Preliminary study - using RoboCup Rescue Simulations for Disasters Prevention

Tomoichi Takahashi
Meijo University
Faculty of Science and Technology
Shiogamaguchi, Tenpaku, Nagoya, 468-8502, Japan
Email:ttaka@ccmfs.meijo-u.ac.jp

Yohei Kaneda and Nobuhiro Ito
Nagoya Institute of Technology,
Dept. of Computer Science,Tsukuri Collage,
Gokisochou, Showa, Nagoya, 466-8555 Japan
Email:{yo_hey, bobson}@phaser.elcom.nitech.ac.jp

***Abstract*— Activities of search and rescue of victims in large scale disasters are not only social problems, but also several research challenges. Evaluations of rescue agents behavior are affected from various standards such as human lives, properties, operation costs and so forth. The scheme of evaluation itself change with lapse of time. And earthquakes occur around the world, so standard evaluation methods that can be applied for various areas are necessary for rescue operations.**

In RoboCup community, rescue operations have been evaluated form a viewpoint of multi agent systems (MAS). They are efficiency, robustness and reliability of MAS, and the performances were analyzed by changing parameters of environments. In this paper, we present a preliminary study to use the evaluations for disaster prevention.

I. Introduction

Activities of search and rescue of victims in large scale disasters are not only social problems, but also several research challenges. Rescue simulation systems are characterized with

- a large number of people are involved,
- rescue teams are composed of people with various abilities,
- interactions between rescue activities and disasters have effects on results.

And the most important one is how simulation results will be used to save and protect human lives.

RoboCup Rescue project was proposed to support managements of rescue teams, analysis and training of rescue activities in large-scale disasters [1]. An evaluation formula is set to rank teams as a rule at RoboCup rescue simulation competitions.

The formula that covers methods for toy problems[2], is insufficient to evaluate rescue activity from various measures and to cover real rescue operations. Although, in RoboCup community, multi agent systems have been investigated in terms of efficiency, robustness and reliability, their MAS performances were analyzed by changing parameters associated with agents in one field [3][4]. The evaluations are also used to check disaster prevention plans of local governments in advance whether the plans will support refugees at disasters.

We have not got any practical solutions so far for social problems, because it has to be evaluated from various standards such as human lives, properties at areas, operation costs and with lapse of time, and so forth. In this paper, we present a preliminary study on using evaluations of social agent's behaviors to prevent disasters. Firstly, a 6-tuple representation is introduced to make clear multi agent system (MAS) structure. Next, we present a normalization method to evaluate rescue agents activities within the 6-tuple representation. Finally, with experimental data, several indexes are discussed.

II. Formalization of MAS

Agents work in environments that change dynamically. Implementing a MAS for social problems requires programming not only agent modules but also environment simulators of the problem. The environment is composed of various components. Not only some of them are related with each other, but also interactions between agents and environment play an important roles in social agent systems. These situations make difficult to evaluate agents' behavior and it causes to make clear MAS's structure itself.

A. 6-tuple Presentation of MAS

A 6-tuple presentation is defined to present a multi agent system's structure. The presentation is

$$S = \{\mathcal{G}, \mathcal{A}g, \Sigma, \mathcal{E}, \mathcal{A}c, \mathcal{C}\}$$

where

$\mathcal{G}$ is a set of goals that agents aim to achieve as a whole,
$\mathcal{A}g$ is a set of heterogeneous agents and is defined as $\mathcal{A}g = \{a \mid a$ is an agent, or a set of agents$\}$,
$\mathcal{E}$ is an environment where agents act,
Σ is a set of environmental component simulators - $\Sigma = \{s_1, s_2, \ldots, s_l\}$,
$\mathcal{A}c$ is a set of actions or protocols that agents can use,
$\mathcal{C}$ represents communication channel among agents and interaction between agents and $\mathcal{E}$.

Agents have their own goals. When the size of applied tasks is small, the agent's goals may be identical with $\mathcal{G}$, goals for the system as a whole. Using the protocols in $\mathcal{A}c$, agents can communicate with each other or interact with $\mathcal{E}$. Simulators in Σ change the environment, $\mathcal{E}$, according to models based on physical laws or artificial models of the components. $\mathcal{C}$ are links with that agents can communicate each other. $\mathcal{C} = \phi$ means that agents act with no communication.

B. Rescue Simulation based on 6-tuple Presentation

Present RoboCup Rescue Simulation is viewed as follows.

$\mathcal{G}$ is to save human lives and extinguish fires. In RoboCup Rescue competition, these factors have been mapped into a scalar value,

$$Score = \quad (P + \frac{H}{H_s}) \times \sqrt{\frac{B}{B_s}}$$

where P is the number of living civilian agent, H is HP(health point) values of all agents and B is the area of houses that are not burnt. H_s and B_s are values at start, the score decrease as disasters spreads. The higher score shows the better rescue operations.

$\mathcal{A}g$ is a set of civilians who evacuate from disasters, fire brigades that extinguish fires, ambulances that carry hurt civilians to refugees, polices that repair damaged roads and their corresponding rescue center offices.

$\mathcal{E}$ is GIS data, such as roads, crossings, buildings (including refuges) and their initial locations.

Σ is a set of earthquake simulators, fire simulator, building & road collapse simulator, traffic simulator and human health simulator.

$\mathcal{A}c$ are move, extinguish, load, rescue and tell commands that agents in $\mathcal{A}g$ use.

$\mathcal{C}$ represents communication channel among agents and interaction between agents and $\mathcal{E}$ and its constrains on how well it works.

III. Indexes of Rescue abilities

We have not got any standards how may resources are sufficient to disasters, and we usually have used as many resources as possible to reduce damages at normal disasters. In general, more resources are required to rescue larger areas and harder disasters. This general rule cannot be used in earthquakes, because fires occur simultaneously throughout cities. To use finite resources effectively, it is necessary to evaluate $\mathcal{A}g$'s ability.

A. Disaster conditions

Changing one component of rescue simulations and evaluating its effect on simulation results is one of evaluation methods.

1) different rescue agents are used in S_a and S_b:
   $S_a = \{\mathcal{G}, Rescue\_TeamA, \Sigma, \mathcal{E}, \mathcal{A}c, \mathcal{C}\}$,
   $S_b = \{\mathcal{G}, Rescue\_TeamB, \Sigma, \mathcal{E}, \mathcal{A}c, \mathcal{C}\}$.
2) rescue operations under disaster conditions $\mathcal{C}_c$ and $\mathcal{C}_d$:
   $S_c = \{\mathcal{G}, \mathcal{A}g, \Sigma, \mathcal{E}, \mathcal{A}c, \mathcal{C}_c\}$,
   $S_d = \{\mathcal{G}, \mathcal{A}g, \Sigma, \mathcal{E}, \mathcal{A}c, \mathcal{C}_d\}$.
3) disasters occurred at different areas $\mathcal{E}_d$ and $\mathcal{E}_e$:
   $S_e = \{\mathcal{G}, \mathcal{A}g, \Sigma, \mathcal{E}_d, \mathcal{A}c, \mathcal{C}\}$,
   $S_f = \{\mathcal{G}, \mathcal{A}g, \Sigma, \mathcal{E}_e, \mathcal{A}c, \mathcal{C}\}$.

Differences between $\{S_a, S_b\}, \{S_c, S_d\}$ and $\{S_e, S_f\}$ indicate effect of corresponding components.

Fig. 1 shows the scores of preliminary games at RoboCup 2001. Seven teams (from team A to G) participated in competition and each team did rescue operations at different initial disaster conditions from 1 to 7 using Kobe map. The initial conditions were created by changing parameters such as the number of ignition points, their locations, the positions of rescue agents and other agents

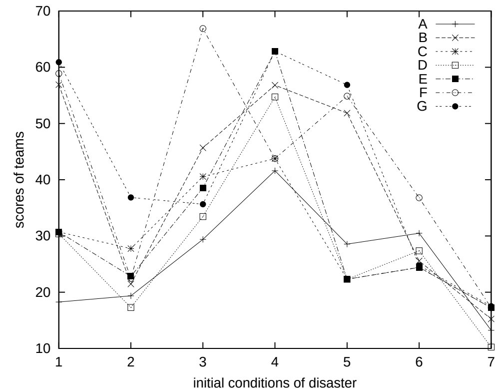


Fig. 1. Scores at 2001 preliminary games

Their rescue performances vary from disaster situations to other ones. This indicates

- one performance at one disaster condition does not guarantee their performances in other conditions,
- these factors are dependent each other.

B. Features of GIS as rescue Fields

It is necessary to evaluate agent's behaviors under being aware of $\mathcal{E}$. There are two kinds of parameters specifying $\mathcal{E}$. One kind of parameters is initial conditions on $\mathcal{E}$. Competitions at 2001 were done by changing parameters of this kind. The other is the structure of $\mathcal{E}$ itself. From 2002, other maps in addition to Kobe have been used in competitions Fig. 2 shows maps of Kobe, Virtual City and Foligno. Kobe map was the first made and next VC map was made as large as Kobe. Foligno map with three times larger than Kobe was made by a research project in Italy [4].

In a case of rescue simulation, they are components of $\mathcal{E}$ and are given in a form of Geographic Information System (GIS). The data is represented in a form of network and nodes and edges are fundamental quantities of a graph. With the same number of nodes and edges, there are different maps. It is clear that the difference of two maps in Fig. 3 affects the efficiency of rescue team abilities and civilians' evacuation.

Characteristic path length(CPL) - features used in "small world" [5] - and area per Euler numbers are used to represent the difference. CPL is the median of the means of the shortest path lengths connected each nodes to all nodes is used to show the difference (cf: appendix). Table I shows specifications of maps - area, node, edge and CPL.

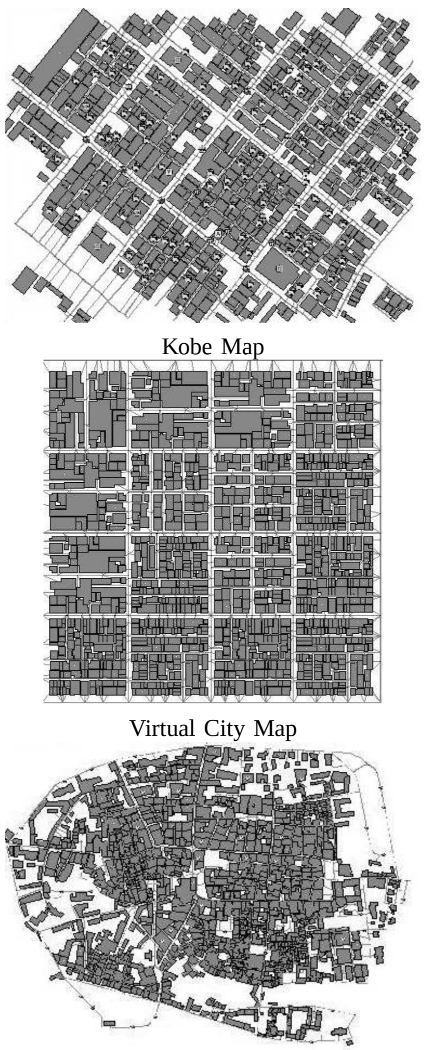
C. Normalization of disaster parameters

Earthquakes have occurred and will occur around the world. Not only analyzing and comparing these earthquakes but also simulating them, it is required to normalize the situations. We use followings to normalize rescue simulation conditions.

TABLE I

SPECIFICATION OF MAPS

	Kobe	VC	Foligno
area(km^2)	0.25	0.29	0.74
node number	765	531	1369
edge number	820	622	1480
CPL	29.55	17.08	37.24



Kobe Map

Virtual City Map

Foligno Map

Fig. 2. RoboCupResuce Maps

rescue powers:

Fire stations, police offices and ambulance centers are located per local government units, so we set one agent for each around the center of maps. Staffs of rescue teams and refugees are assumed to be located in proportion to the size of maps.

disaster powers:

Disasters such as fire, building collapses and so on occur at earthquakes. In rescue simulations, the disasters are calculated from magnitudes of earthquakes. The magnitudes are set equal magnitude four to all

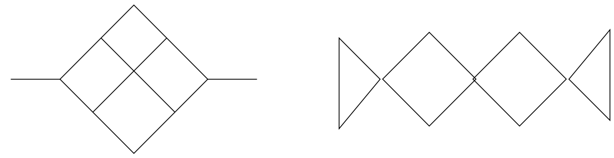


Fig. 3. Maps with the same number of nodes and edges (node=11, edges=14)

TABLE II

DISASTER SIMULATION PARAMETERS

	Kobe	VC	Foligno
Fire brigade	8	9	24
Ambulance	6	7	18
Police offi ce	8	9	24
Civilian	20	23	60
Refuge	3	3	9
Ignition point	2	2	6
magnitude of maps	4	4	4

maps.

disaster situations:

Damages to people and cities are different when earthquakes occur. For example, people sleep at their own houses in the midnight, while they are in offices at noon. Some of them cook lunch with gas, and there are more fires at noon than at night. All civilians are set to be in houses and fire ignition points are located uniformly over the map.

Table II shows initial normalized parameters for three maps.

IV. Disaster simulations

In following experiments,

1) Two rescue agents, NITRescue and YowAI, are used as $\mathcal{A}g$,
2) P, H and B are not the same values for simulations, so the initial scores do not become the same value. Relative score, $Score(t)/S_{start}$, is used to compare rescue abilities for maps.

A. Experiment I

1) simulation results:

Rescue operations of two teams are simulated for three maps. Random seeds in disaster simulations and communication using UDP do not output the same score, so average scores of ten simulations that simulation times were 300 cycles are listed in Table III. From the table,

- The decrease of relative scores for VC are least among three maps. VC map is created by hand and it may be said to be a well-planned city. It can be said that VC is a town where rescue operations are easier than the other two cities.
- While NITRescue and YowAI show similar tendencies for Foligno map, their behaviors are quite different for Kobe map. This difference indicates some other indexes are necessary to evaluate rescue agents behavior properly.

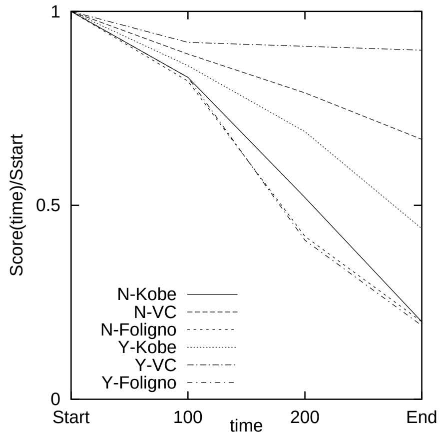


Fig. 4. Relative score changes with elapse of time

2) time elapse model of rescue operation:
E_i is an index that shows area are easy or tough for rescue agents to save lives or extinguish fires. Candidates for E_i have following properties: (Fig. 5).

normalization:
: it can be used to compare rescue abilities at different cities,

time dependence:
: it shows different tendencies when rescue teams start their operations at different initial conditions and it changes monotonically,

agent dependence:
: effect of rescue is the result of successive agents' behaviors and it follows 'a stitch in time saves nine' principle.

Graphs for Kobe map in Fig. 4 show that disasters spread further, while others seem that they begin to put out disasters. Two models for $Score(t)/S_{start}$ are presented to compare rescue abilities for maps.

model 1: uses $f(x) = e^{-kx}$ that monotonically decreases and saturates finally.

model 2: uses $f(x) = 2 - e^{kx}$ that decreases exponentially and all houses are burnt at the end.

The models satisfy the four properties. Less $k(> 0)$ indicated less decrease at both models and it means that it show easy environments for rescue operations. k is calculated to minimize the least square,

$$sum = \sum_i (Score(i)/S_{start} - f_{model}(i))^2. \qquad (1)$$

Three k_is are calculated or cases where $\{100\}$, $\{100, 200\}$ and $\{100, 200, 300\}$ are used for i in $\sum_i$ respectively. The k_1, k_2 and k_3 in Table III are normalized values as the values for Kobe are set 1.0.

From k_is in Table III,

1) By fixing rescue agents (it means using one $\mathcal{A}g$), comparisons among normalized k_is become evaluation of $\mathcal{E}$s. It shows whether $\mathcal{E}$s are easy or tough for rescue agents to save lives or extinguish fires. VC is the easiest one to rescue, especially for YowAI.
2) The normalized k_is are more similar to CPL ratio and area/Euler than to simple ratio of areas. It indicates CPL and area per Euler number are good indexes for $\mathcal{E}$ that shows area are easy or tough for rescue agents.
3) By fixing maps (it means using one $\mathcal{E}$), comparisons among normalized k_is become evaluation of $\mathcal{A}g$ that rescue agents are robust to geographical changes. NITRescue is robuster than YowAI because variations of NITRescue's k_is are smaller than YowAI's, while YowAI is more efficient than NITRescue from scores at Kobe and VC.

B. Experiment II

1) simulation results:
Similar simulations have done to random maps with intent to investigate effect of maps' CPL. RandomMapGenerator v1.0 is a tool that generates maps with various CPL [6]. Eighteen maps were generated for simulations and twelve of them have the same area($1.0km^2$).

TABLE IV
NORMALIZATION OF DISASTER PARAMETERS(RANDOM MAP)

Map	1 . . . 12	13	14	15	16	17	18
Area Ratio	1	0.81	0.64	0.5625	0.49	0.36	0.25
Fire Brigade	20	16	13	11	10	7	5
Ambulance	20	16	13	11	10	7	5
Police Force	16	9	13	11	10	7	5
Civilian	40	32	26	23	20	14	10
Refuge	8	6	5	5	4	3	2
Ignition Point	4	3	3	2	2	1	1

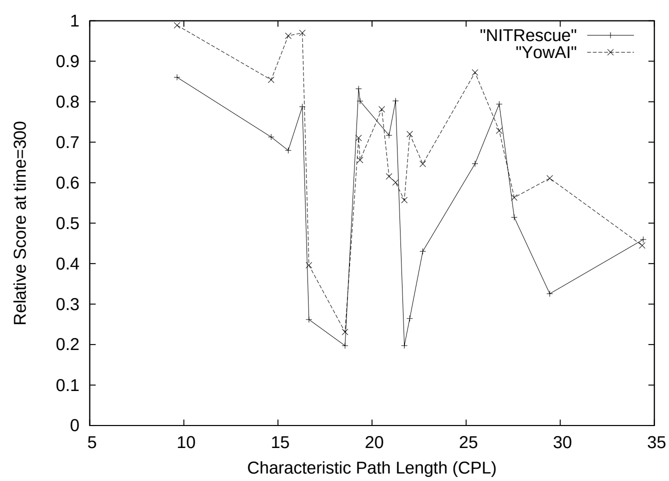


Fig. 6. The Relation between Score Ratio and L

2) Score vs. CPL:
Table IV shows initial parameters, which are normalized, for eighteen random maps. Fig. 6 shows results for random map and relationship between the capabilities of MAS(rescue

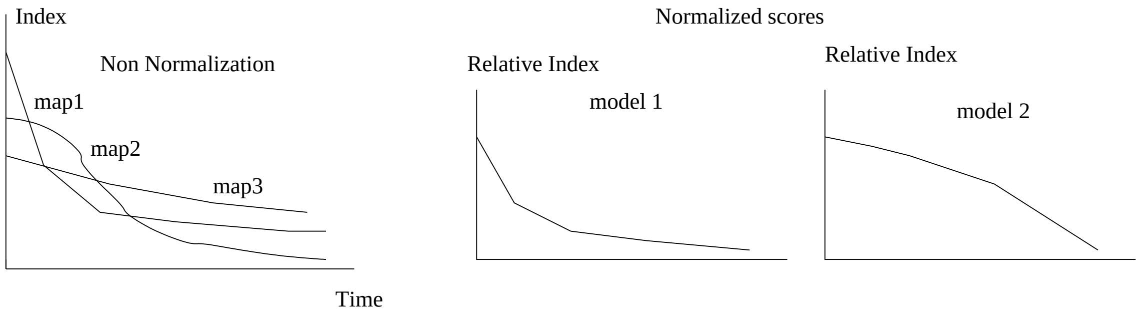


Fig. 5. Illustration of normalized models for E index

TABLE III

NUMBER OF AGENTS

		NITRescue			YowAI		
		Kobe	VC	Foligno	Kobe	VC	Foligno
Experiments							
score	start	43	49	127	43	49	127
	100	35.79	43.72	104.06	36.9	45.09	105.78
	200	22.34	38.47	53.92	29.84	44.73	51.88
	end	8.46	32.83	25.07	19.1	44.23	24.03
relative score	100/start	0.83	0.89	0.82	0.86	0.92	0.83
	200/start	0.52	0.79	0.42	0.69	0.91	0.41
	end/start	0.2	0.67	0.2	0.44	0.9	0.19
Indexes							
GIS	area	1	1.16	2.97	1	1.16	2.97
	CPL	1	0.58	1.26	1	0.58	1.26
	area/Euler number	1	0.7	1.47	1	0.7	1.47
Model1	k_1	1	0.62	1.09	1	0.54	1.19
	k_2	1	0.42	1.23	1	0.31	1.98
	k_3	1	0.35	1.11	1	0.19	1.85
Model2	k_1	1	0.66	1.07	1	0.58	1.16
	k_2	1	0.51	1.16	1	0.37	1.65
	k_3	1	0.49	1.04	1	0.26	1.41

agents) and the characteristic path length of random map. Longer CPL means it takes more cost to move through town. We predicted that relative scores become less with CPL's increase. However, Fig. 6 showed that the result differs from the prediction.

One of reasons of unpredictable results is as following. CPL is calculated for map data before earthquake occurrence of disaster simulation. The value of CPL changes with passage of time. Even if it can pass through a road at the time of usual, it may be unable to be passed through a road at the time of disaster occurrence.

That is, it is thought that the complexity of map data changes with progress of time.

V. Conclusion

Practical evaluations of agents' behavior are required as multi agent paradigm is applied to various social activities. The social agent behavior is composed of various factors. It makes difficult to evaluate social agents behavior without influences from these factors.

In this paper, followings are proposed and discussed:

- proposal of 6-tuple presentation for MAS to make clear the components,
- applying the 6-tuple presentation to RoboCup rescue simulation system,
- proposal of normalization methods for disasters conditions,
- simulation results analysis from time-elapse model and maps indexed with characteristic path length.

Our analysis process indicates some indexes that shows easiness to rescue activities.

The authors would like to thank members of NITrescue, YowAI, developer of RandomMapGenerator AutoRun and logAnalyser. With their codes, we could do our experiments efficiently.

References

[1] T. Takahashi, S. Tadokoro, M. Ohta, N. Ito: Agent Based Approach in Disaster Rescue Simulation - From Test-Bed of Multiagent System to Practical Application -, RoboCup 2001: Robot Soccer World Cup V, pp. 102-111

[2] S. Russell, P. Norvig: Artificial Intelligence: A Modern Approach, Prentice Hall; 2nd edition, 2002

[3] G. Kaminka, I. Frank, K. Arai, K. Tanaka-Ishii: Progress through performance competitions? A large-scale comparative study of multi-agent teams, Journal of Autonomous Agents and Multi-Agent Systems, 108–127, 2003

[4] A. Farinelli, G. Grisetti, L. Iocchi, S. Lo Cascio, D. Nardi: RoboCup Rescue Simulation: Methodologies, Tools and Evaluation for Practical Applications, In Proc. of RoboCup Symposium, 2003.

[5] D. J. Watts, Small Worlds - The Dynamics of Networks between Order and Randomness, Princeton, 1999
[6] Random Map Generator ver1.0 http://sourceforge.net/projects/rescuecore.

APPENDIX

A. The Characteristic Path Length

The characteristic path length (CPL) is the typical distance between every vertex and every other vertex. "Distance" here refers to simply minimum number of edges that must be traversed in order to reach one vertex from another vertex, or in other wards the shortest path length between two vertex.

Definition 1 (Characteristic Path Length): The characteristic path length L of a graph $G = (V, E)$ is the median of the means of the shortest path lengths connecting each vertex to all other vertexes. That is, distance of two vertex v_i, v_j $(v_i, v_j \in V, 1 \leq i, j \leq n)$ is $d(v_i, v_j)$, and the means of distance between vertex v_i and all other vertexes is $\bar{d}_i = \frac{1}{n}\sum_{j=1}^{n} d(i,j)$ where n is number of vertexes in a graph G. Then define L as the median of $\{\bar{d}_i\}$.

B. The Clustering Coefficient

The clustering coefficient (C) characterizes the extent to which vertexes adjacent to any vertex are adjacent to each other. First, the neighborhood Γ_i of a vertex i is the subgraph that consists of the vertexes adjacent to i (not including i itself).

Definition 2 (Clustering Coefficient C_i of a vertex i): The clustering coefficient C_i of an arbitrary vertex i $(v_i \in V, 1 \leq i \leq n)$ is

$$C_i = \frac{|E(\Gamma_i)|}{\binom{k_i}{2}}$$

where $|E(\Gamma_i)|$ is the number of edges in the neighborhood of i, k_i is degree of a vertex i, $\binom{k_i}{2}$ is the total number of possible edges in Γ_i.

Definition 3 (Clustering Coefficient C): The clustering coefficient C of a graph G is

$$C = \frac{1}{n}\sum_{i=1}^{n} C_i$$

where n is the number of vertexes in the graph G.

C. A Graph in Map Data

In a case of RoboCupRescue simulation system, $\mathcal{E}$ is given according to a format of Geographic Information System (GIS) and represented based on graph structures. A vertex expresses a building, its entrance and a crossing. An edge expresses a road. Graphs of map data are shown as following.

Undirected:
The current system assumes that there is no one way.

Simple:
There is no road between a crossing and the same one. And there is also no multiple-road between a crossing and the adjacent one.

Sparse:
$M \ll n(n-1)/2$ in RoboCupRescue Map.

Connected:
There is no isolated region.

Therefore, we can apply the concept of small world to map data of RoboCupRescue and analyze map data by using L and C. However, the calculation result of C of map data vanishes. Because there is no edge in the subgraph Γ_i of an arbitrary vertex i, in the case of RoboCupRescue map data.