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A METHOD FOR MICRO-DYNAMICS ANALYSIS BASED ON CAUSAL STRUCTURE OF AGENT-BASED SIMULATION

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ABSTRACT

Micro-dynamics analysis plays an important role in decision making in a complex social system. It has been used to analyze how macro-phenomena arise from the viewpoint of individual agent behavior. However, the causes extracted during the analysis often include two types of useless causes: *simple* causes, which are not useful for decision making regarding new policies, and *small* causes, which suggest inefficient policies. In this paper, we propose a method to extract causes that include at least one feature from the "attribute," "perception," and "action" variables of model parameters and logs. We extracted the causes of the specific congestion and created a policy based on results obtained via a simulation of an airport terminal and showed that the proposed method can eliminate both *simple* and *small* causes.

1 INTRODUCTION

Agent-Based Social Simulation (ABSS) is a promising method to aid decision making in social systems. For example, in large-scale facilities such as shopping malls (Hui et al. 2009; Doniec et al. 2020), airport passenger terminals (Fayez et al. 2008; Chen et al. 2018; Wu and Chen 2019) and hospital (Wu et al. 2020), managers employ different policies to reduce the waiting time and walking distance of customers to improve customer satisfaction. However, testing these policies in the field requires a significant amount of time and money and may also reduce customer satisfaction. Using ABSS, managers can evaluate various policies by reproducing human behavior in a virtual field.

However the analyses for ABSS can be quite difficult of while the agent-based models are often simpler than other types of simulations (Sanchez and Lucas 2002). ABM modelers need to obtain important knowledge from a large amount of output data by making full use of various analytical methods. In previous studies, some analysis methodologies via ABSS have been proposed, as shown in Figure 1. Goto and Takahashi (2011) proposed a landscape analysis method to evaluate a range of possible outcomes of a social system after implementing policy alternatives under uncertainties from a macro viewpoint. Tanaka et al. (2016) proposed a method to clarify typical simulation dynamics by clustering simulation. In addition to the methods, there are various types of techniques to process model behaviors over time and space (Lee et al. 2015). On the other hand, micro-dynamics analysis in ABSS is an effective method to explain the causes of a social phenomenon from a micro viewpoint by observing the dynamic changes of agents' behaviors (Ohori and Takahashi 2012). The purpose of the micro-dynamics analysis is to determine a set of elements that can greatly improve the overall system. The analysis plays an important role in decision making in a complex social system as it promotes communication among stakeholders (Ohori et al. 2016). However, as the analysis is carried out through trial and error by analysts, its quality greatly depends on their analytical skills. Thus, it is impossible to determine all the significant causes affecting a target social phenomenon. As a result, decision making regarding new policies based on the causes in the field takes a considerable amount of time.

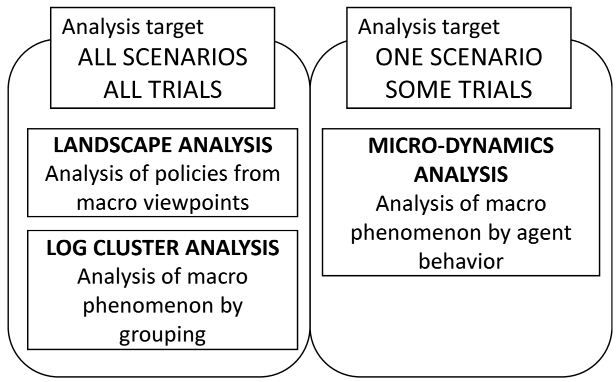

Figure 1: Relationship among methodologies for analysis of ABSS.

In order to resolve the issue, Yamane et al. (2018) proposed a micro-dynamics analysis method to analyze how macro-phenomena arise in terms of individual agent behavior. This method is performed according to the following five steps. Step 1: Define the macro-phenomenon to be explained. Step 2: Select agents causing the macro-phenomenon as target agents. Step 3: Cluster agents' parameters and logs to represent agents' characteristics as a set of clusters they belong to. Step 4: Evaluate the similarity between candidates of causes and target agents by calculating the *F-measure*, where the candidates are intersections of all combinations of clusters created in step 3. Step 5: Output causes in ascending order of importance using *F-measure*.

Using this method, analysts can comprehensively extract the features of agents related to a target phenomenon. However, the causes extracted by this method often include two types of useless causes. The first type is *simple* cause, which is not useful for decision making regarding new policies. For example, in an attempt to explain the causes of a long queue at a certain facility as a target phenomenon, Step 4 often extracted causes such as the agents waiting for a long time and the agents having a preference for the facility. Since the *simple* causes are often related to the target phenomena directly. However, the causes cannot suggest policies other than improving the capacity of the facility because they do not indicate why the agents spent a long time in the queue. The second type is *small* cause, which suggests inefficient policies. For example, causes such as, the agents came from 10am to 11am, waited for a long time, prefer to the facility, looked at a specific sign and exited before 12am always stood in the queue, provide considerable information, but policies for changing the behavior of such agents are less effective because the number of the agents that exhibit all the features is very small.

Our goal is to develop a method to obtain effective and useful causes for decision making by eliminating *simple* and *small* causes. In this paper, we first define the basic procedure of the methodology by Yamane et al. (2018), then propose a method to eliminate *simple* causes. Finally, we evaluate our method by analyzing a simulation of signage systems and demonstrate the method can eliminate *small* causes.

2 PROPOSED METHOD

2.1 Conventional Micro-dynamics Analysis

Conventional micro-dynamics analysis (Yamane et al. 2018) is composed of five steps, as shown in Figure 2.

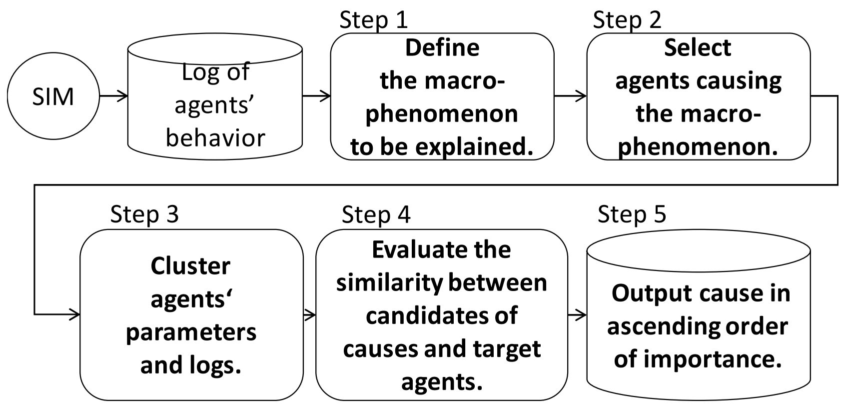

Figure 2: Conventional micro-dynamics method.

Step 1: Define the macro-phenomenon to be explained.
Provide an operational definition for the macro-phenomenon whose cause is to be analyzed. In the case of analyzing the causes of congestion in a facility, define the congestion using spatial and temporal indicators via which the congestion can be distinguished from non-congestion. For example, define the congestion through certain places where the crowd density exceeds a threshold and the corresponding time.

Step 2: Select agents causing the macro-phenomenon.
Select agents relevant to the macro-phenomenon as target agents, specifically select agents who were present at the location defined in step 1 at the corresponding time. Since the macro-phenomenon clearly arises from the target agents, or at least the target agents are one of the crucial factors of the macro-phenomenon, in the method, the target agents are considered to be a micro-level cause. Then, a cause of the macro-phenomenon is described by the target agents' features. Based on the definition proposed in Yamane et al. (2018), we define "cause" as the features of the target agents.

Step 3: Cluster agents' parameters and logs.
There are static and dynamic variables in the agents' parameters and logs. To summarize the agents' features, apply clustering methods to create agent clusters for each variable. An agent feature can be represented using clusters that the agent belongs to for each variable.

The clustering method is selected according to the data type. Algorithm 1 shows a k-means clustering algorithm. Here parameter k is to be determined; k represents the number of clusters needed to maximize the F*-measure* between the clusters and the target agents picked at step 2. The F*-measure* indicates the degree of similarity between two clusters.

Step 4: Evaluate the similarity between candidates of causes and the target agents.
To evaluate the similarity between candidates of causes and the target agents, calculate the F*-measure* between the candidates and the target agents. Here, the candidates are intersections of all combinations of clusters created in step 3. Since a cluster represents an agent's features, the intersection indicates a vector of features. The intersections include all possible causes.

1. Generate intersections of all combinations of clusters created in step 3 as candidates of causes.
2. Calculate the F*-measure* between the candidates and target agents following equation (1).

Algorithm 1 Calculate $k(agents\text{-}log, target\text{-}agents, k_{min}, k_{max})$

```
for k = k_min to k_max do
    clusters ⇐ k-means(agents-log, k)
    f1^k ⇐ 0
    for cluster in clusters do
        f1 ⇐ F-measure(cluster, target-agents)
        f1^k ⇐ max(f1^k, f1)
    end for
end for
k ⇐ min(argmax_k f1^k)
return k
```

$$F\text{-}measure = \frac{2 \cdot Recall \cdot Precision}{Recall + Precision} \quad (1)$$

The *F-measure* between the candidate and the target agents indicates the importance of the candidate as a cause. The higher the *F-measure* of a candidate, the more exactly it represents the target agents in a summarized manner. Here, candidates with $F\text{-}measure > 0$ are causes and candidates with $F\text{-}measure = 0$ are not causes.

Step 5: Output causes in ascending order of importance.
Output causes in order of importance by sorting the causes in ascending order of *F-measure*. Here, each cause is shown as a list of agents' features summarized as clusters.

2.2 Leverage Point

The purpose of micro-dynamics analysis is to determine a set of elements that can greatly improve the overall system. However, in the social system, since the elements are individuals with spontaneous behaviors, it is difficult to change their behaviors directly. Thus, we must determine the triggers of their behavior. In this paper, we consider the triggers of behaviors are "leverage points" according to Holland (1992). The leverage points are levers that can easily change the individuals' behaviors, thereby changing the overall social system. We do not consider causes containing leverage points as *simple* causes, because managers can obtain insights regarding the varying behaviors of individuals from the causes. In the next paragraph, we analyze the leverage point of the social system.

Accordioning to an informatics perspective, individual's behavior consists from mechanisms effectively selecting actions to be carried out, according to the perceptions of environment and internal state of the individual(Bandini et al. 2009). Therefore, environmental factors are one of the leverage points that are perceived by individuals and cause them to change their actions. Tendencies of each individual, such as preferences, strongly shape an individual's actions, thus the tendencies also are the leverage points. The former is an external trigger, and the latter is an internal trigger. We consider the environmental factors and the tendencies of the individuals as leverage points of the social system.

2.3 Eliminate Simple Causes via Action-perception Linking

We propose micro-dynamical analysis method analyzing the macro-phenomenon not only with respect to the individual agents' actions but also from the viewpoint of environmental factors and the tendencies of the agents, namely leverage points. The analysis is furthered by focusing on agents' perception variable logs, which reflect the causal effects from environmental factors, and attribute variables, which are parameters that characterize the uniqueness of the agent. As a result, we can eliminate *simple* causes. We name this deeper analytical framework as "action-perception linking."

In the action-perception linking framework, we first classify agents' variables and logs into action, attribute, and perception variables. Action variables are values produced as a result of an agent's action. Attribute variables are parameters characterizing the uniqueness of the agent. The values of attribute variables are linked with action or decision tendencies. Perception variables are dynamic variables representing an agent's cognitive state, which are changed via interactions with the environment or other agents. Changes in perception variables causes changes in the action and decision patterns of an agent. The category of each variable can be distinguished via the agent's model structure. Then, we link the macro-phenomenon to the action variables. Next, the action variables are linked to the perception variables and to the attribute variables. Via the action-perception linking, the target agents can be linked to the triggers of the actions, namely leverage points.

This idea is implemented by modifying step 4 of the conventional method mentioned earlier in section 2.1:

Step 4': Evaluate the similarity between candidates of causes and target agents.

1. **Conventional step 4 operation**
2. **Select causes having at least one feature in the three categories:** Select only causes having at least one feature in the categories of action variables, attribute variables, and perception variables (Figure 3). Via this operation, one can obtain only the action of the target agents with the triggers (attribute and perception).

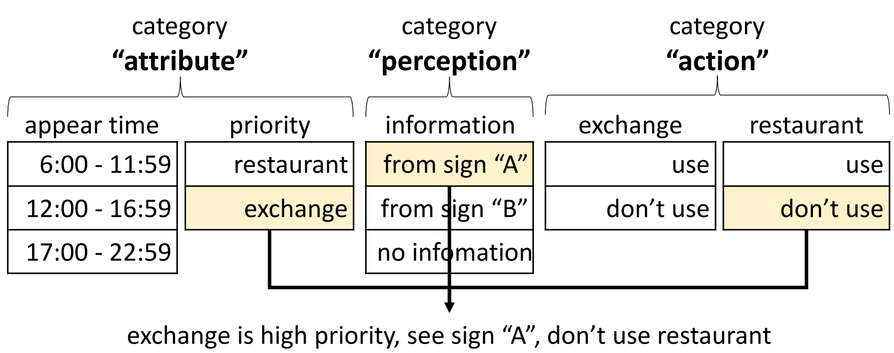

Figure 3: Select causes having at least one feature in the three categories.

3 EXPERIMENT

3.1 Simulation Model

A simulation model of a signage system was developed to investigate appropriate sets of signs in an airport terminal. In the simulation, agents can obtain information regarding service facilities from signs. A signage model representing the signs is composed of information for agents and a range where the agents can obtain the information. An $Agent_h$ has an $evoked\_set_h$ representing service categories the agent wants to achieve. In the simulation, the $Agent_h$, firstly, probabilistically selects a service category from the $evoked\_set_h$. Secondly, the $Agent_h$ chooses a facility corresponding with the service category from $choice\_set_h$. The $choice\_set_h$ represents a set of facilities related to the service category that the agent has obtained from signs. $Facility_i$ is selected following probability $p(i)$ defined in equation (2)(3).

$$p(i) = \frac{\exp U(i)}{\sum_{j \in choice\_set_h} \exp U(j)} \tag{2}$$

$$U(i) = \alpha_{hi} + \beta \cdot time_{hi} \tag{3}$$

Here, a_{hi} denotes the level of attraction of $Agent_h$ to $Facility_i$, and β is the weight of time spend traveling $time_{hi}$.

Figure 4 shows an image of the simulation. This simulation considers only the Departures level of the airport terminal. This level is divided into seven sections (A, B, C, D, E, F, G). The signs providing service facility information are given unique names (a, b, c). There are eight types of facilities: restaurant, mobile phone, exchange, ATM, book, lounge, souvenir, and insurance on the Departures level. Figure 5 shows the locations of the facilities. Each agent has one necessary service category and some additional service categories. The necessary service category is randomly assigned as restaurant, souvenir, exchange, or ATM. The additional service categories are chosen from the remaining categories. In the model, each agent has an agent type defined by the agent's necessary service category.

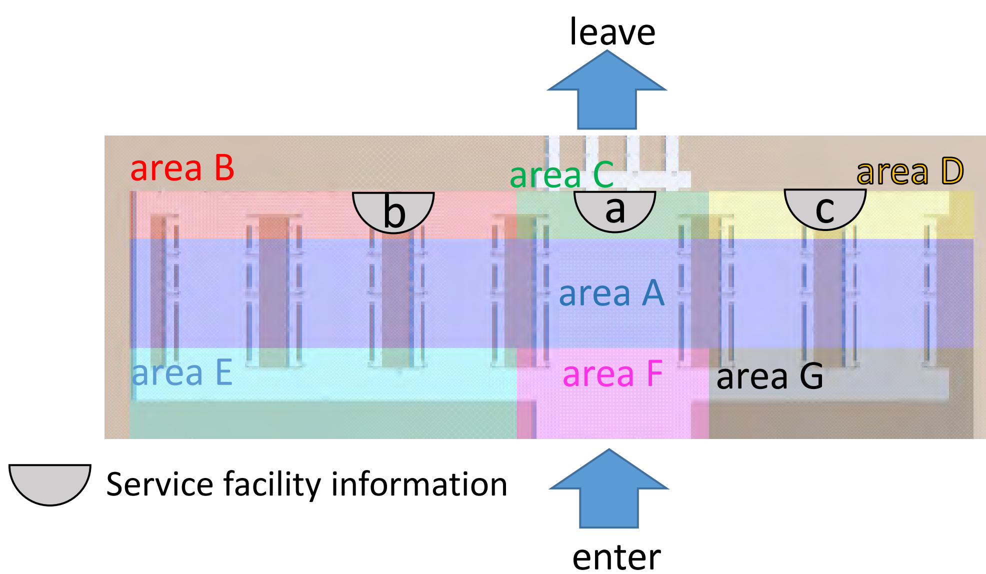

Figure 4: Signs and areas of the Departures level.

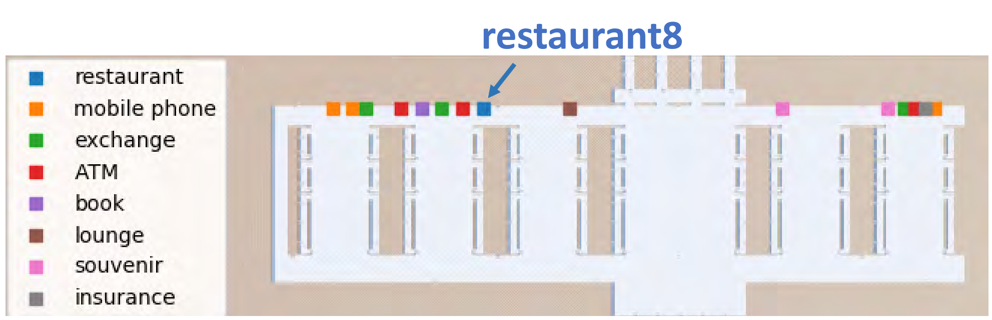

Figure 5: Types and locations of the facilities.

Figure 6 illustrates the average transition of the restaurant 8 queue in 10 trials, when 2000 agents were generated in the simulation. In this study, we analyzed the causes of congestion at restaurant 8 (Figure 5), because this restaurant is particularly crowded.

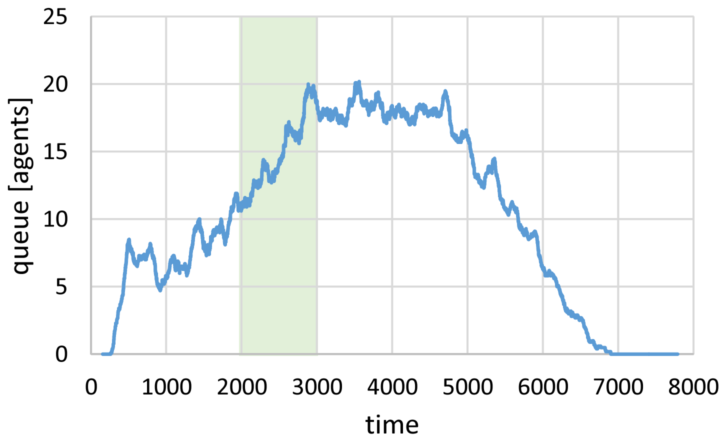

Figure 6: Transition of the queue at restaurant 8.

3.2 Parameters and Logs

Table 1 shows the parameters and logs possessed by an agent. Arrival time, exit time, agent type, and evoked set are attributes of the agent. Facility route and area route are the results of the action of the agent. Information signs represents the result of the perception of the agent. Each parameter and variable log of all agents is clustered in the analysis. The arrival time and exit time are clustered via two-dimensional k-means using Euclidean distance. The agent type is not clustered. The evoked set is encoded in an 8-bit binary depending on whether each service category is included in the set or not. Furthermore, the 8-bit binary is clustered by one-dimensional k-means using Hamming distance. The facility route, which represents the trajectory of visiting facilities, is clustered via one-dimensional k-means using Levenshtein distance. The area route, which denotes the trajectory of visiting areas, is clustered via one-dimensional k-means using Levenshtein distance. The information signs, which signifies the trajectory of signs seen by an agent, is clustered via one-dimensional k-means using Levenshtein distance. In the k-means procedure, the number of clusters is determined using Algorithm 1.

Table 1: Parameters of the model and clustering methods.

category	parameter	explanation	clustering methods
attribute	Arrival time	Time to arrive at the Departures level	2dim k-means
attribute	Exit time	Time to leave the Departures level	
attribute	Agent type	Restaurant, souvenir, exchange, or ATM	Not clustered
attribute	Evoked set	List of service categories an agent has	K-means
action	Facility route	List of facilities an agent visited	K-means
action	Area route	List of areas an agent went through	K-means
perception	Information signs	List of signs an agent saw	K-means

3.3 Micro-dynamics Analysis

We analyze the results of 10 simulation trials based on the steps mentioned in section 2.

Step 1: Define the macro-phenomenon to be explained.

We define congestion as a situation where queue length is greater than 10. In this experiment, for simplicity, we only focus on restaurant 8 as the most crowded facility, and the time period from 2000-3000 as the first 1000 time periods where average queue length is greater than 10.

Step 2: Select agents causing the macro-phenomenon.
As a pretreatment, we remove features which are never relevant to the target agents. In this experiment, the non-relevant features are evoked sets which do not contain "restaurant." Agents having non-relevant features are removed from the set of agents to be analyzed. After the pretreatment, the average number of analysis agents is 887.4 (SD:17.6) in 10 trials. The average number of target agents is 55.9 (SD:8.6), which represents the agents that accessed restaurant 8 in the time period from 2000-3000.

Step 3: Cluster agents' parameters and logs.
All parameters and logs of the model (Table 1) are clustered. Herein, we show the clustering results of the facility route and information signs as examples. Table 2 presents the clustering results of the facility route. Table 3 presents the clustering results of information signs.

Table 2: Facility route clustering results. The rows represent each cluster. The "facility" columns are rates of agents that accessed the facility in each cluster. Here, "8" denotes restaurant 8. The "sum" column represents the average number of facilities an agent accessed. The "size" column denotes the average number of agents belonging to each cluster.

No	facility															sum	size
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15		
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	633.8
1	0.17	0.07	0.15	0.27	0.29	0.24	0.14	0.64	0	0.24	0.15	0.12	0.17	0.25	0.1	3	5.9
2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	72.6
3	0	0.38	0.31	0.31	0.25	0.25	0.12	0.81	0	0.19	0.12	0.31	0.19	0.5	0.25	4	1.6
4	0.05	0.08	0.13	0.09	0.21	0.13	0.15	0.67	0	0.15	0.06	0.07	0.06	0.09	0.06	2	71.6
5	0.1	0.08	0.25	0.36	0.26	0.26	0.21	1	0	0.18	0.02	0.08	0.03	0.1	0.07	3	6.1
6	0.02	0.05	0.06	0.06	0.13	0.06	0.09	0	0	0.22	0.06	0.06	0.06	0.07	0.06	1	95.8

Table 3: Information signs clustering results. The rows represent each cluster. The "sign" columns denote the proportions of the number of views by the agents. A larger number indicates that a particular sign was seen more than other signs by the agents. The "head of log (aa)" column indicates the proportion of number of agents who saw sign "a" twice at the beginning of the simulation. The "sum" column presents the average number of signs an agent saw. The "size" column denotes the average number of agents belonging to each cluster.

No	sign			head of log	sum	size
	a	b	c	(aa)		
0	0.71	0.15	0.14	0.02	0.17	469.0
1	0.12	0.44	0.44	0.26	39.25	25.7
2	0.20	0.61	0.19	0.32	23.06	151.9
3	0.30	0.52	0.18	0.41	12.62	240.8

Step 4: Evaluate the similarity between candidates of causes and target agents.
The total number of intersections is 120000. The numbers of clusters of arrival and exit time, agent type, evoked set, facility route, area route, and information signs are 4, 5, 9, 7, 9, and 4, respectively. The total number of the intersections is multiplying numbers of the clusters added empty set: $5*6*10*8*10*5 = 120000$. We evaluate all of the intersections using *F-measure*.

- **Conventional method:** In total, there are 9001 causes of 10 trials.
- **Proposed method:** In total, there are 4766 causes of 10 trials. These causes have at least one feature from the categories of attribute, perception, and action. The number of total causes is approximately half of the conventional method.

Step 5: Output cause in ascending order of importance.
Table 4 presents the top five causes determined by the conventional method in ascending order of *F-measure*. Similarly, Table 5 shows the top causes determined by the proposed method. The rows represent each cause. The *F-measure* column is the *F-measure* of the cause. The "matchNum" column indicates the number of agents belonging to the cause. The "targetNum" column represents the number of target agents that belong to the cause. The other columns denote features; "attribute", "action" and " perception" in Table 5 are categories of each feature. The arrival and exit times are the minimum and the maximum values of the cluster. The agent types are also presented in the table. The values in the evoked set, facility route, area route, and information signs columns are cluster numbers. For example, cluster number 4 of the area route is characterized by the proportion of the trajectories F→A→C... (moving straight ahead in the central area at the beginning of the simulation) larger than the others. "-" implies that there are no significant clusters in the parameter. Agents contained in each cause are overlapped.

Table 4: Top five causes determined by the conventional method.

arrival and exit time		agent	evoked	facility	area	information	*F-measure*	match	target
(arrival)	(exit)	type	set	route	route	signs		Num	Num
-	-	-	-	2	-	-	0.252	72.6	16.2
-	-	-	-	-	-	2	0.242	151.9	25.1
1-1249	3085-5291	-	-	-	-	2	0.232	47.4	12.0
-	-	restaurant	-	-	-	2	0.219	69.1	13.7
-	-	restaurant	-	2	-	-	0.211	38.7	9.9

Table 5: Top five causes determined by the proposed method.

attribute				action		perception	*F-measure*	match Num	target Num
arrival and exit time		agent	evoked	facility	area	information			
(arrival)	(exit)	type	set	route	route	signs			
-	-	restaurant	-	2	-	3	0.141	20.8	5.4
919-2991	4837-6972	-	-	2	-	3	0.137	11.1	4.6
-	-	restaurant	-	-	4	3	0.129	51.2	6.9
919-2991	4837-6972	-	-	-	4	3	0.127	24.5	5.1
-	-	-	6	2	-	3	0.12	15.5	4.3

3.4 Findings

As shown in Table 4, according to the conventional method, for the cause with the highest *F-measure*, "facility route," is an important parameter of the target agents, and cluster 2 indicates target agents that only visit restaurant 8 (Table 2). There is little information regarding the target agents, and we can only consider facility equipment policies, such as increasing the number of seats at restaurant 8. From the cause with the second-highest *F-measure*, cluster 2 of "information signs" is a cluster of agents who often look at sign "b". It implies that agents spend a long time near sign "b". As we do not know the reasons for this, we cannot devise appropriate policies. These are *simple* causes in the sense that they cannot suggest any policies to change the agents' behavior and reduce congestion.

On the contrary, the proposed method can eliminate the *simple* causes. As evident in Table 5, according to the proposed method, for the cause with the highest *F-measure*, "agent type" for "attribute," "facility route" for "action," and "information signs" for " perception" are important parameters of the target agents. We can understand the characteristics of the target agents by investigating the three parameters. From "agent type" of "attribute," we can infer that the cluster is composed of agents who have restaurant as the necessary service category. From "facility route" of "action," it is evident that cluster 2 denotes a cluster of agents who only visit restaurant 8 (Table 2). From "information sign" of " perception," we can understand that the agents in cluster 3 obtain the most amount of information from sign "b," which is the sign nearest to restaurant 8. In addition, the agents in the cluster 3 have a lower value in the "sum" column (Table 3); that is, they obtain information from the signs fewer times than the others. The cluster also has the highest value in the "head of log (aa)" column (Table 3). In summary, the agents are related to the congestion at restaurant 8, have restaurant as the necessary service category, and directly go to restaurant 8 looking at signs "a" and "b". Thus, this cause can lead to some policies suggestions. For example, another sign can be added before sign "a" or between sign "a" and "b" that does not contain information regarding restaurant 8 in order to encourage the agents to go to other facilities that they may have in their evoked set, instead of going directly to restaurant 8. These policies can be suggested because the cause indicates the order in which the agents look at the signs.

As shown in "matchNum" column of Table 4 and 5, both conventional and proposed method can eliminate the *small* causes. Both amount of matchNum is sufficiently large, for example in highest *F-measure* causes those are 72.6 and 20.8.

3.5 Effect to Overall System

The purpose of micro-dynamics analysis is to determine factors that can greatly improve the overall system. Thus, finally, we evaluate the effect of the causes to overall system, specifically whether the causes can adequately reduce congestion or not.

In the experiment, agents who belong to highest *F-measure* cause are removed from the simulation. Figure 7 shows the average number of agents waiting at restaurant 8 in 10 trials. The blue line represents the baseline setting same as that in Figure 6; the average number of waiting agents is 10.23. The orange line indicates the result of the conventional method when an average of 72.6 agents are removed; the average number of waiting agents is 4.8. The grey line represents the result of the proposed method when an average of 20.8 agents are removed; the average number of waiting agents is 7.1. The degree of congestion suppression per agent removed in the conventional method is $(10.23-4.80)/72.6 = 0.075$ and in the proposed method is $(10.23-7.11)/20.8 = 0.150$ (Table 6). The proposed method can extract the causes that can change, at least to the same extent as the conventional method, the overall system.

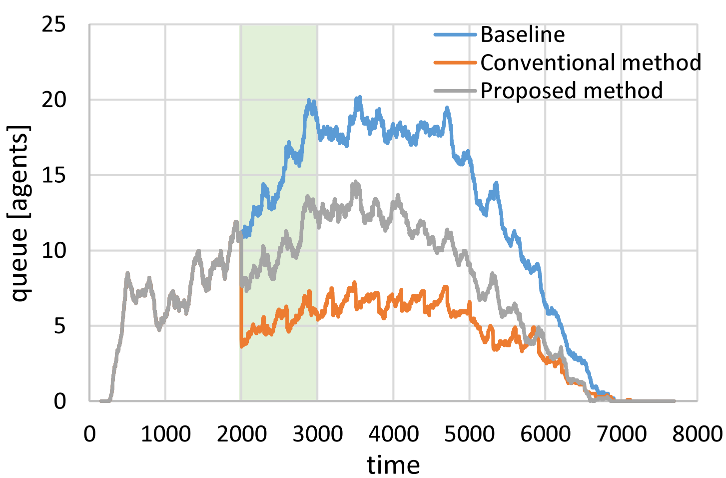

Figure 7: Change in queue lengths at restaurant 8 by removing cause agents.

Table 6: Effect of a cause determined by conventional and proposed methods.

	Baseline	Conventional method	Proposed method
Average waiting number	10.23	4.80	7.11
Number of removing agents	-	72.6	20.8
Effect per removing agent	-	0.075	0.150

4 CONCLUSION

Yamane et al. (2018) proposed a systematic micro-dynamics analysis methodology. However, this method often extracted *simple* causes, which are not useful for decision making regarding new policies, and *small* causes, which suggest inefficient policies. In this study, to overcome the limitations of the aforementioned method, we proposed an improved methodology. Then, based on the simulation of an airport terminal, we extracted the causes of specific congestion and formulated a policy. Our improved methodology can eliminate both *simple* and *small* causes by extracting combinations of clusters that include at least one feature from the attribute, perception, and action categories. Furthermore our methodology can work effectively for other simulations such as the simulation of real airports (Yamada et al. 2017) and supermarkets (Yamane et al. 2012).

Another naive method to eliminate *simple* causes is using *precision* as a measure of important causes. As the method selects causes that exactly represent target agents, causes having a higher amount of detail, namely many features, are assigned higher scores. As a result, we can eliminate *simple* causes. However, the sizes of the highly detailed causes are too small for them to be effective, namely these causes are *small* causes. Therefore, in order to eliminate *simple* and *small* causes, we consider that our method is superior to the abovementioned naive method.

Furthermore, we aim to improve our work considering the following two aspects: 1) Interpretability of clusters must be improved. Because the clustering results include clusters that are similar to each other, the clustering steps or methods to must be improved for human analyst. 2) A systematic technique to create policies from the results of our methodology is required. This technique must show decision makers the causes of a target phenomenon, suggest measures to counter the phenomenon, and indicate how effectively the countermeasures will work.

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