## Team RaiC04

# Improvement of a Cooperative Behavior by Making Use of Teammates' Decision Models

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Abstract. The purpose of this study is to realize and improve cooperative behaviors in a Multi-Agent system. This paper deals with a pass for simulated soccer agents as a cooperative behavior, especially a last pass before a shoot. Receivers' models of recognizing their shoot courses as a teammates' desition models is used for the passer's decision making. The passer tried to learn parameters representing opponents' ability of interceptions for receivers in real-time. The effectiveness was examined through some experiments as compared the passer using teammates' decision models with the passer not using them.

#### 1 Introduction

The purpose of this study is to realize and improve cooperative behaviors in a Multi-Agent system. This paper deals with a pass for simulated soccer agents as a cooperative behavior, especially a last pass before a shoot.

A pass is one of the most basic and important behavior in soccer. A pass may succeed although a passer just kicks the ball without its intention. For the purpose of realizing a good pass, however, the passer requires to consider not only a success of pass but also a current game situation, which receiver should be the best and the receiver's next behavior after receiving the ball. In case of a last pass, the passer has to select a receiver who will be able to shoot. Receivers' models of recognizing their shoot courses as a teammates' desition models is used for the passer's decision making. The passer tried to learn parameters representing opponents' ability of interceptions for receivers in real-time. The effectiveness was examined through some experiments as compared the passer using teammates' decision models with the passer not using them. The soccer agents are adapted in RoboCup Soccer Server System [1–3,5].

## 2 Architecture of a Soccer Agent

Our agent design is based on three layered control model that was proposed by Jens Rasmussen[6]. Fig.1 shows a configuration of the control system. the "Strategic Layer"; the "Behavior Selection Layer", which includes a behavior

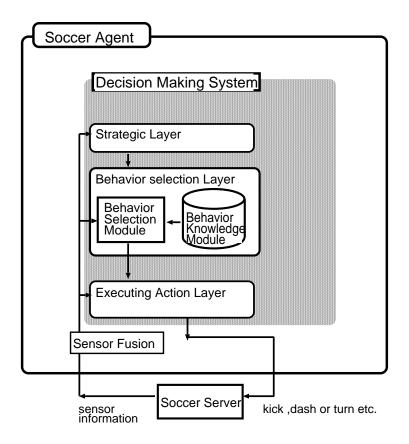


Fig. 1. System configure for a soccer agent

selection and a behavior knowledge modules; and the "Executing Action Layer". The "Strategic Layer" decides on the strategy using the strategic knowledge and sensor information. The "Behavior Selection Layer" selects a particular behavior such as a pass or a shoot. The "Behavior Selection Module" resolves matched rules obtained from the "Behavior Rules" (stored in the "Behavior knowledge" module). A "Behavior Rule" may be represented as follows:

### $IF(Situation_1ANDSituation_2AND...Situation_N)THEN(Behavior_1)$

Based on the information received from the server (through the sensor fusion module) the "Decision Making System" is updated in intervals depending on the vision angle and the resolution quality.

The source codes of UvA Trilearn 2003[4] are utilized as base codes of RaiC04.

# 3 Recognizing shootable situations and Modeling of Opponents' ability

The agent may recognizes a shoot situation, the opponents may intercept the ball and the agent will fail to score. This may be learnt as a not suitable shooting situation, however, if the agent is too strict with the results from this scenario, in the future, it may lose many possible scoring chances against opponents with low interception abilities. In this paper, learnt knowledge gained from games against previous opponents is not saved and the agent learns a parameter (opponents' interception ability) in the Shoot Behavior Rule from each new opponent.

At this stage it would be appropriate to describe both the Interception Ability Model and the Learning Algorithm. With a space for a shoot situation declared by the "Shoot Behavior Rule" the agent has to check opponents' arrangement and look for a shootable direction before continuing with the shooting option.

A shootable direction region is an area that partially covers the goal and falls outside the opponents' intercept-ability sectors. The shooting space recognition process may be explained with the aid of Fig. 2.

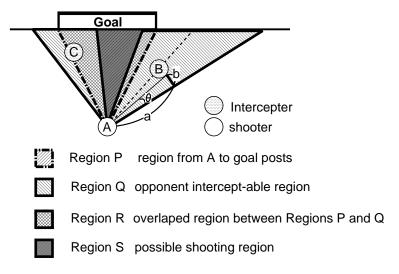


Fig. 2. Modeling of shooting space recognition

Let agent A be the shooter and agents B and C be the intercepting opponents. It is clear from the figure that Region S is the only possible shooting sector for Agent A. When a shoot situation is recognized, Agent A accordingly selects the "Shoot Behavior Rule".

Opponents' interception regions depend on their interception abilities and change in behaviors during a game. The degree of interception ability has to be learnt by the agent in real time during a game to achieve adaptive recognition. In fact the shooting Agent has to avoid two regions described by the

opponent dimensions (as a stationary obstacle) and the other by the blocking scope described by its maneuverability.

The blocking region is described by the angle  $2\theta$ , where  $\theta = \arctan(\alpha)$ ,  $\alpha = b/a$ . Therefore, parameter  $\alpha$  represents opponent's interception ability and the agent recognizes that if  $\alpha$  is large, then the opponent intercept-able region is large too, and vice versa.

Prediction of parameter  $\alpha$  (through experience during a game) will enable the agent to recognize shootable situations without missing a chance. This will not only improve score rates, but is also considered to be more effective in selecting alternative behaviors to shooting, such as centering behavior.

When the agent makes a successful shoot,  $\alpha$  is increased by *delta* When the agent fails to shoot,  $\alpha$  is decreased by  $\delta$ . The parameter  $\alpha$  is a real number from  $\alpha_{min}$  to  $\alpha_{max}$ . and  $\delta$  is a positive constant.

## 4 Recognizing a last passable situation

In case of a last pass, a pass which a receiver is able to receive and shoot is desirable. A passer search the best teammate who will receive the ball and shoot.

The following is the "Last Pass Behavior Rule".

if( I keep the ball

and There is a receiver within a shootable distance.

and There is the receiver within a distance reaching my pass

and A pass course towards the receiver is open

and A shoot course for the receiver is open then(Last Pass)

The recognitions of "A pass course towards the receiver is open" and "A shoot course for the receiver is open" are affected by not only receivers as teammates but also a goalie and defenders as opponents. Therefore, the passer needs to recognize a last passable situation taking the influence into account. To consider it, the passer has the parameters of opponents' ability of interceptions for receivers and use them for its recognition "There is the best receiver who will make a success of a shoot after the pass". The parameters are supposed that receivers use on their recognizing shootable situations.

Fig.3 shows a recognizing models of a last passable situation. The passer sets a space of receiver who is in the good position for its shoot (Fig.3Region T). The passer selects a pass point by finding a receiver's space(Fig.3Region T) overlapped with the passer's pass course(Fig.3 Region U). The passer calculates a maximum region (Fig.3 Region V) where opponents' intercept-able region may exits when the receiver receives the ball at the pass point. The passer regards the shootable space for the receiver as open somewhere in Region V, when the Region X is smaller than Region W (Fig.3). In case that the Region V is smaller than the Region W, The passer also regards the shootable space for the receiver as open.

The parameter  $\beta$  is defined as a parameter which the passer supposes as a receiver's parameter representing opponents' ability of interception on its

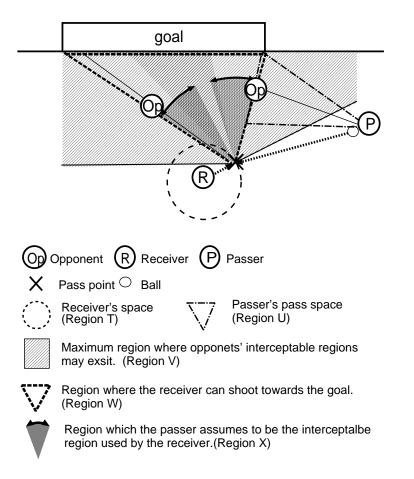


Fig. 3. a last passable situation

shoot. The parameter  $\beta$  is similar to the parameter  $\alpha$  and describes the Region X. The parameter  $\beta$  is learnt by evaluating the receiver's shoot results. When the receiver makes a successful shoot,  $\beta$  is increased by delta When the receiver fails to shoot,  $\beta$  is decreased by  $\delta$ . The parameter  $\beta$  is a real number from  $\beta_{min}$  to  $\beta_{max}$ , and  $\delta$  is a positive constant. The passer has a parameter per a receiver.

# 5 Experimental Results

Experiments were performed to evaluate the effectiveness of "teammates desition models". In this experiments 10 trials are respectively done by three types of passers in a situation which is set. One passer does 50 last passes in one trial. A passer continues to learn during a trial. Fig.4 shows the initial arrangement for a last pass situation. One passer, three receivers and one goalie are arranged in

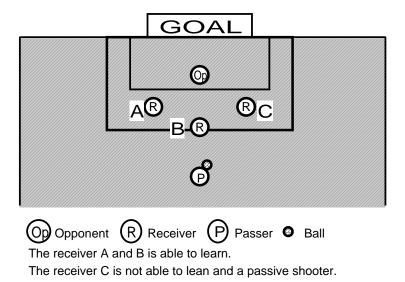


Fig. 4. A last pass situation

the last pass situation. Each receiver makes a shoot by their own decisions after receiving a pass. Receiver A and B have own parameters of goalie's interception abilities during a trial and are able to estimate them. Receiver C has a fixed parameter of it and doesn't estimate. Receiver C is made a passive shooter by setting its parameter  $\alpha$  large. The goalie just tries to chases and block he ball. It doesn't learn. Three types of passers have the following features. The Passer 1 selects a receiver by considering teammates' desition models and their positions. The Passer 2 selects a receiver by considering their positions. The Passer 3 selects a receiver at random.

Table 1. Score and last pass trial(average of ten trials)

	Score	Last pass trial		
		A	В	$\mathbf{C}$
Passer 1	22.3	25.3	11.2	12.9
Passer 2	16.9	23.5	2.8	23.5
Passer 3	19.7	16.3	16.5	16.9

Table 1 shows the result. The average score in case of the Passer 1 was the most highest among them. It indicates the effectiveness of making use of teammates'

decision models when the passer selects a receiver. The number of the Passer 1's last pass to the Receiver C is fewer than the Passer 2's. The number of the last pass to a passive shooter is very few in case of Passer 1. It shows that teammates' decision models worked well. Using these models enable the passer not to pass the ball to a teammate who can't make a shoot because of an accident during a game. The number of the Passer 1's last pass to the Receiver B is greater than Passer 2's. Passer 1 can select a aggressive shooter like the Receiver B even if the Receiver B's position is worser than the Receiver C.

Estimating teammates' decision models enable the passer to select a receiver adaptively and is apt to increase score.

### 6 Conclusion

Using Receivers' models of recognizing their shoot courses as a teammates' desition models for the passer's decision making is proposed to improve a last pass as a cooperative behavior. The passer who employs the Receivers' models and leans the parameters are implemented.

Some experimental results shows the effectiveness of making use of teammates' decision models as compared the passer using them with the passer not using them. The models contribute to improve a cooperative behavior. The passer is able to select a better receiver who can score a goal frequently. In addition that, the passer can recognize the receiver who can't shoot because of an accident during a game.

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