# Behavior Selection System for Robot Using Neural Network

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**Abstract**

With the progress of technology, the realization of a symbiotic society with human beings and robots sharing the same environment has become an important subject. An example of this kind of systems is soccer game. Soccer is a multi-agent game that requires strategies by taking into account each member's position and actions. In this paper, we discuss the results of the development of a learning system that uses SOM to select behaviors depending on the situation.

*Keywords*: Strategy, Self-Organizing Map, team behavior, Tensor SOM, multi-agent system, Human-Robot cooperation.

## 1. Introduction

Recently, the implementation of robots in society has become a possible solution to many problems, such as ensuring the safety of a sustainable society, responding to a rapid population aging and population decrease. Moreover, robots will represent the foundation of the future industry. To properly implement a robotized society, it is necessary to conduct and to present research outcomes in a manner that is easy to understand, avoiding differences between social expectations and the direction of research and development. Therefore, it is essential to discuss how to achieve coexistence with robots and what a symbiotic society should look like. In such a society, humans and robots interact with each other and they are capable of mutual understanding, so not only of their own actions, but also with all the other agents, where agent means each of the active subject involved. Aim is to develop a suitable algorithm which allows to create intelligent robots able to share the environments with humans. Since soccer involves strategies, cooperation, unpredictable movements and common targets, it represents a good test bed for developing such algorithm.

Tensor Self Organizing Map (Tensor SOM)[1] is used for this scope.

### 1.1. Cooperative Behavior

Cooperative behavior becomes a crucial aspect when different autonomous agents interact while performing a common task. Often a single agent is not much effective in accomplishing a task, and in the last years many researchers have been studying multi agent systems (MAS) to solve difficult problems. They interact to each other and with the environment by taking real time decisions based on the data acquired from the sensors.[2, 3] As a test bed of MAS, RoboCup encourages the cooperation of multi-agents using learning methods, such as reinforcement learning and neural networks. RoboCup is a project aimed to win the soccer World Cup against humans[4]. According to Sandholm and Crites[5], reinforcement learning can be used successfully for the iterated prisoner's dilemma, if sufficient measurements data and actions are available. In addition, Arai[6] compared the Q-learning and Profit Sharing methods about the Pursuit Problem in a multi-agent system, when the environment is modelled as a grid, and showed that cooperative behaviors emerge clearly among Profit Sharing. However, these studies have not yet considered applications for robots that operate in a real environment.

As mentioned above, a humans-robots cooperative society is a topic of interest for many researchers and several works have been carried out. So, in such a symbiotic system, it is mandatory for the robots to understand and interpret humans' behavior and act accordingly. However, the target in research is often about the robots' behavior only, or a behavior based on an interaction defined precisely between a specific number of humans and robots. Also, in a multi-agent system the communication between humans and robots is usually carried out by means of some kind of interface, for example command voice or gestures. But this might not be enough, especially when the system is very complex. Accordingly, the robot should be able to understand some situations and adapt its behavior in a predictive manner, just as humans do. The main goal of this research is to consider cooperative behaviors between humans and apply them to robots (see Fig. 1).

The input vector elements for a neural network is chosen so as to achieve the lowest possible gap between humans and robots' actions. To obtain this, it is important at first to understand humans' behavior and develop robots able to understand such behaviors and imitate them. This paper focuses on the study of the

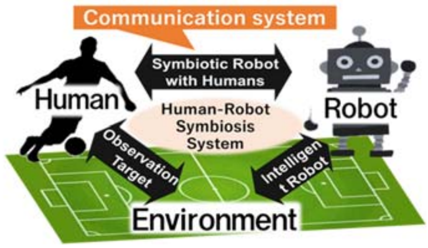


Fig. 1. A human–robot symbiotic system.

humans' and robots' behavior in a futsal game, because this represents a good test bed, with a dynamic environment, several constrains and it requires a real-time planning. These are the characteristics of a common symbiotic system in which the robots may operate in the future. In analyzing a soccer futsal game, at first the elements to be observed are decided, depending on their importance and ease of evaluation. Many valuable info can be obtained from the simulation game: the position coordinates and the velocity of the players and the ball, the elapsed time of the game and the score. In the analysis performed in this work with status of players such as the positions coordinates and the players moving speeds and ball were considered. The Input data was used to train the neural network. In analyzing a soccer futsal game, at first the elements to be observed are decided, depending on their importance and ease of evaluation. Many valuable info can be obtained from the simulation game: the position coordinates and the velocity of the players and the ball, the elapsed time of the game and the score.

In the analysis performed in this work with status of players such as the positions coordinates and the players moving speeds and ball were considered. The Input data was used to train the neural network. The simulator was made by RoboCup project and which also consider about the exercise model of the robots and the ball. The futsal

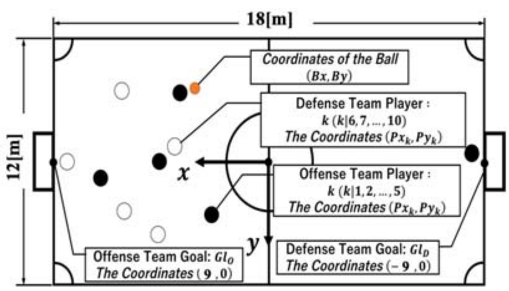


Fig. 2. The field of the game.

game was conducted with five versus five robots, and the coordinates of all players and the ball were observed (Fig. 2). The state vector is expressed by Eq. (1). T he player position coordinate $\boldsymbol{P_k}$ and the ball position coordinate $\boldsymbol{B}$ in the field are shown in Eqs. (2) and (3).

$$\boldsymbol{A} = [\boldsymbol{P_1}, \boldsymbol{P_2}, \cdots, \boldsymbol{P_{10}}, \boldsymbol{B}\ ] \quad (1)$$

$$\boldsymbol{P_k} = [Pk_x, \quad Pk_y] \quad (2)$$

$k$ indicates the ID number identifying a player. We observed a game consisting of a team of $k = 1, 2, 3, 4, 5$ players and a team consisting of $k = 6, 7, 8, 9, 10$ players. By chance, $k = 5, 10$ are the goalkeepers of the two teams respectively.

## 2. Tensor Self-Organizing Map

Self-organizing map (SOM) is an unsupervised learning technique and is known as competitive learning, similar to information processing via neural circuits. Competitive learning is an important concept in hierarchical neural networks. Each input neuron in the input layer (input space) is connected to all output layer neurons, the strength of the relation between two neurons in consecutive layers is decided by a specific weight assigned to each connection. The input vectors "compete" with each other so as to find the best output vector. With best output, it is meant the output vector whose elements are as similar as possible to the input vector elements. To establish this similarity the Euclidean distance is used. By doing this, the clusters into the output map are obtained. The cooperative hierarchy deals with the output vectors. While performing the algorithm, the elements value of each vector is adjusted. If a high change of an element occurs in a vector, the vectors around it change accordingly, but in a way that the strength of this change decreases with the distance in the map from the first vector. In particular, the amount of change of each element is decided by the Gaussian function. Since each vector modifies itself depending on the surrounding vectors, this behavior is said cooperative. Input vectors can have high dimension but the output results are showed in a two-dimensional map. So, with this structure multi-dimensional input vectors can have reduced dimensions in the output layer, and the features are clustered, so as to have similar features in the same area of the map. An applicative example for which SOM is suitable is the visualization of complex scenarios, since the output results are shown in a two-dimensional form. Furthermore, the cooperative hierarchy and the smoothing process performed by the Gaussian function allow to synthesize elements and contents that were not clearly specified in the input vectors. SOM has a high interpolation performance and it can generalize concepts starting from a limited amount of input data. Because of these characteristics, it is well suited for unsupervised learning and highly valid outputs are expected. In this paper, in order to cope with high-dimensional data, analysis is performed using tensor SOM which is SOM expanded to tensor.

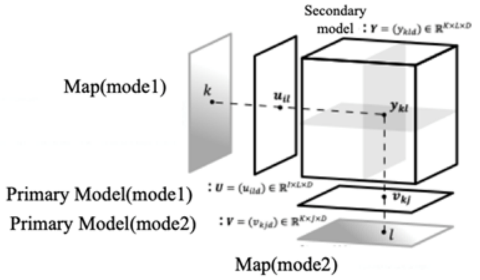


Fig. 3. Overview of the Tensor SOM algorithm.

### 2.1. Algorithm

The tensor SOM algorithm proceeds according to the following steps (see Fig. 3):

#### *2.1.1. Choose Best Matching Unit(BMU)*

The selection of the best matching unit (BMU) $k_i^*$ , $j_j^*$ are carried out for each input vector $u_{ild}$ , $v_{kjd}$ with the following equation, in which the Euclidean distance is calculated.

$$k_i^* = \arg\min_k \sum_{l=1}^{L} \sum_{d=1}^{D} (u_{ild} - y_{kld})^2 \quad (4)$$

$$l_j^* = \arg\min_l \sum_{k=1}^{K} \sum_{d=1}^{D} (v_{kjd} - y_{kld})^2 \quad (5)$$

#### *2.1.2. Calculation neighbor radius*

$$\alpha_{k_i} = exp\left[-\frac{1}{2\sigma^2}\left\|\boldsymbol{\zeta}_{\boldsymbol{k}_i^*}^{(\mathbf{1})} - \boldsymbol{\zeta}_{\boldsymbol{k}}^{(\mathbf{1})}\right\|^2\right] \quad (6)$$

$$\beta_{l_j} = exp\left[-\frac{1}{2\sigma^2}\left\|\zeta^{(2)}_{l_j^*} - \zeta^{(2)}_{l}\right\|^2\right] \tag{7}$$

#### *2.1.3. Update secondly model*

$$y_{kld} = \frac{1}{g_k g_l}\sum_{i=1}^{I}\sum_{j=1}^{J}\alpha_{k_i}\beta_{l_j}x_{ijd} \tag{8}$$

$$g_k = \sum_{i=1}^{I}\alpha_{k_i} \tag{9}$$

$$g_l = \sum_{j=1}^{J}\beta_{l_j} \tag{10}$$

#### *2.1.4. Update primary model*

$$u_{ild} = \frac{1}{g_l}\sum_{j=1}^{J}\beta_{l_j}x_{ijd} \tag{11}$$

$$v_{kjd} = \frac{1}{g_k}\sum_{i=1}^{I}\alpha_{k_i}x_{ijd} \tag{12}$$

## 3. Experiments

The experiment was conducted for a total of three experiments, and the parameters shown in Table. 1. The input data consists of the player's state (position, speed, etc.), player ID, and the action at that time (see Fig. 4).

Table. 1. Parameter settings for the experiment.

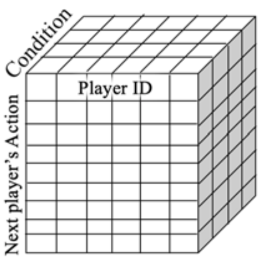


Fig. 4. Image of input data.

| | | |
|---|---|---|
| Number of Iterations | $n$ | 10 |
| Map Size | | 100 × 100 |
| Max Neighboring Radius | $\sigma_{MAX}$ | 2.0 |
| Minimum Neighboring Radius | $\sigma_{min}$ | 0.2 |

### 3.1. Experimental Results and Discussion

The results are analyzed by means of the Unified Distance Matrix (U-Matrix)[7] and the Component Plane Matrix (see Fig. 5). First one aims to find the output vectors with a common
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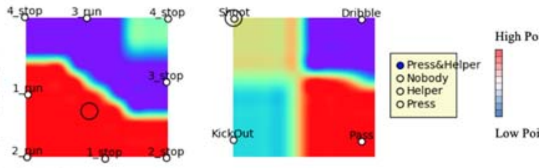


Fig. 5. Result of Tensor SOM expressed by the U-Matrix after learning.

## 4. Conclusions

In this study, Action selection system was developed using Tensor SOM. In the future, further improvements of the input vector are required to obtain some more detailed clusters. This work showed the promising ability of Tensor SOM algorithm to develop a symbiotic system where each agent is able to understand the scenario in which it is operating and work in a predictive manner together with the other agents of the system.

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