Using Potential Field for Modeling of the Work-environment and Task-sharing on the Multi-agent Cooperative Work

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Abstract

This paper describes the modeling of work environment for the extraction of abstract operation rules for cooperative work with multiple agents. We propose the modeling method using a potential field. In the method, it is applied to a box pushing problem, which is to move a box from a start to a goal by multiple agents. The agents follow the potential value when they move and work in the work environment. The work environment is represented as the grid space. The potential field is generated by Genetic Algorithm (GA) for each agent. GA explores the position of a potential peak value in the grid space, and then the potential value stretching in the grid space is spread by a potential diffusion function in each grid. However, it is difficult to explore suitable setting using hand coding of the position of peak potential value. Thus, we use an evolutionary computation way because it is possible to explore the large search space. So we make experiments the environment modeling using the proposed method and verify the performance of the exploration by GA. And, we classify some types from acquired the environment model and extract the abstract operation rule. As results, we find out some types of the environment models and operation rules by the observation, and the performance of GA exploration is almost same as the hand coding set because these are nearly same performance on the evaluation of the consumption of agent's energy and the work step from start point to the goal point.

Keywords:

Multi-agent systems; Cooperative Work; Task-Sharing; Potential Field; Piano Mover's Problem; Genetic Algorithm

1 Introduction

The objective of this paper is to obtain abstract rules for the agents operating in the work environment, in which the multiple agents should cooperative to accomplish tasks. In this paper, a potential field is set up in the work environment and utilized in order to obtain operation rules for the cooperation work of the agents. Work environment modeled based on this potential method, and the operation rules are extracted from the potential-expressed environment model. As a reason using for the potential, we considered that it reduces the calculation cost to acquire effective operation sequences by learning, since it can omit the process which regulates the operation sequence of the agent. Moreover, because each agent takes a simple environment-dependent strategy as it's internal state, it can be controlled based on the environmental information. Therefore, it is regarded the system can to adapt dynamic changes of the environment, without changing the internal state of the agents.

The abstract rules for the agent operation extracted from the potential information in the environment is regarded as becoming a general guideline for the environment. This is because the process of extraction can be viewed as carrying out general plans. For example, a skilled worker who works in a factory recognizes situations roughly such as the trouble of an equipment, and immediately makes a general plan based on their accumulated experience. In similar situations, there is a high possibility that the similar guideline can take effect. Because, in the case of working recognition and decision based on inner accumulated information, if a situation is similar to an experienced situation, then it will be reasonable to make a guideline using the classification of recognized situation based on the similar experience.

Therefore, the ultimate purpose of this study is to realize the above process by engineering approach.Common rules for the agents should be searched and extracted over various situations (workspace shape, or workload). Applying this method to a cooperative work with multiple agents can solve either the calculation cost problem in the centralized planning method[1] or the communication cost problem when each agent plans for coordination[2]. It is because, this method does not directly deal with a sequence of agent operations and communications, but deals with the potential information that is the motive for the agents.

In this study, we take the box pushing problem as a work for the multiple agents. The box pushing problem is closely related to "the piano mover's problem"[3]. The problem contains some subproblems that are obstacle avoidance, the push position changing and pushing direction adjustment. The agent pushes the box to the goal point to solve the problem. It is necessary to set rules for the agent operation in order to solve this problem in the cooperative work of the multiple agents. At first, the environmental modeling is done by setting up the potential field in the work environment. The potential information is read by the agents as their operation rules and evaluated using simulation results. The system takes the potential model that brings the best evaluation as the description of the environment (type of the work and shape of the environment). In addition, the potential information shall be set as an operation rule for the agents based on the potential model generated.

This paper consists of five sections. In section two, the outline of the system is described and our method is compared with other techniques so that features of the system is clearly explained. Section 3 explains the generation of potential information as a preparation of simulation experiment. Section 4 is about simulation results. Finally, in section 5, we discusse the effectiveness of this system.

2 Outline of the Proposed System

As mentioned above, in this paper, the operation rule of the agent is generated based on the potential information in the work environment. Therefore, the system should generate the environment model based on the potential. Conceptual scheme of this system is shown in Figure 1.

This system is composed of three phases. In the first phase, it carries out the search to decide where to set the potential peak value in the work environment using Genetic Algorithm (GA). In the second phase, it generates the potential information by which each agent builds an inner state from bit strings of GA. In the third phase, the agents works for the box pushing based on this potential information and the result is reflected for the calculation of GA.

In this method, the potential set up in work environment is generated by searching the optimum potential peak using GA, and expanding the peak into the whole environment based on a potential diffusion function. Therefore, the bit string of GA is represented in a discretestate-space that is separated at a fixed interval. That is, each bit expresses a corresponding grid of the state-space in the following, The environment means the discrete state-space. Each agent takes its own potential field.

Each agent moves in the environment based on the generated potential field, and carries out the box pushing. Each bit string is evaluated by an objective function through carrying out the box pushing, and the evolution is reflected to the operation of GA. By repeating the calculation, the environment model and the agent operation rule are generated.

Reinforcement Learning is applied[4] to the generation of the operation rule that enables task sharing and the action planning, based on the environment information. As an

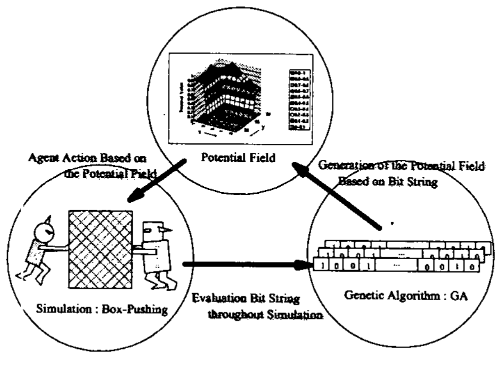


Figure 1 - Concept of the Proposed System

example of the planning for multiple agents systems, there is robot motion planning for the Robo-Cup soccer[5]. However, since Q-Learning is originally a learning process for a single agent, applying the learning method to the action planning for multiple agents simply, will result in bad efficiency. Because each agent learnes its action, including other agents as the environment[6]. And, as the number of agents increases, the number of states increases, so that, calculation cost increases intensively. One way to reduce the cost is to divide the state space and set sub goals to improve the learning efficiency[7]. On the other hand, there also exists research that decomposed complicated task and set state space for subtasks, then learnes individually and synthesized acquired data finally[8]. However, in the latter method, hidden-states emerge due to the interference between the state spaces, which directly causes the increase of the calculation cost. Our method applies a simple greedy strategy to decide agents' moving rules to realize the motion to a higher potential value grid. Therefore, the real information deals with in each state is whether a potential peak value is set at the state or not, then binary data is treated. So, the maximum calculation cost is the product of the number of the agents and the square of number of the states. By this method, it is possible to deal with factors, such as the extent of the state space and the number of the agents which would give string influence on the convergence of learning and calculation cost of the Reinforcement Learning. So it is considered that using potential field is a useful method

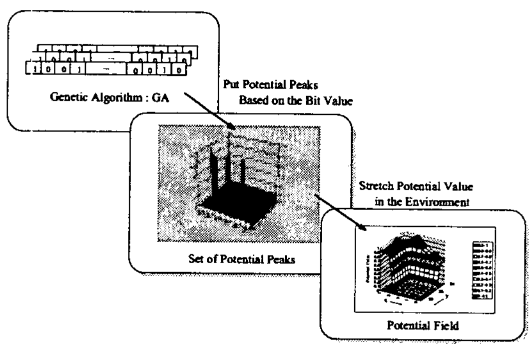


Figure 2 - Generate the Potential Field with Bit-Strings

for this kind of problems. So that, it should be noticed what action of the agent is generated by environment information using the potential field.

By the way, there have been some studies applying a potential field to an agent navigation problem. In these studies potential fields are set up in the space in which there are some obstacles for the path for agents from a start point to a goal point[9][10][11]. Moreover, in the control of the multi-agent systems, some studies have been done controlling the soccer agents of Robo-Cup based on the potential method [12][13]. Especially, the latter has realized the cooperative work by multiple agents without carrying out evaluation on actions of agents at each step. Therefore, using the potential information to generate the cooperative operation rules is considered to be effective. On the other hand, from the view point of the environment modeling, many studies have been done. For examples, an accurate map is constructed with synthesized local sensing data to show where obstacles exist in the environment under the absolute coordinates[14]. An environment model is generated based on acquired sensor data by agent movement[15][16]. In another method, the environment structure was extracted from action sequences of agents in the environment (Action-Based Environment Model: AEM[17][18]). Agent's actions are optimized for environment recognition, and GA is employed to plan action sequences. Therefore, it is different from the acquisition of the environment model relating to the operation of agents in this study.

Finally, some studies have been done trying to apply human recognition/decision process as to Multi-Agent systems, one such example is Focal Point Algorithm[19][20]. In this study, two agents are required to do a room cleaning problem, to which consensus building between multiagents is necessary. However, attribution values for objects which exist in the environment must be set in initial stage, therefore this algorithm could not be applied to unknown environment. Further more, the cost which depends on the number of agents in the consensus building, so that, it increases as the number of agents increases. On this point, it can be expected that our proposed method would reduces calculation cost under actual operation, with a comparatively low communication cost.

3 Generation of the Potential Field

In order to extract operation rules of agents, the environment modeling is carried out using a potential method. One advantage of this method is that it is possible to set potentials directly for the environment, and it is easy to observe and understand a potential value with scalar value expression. The procedure of the potential field generation is explained in the following.

To begin with, the generation of the potential field in the environment which is inside information of the agents is explained as follows. The work environment is divided into grid with a fixed interval, which is also called state-space. Then the potential values are set to each grid. First, the grid in the environment is converted into a bit string, and the map string of the grid space is made. In the grid space, GA searched to decide where to input a potential peak value. From these peak values placed, the potential values for each grid are calculated based on a diffusion function, set beforehand.

$$P(i) = Ae^{-x} \cdots (1)$$

where A indicates positive/negative direction of the potential extent. ***P(i)*** is a variable which shows a potential value of the grid ***i***, and ***x*** is a potential diffusion coefficient which changes in proportion to the distance from a peak position.

The reason for applying this function is that it is possible to set the potential gradient, to distinguish the region of positive and negative surely, and the potential value can not be 0 in extent of the environment. In case of existing multiple peaks in the grid space, the potential values are calculated by superimposing after the calculation of the diffusion from each peak value. The agents carried out the box pushing from a start point to a goal point based on this potential information. The configuration of the potential peak is searched by GA. In this paper, the best expression of the environment with the potential field is taken with as the environment model. Therefore, these strings are evaluated by the consumed inner energy and the moving distance through the box pushing.

$$E(i) = \sum_{k=1}^{n} \left(\frac{1}{Tc(k)} + \frac{1}{Te(k)} \right) \cdots (2)$$

E(i) in equation 2 stands for the evaluated value for the string ***i***. And, ***Tc(k)*** is the number of moving steps in the box pushing from the start point to the goal point of agent ***k***, and ***Te(k)*** stands for the quantity of energy consumption of the agent ***k*** under work.

4 Simulations of the Box Pushing

The objective of the first simulation is to inspect what kind of the environment model can acquired using the proposed method under same condition, e.g. load of work and the number of agent. The second simulation is to see the adaptability a change of the number of agents and a load of work. Moreover, from the environment model and each agent's trajectory data, it is possible to inspect whether there are some potential fields as common rules that regulate the agent operation.

In these simulations, for the box pushing by the multiple agents, the computer experiment is carried out with box potential data. The box potential field indicates the push point in every transfer steps. It is set based on the diffusion equation from the push point that has a peak potential value. This information is utilized by the agent as the key information. The potential diffusion function is shown in the following.

$$P(i) = a \times Pa(i) + \beta \times Pb(i,t) \cdots (3)$$

Pa(i) is a potential value of the agent in the grid ***i***, and ***Pb(i, t)*** is a potential value of the box in the grid ***i*** at the box pushing step ***t***.

As mentioned above, transfer directions of boxes are set beforehand in this simulation. And, the push point of the box also was set for every step beforehand. When agent came to the push point, the box is moved by agent(s). The transfer of the box is shown in figure 4. The work environment is a L-shape in which it is necessary to turn in the middle point of the box-pushing. We expect that this task and environment is possible to inspect the appearance of cooperative work, i.e. task sharing, by the potential field for controlling agent.

Next, we explain the setting of the agents. It is assumed for the agents to observe the condition of the circumference of their eight vicinity. The strategy of the agents is the greedy selection of the potential value in their eight vicinity, i.e., the agents move to a place where the potential value in the eight vicinity is the highest. Therefore, from a current place, the agent can move in eight directions (Figure 3). The initial population for GA is 100, and the crossover is carried out using the roulette selection, and the mutation probability is 20%, and low order 10% population is replaced by children. And, when the agent pushes a box, it consumed it's own inner energy shown in Table 1. The energy consumption is set as a linear type in this time.

4.1 Simulation 1

First, the case that the number of agents and a load of work are same condition is experimented with a computer simulation. The potential information on the transfer of the box indicates the position that must be pushed, when the box moves in each time. And then, it is possible to push the box when the agent moves to the grid that is the push point at each step. A Potential field that enables box-pushing in the grid is indicated with the potential peak value. A potential field of the box is prepared at each step in the transfer of Figure 4, and it piles potential information of all agents' potential field were piled. The manually set agent potential field is shown in Figure 5.

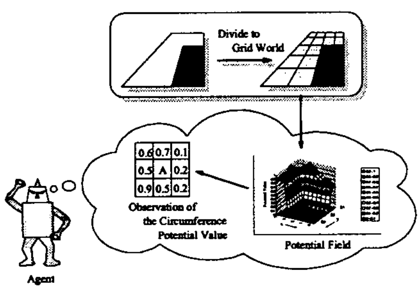


Figure 3 - Agent observes eight vicinities in the circumference of the self, and then moves to the highest potential value gridment

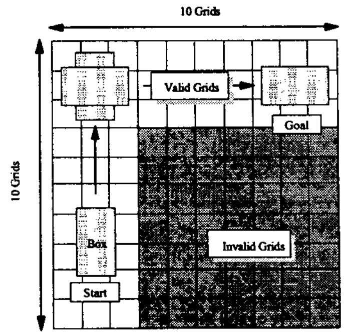
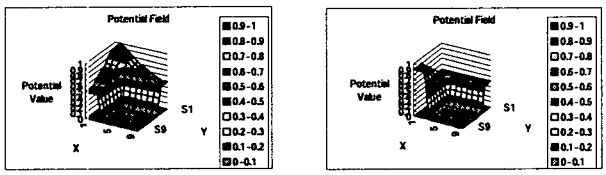


Figure 4 - Simulation Environment

Table 1 - Energy Consumption Ratio

Work Style	Single	Cooperative	Non Pushing
Energy Consumption	4	2	1



(a) Agent 1 *(b) Agent 2*

Figure 5 - Hand Setting of Potential Fields

In this case, it sets the potential peak at the corner and the start point in the L-shaped environment, because it can be viewed as occurrence of the task sharing and improvement of the work efficiency in this setting subjectivity. As a result, the agents acquired the shortest working steps from the start point to the goal point. It was the cooperative box pushing by two agents from start to finish, however there is no characteristic of the work sharing in the L-shaped midpoint.

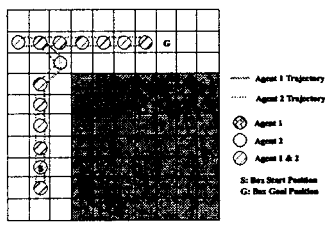
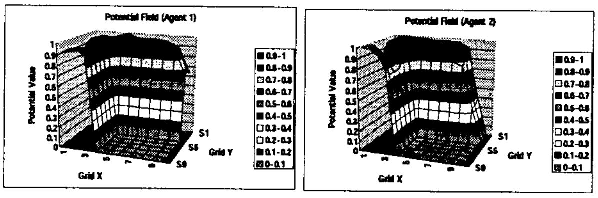


Figure 6 - Trajectory of Agents

The next figure shows the case in which GA is used in order to create potential information of each agent (Figure 7).

The graph which showed the potential field of the agent was acquired in this simulation. These were extracted from potential information acquired in the last stage of the calculation. The graph which shows each moving trajectories is as follows.



(a) Agent 1 *(b) Agent 2*

Figure 7 - Acquired Potential Field

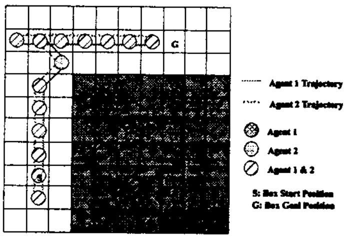


Figure 8 - Trajectory of Agents

Table 2 - Simulation Result of Work• •

Type	Hand Coding	Result (Min)	Result (Max)	Average
Step	15	16	18	17.31

From the above result, acquired trajectories were same type under potential fields with the hand setting and GA. Because it is considered that the potential field of the box cancels out agent's potential field in the potential composition. Thus agents were attracted the potential field of the box, and they did the box-pushing work with the same trajectory.

Furthermore, we tried same computer experiment repeatedly, and checked whether there are the characteristic of the work and the focal point of agents from the potential peak point of the agent. Results from computer experiments shows in Table 2. In this table, it shows the minimum work step about box pushing from the start point to the goal point and the average of the minimum solution each calculations. And the graph

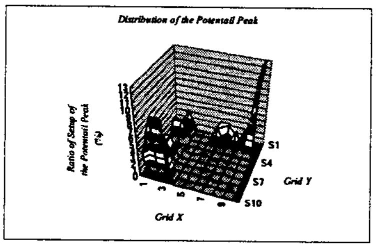


Figure 9 - Distribution of the Potential Peak

which shows the distribution of potential peak in the environment is as in Figure 9.

From the point of modeling of the work environment, high ratio areas of setting the potential peak were the start area and the goal area. Furthermore, another setting potential peak area was middle in the L-Shaped environment - agents turn the box at this area. Accordingly, from making a comparison these results - about potential fields of Figure 5, Figure 7 and Figure 9, it was considered that environment models as the indication of the characteristic of this work were potential field type of Figure 5 and Figure 7, because it matched an inclination of the distribution of the potential peak and shapes of acquired potential fields - they were almost able to classify into Figure 5 type one or Figure 7 type one.

4.2 Simulation 2

The next simulation is the applied to a change of the number of the agent and a load of the work. In this section, we show three types simulations. One is the change of the number of agents, the other is the change of a load of the box pushing work. Finally, it adds a parameter of the fatigue related to the continuation work to the calculation of the energy consumption. From results of these computer experiment, it is possible to inspect whether there are some potential fields as common rules that regulate the agent operation.

At first, Figure 10 shows that showed the potential field and agent's trajectory are acquired in this simulation that is carried out the box pushing with three agents.

In this case, each agents pushed a box. They work vaguely because the objective function which evaluates bit-strings is attending the agent's energy consumption with their work, so they work cooperatively, stop their work and only moved irresponsible.

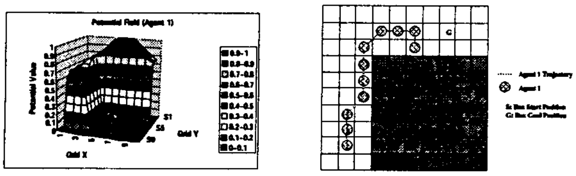
Next is a case of the change of a load of the box pushing work (Figure 11). In these graphs, they show the share of their work in the first half and the latter half of the environment, because it is that agents are affected by the configuration of the work environment. Their potential fields and trajectories showed as follows• •And the table that showed a change of parameters about the work load is listed in Table 3.

Results of Simulation 3 shows in Figure 12. We define the energy consumption that is increased by the continuation of the work as equation 4,

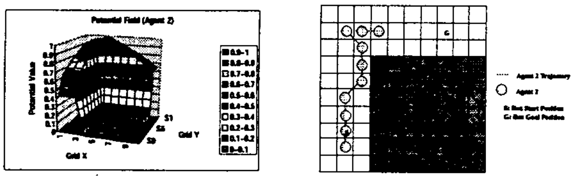
$$E(t+1) = E(t) - aR^2(t)C_i \cdots (4)$$

where $E(t)$ is the quantity of agent's energy, $R(t)$ is the continuation of the work steps, and Ci is the consumption energy of the current work.

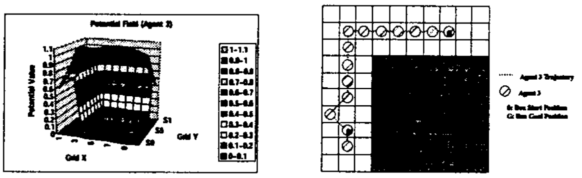
From these results of the simulation 3, it is shared the box pushing work by each agents, the start part, the middle part



(a)Agent 1



(b) Agent 2

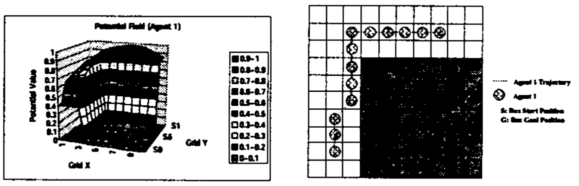


(c) Agent 3

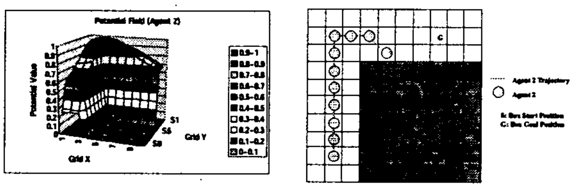
Figure 10 - Potential Field and Trajectory of Simulation 1

Table 3 - Energy Consumption Ratio

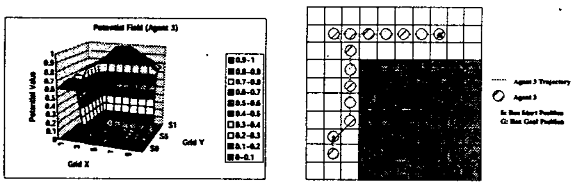
Work Style	Single(First)	Cooperative(First)	Single(Latter)	Cooperative(Latter)	Non Pushing
Energy Consumption	4	2	6	3	1



(a) Agent 1

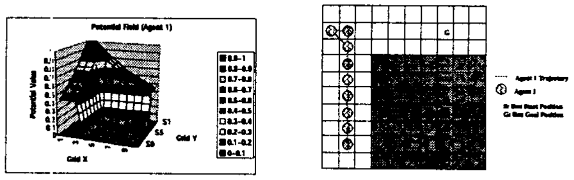


(b) Agent 2

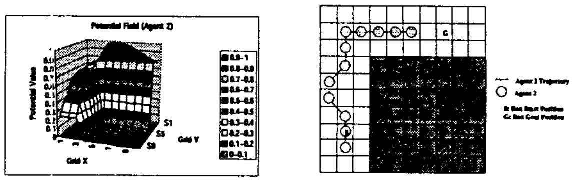


(c) Agent 3

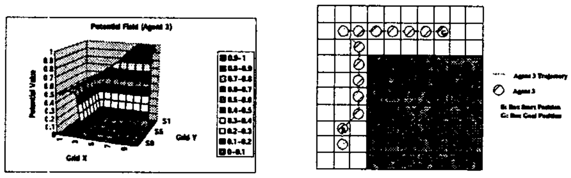
Figure 11 - Potential Field and Trajectory of Simulation 2



(a) Agent 1



(b) Agent 2



(c) Agent 3

Figure 12 - Potential Field and Trajectory of Simulation 3

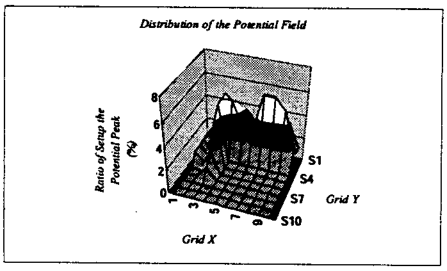
and the end part. It is necessary for the agent to relieve, because the energy of the agent is decreased to empty by the continuous work. Therefore it is considered that it occurs the task-sharing.

From these above results, in case of attention as for the potential peak, there is an inclination for the distribution of the potential peak that placed in the latter half of the environment frequently in the simulation 2. Moreover, in the simulation 3, it occurs the share of this task with each agents - the start part, the middle part, and the end part. Therefore, it is considered that they reflect the feature of the work environment, because stretched potential fields are acquired by the computational experiment that moves the box from the start point to the goal point with agents.

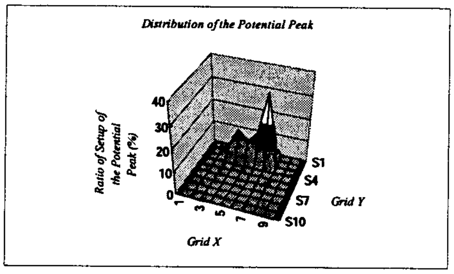
In the extraction of the task share rule and the environment model from the potential field, we can consider that it is possible to extract of the environment model because thefeature of the work environment is represented by the inclination of the distribution of the potential peak position. And we can also consider that it is possible to extract the abstract rule because the potential field with which the behavior of agents are controlled is stretched based on the constitution of this problem. Thus, it is considered that there are the possibility of representing of abstract rule from data of the distribution of the potential peak.

5 Conclusions

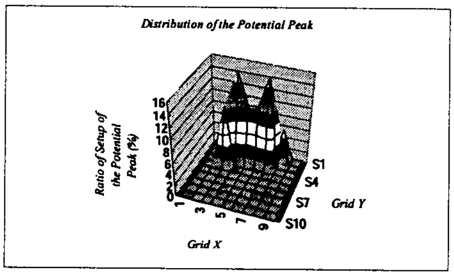
In this paper, we constructed and evaluated the proposed system that models the work environment with the potential field and shares of the work for the multiple agents. And we considered the environment modeling and the extraction of



(a) Case of Simulation 1



(b) Case of Simulation 2



(c) Case of Simulation 3• • • •

Figure 13 - Distribution of the Potential Peak

the abstract operation rule. The environment modeling were based on the potential information by extracting the agent operation rule with simulations under the cooperative work. And, it is investigated the possibility of the generation of task sharing in the cooperative work from the trajectory of the agent was investigated.

From the presented simulation result, it is considered that characteristic data could be acquired to show sharing of the task between agents. Task-Sharing that was shown in the computer experiment reflects by the constitution of the work.

In this paper, we carried out a task-sharing problem that puts each agents in the work environment - the general arrangement problem for agents. However, we are considered that there is the other problem in the box pushing problem. It is how to push the box with cooperative work between agents. Thus we try this problem in the future.

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