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A New Decision-Making System of an Agent Based on Emotional Models in Multi-Agent System

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Abstract: In this paper, a new behavioral decision method of the robot based on a Markovian emotional model is proposed and it is applied to environmental identification problem. Noting the role of emotion in communication, behaviors of multi-robot implementing the emotional transition model are optimized. The autonomous decentralized robot group with the proposed method is applied to identify an unknown environment. Specially, each robot in this autonomous decentralized system can communicate with other robots located within a certain distance. While searching and exploring the environment, each robot independently generates local topological maps, and uses the map for planning of actions. Finally, the effectiveness of the proposed method is verified using own simulator through evaluating the exploration time and the number of double-visited nodes for different complex environments.

Keywords: decision making system, Markovian emotional model, multi-agent system

1 INTRODUCTION

There exists much literature on the study which focuses on the concept of emotion that animals have, for developing autonomous systems in various fields. Emotion of animals are more attractive from the points of view that it flexibly represents influence from the environment and internal states of them, and that it makes communication with others facilitate. Emotion has been considered as a significant impact on decision making of autonomous robots. There have been many studies of artificial emotion[1-4].

The purpose of this study is to optimize the decision making of a robot by introducing emotion to a multi-robot control system. The autonomous decentralized robot group in which each robot has the proposed system is applied to identify an unknown environment. This task is to explore all areas in unknown environment and to generate an accurate map. Getting the map leads to effective determining of behaviors of the robot because it can be used in order to path planning.

Assuming that each robot in the robot group has signal emitting and receiving functions, the robot can communicate with other robots located within a certain distance. While searching and exploring the environment, each robot independently generates local topological maps, and uses the map for planning of actions.

The proposed behavior selection system incorporates with a Markovian emotional model which is represented as a finite state machine, and the emotional state is determined by the internal state and used for behavior selection.

In addition, by optimizing the parameters related to behavior selection and generation of emotional value by a genetic algorithm (GA), one of evolutionary optimization method, the action along objective of the task is selected automatically.

The proposed method is evaluated through an unknown environmental identification problem. The simulation results showed the effectiveness of the proposed method.

The paper is organized as follows. Section 2 describes the proposed Markovian emotional model. In Section 3, the proposed behavior selection system with the Markovian emotional model is described. In Section 4, the simulation results of the proposed method are presented. Finally, Section 5 summarizes the effectiveness of the proposed method and future works.

2 The Markovian emotional model

The Markovian emotional model referenced in this paper is a probabilistic model[5] that consists of finite state machine. It consists of four basic emotions: joy, anger, fear and sadness (Fig.1).

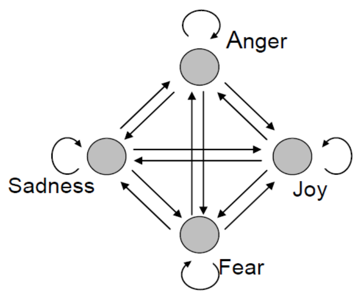


Fig. 1. Topology of Markovian Model

Emotional state transition is given by Eq.1

$$Y_{k+1} = CY_k \tag{1}$$

with emotional state points:

$$\Omega = \{Joy, Anger, Fear, Sadness\}, \tag{2}$$

where Y_k represents the current emotional state, and C is the emotional state transition matrix, which can be expressed as follows:

$$C = \begin{bmatrix} P_{joy/joy} & P_{joy/anger} & P_{joy/fear} & P_{joy/sadness} \\ P_{anger/joy} & P_{anger/anger} & P_{anger/fear} & P_{anger/sadness} \\ P_{fear/joy} & P_{fear/anger} & P_{fear/fear} & P_{fear/sadness} \\ P_{sadness/joy} & P_{sadness/anger} & P_{sadness/fear} & P_{sadness/sadness} \end{bmatrix}, \quad (3)$$

where $P_{A/B}$ is the probability of transition from state B to state A. Each value $P_{*/*}$ is initially set as basal values $q_{*/*}$, elements of matrix named Q which gives the basal state transition matrix (See Eq. 4). These values $P_{*/*}$ can be changed online by the influence of emotion-inducing factors: α, β, γ, and δ for joy, anger, fear, and sadness, respectively. These factors vary depending on the internal state and information given by certain other robots and have the role to stimulate each emotion. For example, the probability of state transition from joy to other state expressed by the following equations:

$$\begin{aligned} P_{anger/joy} &= q_{anger/joy} + (\beta - \alpha) q_{anger/joy} \\ P_{fear/joy} &= q_{fear/joy} + (\gamma - \alpha) q_{fear/joy} \\ P_{sadness/joy} &= q_{sadness/joy} + (\delta - \alpha) q_{sadness/joy} \\ P_{joy/joy} &= 1.0 - (P_{anger/joy} + P_{fear/joy} + P_{sadness/joy}) \end{aligned} \quad (4)$$

The emotional state Y is used to determine the behavior.

3 A Behavior Selection System

The proposed behavior selection system is achieved by incorporating the Markovian emotional model described in section 2 into a general action selection system. The overall structure of the system can be shown in Fig.2. The system consists of five modules, cognition, database, emotion, behavior selection, and behavioral system. The cognition module performs recognition and mapping of the environment. The map created by the cognition module is recorded in the database module. Then, the cognition module determines emotion-inducing factors $(\alpha, \beta, \gamma, \delta)$. For example, these factors are determined based on remaining battery capacity, the number of frontiers and the emotional state of other robots in communicable area. The emotion module generates and updates the emotional state Y by Eq.1, changing C by emotion-inducing factors determined by the cognition module, and transfers it to the behavior selection module. The behavior selection module determines the behavior selection probability vector X by Eq.5:

$$X_{k+1} = AY_{k+1} + V_{k+1} \ , \quad (5)$$

where X_{k+1} consists of probabilities of next actions. A expresses the probability transition matrix and is predefined. The parameter vector V that affects instinctive action selection is generated by the cognition module. The reason for adding V is if use of only a simple emotional transition model, it is difficult to realize behavior selections in accordance with the rules. For example, while charging of the battery, the selection probability of the particular behavior increases due to the rise in the transition probability of the joy. However, it will be more efficiency, waiting until the completion of the charging. A behavior is selected stochastically according to the selection probability of each behavior. The behavioral system module generates a control input u taking into account the posture of the robot received from the cognition module to perform the action that has already been decided.

In this model, the policy of behavior selection depends on transition matrices of Q and A. By adjusting the parameters being included in these Matrices, it becomes possible to make various methods for behavior selection.

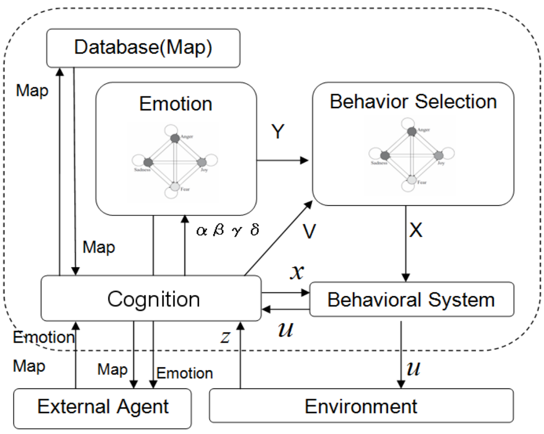


Fig. 2. A behavior selection system proposed here

4 Simulation

The simulation was performed with a simulator which we developed independently. The purpose of the simulation is to identify an unknown environment by multi-agent. In the simulation, a mapping method was simplified under the assumption that the robot is able to exact mapping. So, the environment was represented by a set of cells, and the robot transitioned between cells (Fig.3). First, transition matrices whose value was manually set was used and the proposed system evaluated by the result. Second, GA was introduced to parameter setting, to automatically optimize the behavior selection.

4.1 Common term

The environment was constituted by "Passage" where the robot can reach and "Wall" where the robot cannot

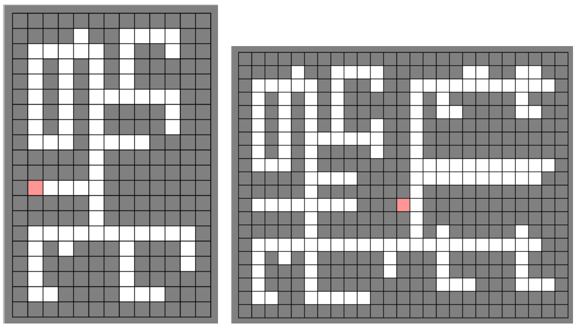


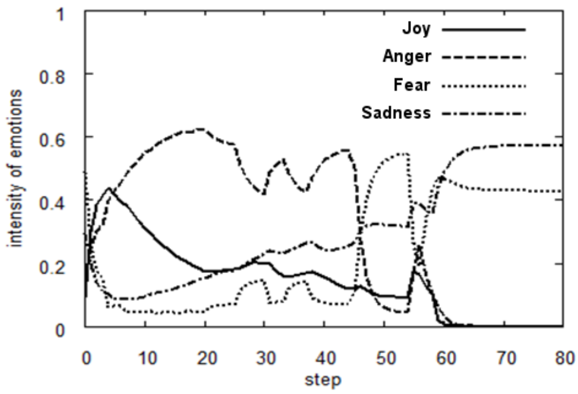
Fig. 3. Environments used for exploration

reach (Fig. 3). The following terms are assumed about robots: i) The robot gets the local coordinate information; ii) The robot can move to four neighboring cells adjacent to the location in the action of one step. However, if the destination is "Wall", it does not change the coordinates; iii) The robot can perceive eight neighboring cells adjacent to the location as the information from the sensor; iv) During the search, the robot creates a local map of its own, and shares the map with other robots exist in the predetermined distance; v) There is a base point in the environment, the robot starts from the base point, and then returns to it; vi) The robot consumes battery by moving, it cannot do *a*ny behavior if there is no amount of battery. When all robots return to the base point and all passages in the environment are visited simulation will be terminated.

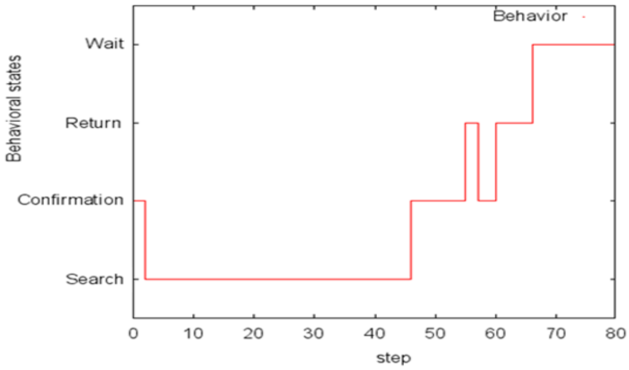
Each robot selects one of the following four behaviors "search", "confirmation", "wait" and "return", and determines the destination based on concepts of the behavior. The "search" is an action which sets the most valuable frontier area to destination by referring to the map. At this action, the robot does not select the area which is already mapped by other robots. The worth exploring of the area is determined depending on the distance and the number of unmapped areas around it. The "confirmation" sets the area that the robot has not done mapping in its own to destination even if the area has already been mapped by the other robots. The "return" means to return to the base point by the shortest route which is derived from the map. The robot learns the knowledge about the environment by creating a local map. By doing this, it is possible to calculate the shortest route to the target by using a graph search algorithm.

4.2 The identification simulation of the unknown environment by the proposed method

The simulation which deals with the task for identification of unknown environment by three robots using the proposed method was performed. First the result of simulation for the narrow environment (left in Fig. 3), and then for the wider environment (right in Fig. 3) are



(a) Emotional Intensity vs step



(b)Behavioral state vs step

Fig. 4. Relationship between emotional state and behavioral state

described. In these simulations, Q and A were set manually by trial and error. The emotional state transition of one robot out of three in simulation for narrow environment is shown in Fig. 4(a), and the behavioral state transition is shown in Fig. 4(b). By comparison of state transitions of the emotion and the behavior, it is apparent that the emotional state was reflected to the behavior selection. For example, in the vicinity of step 50, the behavioral state changed from "search" to "confirmation" with increasing the probability of the "Fear". The reason for this is because the robot had finished mapping of all areas in the vicinity of him, and changed the target to the area that was allocated to the other robots.

Next, the simulation was performed for the wider environment. In this case, the robot needs returning to the base point during one trial, for charging battery. At this time, the number of visited areas by each robot was 33, 34, 33, respectively, and this result shows that three robots shared target areas equally.

These results showed that the Markov emotional model worked properly.

4.3 Parameter setting by GA

Next, the transition matrix A and Q were optimized in proposed system by GA. 80 individuals were used. Five environments with different sizes and structures were prepared, the four was for learning and the other was for test. Fitness was determined by degree of achievement, the time required for attainment, and the consumption of the battery and such. So the higher the fitness became, the less the energy consumption and the amount of time spent by the end of the task were.

The result performed under five environments using excellent individual parameters in the last generation was compared with the result of the parameters set manually. Fig. 5 shows the average value of the number of steps required to finish the task in 100 trials each. As a result, it was confirmed that the methods for determining the behavior using the parameters optimized by GA was better than those of manual parameter setting.

Then the change in the number of areas which were already visited was observed in the environment 1. As a method for comparison of the proposed method, the search algorithm (named "conventional") was prepared, that determines behavior sequentially from the number of areas not visited yet. Fig. 6 shows the changes in the average number of visited area of 100 trials, respectively, for two types of the proposed methods (settings of parameters by GA or manually) or the conventional method. Stagnation of the change in the graph results from the interruption of the task due to the charging of the battery. Comparing steps required to map all the 149 passages, it is clear from the graph that the proposed method using GA is the smallest. Observing the behavior of robots during the simulation in the conventional method, we found there were inefficient behaviors, for example, multiple agents charged batteries at the same time or set the unreachable area as a destination. On the other hand, in the proposed methods, the robots charged batteries in a timely manner and shared the roles efficiently.

5 CONCLUSION

In this paper, we proposed a method of a robot's behavioral plan using a Markovian emotional model for identifying an unknown environment by multi-agent. The simulation was performed with the simulator which we have developed independently. The results showed that valid action decisions were made by the proposed system. The policy of robot's behavioral decision depends on the parameters being included in basal parameter matrix Q and A. By adjusting these parameters, it is possible to make various plans for determining the robot's behavior. The optimization of the parameters was performed through the use of genetic algorithm. From the results, it became clear that the optimization of the parameters by GA led more

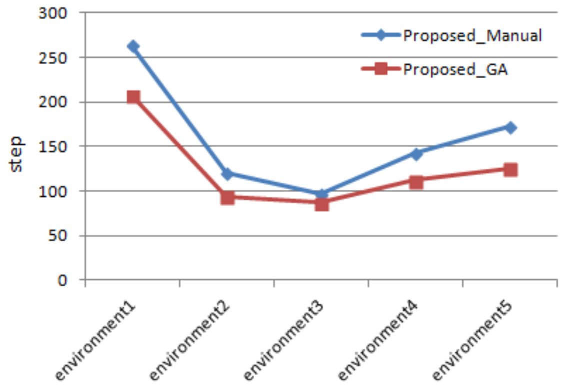


Fig. 5. Average step

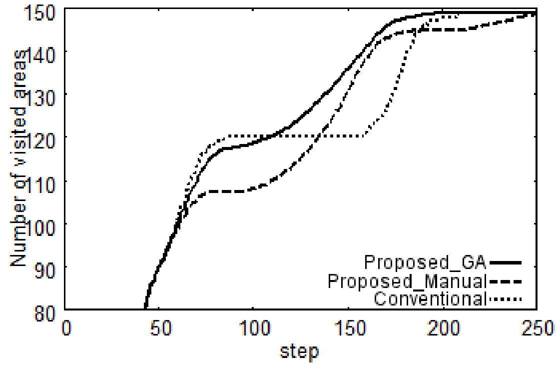


Fig. 6. Average number of areas visited vs step

sophisticated methods of robot's behavioral plan than setting the parameters manually.

In this study, the basis of evaluation was such factor as the search time and so on, however there are various optimal solutions depending on the purpose of the task. By setting the fitness function in line with objectives of those tasks, it is possible to automatically design the methods for determining the behavior of agents in the proposed system. The basal parameters optimized by genetic algorithm were treated as the parameters that were common to all agents. As future works, we think it is possible to find a new optimal solution by giving the different personality to different agent which may be realized by performing different parameter settings for each agent.

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