11], another similarity metric, Vector similarity is proposed. This similarity metric is represented by the following equation. The idea comes from that two graphs are similar if their edge weight vectors are close.

$$sim(G_A, G_B) = |\boldsymbol{G_A} - \boldsymbol{G_B}| \tag{2.7}$$

(4) Graph edit distance

In addition to above mentioned metrics, the similarity metric based on graph edit distance is proposed in [12]. This similarity metric is represented by the following equation. The idea comes from that two graphs are similar if one graph is converted by small changes.

$$sim(G_A, G_B) = |V_{G_A}| + |V_{G_B}| - 2|V_{G_A \cap G_B}| + |E_{G_A}| + |E_{G_B}| - 2|E_{G_A \cap G_B}| \tag{2.8}$$

Chapter 3

Field experiments

3.1 Settings

Field experiments were conducted in a nursing home on May and August in 2013. The main purpose of the experiments is to evaluate communication effectiveness when Smart Voice Messaging System is introduced in the nursing home. The floor plane of the nursing home is depicted in the Figure 3.1. In the experiments, 5 or 6 care staffs waring smart devices were working on the floors. As a result of the experiments, voice messages and location information are collected and stored in a database. In this research, we focus on location information of care staffs. The location information is recorded whenever each care staff enters or exits a room. We call this a behavior logs. The format of the recorded data has the following form:

$$(\textit{Time stamp}, \textit{Staff ID}, \textit{Room name}, \textit{Enter or Exit}) \tag{3.1}$$

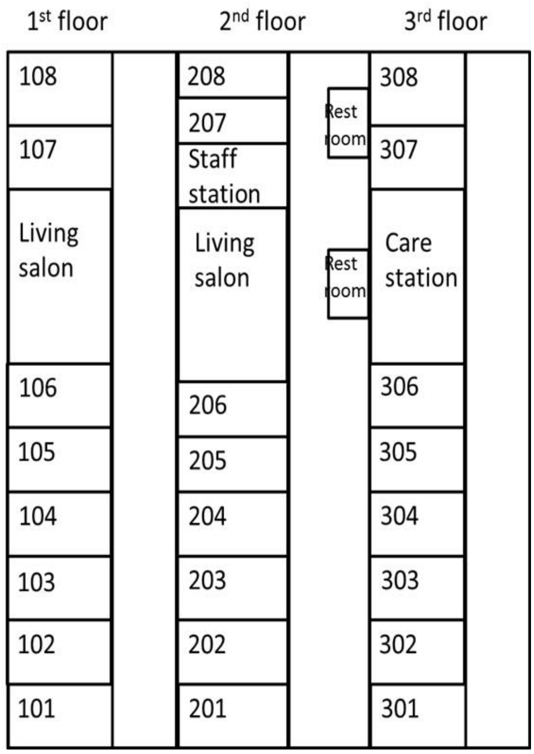

Figure 3.1: The floor plane of the nursing home

3.2 Observation in the field experiments

In the field experiments, members of our research group observed features of 4 types of operation situations in each time period. Each of these operation situation types is described as the followings in tern.

(1) Oral health care

During oral health care operation, some care staffs visit each patient room by terns, and as a result, care staffs spread over the facility as shown in the Figure 3.2.

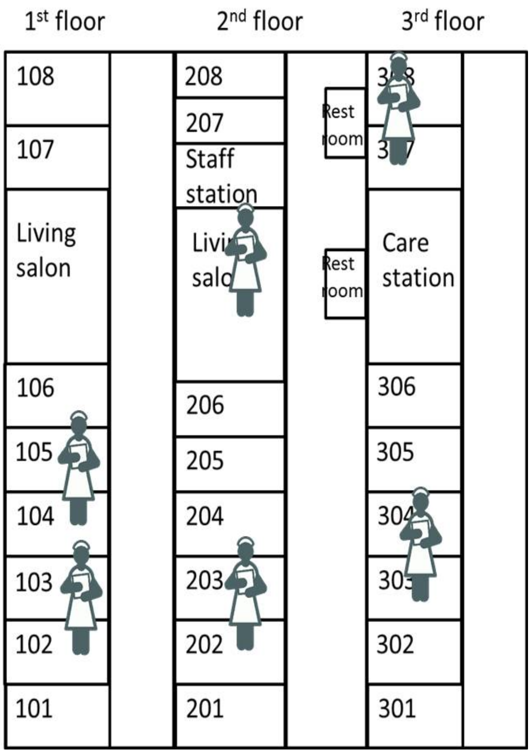

Figure 3.2: Oral health care

(2) Meal care

In meal care operation, all care staffs are divided into two parts: 1F living salon and 2F living salon as shown inn the Figure 3.3.

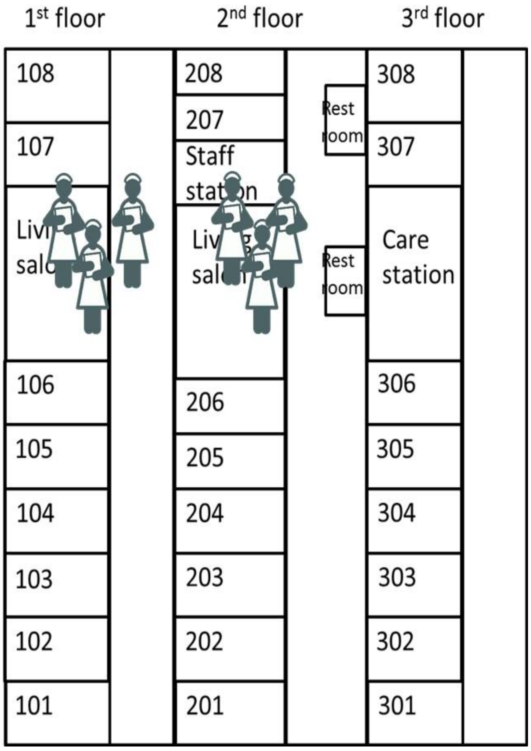

Figure 3.3: Meal care

(3) Recreation

During recreation time, most of care staffs assemble in the 2F living salon as shown in the Figure 3.4.

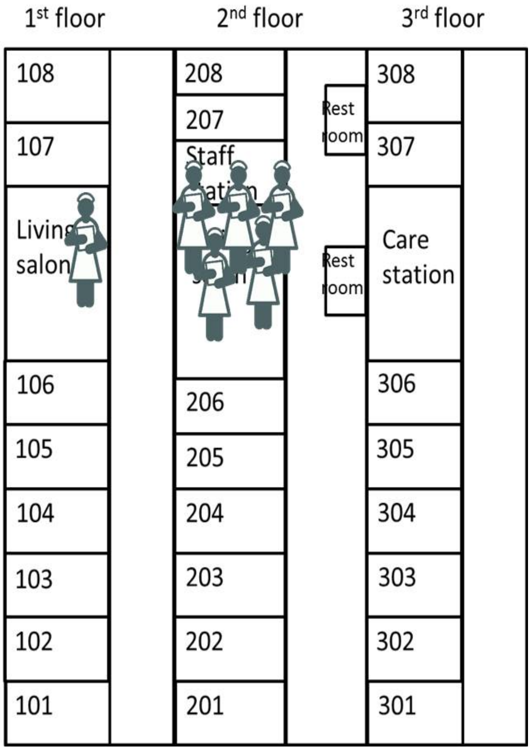

Figure 3.4: Recreation

(4) Excretion assistance

During excretion assistance operation, care staffs tend to move among different areas frequently as shown in the Figure 3.5

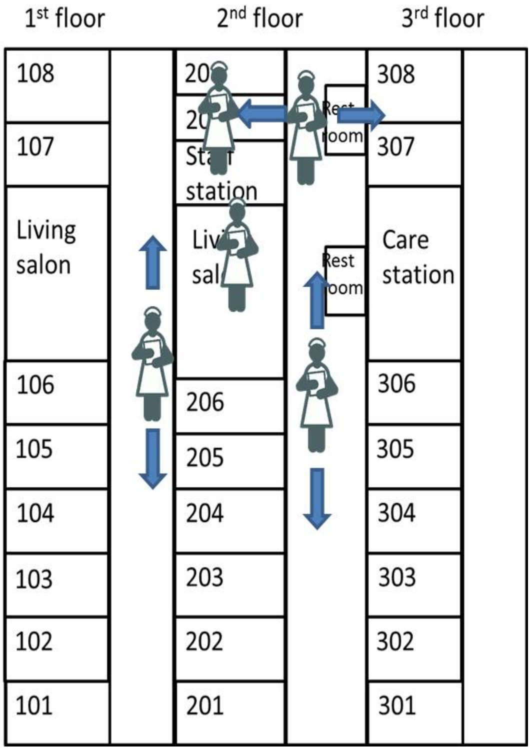

Figure 3.5: Excretion assistance

Chapter 4

Proposed operation situation recognition method

In this chapter, our proposed operation situation recognition method is described together with the motivation.

The proposed method aims to comprehend operation situations of a care staff group at each time stamp, which should be originally the role of human brain, but is difficult to recognize by themselves because of the sensing limitation of human organs. In terms of Situation Awareness in human decision making, the proposed method is assumed to substitute perception and comprehension stages as shown in the Figure 4.1.

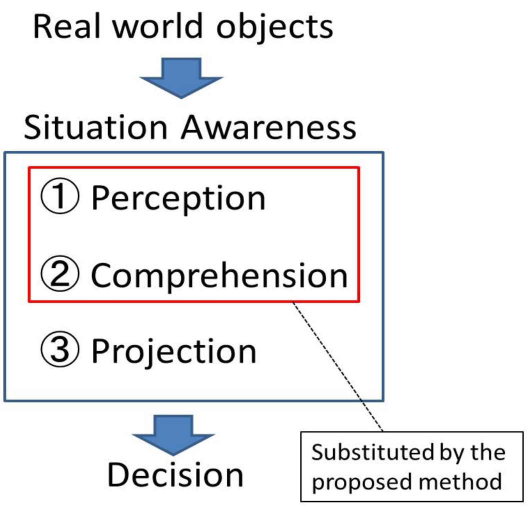

Figure 4.1: The proposed method in SA

According to the perception definition of Situation Awareness described previously, a person is required to select the input information depending on objectives of their situation awareness. In constructing the proposed method, observation during field experiments is a clue for such selection of input information. Thus, we set the following hypothesis based on observation in the field experiments.

When applying data mining techniques to real world data, according to [13], generally it consists of 3 phases: pre-processing, data mining itself, post-processing. The whole process is shown in the Figure 4.2

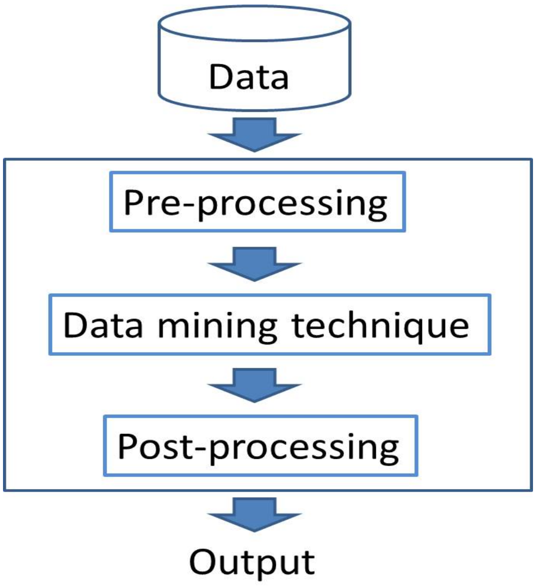

Figure 4.2: The whole process of a general data mining technique

In the pre-processing stage, deciding which feature of obtained data should be used for the clustering technique is the main purpose. This process requires standardizing the format of the obtained data and treating properly exceptional data which may affect to the final result of the method. On the other hand, post-processing is the process that derived clusters in the second stage are interpreted, or helps the interpretation by visualizing or filtering the result of the 2nd stage.

Our proposed method basically follows the 3-stage procedure, but a little modification of the procedure is required to reflect the hypothesis we mentioned previously. To reflect two main features of operation situations, distribution and the amount of movement of care staffs, we propose the 5-stage procedure as shown in the Figure 4.3.

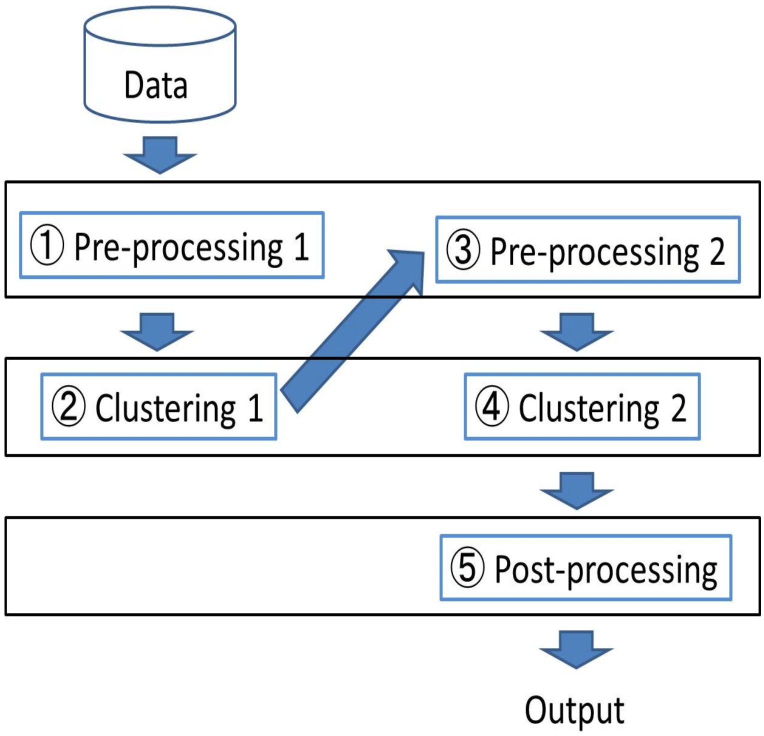

Figure 4.3: the 5-stage procedure

(1) Pre-processing 1

In the first step, distribution information of care staffs is extracted from the behavior logs, and represented by vector format (we call this“ Place vector ”). To generate the place vector, we first divide the nursing facility into 10 areas as shown in the Figure 4.4. The 10 areas correspond to components of the place vector, and each component represents the number of care staffs staying in each area.

For example, the case that one staff is in area 2, two staffs are in ares 4, two staffs are in area 5, and one staff is in area 9 is represented by the following place vector

Place vector : [0, 1, 0, 2, 2, 0, 0, 0, 1, 0]

Also, if there are some staffs who are moving from one area to another area, the values of the moving staffs are added in half to the components of areas that the staffs leave from and go to. In the Figure 4.4, for example, an operation situation such that three staffs are in area 4, two staffs are in area 5, and one staff is moving from area 2 to area 5 represented by the following place vector.

Place vector : [0, 0.5, 0, 3, 2.5, 0, 0, 0, 0, 0]

As an output of this phase, time series of place vectors at all time stamps is generated as shown in the Figure 4.5

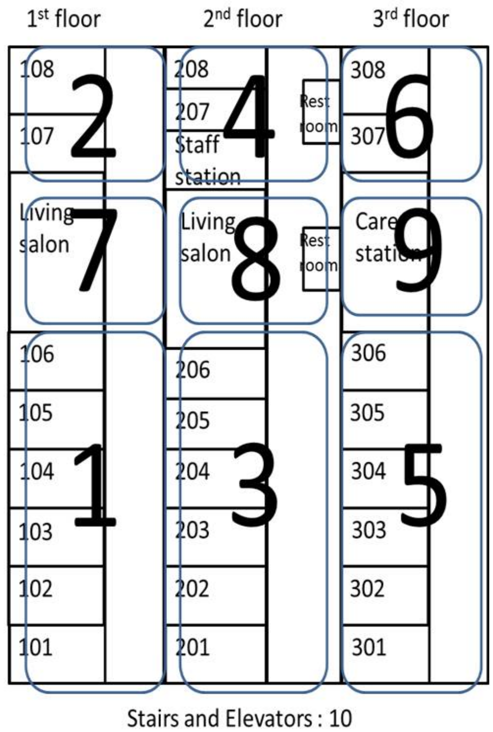

Figure 4.4: 10 separation of the nursing home

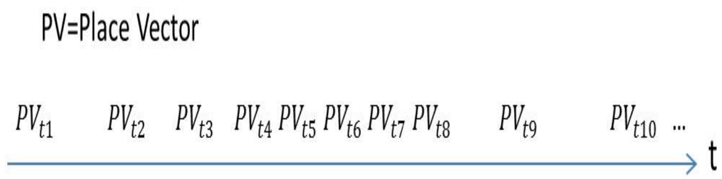

Figure 4.5: Time series of place vectors

(2) Clustering 1

Once time series of place vectors is generated, all types place vectors are clustered into some classes based on their similarities. This procedure is shown in the Figure 4.6. In this way, Hierarchical clustering [8] as the clustering technique, and Ward method as the similarity metric are used. The motivation that we choose Hierarchical clustering is as follows: we do not have to decide the number of clusters beforehand. This characteristic is beneficial especially for the second clustering, fourth stage of the whole method. Thus, we discuss about the motivation again in the fourth stage.

The clustering in this stage just focuses on distribution information of care staffs. We do not care about any temporal information at all.

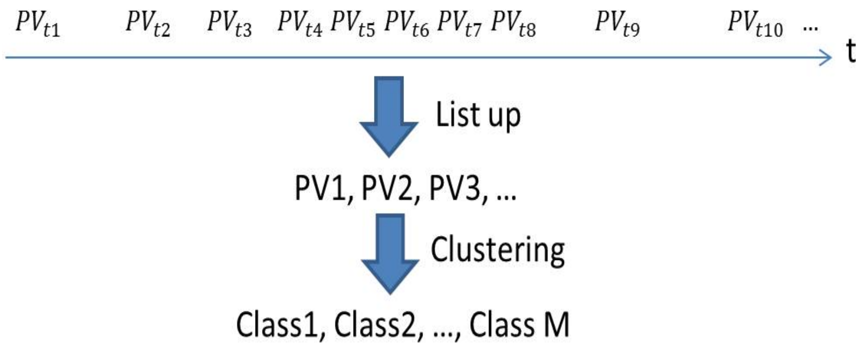

Figure 4.6: Clustering of place vectors

(3) Pre-processing 2

In this stage, graphs are constructed from the derived clusters in the previous stage. The constructed graphs are intended to represent movement information of care staffs by connecting the derived clusters at successive timestamps. The graph generation procedure is described in detail as followings.

At first, as shown in the Figure 4.7, arranged place vectors on their time series are transformed into the corresponding clusters on the same time series, based on the clustering result of the previous stage.

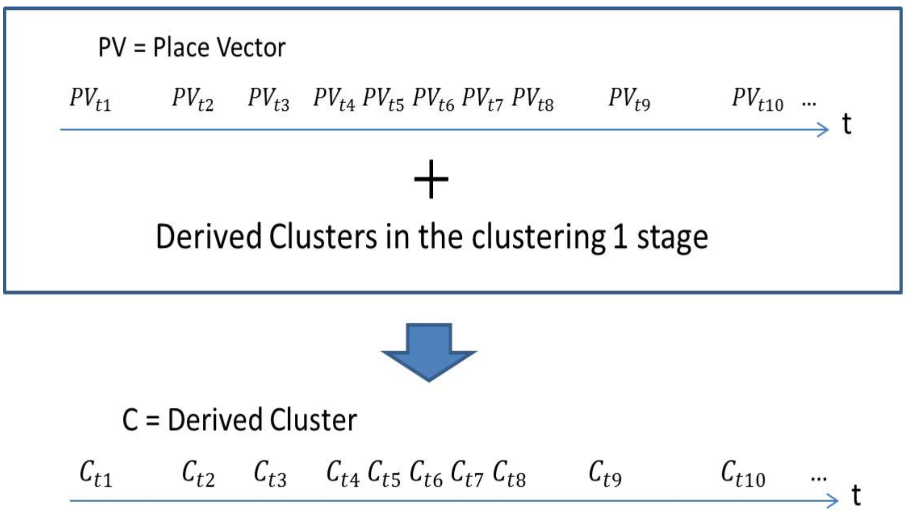

Figure 4.7: The first procedure of graph generation

Next, a fixed time interval α is applied to the time series of clusters as shown in the top of the Figure 4.8. Then, each time interval is further split into 10 partitions and one representative cluster from each partition is derived, as shown in the middle of the Figure 4.8. In the selection of representative clusters, the most dominating cluster on the time axis in each partition is selected as the representative cluster. As a result, 11 representative clusters in each partition are generated. The purpose of the procedure shown in the Figure 4.8 is to normalize the number of transitions in each graph of each interval to 10.

Finally, the 11 selected clusters in an interval are connected in order of their time series. Then, graphs are generated from all time intervals. Each graph consists of 11 clusters as nodes and 10 transitions among the clusters as direct edges. As a result of this stage, adjacency matrices of all of generated graphs at all time intervals are lined up on the time axis as shown in the bottom of the Figure 4.8

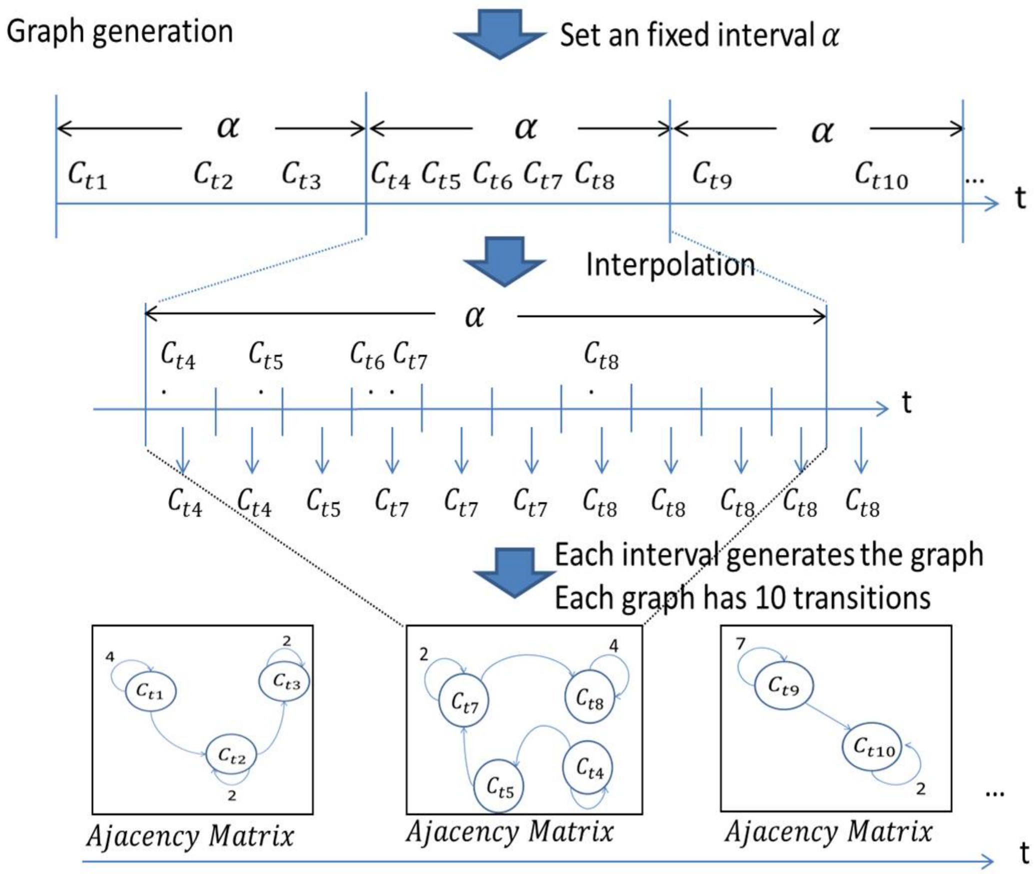

Figure 4.8: The second procedure of graph generation

(4) Clustering 2

A large part of this stage is same as the second stage of this method. In this stage, all types of adjacency matrices are listed up from the time series, and clustered into some classes as shown in the Figure 4.9. Hierarchical clustering and Ward method are also used in this stage as used in the Clustering 1 stage. The number of clusters is decided based on analysis of the derived dendrogram. Although the number of derived clusters in this stage is same as the number of operation situations in the caregiving service, we do not know how many operation situations are conducted in a day' s caregiving work. Therefore, Hierarchical clustering is suitable as a part of the proposed method because the clustering technique do not have to decide the number of clusters beforehand.

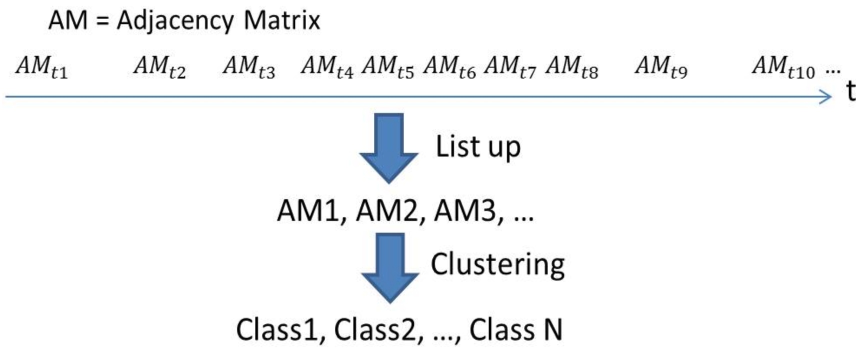

Figure 4.9: Clustering of adjacency matrices

(5) Post-processing

In the last stage of the proposed method, derived clusters in the fourth stage are mapped into operation situations appear in the caregiving service. The mapping is conducted by comparing features of derived clusters and operation situations as shown in the Figure 4.10. In the left hand side of the figure, time series and center vectors of derived clusters are used for extracting features of clusters. In the right hand side of the figure, on the other hand, observed features of 4 types of operation situations in the field experiments are used, which mainly compared to those of center vectors of derived clusters. Knowledge about reasonable sequence of operation situations obtained during the experiments is also used, and mainly compared to those of time series of derived clusters.

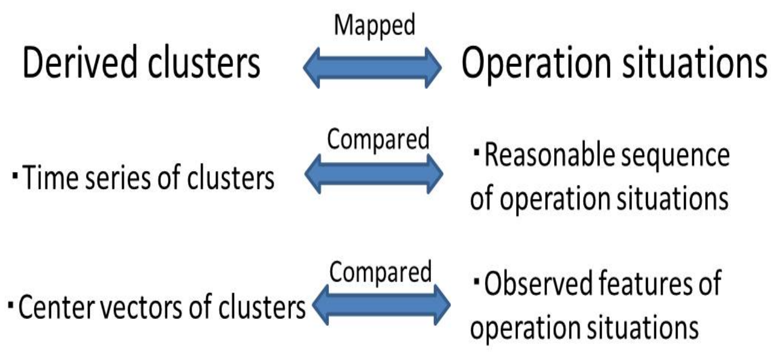

Figure 4.10: Mapping derived clusters into operation situations

Chapter 5

Results and Discussion

To evaluate the effectiveness of the proposed situation recognition method for real caregiving services, the proposed method is applied to the use logs obtained in the field experiments. In this chapter, the results are shown and subsequently we discuss about the effectiveness of the proposed method based on the shown results.

Before going into main topics of this chapter, results and discussion, settings of the field experiments and parameters of the proposed method are described briefly in the followings.

Settings

- In use logs obtained in the field experiments, we use 3 days of the use logs. Since use logs of each day have lunch time and dinner time, in total 6 times worth of the results is shown and discussed.
- In the 3 days of the use logs, the number of care staffs is fixed to 6.
- As initial parameters of the proposed method, time interval α described in the Pre-processing 2 stage in the chapter 4, is set to $200s$.
- Also, the number of clusters in the clustering 1 stage is set to 8.

The results are shown in the order of the proposed 5 stages as follows.

1. Pre-processing 1
2. Clustering 1
3. Pre-processing 2
4. Clustering 2
5. Post-processing

5.1 Results

(1) Pre-processing 1

This stage does not produce any notable result.

(2) Clustering 1

In the second stage of the method, Clustering 1, 1057 types of place vectors are listed up. Center vectors of derived 8 clusters in this stage are shown in the followings.

Class 0 : [0.12, 0.00, 0.49, 3.56, 0.21, 0.20, 0.08, 0.78, 0.08, 0.48]

Class 1 : [0.21, 0.11, 0.13, 0.98, 0.00, 0.51, 0.22, 0.82, 0.24, 2.78]

Class 2 : [0.19, 0.01, 0.30, 1.70, 0.08, 0.17, 0.05, 2.83, 0.03, 0.64]

Class 3 : [0.28, 0.02, 0.31, 0.28, 0.20, 0.14, 0.75, 3.63, 0.03, 0.36]

Class 4 : [0.20, 0.06, 1.66, 0.39, 0.80, 0.11, 0.16, 1.39, 0.15, 0.77]

Class 5 : [0.20, 0.14, 0.45, 0.21, 0.33, 0.10, 2.34, 1.94, 0.07, 0.24]

Class 6 : [0.41, 0.14, 0.37, 0.46, 0.26, 0.42, 0.84, 2.32, 0.08, 0.70]

Class 7 : [0.32, 0.14, 0.24, 1.55, 0.71, 0.17, 0.57, 1.26, 0.31, 0.62]

(3) Pre-processing 2

As mentioned in the settings, field experiments were conducted during lunch time and dinner time. Firstly, 3 days time series graphics of clusters derived in the previous stage, during lunch time, are shown in Figure 5.1, Figure 5.2, and Figure 5.3.

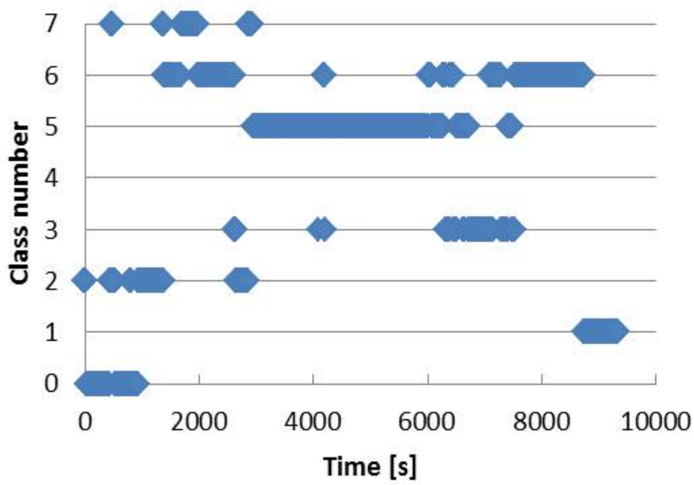

Figure 5.1: The first clustering result during first day's lunch time

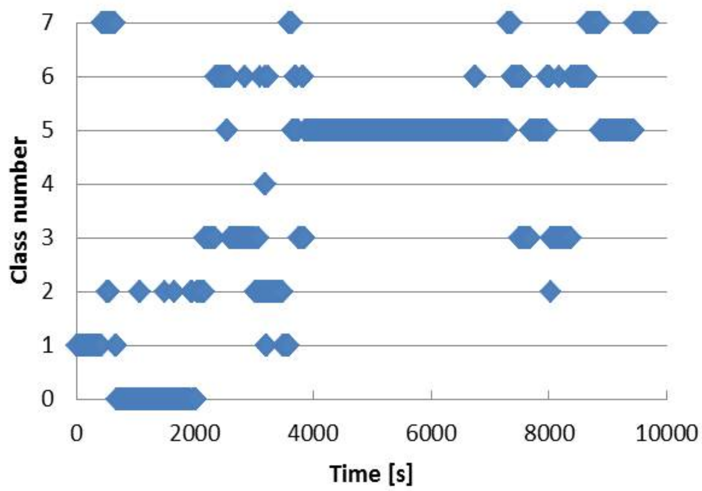

Figure 5.2: The first clustering result during second day's lunch time

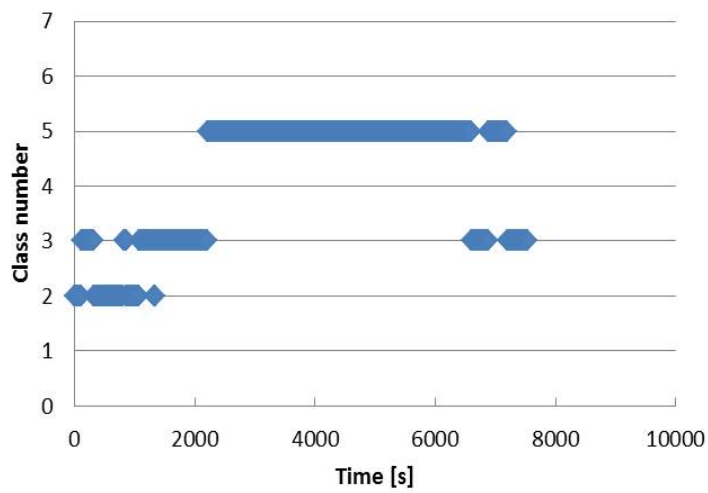

Figure 5.3: The first clustering result during third day's lunch time

Next, 3 days time series graphics of clusters derived in the previous stage, during dinner time, are shown in Figure 5.4, Figure 5.5, and Figure 5.6.

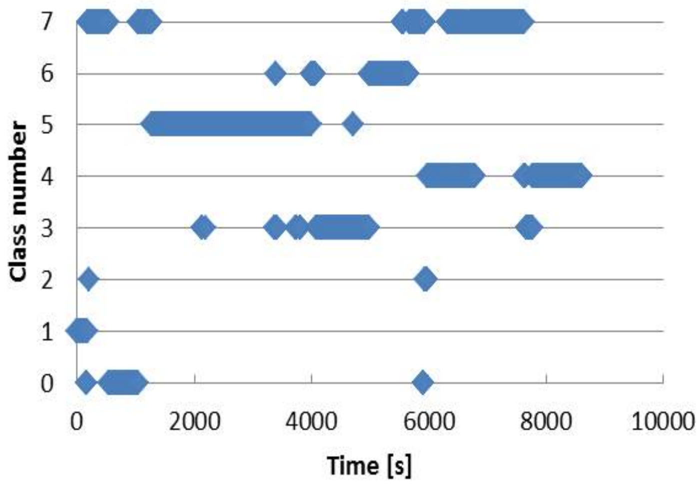

Figure 5.4: The first clustering result during first day's dinner time

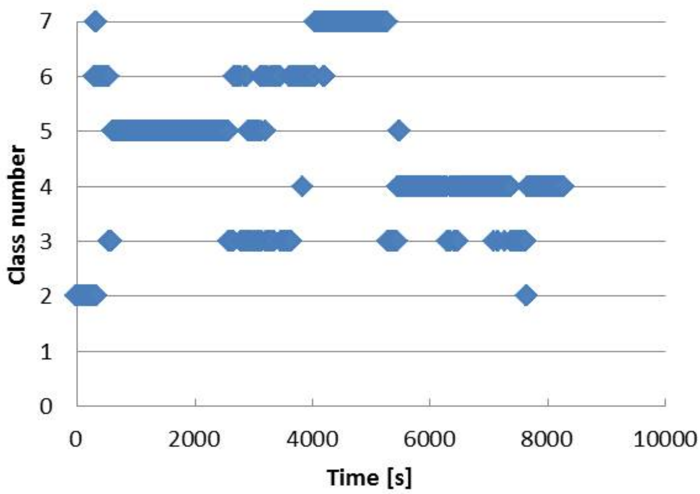

Figure 5.5: The first clustering result during second day's dinner time

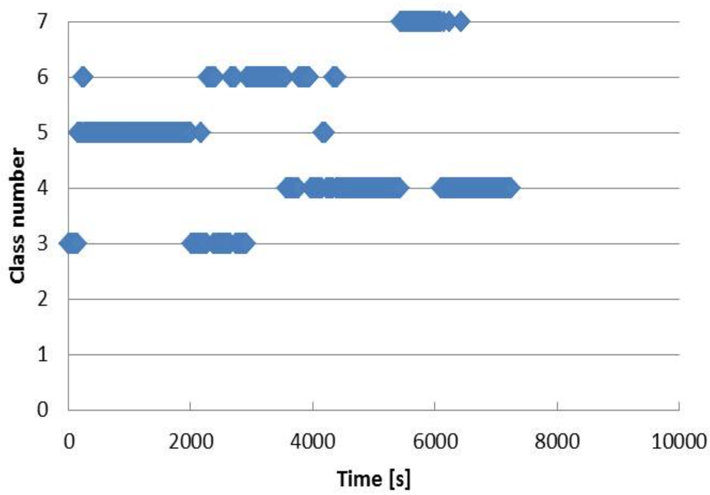

Figure 5.6: The first clustering result during third day's dinner time

(4) Clustering 2

In the fourth stage of the method, Clustering 2, 144 types of adjacency matrices are listed up.

As an output of the Hierarchical clustering in this stage, the dendrogram shown in the Figure 5.7 is produced. In the figure, the dendrogram is cut at the dotted line, and 5 clusters are generated as products of this stage. The reason why the dendrogram is cut as the point is that the difference between the previous and following merges is greater than the previous one and the following one.

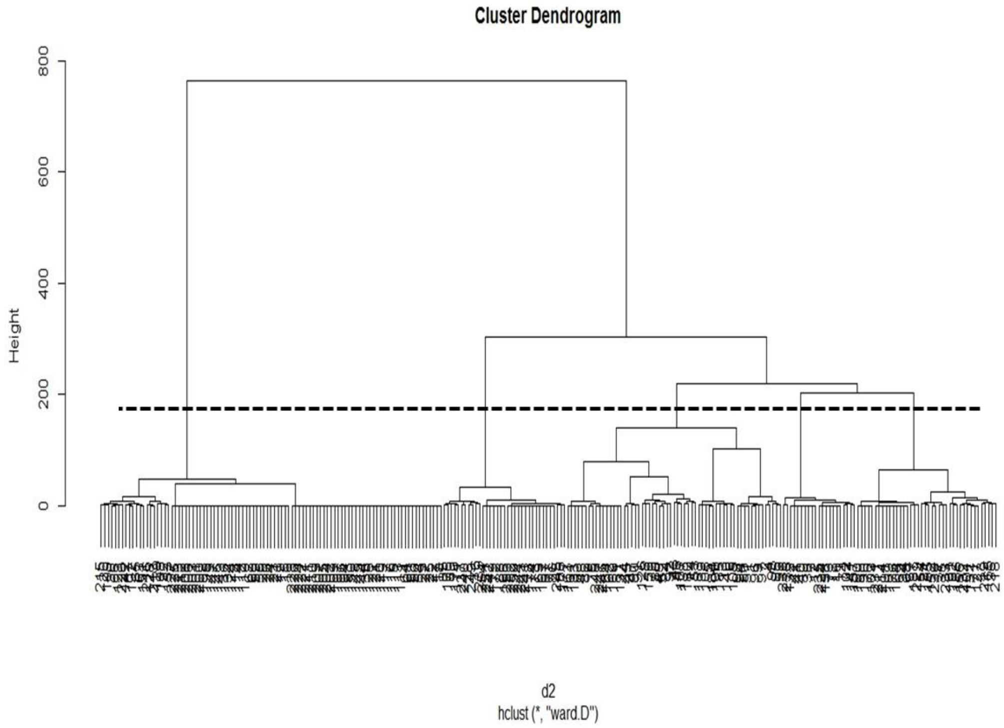

Figure 5.7: The dendrogram of the second clustering

Features of center matrices of the derived 5 clusters in this stage are summarized as follows.

Class 0 : Graphs in this class mainly consist of many self-loops of class 4 in the first clustering phase

Class 1 : Graphs in this class mainly consist of self-loops of class 6 in the first clustering phase

Class 2 : Graphs in this class mainly consist of many self-loops of class 3 in the first clustering phase

Class 3 : Graphs in this class mainly consist of many self-loops of class 5 in the first clustering phase

Class 4 : Graphs in this class mainly consist of some types of self-loops, which are class 0, class 1, class 2, and class 7 in the first clustering phase

Firstly, 3 days time series graphics of clusters derived in this stage, during lunch time, are shown in Figure 5.8, Figure 5.9, and Figure 5.10.

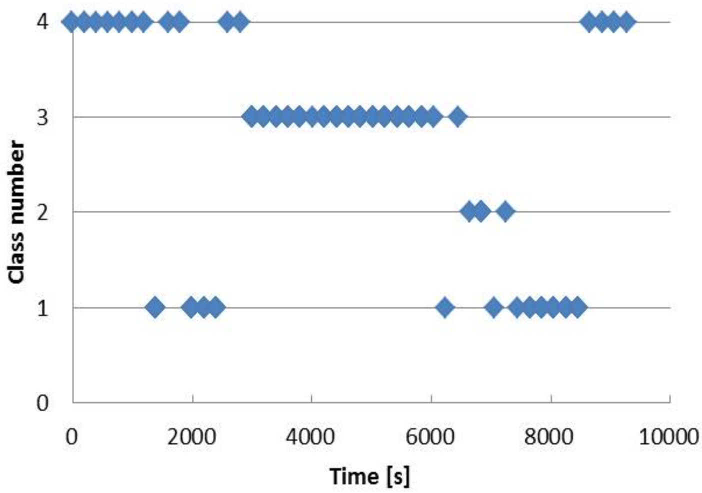

Figure 5.8: The second clustering result during first day's lunch time

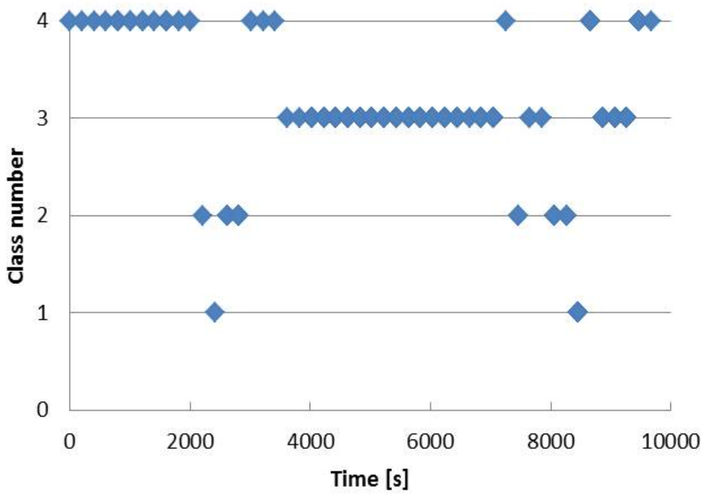

Figure 5.9: The second clustering result during second day's lunch time

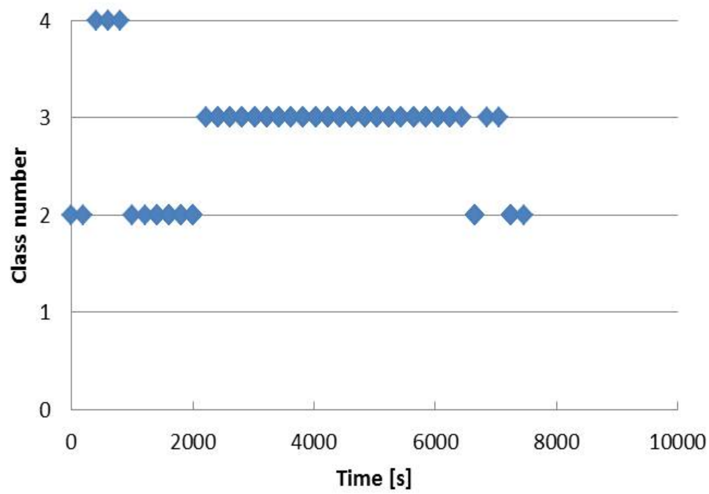

Figure 5.10: The second clustering result during third day's lunch time

Next, 3 days time series graphics of clusters derived in this stage, during dinner time, are shown in Figure 5.11, Figure 5.12, and Figure 5.13.

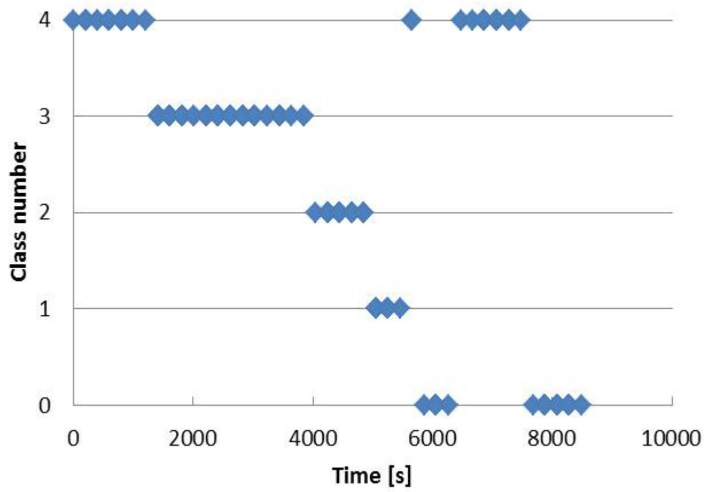

Figure 5.11: The second clustering result during first day' s dinner time

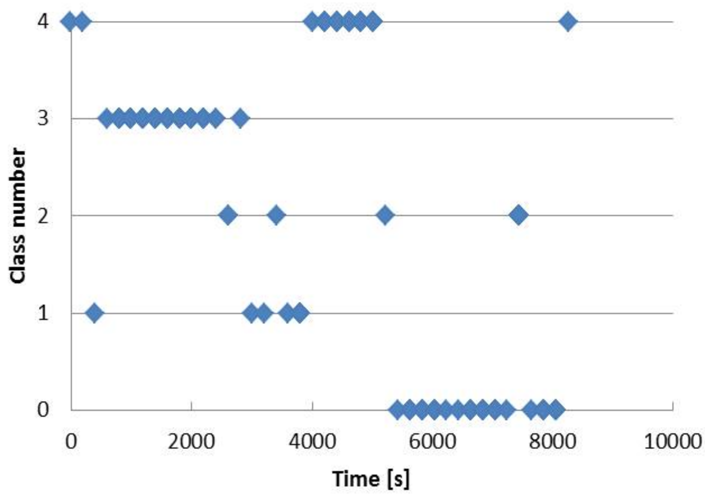

Figure 5.12: The second clustering result during second day's dinner time

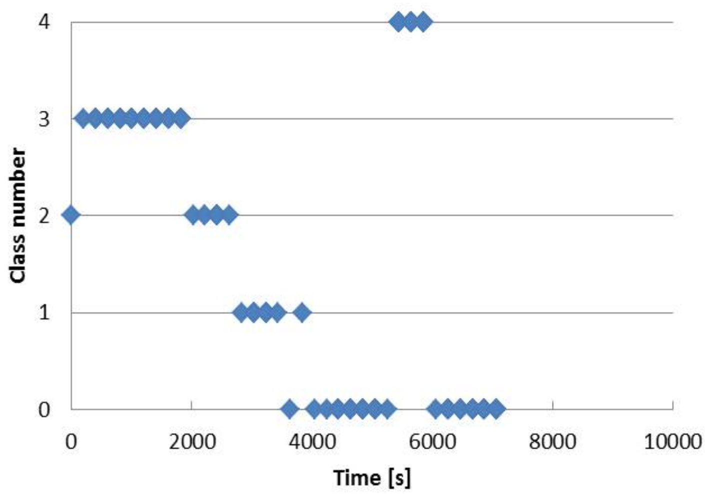

Figure 5.13: The second clustering result during third day's dinner time

(1) Post-processing

In the last stage of the method, Post-processing, mapping of derived clusters and operation situations is conducted based on the analysis of time series of clusters and center vectors of clusters, shown previously. The analysis of time series of clusters and center vectors of clusters is summarized as the followings.

Class 0

- Time series of clusters

  - This class tends to be appear in the last periods of dinner time
- Center vectors
  - Care staffs tend to spread over the facility, mainly patient rooms

Class 1

- Time series of clusters
  - This class tends to be appear in the last periods of lunch time
- Center vectors
  - Care staffs tend to spread over the facility, but always 2 staffs are in area 8

Class 2

- Time series of clusters
  - This class tends to be appear after the class 3
- Center vectors
  - Most of care staffs are in area 8

Class 3

- Time series of clusters
  - This class is certainly appear in the middle of lunch and dinner time
- Center vectors
  - All care staffs are split into area 7 and area 8 by half

Class 4

- Time series of clusters
  - This class tends to be appear in the beginning of lunch and dinner time
- Center vectors
  - Care staffs might transit different areas frequently because this class contains 4 different classes in the first clustering phase

Based on these analysis, one of the possible mapping of the clustering result and operation situations ts as follows.

Class 0 : Oral health care in each patient room on dinner time

Class 1 : Oral health care in each patient room on lunch time

Class 2 : Activity after the lunch or dinner such as singing, playing games, and exercise

Class 3 : Meal care

Class 4 : Excretion assistance before the lunch or dinner

5.2 Discussion

In the time series graphics of the first phase clusters, some clusters dominate the time axis continuously. However, although there are some clusters which dominate other areas of the time axis continuously, there exists some periods that clusters transit frequently, and some dots of clusters are scattered on those figures. Therefore, it is difficult to map the clusters to the operation situations one-to-one.

In the time series graphics of the second clustering phase, on the other hand, each of the 5 classes dominates different period of the time axis continuously, and scattered dots, appeared in the time series graphics of the second phase clusters, almost disappear. Therefore, the second clustering phase might contribute to solving the problems occurred in the first clustering phase.

The reason why all of the representative graphs, center adjacency matrices, mainly consist of self-loops is likely that the number of directed edge types is very large. In this case, the number of nodes in a graph is 8, and hence the number of directed edge types between different nodes in the graph is 56. The large amount of the edge types causes that graphs having the same directed edge types rarely exist in a cluster. Therefore, the representative graphs of each cluster contain almost no directed edges between different nodes.

Chapter 6

Application

As mentioned in the chapter 1, there are two types of applications which utilize the proposed situation recognition method. In this chapter, those two types of applications are described in detail.

6.1 Decision Making Support System

In terms of Situation Awareness, the proposed situation recognition method substitutes the perception and comprehension phases instead of human brain as mentioned in the chapter 4. This automation of a part of Situation Awareness might improve the operation efficiency.

Originally it is impossible that care staffs recognize their entire operation situations with they doing their own operations by their direct senses because operation rooms are separated each other by walls. However, in team operations, what each member is aware of the entire situation of their own team is important for doing their business. You can see the importance, for example, in field team sports like soccer. That is the case that one player modifies his position based on other member' s positions.

According to [14], Situation Awareness is a part of human decision making. Thus, we assume that the proposed method is used to help care staffs recognize the entire operation situations in real time manner, and as a result, help their decision making. This use case is shown in the Figure 6.1. By recognizing the entire operations in real time, the chief staff can direct other staffs based on the current operation situation. Also, novice of the caregiving service operation can keep track of what they should do in the operation situation.

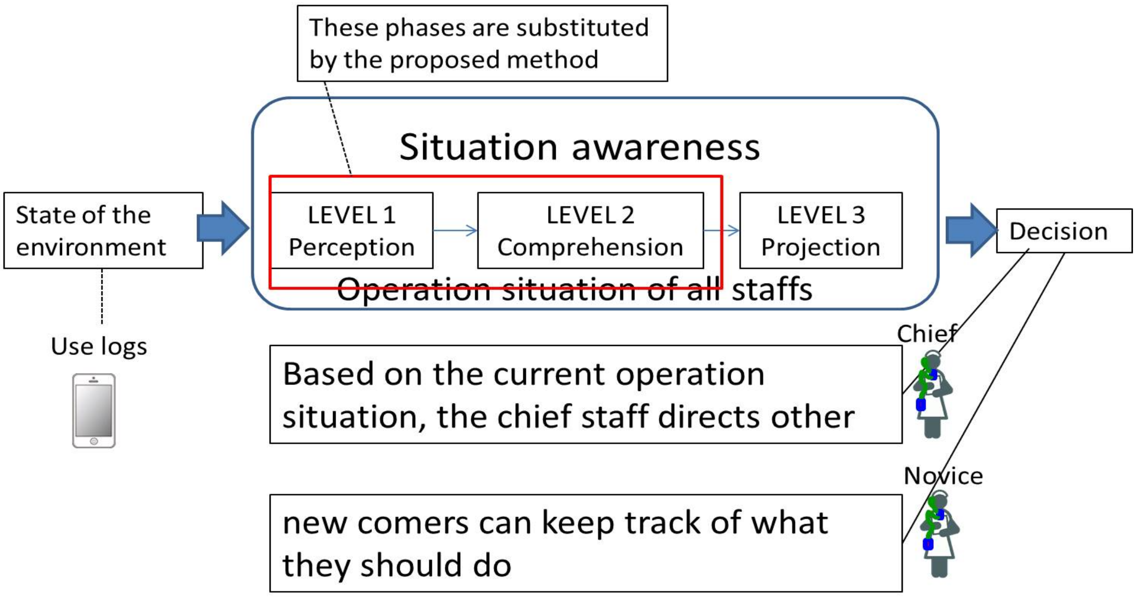

Figure 6.1: The decision making support system

6.2 Automatic Extraction of Anomaly Situations

As the next application, the proposed method is used to extract anomaly situations automatically from the past use logs. This anomaly detection method is based on the clustering based anomaly detection technique [15]. The whole procedure is shown in the Figure 6.2. Tn the process, at first operation situations are extracted from the past use logs. This phase is the part of the proposed operation situation recognition method. Next, the feature of each use log at each time stamp is compared with the corresponding operation situation with the same time stamp. As a result of the comparison, anomaly score at each time stamp is generated. Periods showing high anomaly score can be said that some unusual things happened during the periods.

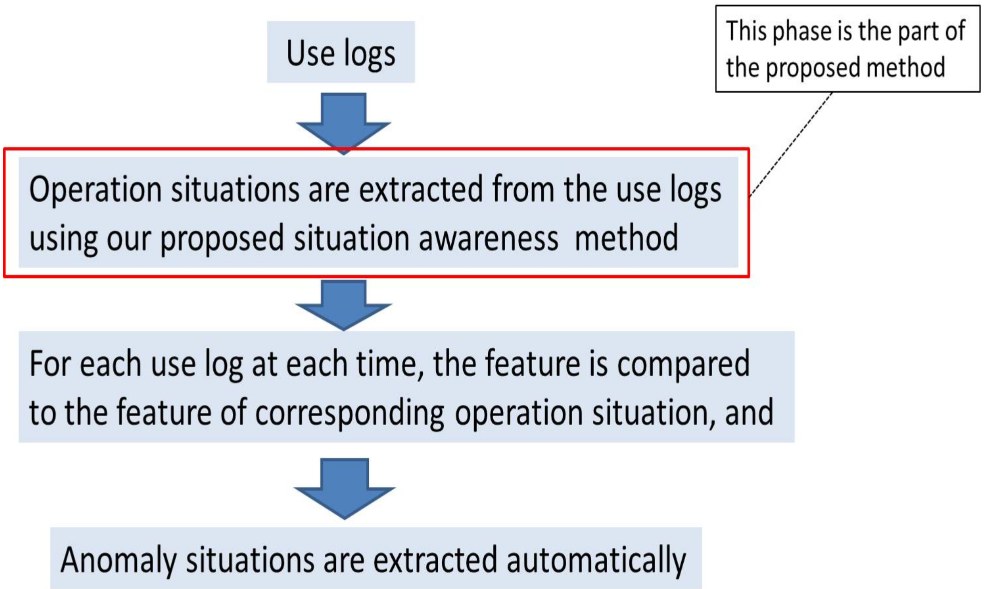

Figure 6.2: Automatic extraction of anomaly situations

Chapter 7

Conclusion

The research in this thesis is concluded as the followings.

- The concept of Situation Awareness is applied to automatic extraction of collective behaviors in physical and adaptive intelligent services [16].

- Operation situations in caregiving services are estimated based on distribution and movement of care staffs.

- As an operation situation recognition method, the method consisting of 5 stages is proposed. Each stage is the followings: (1) Pre-processing 1, (2) Clustering 1, (3) Pre-processing 2, (4) Clustering 2, and (5) Post-processing.

  In the Clustering 1 and Clustering 2 stages, Hierarchical clustering is used as the clustering method. Also, the concept of the graph generation in the Pre-processing 2 stage is based on Graph similarity.

- According to the results, the second clustering phase of the proposed method might contribute to solving the problems occurred in the first clustering phase.

- The proposed method might contribute to improve the efficiency of the outlier detection method proposed in [3].

- Two types of applications are assumed, which are decision making support system and automatic extraction of anomaly situations.

List of Publication

- K. Sato, K. Hiraishi, and K. Kobayashi, "Situation Recognition from Action Logs in Caregiving Services", Proc. The 57th Workshop on Discrete Event Systems, pp 7-10, March, 2015, Ishikawa.
- K. Sato, K. Kobayashi, and K. Hiraishi, "Situation Recognition from Behavior Logs in Caregiving Services", The 30th International Technical Conference on Circuits/Systems, Computers and Communications (ITC-CSCC), June, 2015, Seoul.

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