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ORIGINAL ARTICLE

## Human versus virtual robotics soccer: A technical analysis

PEDRO ABREU<sup>1</sup>, JOÃO MOREIRA<sup>1</sup>, ISRAEL COSTA<sup>2</sup>, DANIEL CASTELÃO<sup>2</sup>, LUIS REIS<sup>1</sup>, & JÚLIO GARGANTA<sup>2</sup>

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### Abstract

Soccer is a team sport in which the performances of all team members are important for the outcome of a match. Even though the analysis of game events can be used to measure the team's performance, their perception, especially during the match, is extremely difficult, even for the involved agents. Soccer has been used as a simulation environment in many studies, mainly in the area of robotics. The RoboCup is an international robotics competition with an ambitious goal: in 2050 a robotics team will be capable of defeating the human world champion at the time. In this context, we compared technical similarities between human and robotics soccer. Based on an off-line automatic event detection tool, game statistics for the finals of both human and robotics soccer tournaments were collected and compared using the Wilcoxon test. The results show that the most frequent event in both forms of soccer is successful passes. Analysing the two types of passes considered (successful and missed), we conclude that there are significant differences between the two forms ( $W = 2$ ,  $P = 0.000354$ ), with human soccer presenting a higher percentage of successful passes (77.89% vs. 66.97%). Of restart events ( $W = 0$ ,  $P = 0.00048965$ ), the most frequent one, in both forms, is the throw-in (human 59.91%, robotics 66.4%), and the least frequent is the corner (human 13.7%, robotics 14.09%). Regarding the frequency of shots, in the robotics environment "shots" were the most predominant type (43.27%), whereas in human soccer "shots on target" predominated (71.25%;  $W = 64$ ,  $P = 0.000085641$ ). Finally, the number of faults is minor in robotics soccer.

**Keywords:** Soccer, technical analysis, performance assessment, robotics soccer, human soccer, game statistics

### Introduction

Successful performance in team sports is achieved through a long-term and methodical training process planned to improve the skills and competence required to meet competitive demands (Garganta, 2009). Over the last decade, the increase in research on match analysis in soccer (Hughes, 1996; Hughes & Bartlett, 2002; Pettit & Hughes, 2001) has led to the refinement of observational systems and strategies to analyse teams' performance and players' behaviour. For coaches, players, and researchers, analyses of tactical and technical behaviours can be helpful, since they offer the opportunity to identify match regularities and random features of game events (Garganta, 1997). However, as Franks and Miller (1986) show, coaches' observation and memory, even with many years of experience, are not reliable enough to provide accurate and objective information to athletes in high-performance environments, since they are only capable of memorizing 30%

of all game events. As a consequence and to continuously provide useful information to players so that they can strive to attain the highest level of performance possible, coaches use analysis systems. The information produced by these systems is crucial to achieve individual and team efficacy, and it also constitutes a basic criterion for the training process. Once tactical features are identified, they can inform training and performance enhancement programmes (Garganta, 2009).

In most previous research, such analysis systems were used to analyse data derived from studies of the major soccer leagues around the world or international competitions (Di Salvo et al., 2007; Hughes & Franks, 2005; Szwarc, 2007). The justification for this is based on the competitiveness of these championships and also the presence of the best practitioners within the sport. To obtain good performance indicators to aid soccer coaches in the detection of trends/behaviours of

players and teams, the analysis system must be constituted by complex algorithms. These algorithms are normally developed by researchers in artificial intelligence and tested in simple simulated environments, which usually enhance the interest of the researcher's community. One of the projects that emerged from this process was "RoboCup" (Kitano, Asada, Kuniyoshi, Noda, & Osawa, 1995; Kitano et al., 1997). RoboCup is an international research and educational project whose main objective is to promote artificial intelligence and intelligent robotics (the goals of RoboCup are given by the RoboCup Federation at: <http://124.146.198.189/overview/22.html>). To promote investigation in this field, a long-term objective was proposed: by the year 2050, a humanoid robotics team should be capable of defeating the world champion human team in a soccer match according to FIFA rules (Kitano, 1997).

Here, we focus only on the RoboCup 2D simulation league (virtual robots). This league is based in a system called Soccer Server (Noda, 1995; Noda, Matsubara, Hiraki, & Frank, 1998), which enables two teams of 11 players to play a soccer match in a simulated 2D environment. The system allows research in many different areas, including tactics (Reis & Lau, 2003), formations (Reis, Lau, & Oliveira, 2001; Stone & Veloso, 1999), and roles (Reis et al., 2001; Stone, 1998).

The main aim of the present study is to compare the soccer practised by virtual robots and humans, by evaluating the players' behaviours during matches. Such an analysis is important to understand how far these two realities have progressed, and identification of distinct technical features will help professional soccer coaches to improve their training sessions and also RoboCup developers in their approximation process to human reality.

## Methods

The human soccer data used in this study were approved by a review board (constituted exclusively by members of the Centre of Research Education, Innovation, and Intervention in Sport) and the robotics data are available online (in the public domain).

In a soccer competition such as a European or a World Championship, only the best teams, with specific characteristics, are able to progress to the final. In this study, 82 games, corresponding to different tournament finals, were selected to compare robotics and human soccer. To this end, three human soccer games (finals of Euro 2004, World Cup 2006, and Euro 2008) and 79 robotics soccer games (RoboCup 2006, RoboCup 2007, RoboCup 2008, and 2009 competitions) were chosen (only games played by the two finalists in the final phase

and final double elimination tournament, thus ensuring that only games between the best teams were evaluated). For human soccer, the games were recorded in DVD format, whereas for robotics soccer we used a log file format (see explanation in the next sub-section).

A set of soccer concepts was defined and a sequential analysis technique used to better characterize the game events. The first definition in this soccer language is called a "kick". Generically, this event is based on the increase/change of the ball velocity vector. In this situation, one of several events can occur, such as a pass, a shot or even a goal. A successful pass occurs when a player kicks the ball and, after a finite period of time, a teammate receives it. If an opponent intercepts the ball, the event will be marked as an intercepted pass.

Shot events were divided into three categories: a shot on target, an intercepted shot, and a shot. A shot on target occurs when a player kicks the ball in the direction of the goal and the kick has enough strength for the ball to reach the goal line, with a tolerance of 0.5 m either side of the goal. In contrast, if the ball is not on target but leaves the field of play via the 18-yard box, this event will be marked as a shot. Finally, if an opponent intercepts the ball – and all the conditions to be classified as a shot on target or a shot are met – this event will be classified as an intercepted shot.

For the offensive style used by the robotics team, four different types were defined: organized offence, counter-attack, set piece, and long pass. A counter-attack is defined as a collective move, in which the team recovers the ball and reaches the last third of the field (their attacking third) in a short time, which is dynamically defined depending on the position where the team recovered the ball. A restart is defined as a throw-in, goal kick or a corner, after which a combination of passes between teammates (always involving four players or less) is performed and the time taken to reach the penalty area is relatively short (depending of the area of the field). If a team, in its attacking movement, performs a combination of passes among teammates and the duration of this process is longer than that for a counter-attack, this event is classified as an organized offence movement. Finally, a long pass occurs when a player executes a pass to a teammate at a distance greater than 30 m.

In terms of movement that precedes the goal, in this study four distinct situations were defined: combination play, individual action, direct shot, and own goal. For a direct shot, a player recovers the ball and instantly shoots the ball in the direction of the goal. In contrast, to be an individual action, a player must recover the ball but, before shooting, execute many individual actions, such as a slalom

movement (i.e. without losing the ball, passing through a number of opponents). A combination play is a movement that involves at least two players. Finally, an own goal, as the name implies, is when a player puts through his own goal.

The other two events detected and used in the present research (goal and offside) are based directly on FIFA rules (more information available at: <http://www.fifa.com/worldfootball/lawsofthegame.html>). Regarding the offside rule, sometimes when an attacking player is offside, if an opponent captures the ball, the referee does not interrupt the game to mark the offside. In this study, such a situation was classified as an intercepted offside. Finally, it is important to note that the number of faults is not considered, because in the RoboCup Soccer simulation competition, the average was less than two faults per game.

Regarding detection of this set of events, one of two tools was used depending on the form of soccer in question.

#### Robotics soccer

Using the RoboCup 2D simulation league log files as a basis, we developed a tool capable of automatically calculating the final game statistics. The log files were produced by the Soccer Server tool (Chen et al., 2001) at the end of each robotics game and contained detailed information regarding the game, such as position of the players and the ball in the field of play in each cycle, player's stamina, and player's angle of vision. To calculate the final game statistics, only information related to the players and position of the ball was used.

The robotics game in the 2D simulation league presents some differences compared with human soccer. Each game is composed of 6000 cycles, which means that one cycle corresponds to 0.9 s (assuming that a game of soccer lasts 90 min). To perform a sequential game analysis, a vector was constructed as illustrated in Figure 1.

Each vector position is designated as a scene and corresponds to one game cycle. So, at the end of each match, the vector will have 6000 positions filled with the corresponding scenes/cycles. Each position includes information concerning, for example, players and position of the ball. After breaking the game into a vector structure, a detection event algorithm is then used to analyse it, starting with the detection of the kick events, which is the basis for our automatic event detection process. After that, the algorithm tries to identify the game events that occurred in the match according to the start conditions specified in Table 1.

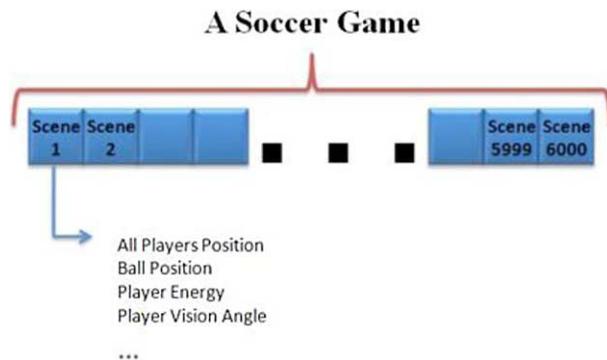


Figure 1. Soccer game structure.

#### Human soccer

From the DVDs of the human soccer games, a spreadsheet was created to classify the different events using a method of observation. The main features that this tool supports are: identify all players that participated in the match, the different sets of events, the duration of the events and, finally, filter all events by time. This spreadsheet is also able to display, at the end of the monitoring process, the final game statistics.

#### Data analysis

All data were analysed using R Software version 2.4.1 (more information about R software is available at: <http://www.r-project.org>). To perform the comparison between quantitative variables and, in the absence of sufficient power to confirm normality of the data used, we chose to use a non-parametric test instead of, for instance, the  $t$ -test. Following the guidelines set out by others (Demsar, 2006; Salzberg, 1997), we used the non-parametric Wilcoxon test (using  $W$  as the value of the test statistic and  $P$  as the significance for the test). Statistical significance was set at  $P < 0.05$ , as recommended by Dietterich (1998).

#### Results

When analysing the human soccer data, it is relevant to note that the three finals were played by six different European teams and only one game needed extra time and a penalty shoot out to determine the winner of the tournament (World Cup 2006 final). It is also interesting to note that the average number of goals (per match) in these matches is less than two, which could be explained by the high pressure that normally is present in these games and by the similar values between the two teams at this phase of a competition.

When the final game statistics (Table 1) are evaluated, it can be seen that the mean number of passes per games is significantly different between

Table 1. Generic comparison between human and robotics soccer

Groups	Game statistics	Human soccer		Robotics soccer	
		mean $\pm$ s	%	mean $\pm$ s	%
Pass	Successful pass	272.00 $\pm$ 67.02	77.89	96.12 $\pm$ 36.91	66.97
	Missed pass	77.16 $\pm$ 12.82	22.11	47.38 $\pm$ 12.19	33.03
Shot	Shot on target	8.66 $\pm$ 4.50	71.25	1.05 $\pm$ 1.41	32.27
	Shot	1.33 $\pm$ 0.81	10.95	1.41 $\pm$ 1.71	43.27
	Intercepted shot	2.16 $\pm$ 2.13	17.8	0.79 $\pm$ 1.14	24.36
Offside	Offside	3.16 $\pm$ 1.47	100	1.61 $\pm$ 2.23	67.82
	Intercepted offside	0 $\pm$ 0	0	0.76 $\pm$ 1.33	32.18
Not applicable	Faults	31.0 $\pm$ 2.9	100	1.32 $\pm$ 0.20	100
Restarts	Goal kick	8.66 $\pm$ 2.16	26.39	1.66 $\pm$ 1.98	19.51
	Corner	4.50 $\pm$ 3.14	13.7	1.20 $\pm$ 1.95	14.09
	Throw-in	19.66 $\pm$ 3.20	59.91	5.66 $\pm$ 3.36	66.40

human and robotics soccer games ( $W=2$ ,  $P=0.000354$  for the total numbers of passes for a data set of 79 robotics games and 3 human soccer games). In human soccer, successful passes represented almost 78% of the total executed in games (with  $\sim 22\%$  of missed passes). In robotics soccer, 67% of passes were successful passes and 33% unsuccessful. Thus although passing in robotics soccer was not as accurate as in human soccer, in both formats successful outnumbered unsuccessful passes.

For total number of shots, there was also a significant difference between the two formats ( $W=64$ ,  $P=0.000085641$  for the total numbers of all three types of shots for a data set of 79 robotics games and 3 human soccer games). There was a predominance of “shots on target” (71.25%) in the human environment and of “shots” (43.27%) in the robotics environment.

Of restarts (goal kick, corner, and throw-in), the most common event is the throw-in. This particular event is more frequent in robotics soccer, with the other two events occurring predominantly in human games ( $W=0$ ,  $P=0.00048965$  for the total numbers of these three events for a data set of 79 robotics games and 3 human soccer games).

### Goal events

In a more careful examination of the goal event, 75% of goals in human soccer were scored in the first half and only 25% in the second half of games. In contrast, for robotics soccer, more goals were scored in the second half (52.01%) compared with the first (47.89%) ( $W=522$ ,  $P=24.5$  for the total number of goals scored for a data set of 79 robotics games and 3 human soccer games) (Figure 2). Thus the two formats are statistically different in terms of goals scored in the two halves of matches.

For the type of offence when goals were scored (Figure 3), there was a difference between the human and robotics games ( $W=571.5$ ,  $P=31.632$  for the total number of offensive styles for a data set of 79 robotics games and 3 human soccer games). In the robotics game, the style of offence that most often led to a goal being scored was the counter-attack (58% of the total), while in the human game the predominant style was a set piece (75% of the total). In the three human soccer games, no goal was scored from a counter-attack. The other types of offence (organized defence and long pass) together accounted for 25% and 18.1% of the total goals scored in human and robotics games respectively.

In the robotics matches, most goals resulted from combination play (86.5%), followed by individual actions (11.25%), long passes (1.5%), and own goals (0.75%) (Figure 4). In the human matches, the results were somewhat different: direct shots (25%), combination play (25%), and long passes (50%). These differences, however, were not statistically significant ( $W=525$ ,  $P=11.845$  for goal actions for a data set of 79 robotics games and 3 human soccer games).

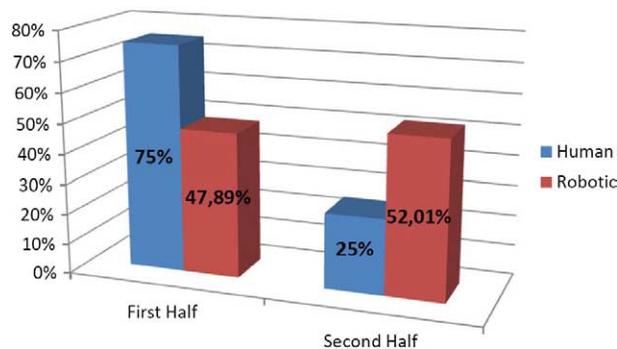


Figure 2. Frequency of scoring by in the first and second half for human and robotics soccer.

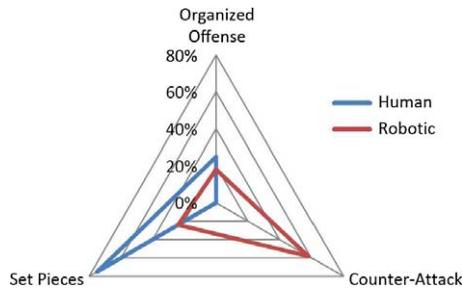


Figure 3. Type of offence used to score a goal for human and robotics soccer.

These actions prior to a goal being scored interfere dramatically with the frequencies of the restarts observed in the two forms of soccer. In robotics soccer, only throw-ins were observed, constituting 21.5% of the total goals scored. In contrast, in human soccer, 53.3% of goals were the result of a corner kick and 26.6% of a penalty kick (Figure 5).

The area of the field from where the attack materialized was recorded for the two forms of soccer ( $W=539$ ,  $P=42.85$  for goal scoring area for a data set of 79 robotics games and 3 human soccer games). In the robotics matches, almost 74% of goals were scored from within the penalty area, whereas in the human matches, all scored goals were from inside the penalty area (50% from the goal area and the other 50% from elsewhere inside the penalty area) (Figure 6).

*Extra time*

We also assessed games that needed extra time to find a match winner. As the data set includes only three games that needed extra time (one human and two robotics), and since one robotics game was won at the beginning of extra time due to the golden goal rule, the values listed in Table 2 pertain to one human game and one robotics game.

Normally in extra time (two halves of 15 min in both formats) neither of the teams likes to take risks.

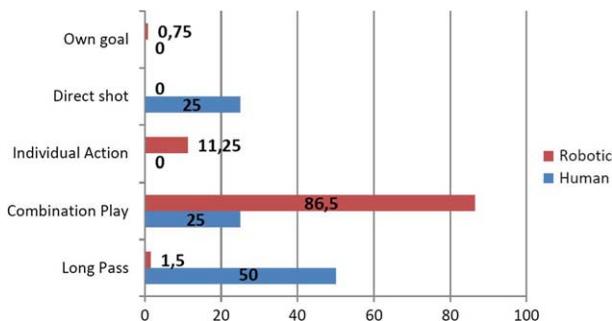


Figure 4. Action prior to a goal for human and robotics soccer.

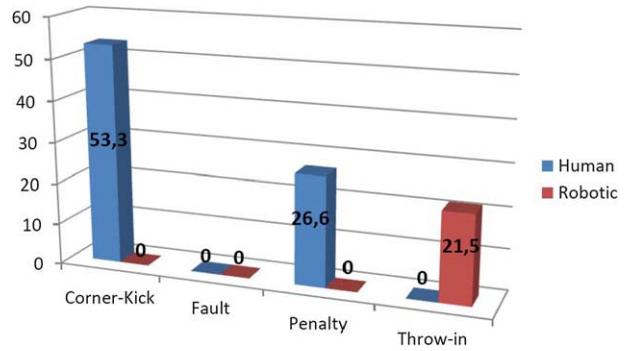


Figure 5. Frequency of set pieces for human and robotics soccer.

Instead, they prefer to execute a more defensive game plan and, if an attacking opportunity presents itself, they will try to exploit it; otherwise, they will wait until the end of extra time and take their chances in a penalty shoot out. As a consequence, both teams' statistics usually drop during this period. Table 3 shows that the reference values calculated empirically (taking the games that ended in regular time as an indicator and using a proportional rule) do not have many similarities with extra-time games. Analysing the robotics and human data together, the only extra-time values that are better than the reference values are the number of shots (successful and miss); the other statistics experienced a dramatic decline. When the two forms of soccer are evaluated separately, the results show that there are no differences between them in terms of pass ( $W=6.0$ ,  $P=14.62$  when comparing the total number of passes in extra time to the reference value for a data set of 2 robotic games and 1 human soccer game), shot ( $W=2.5$ ,  $P=18.2$  when comparing the total number of the three types of shots in extra time to the reference value for a data set of 2 robotic games and 1 human soccer games), and restarts ( $W=7$ ,  $P=25.4$  when comparing the total number of restarts in extra time to the reference value for a data set of 2 robotic games and 1 human soccer games).

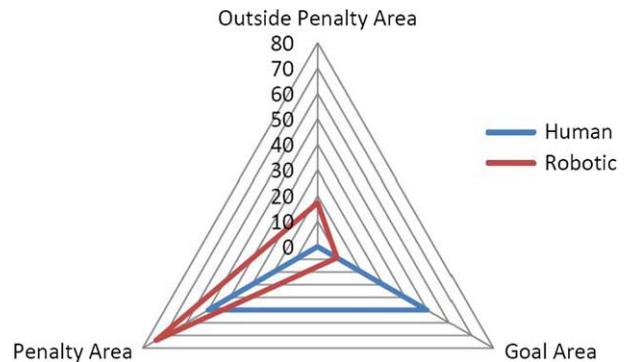


Figure 6. Area from which goals were scored.

Table 2. Extra-time comparison

Groups	Game statistics	Human soccer		Robotics soccer	
		Number observed	Expected average value	Number observed	Expected average value
Pass	Successful pass	236	191	27	10
	Missed pass	57	49	20	9
Shot	Shot on target	3	5	0	4
	Shot	1	1	0	8
	Intercepted shot	1	2	0	6
Not applicable	Faults	4	11	0	1
Restarts	Goal kick	4	6	0	4
	Corner	2	3	2	5
	Throw-in	11	13	6	7

### Final games view

To conduct a more detailed analysis of each game, we started by analysing the human games. We observed that two of them ended in regular time, with only one goal scored in each (2004 and 2008 finals), and one game (2006 final) went to penalties. For executed passes in regular time, over the three finals, the frequency of successful passes increased and the opposite was the case for missed passes (Figure 7). Using only passes as the criterion of comparison, we conclude that the most balanced final match was the 2006 final and, curiously, this game was also the only one that needed extra time to determine the winner. In the 2004 final, the winning team (Greece) performed fewer successful passes ( $n = 171$  vs. 216) than its opponent, as did the winning team (Spain) of the 2008 tournament. However, in the 2008 final, the Spain (the winning team) completed more than 84% of their total versus 83% for their opponent, unlike the 2004 final.

If we focus on other statistics such as shots (Figure 8), the results show that in the first two finals, the winning teams (Greece and Italy) had fewer shots than their opponents but still won the game. However, in the third final, the winning team (Spain) had almost four times

more shots on target than Germany and of the other types of shots, only intercepted shots were similar for the two teams.

Undertaking a similar analysis for the RoboCup, and starting with passes (Figure 9), it is interesting to note that, through the years, the median of missed passes decreased. This fact could be explained by the increased competitiveness of the best teams. Regarding the number of successful passes, they also increased, especially between the 2006 and 2008 competitions.

Analysing only the robotics finals, in all of them except one (2007), and unlike human soccer, the winning team always had a higher number of successful passes and a lower number of missed passes than its opponent (the data shown in Figure 10 is filtered by year and winning team). Also, it is important to note that, in four finals, two ended in extra time and the total goals scored in regular time was eight.

Over the years, there were no marked variations in terms of shot statistics in the robotics games (Figure 11). A possible explanation for this is that they prefer to play a more conservative game and only shoot with a high probability of success (thus reducing the number of shots).

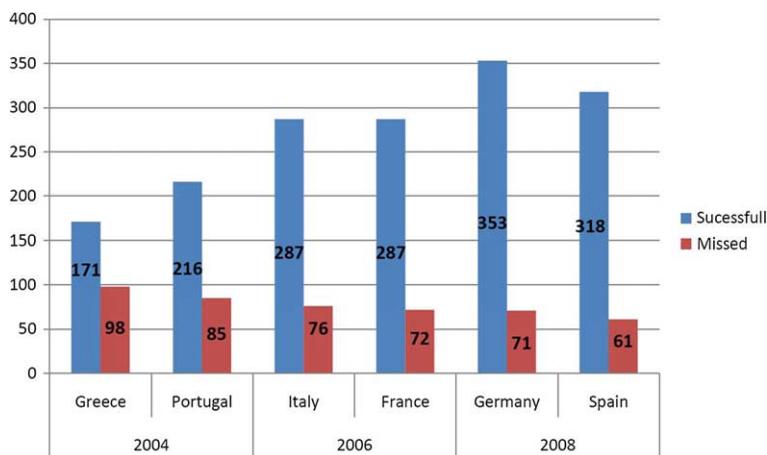


Figure 7. Pass statistics for human soccer finals by country.

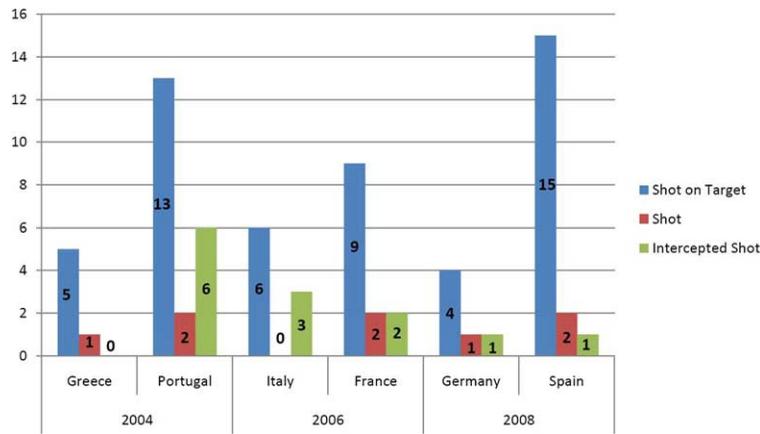


Figure 8. Different types of shots in human soccer finals.

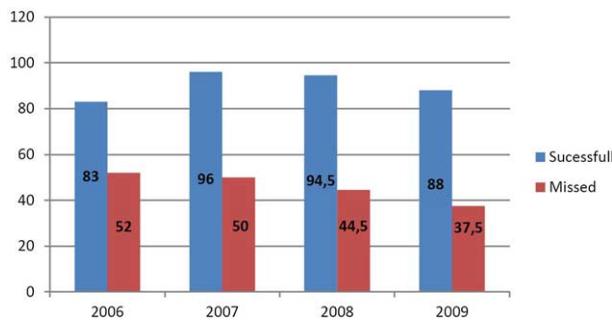


Figure 9. Median pass statistics for RoboCup games between 2006 and 2009.

For the robotics finals, although the number of shots was on average similar to the human finals, the other two types of shots show very different frequencies (Figure 12).

**Discussion**

Many researchers have tried to evaluate the development of human soccer, focusing in particular on goal characteristics (Garganta, Maia, & Basto, 1997;

Yamanaka, Hughes, & Lott, 1993). To carry out a higher level comparison between robotics and human soccer, a parallel with some research works will be produced.

Reep and Benjamin (1968) analysed more than 3000 matches and concluded that approximately 80% of all goals resulted from a sequence of three passes or less and a goal is scored every 10 shots. Although this study seems dated, in the past few years other studies have confirmed these findings using different FIFA World Cup finals (Franks, Goodman, & Miller, 1983; Franks, Partridge, & Nagelkerke, 1990; Gréhaigne, 1999; Hughes & Franks, 2005; Hughes, Robertson, & Nicholson, 1988; Partridge & Franks, 1989a, b). In the present research, the teams scored 400 goals, 62.32% of which resulted from a sequence of three passes or less. For the second finding of Reep and Benjamin (1968), we cannot confirm that one goal is scored every 10 shots. Even if the definition of the shot used by Reep and Benjamin only covered the shot and shot on target or only the shot on target as used in our research, the results would still not confirm their theory.

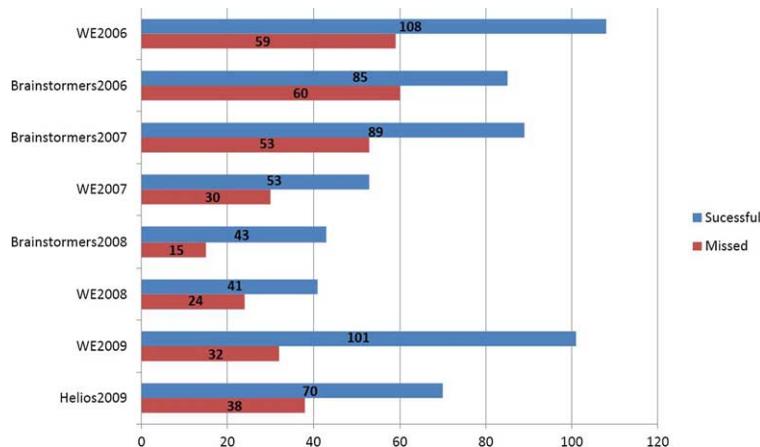


Figure 10. Pass statistics for RoboCup finals by team.

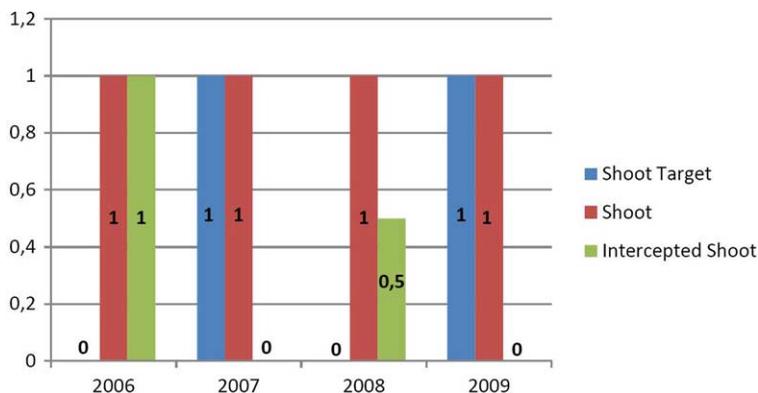


Figure 11. Median shot statistics in RoboCup games between 2006 and 2009.

Many studies have aggregated goals according to time scored (first vs. second half or even per periods of 15 min in each half) showing that the frequency of goal scoring is time dependent (Abt, Dickson, & Mummery, 2002; Bekris, Louvaris, Souglis, Hountis, & Siokou, 2005; Saltas & Ladis, 1992; Sotiropoulos, Mitrotasios, & Traulos, 2005). The results of our research show that, in the human game, more goals are scored in the first than the second half. However, in the robotics environment, similar proportions of goals were scored in each half (47.89% and 52.01% for the first and second half respectively).

Regarding the type of offence during goals, Piecnicz (1983) concluded that 27% of goals resulted from a quick offence and only 28% were the result of organized offensive actions. However, a decade later Dufour (1993) concluded that this trend had reversed: 88% came from organized offence and 12% from quick offence. More recently it has been noted that, in modern soccer, 16.9% of counter-attacks lead to a goal and only 11.1% of organized offences are successful (Armatas, Yiannakos, Ampatis, & Sileoglou, 2005).

In human soccer today, the execution of set pieces constitutes an important part of a team's tactics. As

in the present study, others have noted that more than a third of goals scored in many competitions result from set pieces (Bekris et al., 2005; Garganta et al., 1997; Olsen, 1998). In contrast, we observed that, in the robotics environment, the most successful tactic for scoring goals was the counter-attack (58% of goals).

Of the actions that lead to a goal, our findings show that in the robotics world most goals result from combination plays (86.5%), whereas in the human game it is long passes that predominate (50%). These findings are similar to the results obtained for human finals by Yiannakos and Armatas (2004), which demonstrates that the long passes are the most frequent type of action leading to a goal.

In the robotics environment, only 21.5% of goals scored were preceded by a set play (throw-ins). In the human game, the most common type of set play was corner kicks (>53.3%), followed by penalties (>26%). However, other studies (Jinshan, Xiakone, Yamanaka, & Matsumoto, 1993; Pappas, 2002) indicate that, in spite of corner kicks resulting in a goal being scored (27% and 24.4% respectively), the

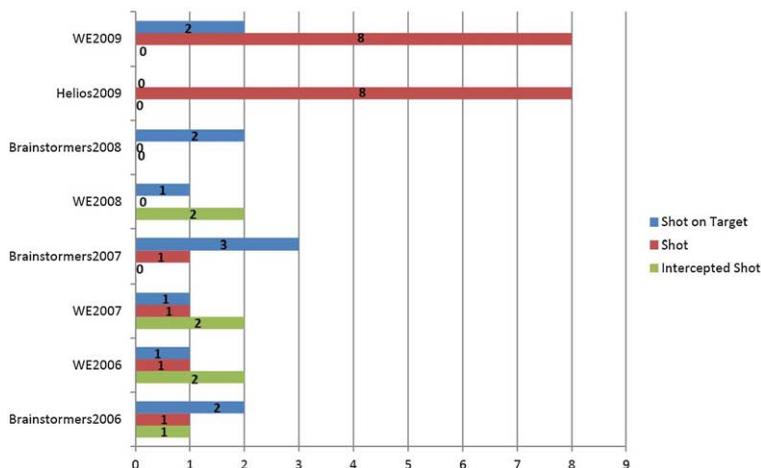


Figure 12. Shot statistics in RoboCup finals by type.

most important set play is the free kick (37% and 39% respectively). Another recent study (Yiannakos & Armatis, 2004) showed that corners were the major set play for goal scoring (40% followed by free kicks with 30%). Although the comparison of these studies shows, to a certain degree, dissimilar results, it is clear that corner kicks result in a high percentage of goals scored. It is also relevant to note that, as previously stated, in the robotics environment, as faults were rare (less than 2 faults per match), the most common set piece before a goal was the throw-in.

Regarding the area where the final effort materialized, the findings of our research indicate that most robotics goals were scored from inside the penalty box (82.74%). However, in human soccer goals scored were divided between the goal area (50%) and the rest of the penalty area (50%). In the literature, the results reported are very similar to ours. In the 2002–2003 Champion's League season, Michailidis and colleagues (Michailidis, Michailidis, Papaikovou, & Papaikovou, 2004) concluded that more than 64% of goals were scored from inside the penalty area and 36.5% from within the goal area. Other studies (Dufour, 1993; Sotiropoulos et al., 2005) indicated that approximately 80% of goals were scored from inside the penalty area and 16% from within the goal area.

In summary, the robotics teams' behaviours show some significant differences from human soccer, especially regarding the frequency of restarts, frequency of shots, and frequency of successful and missed passes.

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