

# KUres2002 Team Description

Keisuke Matunaga , Shingo Yoneda

Department of Electronics, Faculty of Engineering, Kansai University

matunaga@joho.densu.kansai-u.ac.jp

April 15, 2002

## 1 Introduction

We have developed rescue agents in the RoboCup Rescue, which is a rescue issue in the large-scale disaster. The RoboCup Rescue is a multi-agent system where some agents cooperate with the others, and is also the partial observable Markov decision process where the agents cannot know many information, e.g. damage situations, as well as the real world. Hence, the agents need to collect the unknown information relevant to rescue activities while rescuing. However, the necessary information for the rescue actions cannot be obtained enough at the initial simulation environment so that the agents cannot act the optimal rescue. The final rescue evaluation consequently deteriorates because the initial rescue actions are failed.

We have therefore developed the agents that predict unobservation environments from the surround information and rescue based on the prediction information. The agents have a priori knowledge (damage prediction data) relevant to rescue actions, e.g. road blockade, building collapse, fire, and traffic jam. We have equipped the a priori knowledge with the agents as the internal model that is the prediction map on the damage environment. Hence, all agents can rescue based on the internal model (the damage prediction data). Moreover, the accuracy of the internal model is improved by the new obtained information so that the rescue actions of the agents become more efficient.

## 2 Bayesian Learning

Bayesian Learning constitutes a probabilistic view of learning, based on Bayes Theorem[1]. The underlying assumption that there is a set of hypotheses is each having a certain probability of being correct. Receiving more information changes the probabilities from a learner's point of view. For instance, an observation might contradict a hypothesis, or strengthen the belief in it. The aim in this setting is to be able to find a hypothesis with highest probability of being correct, given a specific set of data / piece of information.

Let  $H_i$ ,  $i=1, \dots, n$  be a set of hypotheses, and  $P(H_i)$  be the probability of  $H_i$  being correct in the general case, that is without being given any additional

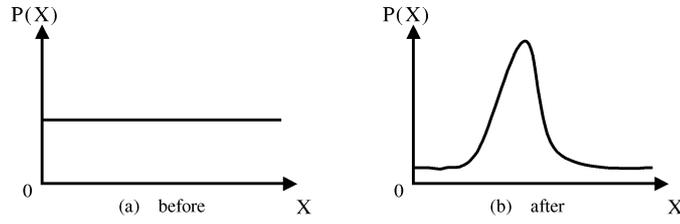


Fig. 1 Bayesian Learning

information.  $P(H_i)$  is called the prior probability of  $H_i$ . Also, let  $D$  denotes a set of data, and  $P(D)$  be the probability of the information denoted by  $D$  being correct in the general case. Then  $P(H_i|D)$  denotes the probability of the information  $D$  being correct, given the correctness of hypothesis  $H_i$ . Moreover,  $P(H_i|D)$  denotes the probability of the correctness of hypothesis  $H_i$ , given the additional information  $D$ . This is called the posterior probability of hypothesis  $H_i$ . Bayes theory, which is the basis of this learning method, is expressed by the following equation.

$$p(H_i | D) = \frac{p(D | H_i) \cdot p(H_i)}{p(D)} \quad (1)$$

This theorem allows us to find a hypothesis  $H'$  with maximum posterior probability, given the prior probabilities of all hypotheses and the probabilities of  $D$  being correct under the assumption of each single hypothesis being correct:

$$H' = \text{Max} [p(D|H_i) \cdot P(H_i)] \quad (2)$$

### 3 Rescue Actions Based on the Prediction of Unobservation Environments

#### 3.1 Prediction of Unobservation Environments

We have constructed the internal model, which is the a priori knowledge of unobservation environments. Concretely, the damage information on road blockade, building collapse, fire, and traffic jam is collected in the case where `gisinit.txt`, `galpolydata.dat`, and `shindopolydata.dat` are varied, Bayesian learning is carried out by using the obtained information. Finally, the expectation value of the probability density distribution on the damage becomes the predicted damage of unobservation environments.

#### 3.2 Rescue Actions Using the Internal Model

The obtained internal model is equipped with all agents. The agents select the optimal rescue action based on the known environments and the internal model,

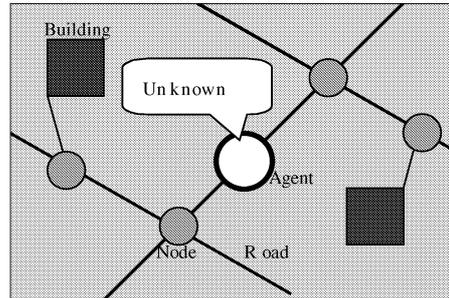


Fig. 2 Unobservation environment

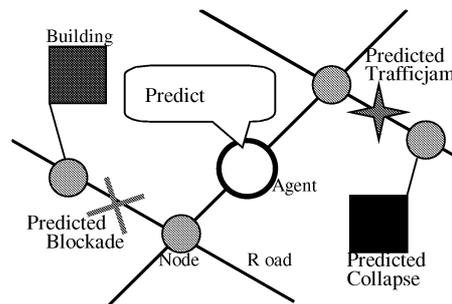


Fig. 3 Estimation of the unobservation environment by using the internal model.

concretely; select the optimal action from some possible rescue actions based on the corresponding difficulty calculated by the possessing information. Figures 2 and 3 show the situation. The internal model is a prediction so that using the internal model may make the rescue actions fail in the actual rescue. Moreover, the environment varies as rescuing. Hence, the internal model must be updated according to new information, which is informed by all agents. As a result, the error between the internal model and the actual environment becomes small, and all agents can select the optimal rescue action.

## 4 conclusion

We have developed rescue agents which mount an internal model for RoboCup 2002 Rescue Simulation League. Our agents would consequently acquire more optimal rescue actions.

## 5 Acknowledgments

We have been developing our agents since last June. Our agents are based on YabAI's agents, which were exhibited in JapanOPEN2001. We are thankful to the developer of YabAI.

## References

- [1] Kazuo Shigemasu.:Introduction to Baysian Statistcis (in Japanese). University of Tokyo Press. Tokyo.1985