Cooperative behavior of human players in simulated soccer

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Abstract – Human cooperative behavior in virtual soccer simulated fields is analyzed to extract characteristics of human cooperation. Results of analysis of the public human virtual soccer matches in RoboCup JapanOpen 2004 are shown using OZ-RP system that can store human behavior data. A novel macroscopic linguistic analysis using multi-dimensional fuzzy subset is introduced and used as well as ordinary local statistical analysis methods. As a result human adaptation ability are shown especially in higher level behavior such as cooperation and strategic play, and scenario play based on predictions.

I. INTRODUCTION

Virtual soccer simulation is an empirical environment to research human cooperative behavior. The RoboCup soccer simulation league is a test field to develop cooperation algorithms on artificial intelligence, which is a standard open platform for cooperation behavior researches[1]. Data of human players' playing log is obtained under these environment and analyze them to extract characteristics of human cooperation.

According to previous studies, human players' behavior in soccer games were analyzed focused on especially forward human players[2] or mid-field human players[3]. As a result of those analysis, although human players move much slower than computers, human players have macroscopic recognition ability, incredibly quick adaptation ability , and precise predictable actions.

In this paper, analytic results of games on JapanOpen in May 2004 are shown. They are analyzed with macroscopic analysis using fuzzy linguistic methods as well as with locally area statistical methods.

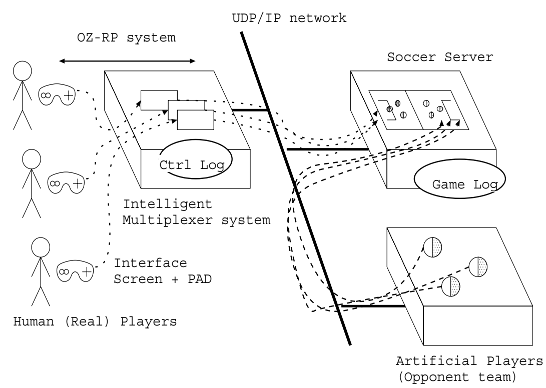

Figure 1: OZ-RP system overview

II. Human behavior logging system OZ-RP in simulated soccer

A. OZ-RP system

OZ-RP[2]is a system to make human players dive into the RoboCup soccer simulation games. The system configuration is shown in the figure 1.

Human pilots control players in a virtual soccer field using TCP/IP network data line. The pilots could obtain limited sensory information around their players in a simulated field. As a specification of the soccer server according to league rules, for each player one action can be done every 0.1 second and players can obtain limited field of view in typically 90 degrees.

B. Matches result

In the JapanOpen 2004 games in May 2004, the team OZ-RP with human players won the 1st. and 2nd. round robbin preliminary matches among 24 teams. And OZ-RP also won and held the 3rd. place in the final tournament with best 8 teams. Finally OZ-RP had 12 games in

Table 1: Game results of team OZ-RP in JapanOpen2004

match number	opponent	goals
First Round robbin		
1	Raic04	0-1
2	ikuei	13-0
3	F-Blitz	0-0
4	NITStones2004	1-0
Secondly Round robbin		
5	XX	0-0
6	CHELLO	0-1
7	TokyoTechSFC	0-0
8	F-Blitz	0-0
9	Puppets	0-0
Final tournaments		
10	Raic04	1-0
11	WinKIT	0-0 x
12	TokyoTechSFC	1-0

the league. Team configuration contained 6 human players including 3 forward players and 3 mid-fielders, and 5 artificial players including four defenders and a goalie player. Each human pilot had experience from one to three years on virtual soccer games with OZ-RP system.

The published game results and the data can be obtained from WWW[4]. Logs analyzed in this paper are included in the *JapanOpen04* entry. The table 1 shows final results.

III. Analysis methods for multi agent soccer games

In order to see how human play soccer, both statistical analysis for local play conditions and macroscopic analysis with linguistic labels are adopted.

A. Local play statistics

Ball keeping ratio is a statistics with local players condition. The number of players on local statistics is four at most.

The ball keeping ratio K is derived from data log with the equation

$$K = \frac{\sum_{t=1}^{6000} A_{keep}(t)}{6000}, \qquad (1)$$

where $A_{keep}(t)$ is a function which take value 1 or 0 at time t, whether if the team A keeps the ball or not. 'Keep a ball' stands for that the same team touch the ball among pass plays. The rate is an amount of time steps divided by a total game steps 6000. The sum of both team keep ratios does not became 100 %.

B. Macroscopic analysis with linguistic labels

Macroscopic estimation like as human beings making on game states based on intuition could give us useful information to understand a game over view. Fuzzy set associated with linguistic label is introduced to implement macroscopic game state analysis and estimation. Macroscopic estimation is derived from whole game state i.e. ball and players states with 46 variables rather than only a ball and a player position.

A linguistic estimation label 'superior' in play and/or 'inferior' can be described as fuzzy subsets in the 46-dimension state space. In general, these qualitative, subjective and macroscopic words are very complex notions. A fuzzy set notation in multi-dimensional space can be handled easily with computers.

C. Sample data based fuzzy set

Sample Data Based Fuzzy set (SDBF) is a computational definition of fuzzy set in multi-dimensional space. It consists of the amount of couples of sample data with its membership grades. Membership grades on non sample points are obtained by interpolation with sample data set. The SDBF can descrive more arbitrary shaped fuzzy subset in two or higher dimension state space.

Sample data set of SDBF A is

$$M_A/S_A = \{\mu_A(x_1)/x_1, \cdots, \mu_A(x_m)/x_m\}, \qquad (2)$$

where m is the number of samples and $\mu_A(x_i)$ is the membership grade at x_i.

Interpolated value on given x is calculated from only the k-nearest sample data set $H_k(x)$ around x. In this paper k is 10. Membership grade interpolation is done with

$$\mu_A(x) = \frac{\sum_{i=1}^{k+j} w_i(x)\mu_A(x_i)}{\sum_{i=1}^{k+j} w_i(x)}, \qquad (3)$$

$$w_i(x) = \prod_{l \neq i} \|x - x_l\|. \qquad (4)$$

SDBF fuzzy set operations are calculated only on points in the union of given sample data sets.

D. Macroscopic linguistic fuzzy sets for soccer game

Table 2: Strategic soccer words

superior*	inferior *
midfield play	defence play
through-pass	shoot
side running up	hard defence

Table 3: number of samples

linguistic label	number of samples
superior	4114
inferior	3174

analysis

The words of trategic notions is made for describing soccer players' behavior with game logs. Construction method of fuzzy sets is as follows.

First of all, natural words has to be selected to express soccer games from manuscripts that are written in natural text sample. The words are listed in table 2. The '*' marked words are mentioned in this paper.

Next, in order to make a fuzzy set associated with a word, volunteers are employed. They watch several soccer scenes from RoboCup soccer logs and then select scenes that is matched with notion of the word. Selected samples number are listed in the table 3.

E. Linguistic analysis on soccer state

A game includes 6000 steps, and each step consists of a state vector $x(\in R^{46})$. Each game is divided into 60 segments for every 100 time steps.

Each segment is defined as a subset A with 100 elements. Degree of inclusion of subset A with a soccer 'word' W defined as fuzzy set is calculated for all 60 segment sets. It is denoted by

$$D_W(A) = \frac{|W \cap A|}{|A|}, \tag{5}$$

where cardinality of SDBF fuzzy set A is defined as

$$|A| = \sum_{x \in S_A} \mu(x). \tag{6}$$

A sequence of degree on 60 segments on W can be understood as a linguistic estimation of game situations.

Table 4: mean value of ball keeping ratio

Team name	mean value [%]
best 4 teams	
YowAI	59.1
WinKIT	36.0
OZRP	30.9
TokyoTechSFC	59.8
best 8 teams	
Raic04	54.1
F-Blitz	61.8
ANCT	37.6
CHELLO	51.4
Second Round Robbin teams	
FUK2	51.5
hana	44.2
Puppets	58.5
XX	60.9

F. Statistical and Macroscopic analysis results

A mean value of ball keeping ratio calculated with equation (1) for every team is listed in the table 4.

Game status transition with words of match 11 and 12 from the final tournament is shown in the figure 2 and 3 respectively. The x axis indicates time segments number divided into 60. Along the ordinate, a linguistic estimation degree difference

$$D_{'superior'}(A) - D_{'inferior'}(A), \tag{7}$$

is plotted. This difference indicates total superior value at time segment A.

IV. Discussion

Human team OZ-RP won out from second round robbin without getting much goals as shown in the table 1. The other hand in the final tournament where many strong teams took part, team OZ-RP obtained goals from teams that had beaten OZ-RP in match 10 and 12. The reason of these phenomena is a quick adaptation of human ability pointed out in previous studies. In this experiment human can adapt only in two days to several opponent teams' characteristics. From precise game observations, cooperative playing knowledge and strategy

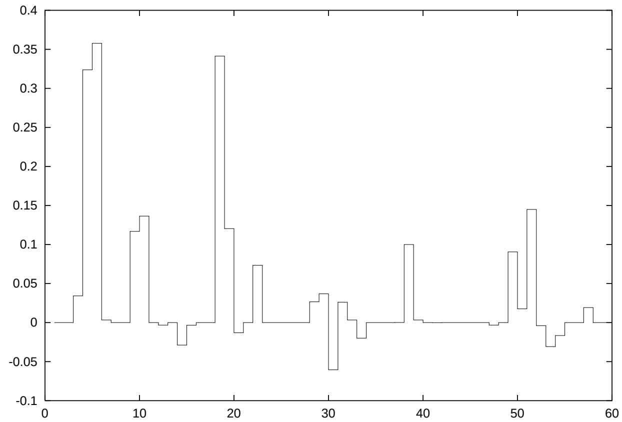

Figure 2: Superior transition result OZRP vs.WinKIT

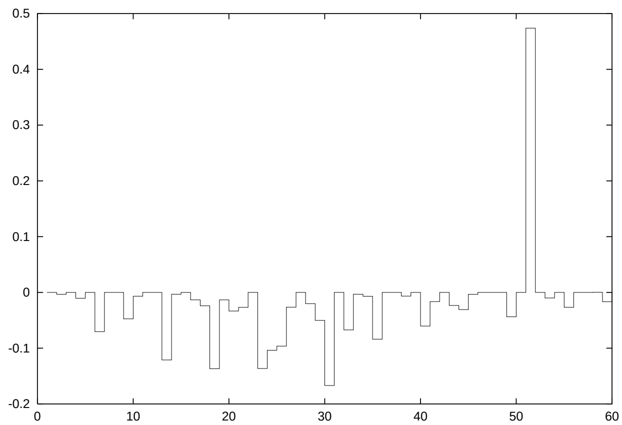

Figure 3: Superior transition result OZRP vs. TokyoTechSFC

seems to become better instead of each players' skill. Human adaptation ability depends on high level decision makings such as cooperative and/or strategic behavior.

The table 4 shows a very low rate of human team ball keeping ability. In general high performance teams that won the second preliminary round robbin perform over 50 % of ball keeping ratio. This value 50 % stands for a high rate because the total is less than 100 %. Although human team OZ-RP had only 31 % ball chance, the team won the third place. This is a result from effective use of the chance to touch a ball by human players. To realize goal with rare chances, human players employ a scenario based cooperative play such as 'set plays'.

The match 12 against the team TokyoTechSFC which was one of the strongest team was under condition of inferior for the whole game. This situation can be seen by human observation. By the proposed linguistic analysis, this inferior situation is shown in the figure 3. Finally human team won one goal with rare chance in this game. This one point chance situation can be detected by linguistic method at around t=5000.

In addition advantage of a linguistic analysis can be found in the figure 2. Team WinKIT used counter attack strategy from defence position. The linguistic analysis result shows this team characteristics.

V. Conclusion

Some characteristics of human cooperative behavior under soccer simulation environment are shown. To realize these experiments a game data logging system OZ-RP is developed that makes us be able to dive into virtual soccer field.

Empirical result shows that human players have and use a high level adaptation and scenario based play making rare chances become more effective. In addition, behavior based on predictions can be also observed in game logs.

Linguistical analyzing method using multi-dimensional fuzzy set is also introduced and an effectiveness of this method is shown. Ball keeping ratio can be calculated from only a few players near a ball. In contrast with this small local statistical estimation, macroscopic linguistical estimation method with fuzzy sets can handle the full scale 46-dimension large situation space easily.

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