RoboCup Rescue 2023
TDP Agent Simulation
Ri-one (Japan)

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Abstract. Ri-one 2023 focused on the development and improvement of Agents. We modified the search method and extended the search area for ambulans teams(ATs), fire brigades(FBs), and police forces(PFs). In addition, the search method is changed when an agent hears the voice of a civilian, making it easier to detect those who are seeking help. In PF, the priority was given to the removal of debris around the voice of a civilian to expand the search range when their voice is heard.

1 Introduction

One of the important challenges for Robocup Rescue Simulation(RRS) is the early detection of buried civilians. In order to achieve, agents need to be dispersed and expanded the search area. Therefore, Ri-one 2023 focused on developing the search methods of Agents, and implemented the methods for searching when citizens' voices are heard. Random walks were used to disperse the Agents, and *Particle Filter* [3] were used to detect citizens who had called for help. Section 2 explains strategy of *Detector*. Section 3 explains search strategy which use *Particle Filter* and *Levy Walk* [4].

2 Detector Strategies

2.1 Purpose

This section explains *Dynamic Task Management* and the purpose of using *Message Manager* in *Dynamic Task Management*

2.2 Explanation of Dynamic Task Management

Dynamic Task Management [1] is the system for flexible evaluation by separating the evaluation of entities and deciding the targets in the Detector modules.

In DTM, Ri-one2021 gives all EntityIDs to Task manager class. In TaskManager class, DTM gives *Priority* and *Unstableness* to these EntityIDs. *Priority* indicates how many entities should be chosen as the targets. *Dynamic Task Management* determines a target which have top *Priority*. *Unstableness* indicates how much *Priority* of entities should be re-evaluated.[2]

A situation of a entity is changed by the elapsed time. The difference between *Priority* and a latest situation is grown by the elapsed time. Therefore, *Dynamic Task Management*introduced

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Unstableness. following own criterion. *Dynamic Task Management*re-evaluate *Priority* in the following order of *Unstableness.* The criterion that have low *Unstableness* is calculated more frequently than the criterion that have high *Unstableness.* According to *Unstableness*, *Dynamic Task Management*can reflect

2.3 Change Point

An agent can make flexible indicators to use information which is able to obtained by *Message Manager.* Agent can determine an appropriate target based on the indicators.

2.4 Developed Indicator using Message Manager

PFs prioritize the removal of debris near buried civilians to efficiently rescue civilians buried in the blocks. they adds the priority of the blocks near them when the PFs hear the civilian's voice. When the PFs hear the civilian's voice, PFs adds the priority of the blocks near them.

2.5 Limitation

Ri-one 2023 can not use messages appropriately. Therefore, we need to develop *Message Coordinator* and *Channel Subscriber.* The method has a high possibility of agents of the same type often select the same target by receiving messages. Accordingly, we must change the way of choosing a target.

3 Search Strategies

3.1 Purpose

Ri-one 2023 developed search algorithms using *Levy Walk* and *Particle Filter* . *Levy Walk* is one of random walk. Random walk is the algorithm which something repeat moving to random position. Particularly, *Levy Walk* decide move direction following Levy distribution. *Particle Filter* is algorithm which find approximate solution for likelihood calculation and re-sampling. The purpose of the search algorithms are to expect the position of civilians who call for help and to disperse agents to expand the search range.

3.2 Particle Filter

3.2.1 Proposed Approach In RCRS, Agents have sense of sight and sense of hearing. Particularly, sense of hearing is important sense to search civilians. Agents are able to hear farther civilian's voices than range of agent's vision. In addition, agent on road is able to hear the voice of civilian inside of a near building. Therefore, Ri-one 2023 expected position of a civilian called for help using *Particle Filter* . Agents need to hear the voice of a civilian who called for help in some positions because Agent's sense of hearing can not obtain the direction which the voice come from. Prediction value of a civilian exist is derived by the below formula 4.

$$
\begin{aligned}
F_t(s_t) &= P(s_t|h_{1:t}, a_{1:t}) && (1)\\
&= \frac{P(s_t, h_t|h_{1:t-1}, a_{1:t-1})}{P(h_t|h_{1:t-1}, a_{1:t-1})} && (2)\\
&\propto P(s_t, h_t|h_{1:t-1}, a_{1:t-1}) && (3)\\
&= P(h_t|s_t)P(s_t|s_{t-1}, a_{t-1})F_{t-1}(s_{t-1}) && (4)
\end{aligned}
$$

s_t means a civilian exist position s when time t. h_t defines event that an agent heard voice of civilian when time t. a_t is agent's position when time t. $F_t(s_t)$ defined Prediction value of a civilian exist position s when time t.

3.3 Levy Walk

3.3.1 Proposed Approach *Levy Walk* [4] is a random walk in which moved distance follows *Levy Distribution* and direction follows a uniform distribution. Probability density function of *Levy Walk* is shown in the equation below. μ and c are constants.

$$F(x) = \begin{cases} 0 & (x = \mu) \\ \sqrt{\frac{c}{(2\pi)}\frac{e^{-c/2(x-\mu)}}{(x-\mu)^{3/2}}}) & (x \neq \mu) \end{cases} \tag{5}$$

Movement direction is determined randomly, and movement distance obtain from formula 5 when x is decided randomly. Execution result of *Levy Walk* is shown below figure.

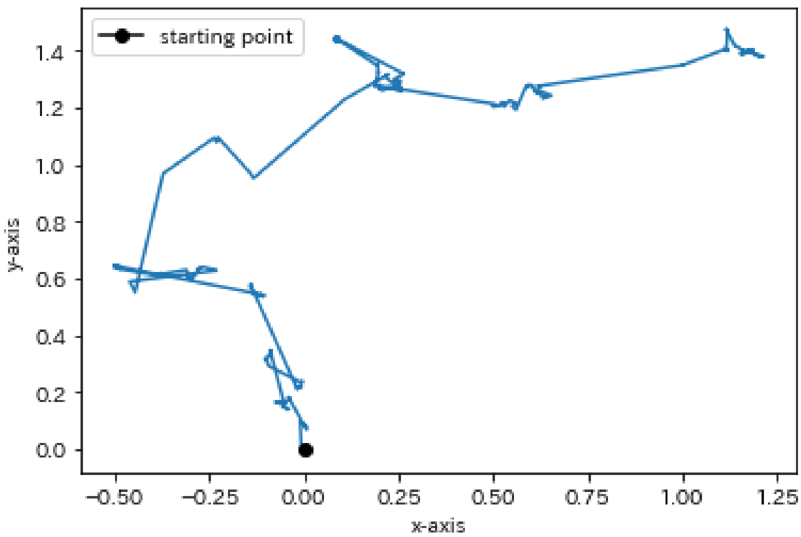

Fig. 1: Execution result of *Levy Walk*

In figure 1, *Levy Walk* is characterized by rarely long distances and frequent short distances. It is that agents can hear civilians' voices in a narrow area and contribute to the expected position of civilians with *Particle Filter* to using *Levy Walk* .

3.3.2 Determining Move Direction If the movement direction of *Levy Walk* follows a uniform distribution, rescue efficiency reduces when civilians crowd part of a map. Therefore, Ri-one 2023 determined the movement direction of *Levy Walk* following distribution calculated by statements around an agent. The probability distribution $p(\theta)$ is calculated using Lagrange's interpolation formula. First, score per directions $p_{\theta_1}, p_{\theta_2}, \cdots, p_{\theta_n}$ are calculated by some indicators. The probability distribution is generated by the following equation.

$$l_k(\theta) = \frac{(\theta - \theta_0)\cdots(\theta - \theta_{k-1})(\theta - \theta_k)\cdots(\theta - \theta_n)}{(\theta_k - \theta_0)\cdots(\theta_k - \theta_{k-1})(\theta_k - \theta_k)\cdots(\theta_k - \theta_n)} \tag{6}$$

$$p(\theta) = \sum_{k=0}^{n} p_{\theta_k} l_k(\theta) \tag{7}$$

The move direction choices randomly using *roulette Selection* from scores per all Entities which are calculated by $p(\theta)$.

3.4 Limitation

In Ri-one 2023, the strategy occasionally get lower score an score average. Therefore, Improving to get a high score stability is expected to improve the way of determining movement direction. We improves *Particle Filter* as agents can predict some civilians when an agent hears some voice of civilians call for help. The way of switching between *Levy Walk* and *Particle Filter* has room for improvement. Priority calculation of *Particle Filter* has an issue. The issue is that the priority of a large area object and the priority of a small area object are the same value. We need to improve the way of priority calculation.

4 Preliminary Results

In this section, we describe the results of the experiments. These experiments aimed to confirm the effectiveness of implemented functions.

4.1 Experiment Conditions

In the experiments, Ri-one 2022 and Ri-one 2023 were compared. Ri-one2022 is an modified implementation of 2022 [2]. Ri-one 2023 refers to the modified version of Ri-one 2022. Ri-one 2023 was implemented the functions described in the Search Strategies section. The simulations were carried out 10 times for each condition. The specifications of the used computer followed the table below.

Table 1: specs of a computer

OS	Ubuntu 18.04
CPU	Intel Core-i9 10850K
Memory	DDR4-2666 32GB

4.2 Score and Analyze

The experiment results followed the table below.

Table 2: Average score for each map

Map	score	
	Ri-one 2022	Ri-one 2023
berlin	72.10007468	72.2006127
jajo	128.9046322	128.6044216
kobe	174.1231558	176.029718
montreal	75.6845544	75.2904735
paris	130.4978186	130.4978186
istanbul	166.6002645	166.6002645

Compared to Ri-one2022, there were maps where scores increased, such as berlin and kobe, and maps where scores decreased, such as jajo and montreal. Additionally, there were maps where scores remained the same, such as paris and istanbul.

First, analyze the maps where scores remained the same from Ri-one 2022.

Table 3: Example of a map where the score remains the same

Map	score	
	Ri-one 2022	Ri-one 2023
istanbul	166.6002645	166.6002645
	166.6002645	166.6002645
	166.6002645	166.6002645
	166.6002645	166.6002645
	166.6002645	166.6002645
	166.6002645	166.6002645
	166.6002645	166.6002645
	166.6002645	166.6002645
	166.6002645	166.6002645
	166.6002645	166.6002645
average	166.6002645	166.6002645

In these maps, all 10 simulations yielded identical scores. These results are considered because the search method did not work effectively, resulting in the inability to rescue civilians.

Second, analyze the maps where scores increased and decreased compared to Ri-one 2022.

Table 4: Examples of maps with increased scores

Map	score	
	Ri-one 2022	Ri-one 2023
kobe	172.8187425	170.8183675
	174.825406	173.824453
	174.8243075	171.818844
	173.821692	175.83469
	173.8239165	175.829315
	174.8234195	176.8331975
	173.8234585	174.8285155
	174.826174	175.829938
	172.8194435	174.8246335
	174.8249975	174.826336
average	174.1231558	174.526829

Table 5: Examples of maps with decreased scores

Map	score	
	Ri-one 2022	Ri-one 2023
montreal	75.683315	75.696024
	75.683919	73.688106
	75.685065	74.68799
	75.684079	75.690691
	75.684808	76.689078
	75.686408	75.694662
	75.684765	75.694662
	75.685211	74.688344
	75.684867	75.68943
	75.683107	74.69071
average	75.6845544	75.2904735

This result is considered attributed to the introduction of randomness in the search method in Ri-one 2023. In the simulation before Ri-one2022, the same map gave the same score every time. As a result of introducing randomness, the deviation of the score is considered to be larger than before Ri-one 2022. Maps with a decreased score are considered to have scored lower as a result of random searches. Scores are considered to be on an upward trend because there are many maps with rising average scores. In Berlin, in particular, the lower limit of the score has not changed and the average has increased, suggesting that the score is trending upward.

These results showed the effectiveness of improvements in Ri-one2023. The increased search area indicates that many more civilians can be rescued compared to R-ione 2022. However, because of the introduction of the random nature, there is a large deviation in the score for each simulation. For the maps with reduced scores, the inefficiency of the Agents' actions is considered to be more pronounced because the Agents were dispersed to some extent.

5 limitation

The problems in Ri-one2023 is that the deviation of the score has increased, so sometimes the score is lower than before. Therefore, in order to increase the lower value of the score, it will be necessary to optimize the search method in the future. In addition, the maps where scores remained the same need to be clarified.

References

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