Abstract—One of the techniques for constructing an adaptive multiagent system based on Evolutionary Robotics (ER) is to generate the robot behaviour which is suitable for its environment. However, it is difficult to understand strategies and features which are indicated by robot behaviours through careful observation. Therefore, we have focussed on information on the environment which is used for the robot to behave. In this research, we try to construct the analysis method using the recognition change in information that affect robot’s behaviour strategy. We propose a functional circle which describes the abstract functional relationships between robots and objects in its world for analysis of perception mechanisms, and its world of recognition is shown by self-organizing maps (SOM).

I. INTRODUCTION

Currently, the much expected robot that interact with human must have advanced autonomy and intelligent behaviour, unlike traditional industrial robots, however, there are still many unknown territories in the control technology for intelligent behaviour. In the study of artificial intelligence, Evolutionary Robotics (ER) is proposed as one of the behaviour acquisition approaches of an adaptive autonomous agent that uses the evolutionary computation [1] [2]. In this area of investigation, an Artificial Neural Networks (ANN) is adopted as the agent controller in many cases, and the feature of this controller that is able to achieve an appropriate capacity for the agent is acquired by evolutionary computing. In the traditional study of artificial intelligence, the designer creates the robot controller in advance. However, in the methodology of embodied cognitive science, an agent with a physical body should become independent of the designer’s control, recognize the surrounding environment and establish its own feature while repeating the interactions with the environment. Therefore, it is necessary that the agent have some basic abilities. This means that the agent has a physical body and an input-output system in order to interact with its environment. The agent which is the target of this study acquires information on the environment through its own sensor system. As a result, the physical features of the agent, namely, the sensory function, sensory performance, and motor-drive system that form the body of the agent, require important consideration.

II. FUNCTIONAL CIRCLE AND SOM

In this paper, we also consider the comprehensive ability of an autonomous agent that mainly depends on three types of factors: physical, constructive and environmental. Physical factors are characterised by the sensory function, sensory performance and features of the motor-drive system. In general, these factors are decided beforehand by the designer. Constructive factors are characterised by the architecture of an ANN for an autonomous agent, the algorithmic structure of an ANN, the design of an evaluation function and the landscape of the search space. Environmental factors are characterised by the kind of task, the execution environment and constraint conditions. These factors are also decided beforehand by the designer, although noise as an environmental factor can influence the agent. Moreover, an environmental factor has a different meaning from the perspective of the designer and that of the autonomous agents in the environment [3]. The perceived environment further varies for each agent because the perceptive systems of the agents differ. Consequently, if environmental factors are different for each agent, then an environmental factor that is formed inside the agent is complex.

Thus, the subjective world that is perceived by an autonomous mobile agent is called ‘Umwelt’, or the world of recognition. A high-performance agent must be able to construct an appropriate world of recognition and acquire important information. Furthermore, the autonomous agent targeted in this study is an active subject in its own world of recognition. When the agent acquires information through its interaction with the environment, the information should address not only what the agent requires in order to act but also the behavioural pattern. In summary, to achieve an adaptive autonomous agent in ER, it is necessary to understand what information the physical body of the agent, the task execution environment and the content of the task require. It is difficult to understand this necessary information required for the agent to behave adaptively as well as to provide it to the agent selectively. However, if we can understand what information is necessary, it might help to design an agent that has the desired features. Ian Macinnes and E. Di Paolo propose to define the
The behaviour of the robot agent with the theory of "Umwelt", as Jakob von Uexküll argued. Uexküll explains that the action of the animal is applied to one independent space, in which the phenomenal world is connected to an effector world of an agent, or the 'functional circle'. In other words, Umwelt is defined as comprising of a functional circle. Furthermore, the functional circle defines the interaction of the agent and the objects in the environment, and is an abstract structure that connects subjective experience, or the perception of the agent (perceptual cue), to the perception as a result of the action of an agent (effector cue). If the Umwelt model is used, an agent’s knowledge and its perceived environment consist of the recognition of the abstract world that was invented by the agent’s perception. Thus, the agent selectively reacts to stimuli, and the functional circle is changed by the perceptual cue. The world of recognition enables the agent to decide whether to react to the stimuli on the basis of its perception, and is classified as a temporal state of perception of the perceptual cue. The perceptual cue functions continuously as a partial process for an agent that interacts with the environment through its body, and its state changes continuously. This state does not comprise of information that exists beforehand in the environment but rather the information that the agent perceives from the environment. On applying this model, the world of perception can be considered to be a series of states that are controlled by the agent acting in the environment, which influences the behaviour of the agent and leads the agent to other states. The information that decides the meaning of the perceptual cue and the state of the perceptual world is selected, and it defines the agent by using evolutionary computing.

Using this concept in this study, the behaviour acquired from the agent by using evolutionary computing is analysed. The behaviour of the agent, however, is understood from the observer’s subjective viewpoint as long as the observer interprets the functional circle. Therefore, it is important to show the world of recognition objectively to effectively use the functional circle for analysis. It is thought that the functional circle can be shown by comparing the input and output relationships because the meaning is derived from these relationships in the world of recognition; however, analysis remains difficult because ANN, the agent controller, has a non-linear property. Moreover, it is difficult to evaluate and classify these input-output relationships visually because they are multi-dimensional data. Therefore, in this study, we suggest the use of self-organizing maps (SOM), which was proposed by T. Kohonen as a method for verifying the world of recognition [5].

SOM are a type of artificial neural network modelled on the visual projection area of the cerebral cortex, and are an effective tool for the visualisation of multi-dimensional data. SOM are able to convert the non-linear relationship between the multi-dimensional data into an image with a simple, geometrical relationship. Thus, multi-dimensional information can be visualised in two dimensions. If the agent has the world of recognition, it is thought that the functional circle can be clustered by using SOM features. In other words, on the basis of the hypothesis of meaning in the relationship of the input-output data that constitute the world of recognition, the agent’s input-output data are used in SOM. The data of each time step until the completion of the task are collected and then clustered. It is thought that the number of clusters of data shows the number of worlds of recognition, because the clustering number may show the difference in the relationships of the input-output data. It is easy to judge which step causes a large change in the input-output data by analysing the time-series data. It is thought that the features of the agent in the world of recognition or the behavioural strategy become apparent by conducting an additional experiment and focussing on this clustered data. We will show the functional circle and analyse the behavioural strategies of an agent using this technique to verify its effectiveness.

III. EXPERIMENTAL SETTING

We use computer simulation to show the effectiveness of the analytical technique proposed in this paper. In the computer simulation, we adopt the car racing game that is a standard problem in ER [6]. Figure 1 shows the overview of the car racing game. In this game, there are three flags, no wall and one or two cars in the field. The objective of the game is to simply reach as many flags as possible within the time limits. The agent should acquire the flags in a particular order. When one agent acquires the first flag, the flag disappears and the second and third flags become the first and second flags, respectively. Simultaneously, a new flag appears at a random position as the third flag. The score is added to the car agent that acquires the first flag, and the car agent that obtains the maximum points before the end of the game is the winner. In order to move, the car agent decides the steering angle to the travelling direction and the acceleration similar to an actual car. The car racing game simulation is executed in discrete time, and the car agent moves to every single step. In this game, there are three kinds of settings for the acceleration and the steering angle. The movement is performed by selecting one of the nine choices shown in Table I.

The car agent receives sensor information as an input from the simulator. There are eight such inputs: the distance and angle to the first flag, the distance and angle to the
The decision strategy is shown in Table I. The formation in SOM is gradually performed twice. A rough shape is formed on the first attempt, and detail is co-ordinated with the second attempt. The operation is repeated several times, and the one that has the smallest margin of error is assumed to be the output result. The input vector of SOM is assumed to be 10 in total (eight sensors and two outputs).

### Table I
**CAR DECISION**

<table>
<thead>
<tr>
<th>Decision</th>
<th>Command</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower left</td>
<td>0</td>
</tr>
<tr>
<td>Down</td>
<td>1</td>
</tr>
<tr>
<td>Lower right</td>
<td>2</td>
</tr>
<tr>
<td>Left</td>
<td>3</td>
</tr>
<tr>
<td>Neutral</td>
<td>4</td>
</tr>
<tr>
<td>Right</td>
<td>5</td>
</tr>
<tr>
<td>Upper left</td>
<td>6</td>
</tr>
<tr>
<td>Up</td>
<td>7</td>
</tr>
<tr>
<td>Upper right</td>
<td>8</td>
</tr>
</tbody>
</table>

In addition, this game has an environment with a very high noise because the position where the flag appears is decided at random, which changes the environment dramatically and tests the car agents’ ability to adapt. Togelius showed that in the evaluation of the fitness, it is preferable to average five or more trials because of the high noise. On this basis, in this study, the trial is repeated five times and the average value is used.

### IV. EXPERIMENTAL RESULTS

In the computer simulation, the car agent acquires successful action from the state that lacked intellectual behaviour, and the obtained behaviour is analysed. In Experiment 1, the agent evolves in a contest against another agent using a heuristic algorithm, and in Experiment 2, two agents by using evolutionary algorithms compete and evolve.

#### A. Experiment 1

The performance of the agent obtained in Experiment 1 is shown in Table III. This individual shows a high score in a solo trial, but the score decreases markedly when it competes with another agent.

In this case, the behaviour is analysed by using a functional circle. Figure 2 shows that the agents’ behaviour in the 500th generation in a competitive trial was made visible by SOM. In a solo trial, the agents’ behaviour is divided into two areas (Fig. 2(a)). Several areas of the map are occupied by command 1 or 2, which means the car agent adopts the behaviour of moving below or left below as a basic strategy. The agent steers to the left while moving backward and creates this behaviour. The small areas in the lower right of the map are occupied by command 6 or 8, which are moving up or upper right. It means that the agent does not recognise the movement of going backward, and the behaviour that heads in the relative opposite direction acts as a brake that fine tunes the behaviour. It seems that the world of recognition in the car racing game was composed only of the functional circle of the search, but the agent adopts the strategy in which the agent switches from a basic action to the fine tuning action. These facts were clarified from this map. The functional circle at this time is shown in Fig. 4(a). Next, from Fig. 2(b), it is understood that the car agent with competition has a more complex world of
recognition. In this game, the same controller as that in a solo trial is used, and there are the areas in the map wherein the agent moves up or upper right and the agent moves below or left below; however, the map is not divided clearly. It is thought that the other agents’ existence creates a complex situation for the car agent.

Figure 3 shows the behaviour immediately after a collision in competition. The agent indicated by arrows is the car agent that acquires behaviour by using evolutionary computation. After the collision, although the car agent is relatively close to the flag, it cannot acquire it. Thus, we can say that this agent lacks a strategy corresponding to such a situation because it stops after the collision. From these results, a functional circle of the agent of Experiment 1 in competition is derived and shown in Fig. 4(b).

![Fig. 4. The functional circles for Experiment 1.](image)

Figure 3 shows the behaviour immediately after a collision in competition. The agent indicated by arrows is the car agent that acquires behaviour by using evolutionary computation. After the collision, although the car agent is relatively close to the flag, it cannot acquire it. Thus, we can say that this agent lacks a strategy corresponding to such a situation because it stops after the collision. From these results, a functional circle of the agent of Experiment 1 in competition is derived and shown in Fig. 4(b).

![Fig. 3. Acquired behaviour of Experiment 1.](image)

**B. Experiment 2**

The performance of the car agent obtained in Experiment 2 is shown in Table IV. In this case, the difference of the fitness between a solo trial and a competitive trial is smaller than the one in Experiment 1.

<table>
<thead>
<tr>
<th></th>
<th>solo</th>
<th>sensible</th>
<th>combined</th>
<th>competition score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>15.26</td>
<td>11.92</td>
<td>13.48</td>
<td>13.22</td>
</tr>
</tbody>
</table>

We analyse how the agent’s behaviour obtained in this experiment differs from the behaviour in Experiment 1. Figure 5(a) shows that the agent behaviour of the 500th generation in a solo trial was made visible by SOM. The world of recognition of this agent is clearly divided into two
areas by the area of command 0 (moving right below) and 2 (moving left below). This pattern indicates that the agent uses both clockwise and counter-clockwise behaviour according to the demand of the situation, and it can select strategies corresponding to the position of the target flag. In addition, because there is no command for moving upwards, to the upper right and upper left, this agent has no braking system and it adopts an effective behavioural strategy in steering dexterously without deceleration. Next, Fig. 5(b) shows that the agent behaviour in a competitive trial was made visible by SOM. The area in the world of recognition of the agent increases from two solo trials to three, and it is similarly occupied by command 0 and 2. It can be said that the lower left part of the area is in the world of recognition generated by perceiving other car agents. Namely, this agent operates the rudder according to other car agents’ positions in addition to operating the rudder according to the position of the target flag. We show the functional circle that is based on these findings in Fig. 6.

C. Discussion

These results of our experiments clearly show that the agent which fights another agent using heuristic algorithms has a behavioural strategy that combines clockwise rotation with braking, and the agent has a behavior different from other agents. This agent might fail to find the position of the target flag because it only has a basic clockwise searching behaviour. It seems that the agent that competes against another agent by using evolutionary algorithms has a behavioural strategy directed toward both the target flag and the other agent.

V. CONCLUSIONS

In this paper, to understand robot agents’ behavioural strategies, we proposed a method of analysis that focuses on the individual’s world of recognition. Moreover, we proposed to use SOM to describe the functional circle that constructs the world of recognition. We used the car racing game to show the behavioural strategies of agents and the world of recognition using SOM. In the future, I would like to develop this technique and demonstrate how the behavioural strategy is formed and how an arms race arises from co-evolution.
REFERENCES


