Evolving Connectionist System Based Role Allocation for Robotic Soccer

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Abstract: Robotic soccer is an intelligent system where a group of mobile robots are controlled to perform soccer play (http://www.fira.net). The allocation of a suitable role for each robot in a team is a key for the success of the play. The paper treats this issue as one of pattern classification, and solves it with an Evolving classification function (ECF), a special evolving connectionist system (ECOS). A robot’s role is determined by and evolves with the states of system (robots and target) in real time. The software and hardware platforms are set up for data collection and learning. The effectiveness of the proposed approach is verified by the experimental studies.

Keywords: Robotic Soccer, Mobile Robots, Evolving Connectionist Systems

1. Introduction

In a robotic soccer system, a robot can be assigned one of the basic roles: attacker, defender and goal keeper, or the additional roles such as (active or strategic) support (Weigel, T. et al, 2002). The attacker tracks the target (ball) and tries to put it into the opponent goal area. The defender blocks the opponents and supports the goal keeping actions. The goal keeper clears the ball from its home goal area. The support assists attacking or defending actions of the team.

In many role allocation approaches, the preferred poses of each role are set by the play strategy. A numerical indication (utility) of a robot for each role is defined as a function of the relative postures among the robots, the ball and the preferred poses of the role. The robot with the highest utility will be allocated the corresponding role (Stone, P. et al, 1999; Stone, P. & Veloso, M., 1999; Weigel, T. et al, 2002). Roles are also allocated through an auction mechanism where the robots are treated as “traders”. The offer of each robot for a role is measured through a matching function based on the attributes of the robot (Frias-Martinez, V., et al, 2004). These approaches tend to quantify, in a closed-form function, the relationship between the system states (coordinates, distance and angle of the robots and the ball) and roles. In practice, it is hard to find or justify such functions.

By viewing the robot roles as patterns, the robot role allocation problem can be reformulated as the selection of a pattern (robot's role) from the system states. This typical pattern classification problem can be handled with many powerful tools such as principal components analysis (Amari, S. et al, 2000), neural network (Haykin, S., 1994), support vector machines (Kececan, V., 2001) and evolving connectionist systems (ECOS) (Kasabov, N. & Song, Q., 2002; Kasabov, N., 2002). In this paper, the ECOS method is adopted for its unique evolving feature and its successful applications.

The paper is organized as follows. In Section 2, the problem formulation is described. In Section 3, the procedure of ECOS-based robot role allocation and some practical issues are discussed. In Section 4, the experimental set-up and the results are presented to verify the proposed approach. The conclusion of the work is given in Section 5.

2. Problem Formulation

The layout of a robotic soccer game (http://www.fira.net) is schematically shown in Fig. 1. With three wheeled robots (dimension: 75mm X 75 mm 75mm) moving in a field (dimension: 150mm X 130 mm), each robotic soccer team tries to push the ball into the opponent's goal net. The states of the robots and the ball (target) are captured by a camera and processed by a computer. The robots receive the motion commands from the computer through wireless communications.

Fig. 1. Robotic Soccer System (http://www.fira.net)
The role allocated to each robot varies with the progress of the game. Fig. 2 shows a scenario when two home robots are near the opponent goal area. The robot in the best attacking posture (the position and the angle of the robot) should be assigned as an attacker, and the others can be defender or goal keeper. For Robot 1 and Robot 2, their positions and angles are denoted as $p_i = [x, y, \theta]$ respectively. The ball’s position is represented by $b$. Combining $p_i$ and $b$, we have a new vector $p = [p_i, b]$.

The role allocation problem now becomes: given $p$, what roles, attacker or defender, Robot 1 and Robot 2 should take?

3. Role Selection

Evolution classification function (ECF) is a special ECOS used for pattern classification, generates rule nodes in an $N$ dimensional input space and associate them with classes (Kasabov, N., & Song, Q., 2002). Each rule node is defined with its centre, radius (influence field) and the class it belongs to. A learning mechanism is designed in such a way that the nodes can be generated.
In the recall phase, the class \( \gamma \). The initial step is to identify the class \( \gamma \), and then go to Step 2; otherwise:

**Step 2**: Calculate \( d_j = |v_j - o_j| \) for any node. If \( d_j \leq r_j \) and \( c_j \) is unique, set \( N_j = (v_j, d_{\text{max}}, c_j) \) and go to Step 3; otherwise:

**Step 3**: If \( d_j \leq r_j \) and \( c_j \) is unique or \( d_j > r_j \) for ALL \( j, c_j \) is the same as that of the node with the minimum \( d_j \) and then go to Step 1.

For the role selection in robotic soccer, the class is defined as \( C = \{ \text{Robot 1 is the attacker}, \text{Robot 2 is the attacker} \} \) given one robot is fixed for the goal keeper. The input vector \( v_j \) is derived after processing the raw data collected. First, the following variables describing the relative postures among the robots and the ball are defined:

- \( d_{\text{ota}} = |p_1 - p_2| \), \( \theta_{\text{ota}} = |\theta_1 - \theta_2| \), \( d_{\text{ota}} = |p_3 - p_4| \), \( \theta_{\text{ota}} = |\theta_3 - \theta_4| \), and \( d_{\text{ota}} = |L - x_t| \tan \theta - W/2| \)

where \( L \) and \( W \) are the length and the width of the field respectively. Next, define a new dimensionless vector \( p_i = [p_{i1}, p_{i2}, \ldots, p_{i9}] \) where \( p_{i1} = \gamma_0 / (\gamma_{01} + \gamma_{02}) \), \( p_{i2} = d_{\text{ota}} / (d_{\text{ota}} + d_{\text{ota}}) \), \( p_{i3} = d_{\text{ota}} / (d_{\text{ota}} + d_{\text{ota}}) \), \( p_{i4} = \gamma_0 / (\gamma_{01} + \gamma_{02}) \), \( p_{i5} = d_{\text{ota}} / (d_{\text{ota}} + d_{\text{ota}}) \), \( p_{i6} = d_{\text{ota}} / (d_{\text{ota}} + d_{\text{ota}}) \), \( p_{i7} = d_{\text{ota}} / (d_{\text{ota}} + d_{\text{ota}}) \), \( p_{i8} = d_{\text{ota}} / (d_{\text{ota}} + d_{\text{ota}}) \), \( p_{i9} = d_{\text{ota}} / (d_{\text{ota}} + d_{\text{ota}}) \), \( \times_i \) are the weights for adjusting the contribution of each element to the role selection. By default, \( \times_i = 1 \). Note that \( p_i \) contains the important information for the role allocation such as the robot’s distances (angles) to the ball and the opponent goal respectively. It is used as a vector \( v_j \) in the learning and recall operation in the ECF.

For a better classification of data, the raw data \( p \) are partitioned according to the position of the ball with respect to the robots:

- **Case 1**: \( x_1 > x_2 \) and \( x_3 > x_2 \) (The ball is in front of all the robots).
- **Case 2**: \( x_1 < x_2 < x_3 \) or \( x_1 < x_2 < x_3 \) (The ball is between the robots).
- **Case 3**: \( x_1 < x_i \) and \( x_3 < x_i \) (The ball is behind all the robots).

where the relative position “in front”, “between” and “behind” are in reference to the attacking direction. The data can be further partitioned according to the distance between the robots and the ball:

**Case 4**: \( d_{12} > k_{\mu}d_{23} \) or \( d_{23} > k_{\mu}d_{12} \) (Big difference between the relative distances to the ball of two robots; \( k_{\mu} > 0 \) is a constant).

**Case 5**: \( d_{12} \leq k_{\mu}d_{23} \) and \( d_{23} \leq k_{\mu}d_{12} \) (Normal difference between the relative distances to the ball of two robots).

**Case 6**: Other cases excluding Case 4 and Case 5.

4. Experimental Platform and Results

The Data collection is the first task of applying ECF in the robotic soccer. To make the data collection and learning more efficient and comprehensive, an application program package is developed. It can capture the system state with a camera in real time and to replay it on the computer screen. The user can select the roles of the robots interactively through a user friendly graphic user interface (GUI). The learning and recall algorithms are also programmed in the package. The data sets for ECF learning are automatically generated and saved as a template file. The GUI of the data collection is shown in Fig. 5.

On the screen, the robot is represented by a color square with its identity number (1 or 2). The line going through the rectangle indicates the direction of the robot. The ball is represented by a circle. By clicking the button "Last" or "Next", the robotic soccer playing process can be played backward or forward. Examining the scenes on the screen, we can select Robot 1 or Robot 2 as the attacker by clicking the button "ONE" or "TWO" respectively.

A picture taken in a real game is shown in Fig. 6. There are 122 data collected, among which, 82 data are used for learning and 40 data are used for verification. Some data are listed in Table 1.
5. Conclusion

This paper addresses the issue of robot role selection for soccer playing based on the concept of evolving connectionist system (ECOS). The role selection problem is converted into one of pattern classification solved by an evolving classification function, a special ECOS. The development of an integrated application program for data collection and learning is described. The experimental study and results are presented to demonstrate the effectiveness of the approach.

8. References

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