Multiagent Approach for Effective Disaster Evacuation

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Abstract: At times of disaster, or immediately prior to such periods, smooth evacuation is a key issues. However, it is difficult to achieve, because people tend to panic when faced with disaster. This paper proposes a system that supports effective evacuation from danger using the framework of the Distributed Constraint Optimization Problem (DCOP). The use of the DCOP facilitates the assisted optimization of people's evacuation timing without a center server. This system enables assistance in terms of evacuation guidance to be given to relieve congestion, by calculating evacuation timing via an ad-hoc network of evacuees' mobile devices (phones, PCs, etc.). In this paper, we focus on the formalization of the disaster evacuation problem and how to solve it using the framework of the Distributed Constraint Optimization Problem.

1 INTRODUCTION

Much effort has been expended in improving disaster prevention countermeasures. Although most of the countermeasures that have been implemented are classified as *Public-help*, which are implemented by the public sector, many people survive in times of disaster based on *Self-help* (countermeasures implemented by individuals) and *Mutual-help* (countermeasures implemented based on mutual help). Therefore, *Mutual-help* and *Self-help* are attracting much attention (CabinetOffice, 2011).

At times of disaster, or immediately prior to such periods, smooth evacuation is a key issues. However, it is difficult to achieve, because people tend to panic when faced with disaster, crowding evacuation passageways of buildings in the event of fire and congesting roads with cars containing people fleeing from predicted hurricanes.

Therefore, although evacuation guidance is very important, the disaster countermeasure office would be unable to guide all evacuees intensively at the time of a disaster. Evacuees need to take refuge based on *Mutual-help*.

We aim to develop a the system that provides optimal evacuation guidance autonomously at the time of a disaster. The system uses the mobile devices of evacuees, performs distributed calculation using the framework of the Distributed Constraint Optimization Problem (DCOP), and does not need a center server. In this paper, we focus on the formalization of the disaster evacuation problem and how to solve it using the framework of the Distributed Constraint Optimization Problem.

2 DISASTER EVACUATION

The authors designed and developed a real-time disaster information mapping system aimed at conjugating facilities such as university campuses for the purpose of assisting *Mutual-help* (Iizuka et al., 2011). This system is a web based system that can handle disaster situation information in places such as university campuses by level of detail, such as classrooms or laboratories in the school buildings by using Wi-Fi devices. It can aggregate the information that is sent by users (informers), store it in a situation database on the server and display a disaster situation map to users on request. However, issues caused by heavily-congested and crowded conditions were not given sufficient consideration in the experiments described above. In the case where an enormous number of evacuees have to move, or they have to pass through narrow aisles, they may become confused and evacuation may take longer. In such cases, a navigating system for evacuees would be effective, preventing them from rushing into a certain passageway, or instructing them to wait just a few moments, in order to meet the flow rate allowance.

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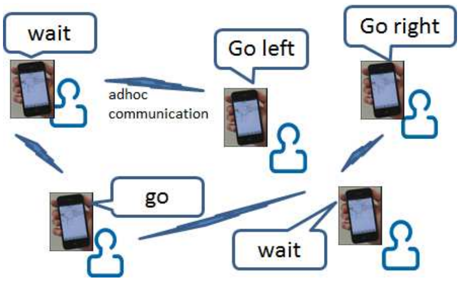

Figure 1: Usage image of the disaster evacuation assist system.

By using a system like that of (Iizuka et al., 2011), people could know "which evacuation route is safe" , the next issue is "how to evacuate safely and effectively." However, smooth and effective evacuation is not always easy. People tend to rush forward to passageways that are perceived to be safe, which results in congestion. The more people rush, the greater the congestion. The provision of additional appropriate information concerning evacuation guidance may make it feasible to avoid congestion, and shorten evacuation times.

Disaster countermeasures offices are set up in organizations in order to determine and provide appropriate evacuation routes. However, planning and providing appropriate information rapidly is not easy with limited resources. Therefore, an effective disaster evacuation assistance system is required to address these issues.

Our proposed system facilitates the assisted optimization of people's evacuation timing, by estimating the location of evacuees. This system enables assistance to be given in the form of evacuation guidance to relieve congestion, by calculating evacuation routes and timing via an ad-hoc network of evacuees' mobile devices (phones, PCs, etc.), intercommunication function and location information. The mobile devices must be equipped with wireless LAN (Wi-Fi). Locations of evacuees are estimated by mobile devices using the positional relationship between the device and the wireless base station. The evacuation route and timing of each evacuee are calculated by distributed processing using the evacuees' devices connected by an ad-hoc network. The framework of the Distributed Constraint Optimization Problem (DCOP) is used in order to solve the problem. Figure 1 shows the concept of the system.

We assume the use of this system on a university campus. University campuses have various unique features and issues when considering disaster prevention. For example, it is difficult to determine how many people there are on campuses. There will be many students studying in libraries, spare rooms, or

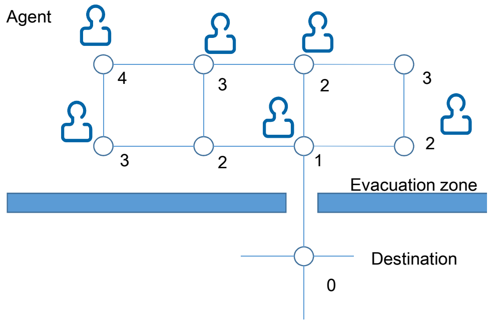

Figure 2: Model of evacuation zone.

cafeterias. Visitors can also use the open spaces. In addition, administrative structural issues exist, which are different from those in companies. University campuses are a prime example of places that require *Mutual-help*.

3 FORMALIZATION OF EVACUATION

In this section we formalize the problem. The evacuation covered in this paper is local adaptation evacuation; we do not consider the planned evacuation of a wide area

3.1 Formalization of Evacuation

In order to use the framework of the DCOP, it is necessary formalize the disaster evacuation problem. Thus, we considered the formalization as follows.

Evacuees with a mobile device are considered to be agent $A = \{a_1, \ldots, a_N\}$.

$\mathcal{P} = \cup\{p_1, \ldots, p_M\}$ are the places from which people must evacuate.

When agent a_l is located in time t at place p_i, it is written as $place(a_l, t) = p_i$. $\mathcal{L}(t)$ is the set of places of an agent who has not evacuated.

$$\mathcal{L}(t) := \cup\{place(a_i, t) \mid place(a_i, t) \in \mathcal{P}\} \quad (1)$$

Agent a_i is assumed to be capable of detecting the number of nearby agents $nr(a_i)$.

At the time of a disaster, the situation is fluid. People may be unable to pass along a passage.

All places P_i have a score of $val(P_i) \in \mathbb{N}$. This score is assumed to decrease toward the refuge direction. It is assumed that the agent can search the evacuation routes, and calculate the scores for the areas on the routes. In this paper, it is assumed that all the agents' score allocation is the same for simplification.

The above modeling can express $\mathcal{P}$ as a graph as shown in Figure 2. At this time, utility function f of

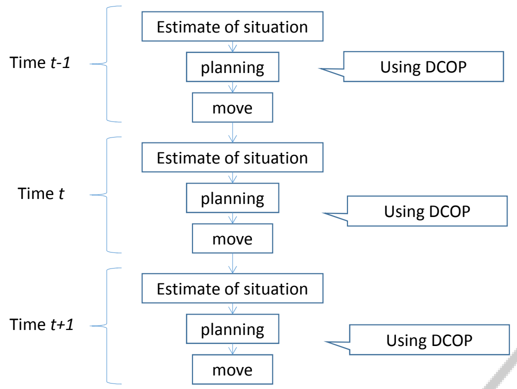

Figure 3: Real-time planning problem.

the entire agent is as follows:

$$f(A,\mathcal{L},t) := \sum_{\{a_i|place(a_i,t)\in\mathcal{P}\}} \frac{val(place(a_i,t))}{nr(a_i)} \quad (2)$$

The numerator expresses the desire to evacuate, and the denominator is a constraint to avoid congestion.

In this study, evacuation is considered to be a real-time planning problem (shown in Figure 3.) The position after moving of the agent in time $t+1$ may not be the position that the system computed in the time t. An agent may be unable to move according to the situation which a system cannot know, or an agent may not follow the guidance of a system.

That is, the evacuation problem at time t is to solve the following expression.

$$\arg\min_{\mathcal{L}}(f(A,\mathcal{L},t+1) - f(A,\mathcal{L},t)) \quad (3)$$

The above $f(A,\mathcal{L},t+1) - f(A,\mathcal{L},t)$ is negative. By solving this expression, the agent knows the appropriate evacuation timing. To solve this, we adopt the DCOP framework.

It is necessary to consider the following conditions further:

1. Short time to complete evacuation
2. Short continuous wait time of each agent
3. Fairness of the agent

3.2 Evacuation Problem as Distributed Constraint Optimization Problem

The Distributed Constraint Optimization Problems (DCOP) are the fundamental framework in distributed artificial intelligence and have recently attracted considerable attention (Yokoo and Hirayama, 2000)D Algorithms used to solve DCOP include ADOPT (Modi et al., 2005)C OptAPO (Mailler and Lesser, 2004), DPOP (Petcu and Faltings, 2005)C NCBB (Chechetka and Sycara, 2006), and distributed stochastic search algorithms (DSA) (Zhang et al., 2005). As for a complete algorithm, an optimum solution is guaranteed, despite the extended computing time. When using DCOP for real-world problems, particularly when solving problems involving robotics and sensor networks, problems must be solved in distributed environments with minimal computation resources (Fitzpatrick and Meertens, 2001)(Zhang et al., 2005). Under such circumstances, seeking an optimum solution with a complete algorithm is not always the best method, and there is a need for a fast and efficient approximation algorithm.

The Distributed Constraint Optimization Problem (DCOP) is defined as a tuple $< A,X,D,F >$ (Modi et al., 2005)(Petcu and Faltings, 2005)D A set of variables $X = \{x_1,x_2,...,x_n\}$ exists, each of which is assigned a value taken from a finite and discrete domain $D = \{D_1,D_2,...,D_n\}$, and each of which is also assigned to multiple agents $A = \{a_1,a_2,...,a_m\}$. (n is handled as $n = m$ here for simplification purposes.) Constraint function $F = \{f_{ij}|D_i \times D_j \rightarrow \mathbb{R}\}$ is defined between x_i and x_j. The agent a_k only has the following information: information about x_k , which is assigned to a_k, and the cost function f_{k*}. In this case, the purpose of DCOP is to obtain an assignment for variable $\mathcal{A}$ that minimizes the summation of the cost function $\mathcal{F}(\mathcal{A}) = \sum f_{ij}(\mathcal{A})$ In DCOP, an assignment $\mathcal{A}_o$ that offers the minimum $\mathcal{F}(\mathcal{A}_o)$ amongst all possible assignments $\mathcal{A}$ is defined as the optimum solution. In DCOP, agents solve problems by exchanging values of the variable through message transmission with other agents whose variable are associated by constraints. The framework of DCOP does not need a center server in order to solve problems.

When treated as a distributed constraint optimization problem, the evacuation problem can be considered as follows.

An agent has a variable to store the place to which the agent should move. And the agent decides the position of the time $t+1$ using DCOP in time t. This is continuously performed as a real-time planning problem (Figure 3). The situation confirmation for every step is indispensable. At this time, minimization of Formula(2), i.e., minimization of Formula(3), is the objective function. The denominator of Formula(2) is the constraint of an agent's move and can be described by binomial constraint. The molecule of Formula(2) becomes a unary constraint.

The above illustrate a simple application of DCOP.

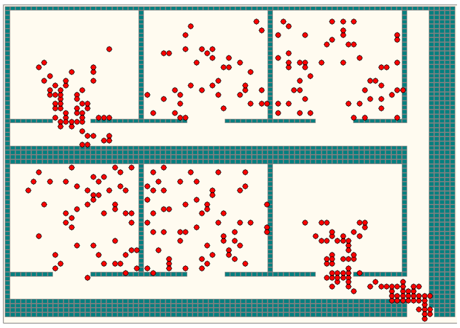

Figure 4: Multi-agent simulation of a disaster evacuation.

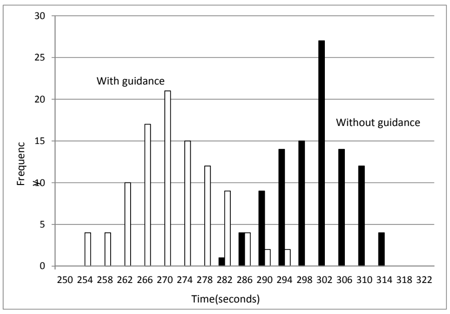

Figure 5: The frequency distribution of the evacuation completion time (with/without guidance).

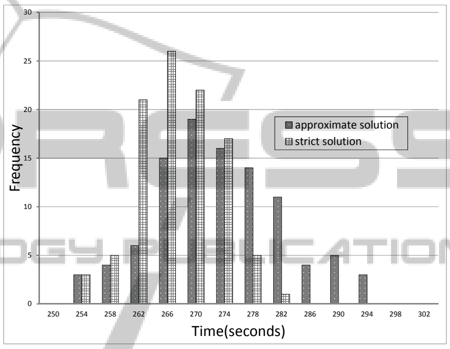

Figure 6: The frequency distribution of the evacuation completion time (approximate solution/strict solution).

4 EXPERIMENT USING MULTI-AGENT SIMULATION

A multi-agent simulation is often used for disaster evacuation experiments, not only for disaster prevention planning, but also building or city planning. We conducted an experiment using multi-agent simulation in order to investigate the validity of the proposed system. In the experiment, we also investigated the influence of an approximation algorithm to solve the problem.

4.1 Experimental Conditions

We set up a 2-story school building with six rooms for the experimental conditions. It was assumed that the evacuation route was limited to only one according to the disaster. The agents shall move rationally to an evacuation place and agents move according to the model of the crowd walking (Kaneda and Okayama, 2007). The evacuee's psychological model is not used in this experiment; the agent shall follow guidance if guidance is available. The number of agents was set to 400. The location of the classrooms and the simulation image are shown in Figure 4.

Evacuation is started from the situation where people are randomly distributed throughout the classrooms and passages. The evacuation guidance in this experiment negotiates only the evacuation start timing from each classroom by DCOP. If the population density of a passage becomes below the threshold value, evacuation will be started from any one classroom on each floor. DCOP shall be used for the selection of the classroom that may start evacuation. In this experiment, in order to solve DCOP, the approximation algorithm DSA (Zhang et al., 2005) was used. It is important to solve the problem in a short time in an urgent situation such as disaster evacuation. In such a case, an approximation algorithm is more suitable than complete algorithm. DSA is a randomized algorithm.

4.2 Experimental Results

We compared evacuation completion time in cases with and without evacuation guidance. If there is no evacuation guidance, evacuation will be simultaneously started from all the classrooms, but if there is evacuation guidance, evacuation will be started from one classroom.

The simulation was performed 300 times under this condition, and the frequency distribution of the evacuation completion time of the result is shown in Figure 5. The evacuation completion time was plotted on the X-axis, and frequency was plotted on the Y-axis. In this experimental result, when there was evacuation guidance by DCOP, evacuation completion time decreased by about 10%. This effect should change according to conditions such as the location of the classrooms, width of the passage, etc.

The approximation algorithm DSA was used for this experiment. For this reason, although evacuation should have been ideally performed from any one classroom of each floor, evacuation might have been simultaneously performed from two classrooms. This is a case where a strict solution cannot be found by DSA.

The case where evacuation is performed only from one classroom is called a strict solution. The frequency distribution of only a strict solution is shown in Figure 6. In the figure, the case of the approximate solution was also plotted for comparison. Although a significant difference was observed in these two as a result of the *t*-test, the difference was very slight. In this experiment, there were only three classrooms on one floor, so the difference between the strict solution and the approximate solution might be small.

5 RELATED WORK

(Lass et al., 2008) discussed the application of DCOP to coordination in a disaster management situation. Authorities must assign tasks and resources in disaster scenarios; unfortunately accomplishing this in real time is currently difficult. They argue the framework of DCOP is uniquely suited to meet the requirements imposed of coordination mechanisms in these settings. (Nguyen et al., 2012) extended DCOP to Stochastic DCOP(SDCOP) in order apply it to disaster management proposed by (Lass et al., 2008)D In SDCOP, the constraint rewards are deterministic values but are sampled from known probability distribution function called reward functions. And they proposed an algorithm that solves SDCOP. These researches are specialized in the resource (or shelter) assignment problem at the time of a disaster, and have not made reference to evacuation guidance.

Evacuation problems can be modeled in dynamic network flows (Hamacher and Tjandra, 2002)D The standard approach to solving dynamic flow problems is to transform the graph into a time-expanded network. However, the expanded graph is larger.The major computational bottlenecks are the time and memory required to construct the expanded network. Some heuristic algorithms have been proposed for this problem (Hamacher and Tjandra, 2002)D (Lu et al., 2005) considered capacity constrained routing heuristics. (Hadzic et al., 2011) considered the problem of planning evacuation routes in deteriorating networks, where nodes become unavailable over time. In these researchs of heuristic algorithms, it is assumed that problem solving is performed in a non-distributed environment.

There are also some related works concerning disaster evacuation simulation systems using multi-agent simulation (Burstedde et al., 2001) (Helbing et al., 2000)(Shi et al., 2009).

6 CONCLUSIONS

We aim to develop a the system that provides optimal evacuation guidance autonomously at the time of a disaster. This system enables assistance to be given in the form of evacuation guidance to relieve congestion, by calculating evacuation routes and timing via an adhoc network of evacuees' mobile devices, without a center server.

In this paper, the problem of disaster evacuation was formalized and how to solve it using the framework of the Distributed Constraint Optimization Problem was examined. In the experiment using a multi-agent simulation, when evacuation guidance using DCOP existed, the evacuation completion time decreased by about 10%. And even when it was solved with an approximation algorithm, the effect on the evacuation completion time was small.

As the formalization in this paper is very simple, it is necessary to introduce a more realistic model. The fairness of an agent's latency time, and minimizing the total evacuation completion time should also be written as a constraint. The fairness of latency time will be realizable if an agent's continuation latency time is minimized. Therefore, it is necessary to write the continuation latency time as a unary constraint. Moreover, it is necessary to examine the guidance method itself to ensure that people are able to follow the guidance.

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