2012 IEEE/RSJ International Conference on
Intelligent Robots and Systems
October 7-12, 2012. Vilamoura, Algarve, Portugal

Automatic Extraction of Goal-Scoring Behaviors from Soccer Matches

Fernando Almeida[1] and Pedro Henriques Abreu[2] and Nuno Lau[3] and Luís Paulo Reis[4]

***Abstract*— In a soccer match, a cooperative behavior emerges from the combined execution of simple actions by players. A cooperative behavior can be planned if players are previously committed to its execution prior to its start or unplanned otherwise. The ability to reproduce some of these behaviors can be useful to help a team achieve better performances.**

This work presents an approach to identify and extract cooperative behaviors that start from set-pieces and lead to a goal while ball possession is kept. The representation of these behaviors is abstracted using a set-play definition language to promote their reusability. A set of game log files generated with the FC Portugal team and collected from the RoboCup 2010 2D simulated soccer competition were analyzed.

The results achieved showed that 25% of the total goals scored originated from set-pieces which attests to the importance of performing this analysis. Several guidelines for the definition of future set-plays were also inferred.

In the future, these behaviors shall be tested to infer which are capable of neutralizing an opponent's team strategy and maximize the creation of goal opportunities.

I. INTRODUCTION

The growing interest in performance analysis has led to the creation of new techniques for match analysis. Modern techniques include video-based statistical analysis systems, video-based tracking and electronic tracking systems [1], [2].

Despite the high performance gap between robotic soccer teams in comparison to human soccer teams [3], the preparation of a robotic team for an opponent also has a great relevance in the achievement of a win. The preparation of a match by a robotic soccer coach is divided in 2 phases: i) Offline phase: detect opponent play patterns in past matches and find the best strategy to neutralize them; and ii) Online phase: analyze opponent behavior during the match and adapt the team strategy.

The first step of this research work consists on the identification and extraction of useful cooperative behaviors that occurred in a soccer match (offline phase). In particular, this work focuses on the extraction of behaviors that start from set-pieces and lead to the uninterrupted scoring of a goal, referred to as goal plans from here on.

[1]Fernando Almeida is with DI, Superior School of Technology of Viseu, Campus Politécnico de Repeses 3504-510 Viseu, Portugal, with IEETA, University of Aveiro, Campus de Santiago 3810-193 Aveiro, Portugal and with LIACC, University of Porto, Rua Dr. Roberto Frias s/n 4200-465 Porto, Portugal falmeida@di.estv.ipv.pt

[2]Pedro Henriques Abreu is with DEI, CISUC, Faculdade de Ciências e Tecnologia, Rua Sílvio Lima, Universidade de Coimbra - Pólo II, 3030-790 Coimbra, Portugal pha@dei.uc.pt

[3]Nuno Lau is with the DETI, IEETA, University of Aveiro, Campus de Santiago 3810-193 Aveiro, Portugal nunolau@ua.pt

[4]Luís Paulo Reis is with DSI, School of Engineering of the University of Minho, Campus de Azurém 4800-058 Guimarães, Portugal and with LIACC, University of Porto, Rua Dr. Roberto Frias s/n 4200-465 Porto, Portugal lpreis@dsi.uminho.pt

A framework that allows the extraction of these behaviors was developed and a set-play [4] definition language was used to describe them and promote their reusability. The behaviors of robotic soccer teams were gathered from a set of log files generated by the 2D RoboCup Soccer simulator. Each log file consists on an ordered description of world states (e.g. players and ball positions) and basic events (e.g. changes in play-mode) observed during the soccer match.

The results achieved showed that goal plans play an important role in the team's performance as they accounted for 25% of the total goals scored. In the future, this work will be included in a soccer analysis framework capable of automatically improving the performance of a soccer team using high-level information.

The remainder of this paper is organized as follows. Section II discusses the related work done regarding this subject. Sections III and IV describes the set-play framework and the process of detecting match events which lead to the extraction of goal plans. Section V presents the methodology followed to validate the proposed approach. Section VI pinpoints and discusses the obtained results. Section VII presents final remarks about the approach and discusses future work.

II. RELATED WORK

Over the years, several researches were developed using the RoboCup soccer environment [5], many of which related to opponent modeling [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17]. These works focused on how an advisor agent (coach), who has a restricted communication with his players using the standard language CLang[1], could improve the performance of his team.

The latest RoboCup Coach League, embedded in the RoboCup Soccer competition, had as its most relevant goal the development of a coach capable of detecting behavioral patterns of simulated soccer teams. The coach is able to receive global and noiseless information from the Soccer Server simulator that supports the competition. This competition [18] is built upon the concepts of Play Pattern and Base Strategy. A Play Pattern describes a predictable behavior executed by a team that can be exploited by a coach, while the Base Strategy is more concerned with the general tactics followed by a team. This strategy can be composed by a set of distinct patterns. At the start of the competition, a set of strategies are made available by organizers to be used as base strategies of the patterns and some matches are played to generate No-Pattern Log Files (NPLF). After that, patterns

[1]More information at http://sourceforge.net/projects/sserver/.

are added to these strategies and more matches are played to generate Pattern Log Files (PLF), creating many NPLF and PLF pairs. When the competition starts each coach receives a set of PLF containing only one specific pattern activated and a corresponding NPLF with the same base strategy but without any activated pattern. During an offline phase the coach agent receives these files and should try to discover the existing patterns. Afterwards, the coach must recognize the patterns used by a test team in an online match and send its pattern recognition reports. The sooner these are sent the higher is the score the coach gets if they are accurate.

Despite the end of this competition in 2006, it sparked a growing interest in the area of agent modeling, leading to the pursuit of many research works in domains such as human imitation [19], [20], game event detection [8], [21], [22] and opponent classification. In the last domain, some works need to be highlighted. Stone et al. [23] presented a low-level positioning and agent interaction approach based on an ideal world in which the opponent's performance is always the best. In this approach, the process of positioning adaptation does not change throughout the game and is opponent-independent which constitutes a severe limitation. An extension of this work is proposed by Ledezma et al. [24] with the main goal of improving the low level skills of the modeled agent. Druecker et al. [25] and Riley et al. [7] proposed methods to identify the opponent team formation based on players positions, but the information obtained is limited in its ability to improve the performance of a team. Based on evidence that set-plays can benefit the performance of a team [26], Riley et al. [27] proposed an approach that relies on a coach to generate adaptive set-plays during set-pieces. The generated set-plays rely on a prior classification of the exhibited opponent behavior into a set of probabilistic movement models for which a probability distribution is kept. This approach assumes that opponent behaviors can be adequately described using unrealistic predefined models. Kaminka et. al [8] proposed an approach for learning behavioral sequences by applying offline unsupervised autonomous learning to a stream of dynamic, complex, continuous and multi-variate observations. The extraction of knowledge (events) proposed is similar to ours, but the knowledge is used to predict future opponent behaviors rather than being reused with their own team to gain a competitive edge. Statistical mining techniques are used to assess the relevance of sequential behavioral patterns and to discard any frequent patterns that are driven by chance.

Many studies have tried to model the behavior of opponent teams by detecting multi-valued variables such as team formation in order to improve team performance. However, none is capable of using high-level information (such as set-plays[4]) to automatically detect the behavior patterns of an opponent and reuse them to adopt a strategy that maximizes the performance of a team against that opponent.

III. SET-PLAY FRAMEWORK

This framework [4] provides a language grammar for defining plans (set-plays) for the soccer domain, a built-in parser and an execution engine that allows them to be interpreted and executed at run-time. Set-plays can be reused in different matches and integrated with other team strategic mechanisms (e.g. formations) to better cope with opponents (e.g. exploit empty spaces in the opponent's penalty area).

A Set-play is described by a name, Player References who participate in its execution and optional Parameters.

A Player Reference is a concrete player described by a team and number or a role to be instantiated at run-time.

A Set-play has one or more Steps which represent states of its execution. Each Step can have a Condition that must be satisfied before entering the Step. A set of Player References identifies the participants of the Step including a Leader which rules the execution. The Leader can change between different Steps. A Step is exited by following one or more Transitions. A Transition can have a Condition which must be satisfied before its list of Directives can be applied. There are 3 types of Transitions that can be defined:

- Next Step: establish a link between different Steps;
- Abort: terminate if no Set-play goal can be reached;
- Finish: terminate if one goal of the Set-play is reached.

A Directive consists on a list of Actions that should (or should not) be executed by the participants. An Action represents a skill (e.g. pass) that can be executed by players.

A Condition imposes constraints over the world state of the soccer domain. Spatial entities are represented through Regions (e.g. points, triangles, arcs, rectangles), Dynamic Points (e.g. player, ball) that refer to the location of moving objects and Named Regions (e.g. opponent defense line) that intuitively model locations that can change during the match.

All participants monitor the execution of the Set-play to decide whether to continue its execution. In each Step the Leader instructs other participants of the start of the Set-play, the entry on a Step and the choice of Transition.

This framework has mostly been tested in the RoboCup 2D soccer simulation for non play-on situations.

IV. SET-PLAY EXTRACTION FRAMEWORK

The process of extracting goal plans from log files is depicted in Fig. 1.

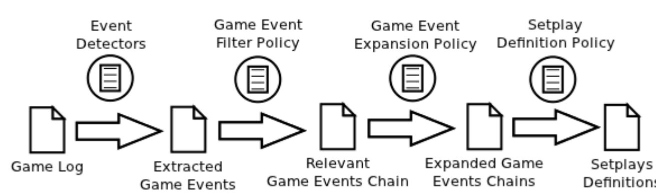

Fig. 1: Set-play extraction process

This process is comprised of 5 different phases:

1) Selection of the source game logs from which the goal plans are to be extracted;
2) Identification of high-level game events (e.g. passes, dribbles, goals) from the previously selected game logs;
3) Filtering of relevant game-events (e.g. uninterrupted pass-chains that lead to goals) from the previous events;

4) Expansion of relevant high-level events (e.g. pass-chain with intermediate dribbles that leads to goal);
5) Representation of an expanded high-level event using the set-play language described in Section III.

A goal plan refers to an uninterrupted pass-chain starting from a set-piece which leads to the scoring of a goal in the opponent's net. Between successive passes, and prior to the shoot on goal, several dribbles and ball holds can occur.

A pass-chain is a complex event which consists of 2 or more consecutive passes between teammates, during which no opponent intercepts the ball. An opponent interception is assumed to occur whenever an opponent kicks the ball at a given time at which the team was considered to own the ball. A pass-chain can start from a set-piece (kick-off, goal-kick, kick-in, corner-kick and free-kick[2]) or during play-on (e.g. after a ball recovery). During a pass-chain, more than one player might kick the ball at the same time. Whenever this happens it is assumed that the closest player to the ball is the intended sender, receiver or shooter as the case. The start and end play-modes of an event (e.g. pass-chain) are the ones observed at the start and end times of its execution (e.g. play-modes at the time of execution of the sender's first kick and the last receiver's first kick respectively).

A. Extraction of events

The event extraction phase is executed on a set of scene data structures previously parsed from a game log using SoccerScope[3]. Each scene data structure is characterized by a time of occurrence, a play-mode and physical data (e.g. position, velocities) for the players and ball.

Several meaningful events can be extracted from the set of scenes parsed from a log file. The definitions of these events and the algorithms used for their extraction were adapted from [22]. In the scope of this work the most relevant events to detect are successful passes, successful dribbles, pass-chains and non own goals (shoots are implicit) which are formally defined in Equations 1, 2, 3 and 4 respectively.

$$\begin{aligned} Pass(p_0,p_1,t_0,t_1) \leftarrow\ & t_0 < t_1 \wedge p_0 \neq p_1 \\ \wedge\ & Team(p_0) = Team(p_1) \\ \wedge\ & KicksBall(p_0,t_0) \wedge KicksBall(p_1,t_1) \\ \wedge\ & \nexists (p,t_0) : KicksBall(p,t_0) \wedge p \neq p_0 \\ \wedge\ & \nexists (p,t_1) : KicksBall(p,t_1) \wedge p \neq p_1 \\ \wedge\ & \nexists (p,t) : t_0 < t < t_1 \wedge KicksBall(p,t) \end{aligned} \tag{1}$$

$$\begin{aligned} Dribble(p_0,t_0,t_1) \leftarrow\ & t_0 < t_1 \\ \wedge\ & KicksBall(p_0,t_0) \wedge KicksBall(p_0,t_1) \\ \wedge\ & \nexists (p,t_0) : KicksBall(p,t_0) \wedge p \neq p_0 \\ \wedge\ & \nexists (p,t_1) : KicksBall(p,t_1) \wedge p \neq p_0 \\ \wedge\ & \nexists (p,t) : t_0 < t < t_1 \wedge KicksBall(p,t) \end{aligned} \tag{2}$$

$$\begin{aligned} PassChain(team,t_0,t_5) \leftarrow\ & \forall (p_0,p_1,p_2,p_3,t_1,t_4) : \\ & t_0 < t_1 \leq t_4 < t_5 \\ \wedge\ & Pass(p_0,p_1,t_0,t_1) \wedge Pass(p_2,p_3,t_4,t_5) \\ \wedge\ & \forall (p_4,p_5,t_2,t_3) : t_1 \leq t_2 < t_3 \leq t_4 \\ \wedge\ & [Pass(p_4,p_5,t_2,t_3) \vee Dribble(p_4,t_2,t_3)] \\ \wedge\ & \nexists (p,t) : t_0 \leq t \leq t_5 \wedge KicksBall(p,t) \wedge Team(p) \neq team \end{aligned} \tag{3}$$

[2]The term free-kick is used to refer to both direct and indirect free-kicks.
[3]More information at http://ne.cs.uec.ac.jp/*koji/SoccerScope2/index.htm.

$$\begin{aligned} Goal(team,t_3) \leftarrow\ & \exists (p_0,t_0,t_1,t_2) : t_0 < t_1 < t_2 < t_3 \\ \wedge\ & KicksBall(p_0,t_0) \wedge Team(p) = team \\ \wedge\ & \nexists (p,t_0) : KicksBall(p,t_0) \wedge p \neq p_0 \\ \wedge\ & Region(Ball,t_1) = GoalieArea \\ \wedge\ & InterceptsBall(OpponentGoalLine,t_2) \\ \wedge\ & CrossesBall(OpponentGoalLine,t_3) \\ \wedge\ & \nexists (p,t) : t_0 < t \leq t_3 \wedge KicksBall(p,t) \end{aligned} \tag{4}$$

where $p, p_i, i = \{0..5\}$ are players, $t, t_i, i = \{0..5\}$ are temporal instants and $team$ is a specific team.

B. Extraction of goal plans

The extraction of goal plans from a set of log-files is described in Algorithm IV-B.1 which requires that all relevant high-level match events have been previously detected. This algorithm essentially takes each game log in a set and selectively extracts a set of high-level events (passes, dribbles and pass-chains in this order) using the algorithms in [22]. For each detected pass-chain an expansion process is applied using Algorithm IV-B.2 which looks for the occurrence of other meaningful events that took place immediately before and after the pass-chain while keeping the ball possession. If an expanded pass-chain is considered relevant, a goal plan definition will be extracted from it using Algorithm IV-B.3.

Algorithm IV-B.1 $extractGoalPlans(gameLogs)$

```
Require: gameLogs ≠ ∅
goalPlans ← ∅
for each gameLog in gameLogs do
    passes ← detectPasses(gameLog)
    if passes ≠ ∅ then
        dribbles ← detectDribbles(gameLog)
        passchains ← getPassChains(passes, dribbles)
        goals ← detectGoals(gameLog)
        for each pc in passchains do
            epc ← expandPassChain(pc, dribbles, goals)
            if isRelevant(epc) then
                newGoalPlan ← extractGoalPlan(epc)
                goalPlans ← goalPlans ∪ {newGoalPlan}
            end if
        end for
    end if
end for
return goalPlans
```

The expansion of a detected pass-chain into a richer set of events is performed using Algorithm IV-B.2. This process consists of merging all relevant events that occurred before, during and after the pass-chain that sustain the goal plan while the ball possession is kept by the team. In particular, some simplifications are applied to smooth the definition of some events (e.g. avoid short straight dribbles).

The abstraction of an expanded pass-chain into a goal plan is described in Algorithm IV-B.3. This process starts with the creation of a set of steps using Algorithm IV-B.4 that are mapped to game scenes associated with the start and end of each event of the expanded pass-chain. After the creation of steps, the players that participated in the goal plan are chosen using Algorithm IV-B.5. Additionally, for each of step a richer characterization of its entry conditions, wait and abort times and transitions is also performed.

Algorithm IV-B.2 $expandPassChain(passchain, dribbles, goals)$

Require: $passChain \neq \emptyset$
$epc \leftarrow \{passchain.firstPass\}$
$team \leftarrow \{passchain.team\}$
for each (p_1, p_2) **in** $passchain$ **do**
  if $p_1.endTime \neq p_2.startTime$ **then**
    $midDrb \leftarrow dribbles.from(p_1.endTime, p_2.startTime)$
    $epc \leftarrow epc \cup \{midDrb\}$
  end if
  $epc \leftarrow epc \cup \{p_2\}$
end for
$goal \leftarrow getFirstGoalAfter(passchain.endTime)$
if $goal.team = team \ \wedge$ $PossessionKept(team, passchain.endTime, goal.time))$ **then**
  $shooterDrb \leftarrow dribbles.from(passchain.endTime, goal.time)$
  if $shooterDrb \neq \emptyset$ **then**
    $epc \leftarrow epc \cup \{shooterDrb\}$
  end if
  $epc \leftarrow epc \cup \{getShoot(goal)\} \cup \{goal\}$
end if
return epc

The condition to enter a step is defined based on the positions of the players in the field at the time of execution.

A transition consists of one or more actions performed by the players participating in a given step. Each transition has a main action which is executed by the leader of that step. Currently, the condition to start the execution of a transition only checks if the main action can be safely executed.

The abort conditions for the goal plan are currently statically defined. As a general rule of thumb, the execution of the plan shall be aborted whenever one of following conditions is met: i) the opponent intercepts the ball during its execution, ii) the game ends or iii) the ball goes out-of-bounds.

Algorithm IV-B.3 $extractGoalPlan(expandedPassChain)$

Require: $expandedPassChain \neq \emptyset$
$setplay \leftarrow createSetplay()$
$steps \leftarrow createSteps(expandedPassChain)$
$decideSetplayParticipants(steps)$
for each $(step_i, step_{i+1})$ **in** $steps$ **do**
  $decideStepParticipants(step_i)$
  $decideStepWaitTime(step_i)$
  $decideStepAbortTime(step_i)$
  $decideStepCondition(step_i)$
  $createNextStepTransition(step_i, step_{i+1})$
end for
$createFinishTransition(steps.lastStep)$
$decideSetplayIdentification(setplay)$
$decideSetplayAbortConditions(setplay)$
$decideSetplayInversion(setplay)$
return $setplay$

The creation of the steps from an expanded pass-chain when extracting a goal plan is described in Algorithm IV-B.4. Essentially, a step is created for each event in the expanded pass-chain. The number of steps and transitions in a goal plan will be equal to the number of game events that result from the expansion of the pass-chain. Between each consecutive pair of **Steps** and for the last **Step** a **Next Step** and **Finish** transitions are created. The player that owns the ball at the start of each event will be deemed as the **Leader** of the underlying **Step**.

The decision for choosing the players that participated in

Algorithm IV-B.4 $createSteps(gameEvents)$

Require: Time-ordered ascendant and non-empty set of game events
$steps \leftarrow \emptyset$
for each $event$ **in** $gameEvents$ **do**
  $step \leftarrow createStepFromEvent(event)$
  $steps \leftarrow steps \cup \{step\}$
end for
return $steps$

the goal plan is described in Algorithm IV-B.5. Essentially, this process takes each of the previously created steps using Algorithm IV-B.4 and considers the union of players that are involved in each of its associated events as participants.

Algorithm IV-B.5 $decideSetplayParticipants(steps)$

Require: Non-empty list of steps
$participants \leftarrow \emptyset$
for each $step$ **in** $steps$ **do**
  for each evp **in** $getEventParticipants(step)$ **do**
    if $evp \notin setplayParticipants$ **then**
      $participants \leftarrow participants \cup \{evp\}$
    end if
  end for
end for
return $participants$

The decision for choosing the players that participated in a given step of the goal plan currently assumes that these should be all that participate in the goal plan even if they do not have an active role in the steps underlying events. This approach assumes that all goal plan participants do something relevant (e.g. off-ball movement) in each of the steps, even though they might not be actively involved in the underlying events. The major drawback of this approach is that the off-ball movements of these players even if performed might not contribute to the success of the execution of the step, but nonetheless will waste their stamina. More clever algorithms can be devised to assess the relevance of the actions executed by players during each identified step.

V. METHODOLOGICAL APPROACH

In order to validate the presented set-play extraction framework 2 experiments were conducted:

1) Extract previously defined goal plans from 25 game logs generated by the FC Portugal team without opponent;
2) Extract goal plans from game logs of the RoboCup 2010 competition in which at least 4 goals were scored.

In the first experiment a set of 25 known goal plans that start from set-pieces and lead to goal were defined based on all the possible combinations of 5 non play-on modes (kick-off, goal-kick, kick-in, corner-kick, free-kick) and different number of participants (2 to 6 players). In this experiment a total of 25 game logs were generated by playing matches with the FC Portugal team without opponent using the previously defined goal plans. In each of the games played, only one specific goal plan was active and was deliberately triggered many times during the match to promote a relevant set of examples for analysis. The goal of this experiment was to assess the correctness of the developed extraction framework in a scenario controlled by the authors.

The goal of the second experiment is to assess the generalization of the extraction framework in a non controlled scenario (log-files were generated without the authors intervention). For this purpose a set of 69 game logs were selected for analysis based on the following criteria:

- To maximize the probability of detecting set-plays that lead to goal, only games in which a combined total of 4 or more goals were scored were considered;
- For the sake of obtaining relevant results to be used in the short term, only the most recent games from the RoboCup 2010 competition were used.

Due to the incipiency of the FC Portugal set-play framework, set-plays can not still be triggered adequately during play-on mode and as such the detection of goal plans in this condition was not attempted although it is supported.

In both experiments, all extracted goal plans were also validated by visual inspecting each of the games.

VI. RESULTS AND DISCUSSION

A. Experiment 1

A total of 285 goal plans resulted from the execution of the predefined set-plays in the 25 generated game logs. The distribution of the executed set-plays per play-mode and number of participants involved is described in Table I.

TABLE I: Goal plans observed in matches played by FC Portugal without opponent and a known set of 25 goal plans

Participants	GK	CK	FK	KI	KO	Totals
2 players	9	14	13	12	11	59
3 players	14	15	14	11	10	64
4 players	13	15	8	11	9	56
5 players	12	14	8	11	10	55
6 players	10	14	8	11	8	51
Totals	58	72	51	56	48	285

Corner-Kick (CK), Free-Kick (FK), Goal-Kick (GK), Kick-In (KI), Kick-Off (KO)

The different number of goal plans executions observed per combination is explained by the fact that execution times varied among different set-plays and also within instances of the same set-play. Also, some set-plays caused an excess of stamina consumption due to their repetition which wore out the players and affected the intended execution flow.

The extraction process supported by the algorithms described in Section IV achieved an accuracy of 100% after corroboration by visual inspection. This result attests the correctness of the process for the controlled cases.

B. Experiment 2

The performance of each team in the 69 observed games and in the competition is summarized in Table II.

A total of 607 goals were scored in the 69 analyzed matches, from which 59 (86%) matches contained goal plans. From the 547 scored goals in these 59 matches, 150 (22%) goals originated from a set-piece. This result reveals that many goals can be scored from such situations. An accuracy of 100% was also achieved in the extraction of these goal plans after corroborated by a visual inspection. However, 2 ambiguous situations occurred during the detections in which ball possession was considered to be kept:

TABLE II: Analysis of team's performance in light of the extracted goal plans and their rank in the competition.

#	Team	W	D	L	GS	GP	Steps	Players	Duration
2	WrightEagle	9	0	0	116	30	10 ± 4	4 ± 1	76 ± 53
9	FC_Pars	8	1	1	63	21	11 ± 8	4 ± 2	112 ± 99
1	HELIOS2010	6	0	2	54	14	9 ± 4	4 ± 1	82 ± 43
5	Nemesis2010	6	0	2	50	12	9 ± 4	5 ± 2	82 ± 53
3	Oxsy	8	0	2	99	12	6 ± 2	4 ± 1	51 ± 28
6	Unique	3	0	3	30	11	8 ± 4	3 ± 1	64 ± 46
8	HfutEngine	5	0	3	35	9	8 ± 5	4 ± 2	84 ± 47
4	ESKILAS	7	0	1	34	7	9 ± 3	4 ± 1	85 ± 35
10	opuCI_2D	4	2	4	37	7	7 ± 2	4 ± 1	88 ± 38
17	Fifty-Storms	2	0	5	22	6	7 ± 1	4 ± 1	63 ± 9
13	Apollo	1	2	4	9	5	8 ± 5	4 ± 2	83 ± 60
14	NCL10	1	1	5	16	5	7 ± 2	4 ± 1	79 ± 51
16	Ri-one	0	2	5	9	4	7 ± 3	3 ± 1	67 ± 36
18	AUA2010	1	0	7	8	3	6 ± 1	4 ± 1	81 ± 30
12	RaiC-2010	2	0	5	16	3	7 ± 3	4 ± 1	69 ± 32
7	FC Portugal	1	2	0	9	1	8 ± 0	4 ± 0	80 ± 0
19	Bahia2D	0	0	9	0	0	-	-	-
15	Iran	0	0	4	0	0	-	-	-
11	KickOffTUG	0	0	2	0	0	-	-	-

Rank (#), Wins (W), Draws (D), Losses (L), Goals Scored (GS), Goal Plans (GP).

- A player shoots at goal and an opponent kicks the ball during its traversal but merely deflects its and is unable to stop it entering the goal;
- 2 players of different teams kick the ball at the same time of a pass and the ball goes to a player of the team which previously had the ball possession.

Moreover, from the 59 games an average of 2.5 ± 1.4 goal plans existed per match. The team which produced the most goal plans (30) was WrightEagle and also scored the most goals (116) and won the most matches (9).

The winner of the competition (HELIOS2010) played one less game than WrightEagle. HELIOS2010 scored less than 50% of the goals (54) of WrightEagle and ranked 3^{rd} as the team which produced the most goal plans (14), which stands for 50% less than WrightEagle. Both teams played against 5 common teams (Iran, Ri-one, Oxsy, opuCI_2D and Fifty-Storms) and different teams in the remaining matches. In these matches, WrightEagle was up against NCL10 (14^{th}), Nemesis2010 (5^{th}) and Unique (6^{th}) (this last one twice) while HELIOS2010 was up against ESKILAS (4^{th}), HFutEngine (8^{th}) and FC_Pars (9^{th}). Based on this year's team rankings to empirically assess their quality, no conclusions can be drawn to support the thesis that WrightEagle was up against inferior teams than HELIOS2010 on average (without a significant difference) or vice-versa.

The Apollo team achieved the highest ratio of goal plans (56%) per scored goals, having achieved a total of 5 in the 7 matches played. However, 2 of these were very simple and consisted on free-kicks that started in the opponent's goalie area and involved 2 participants (pass-and-shoot play).

The steps of a captured corner-kick goal plan executed at cycle 4551 by WrightEagle in the RoboCup 2010 quarter finals game "WrightEagle_14-vs-opuCI_2D_0" involving 4 participants for 27 cycles are depicted in Fig. 2.

In Fig. 2 the players' actions from the team that owns the goal plan between each of the presented scenes are unanticipated by the opponent. The combined execution of

Fig. 2: Game scenes of an extracted corner-kick goal plan with 4 participants. The black, blue and red arrows represent player action: a pass, run and shoot at goal respectively.

these actions allowed the team to set its teammates free in order to receive the ball and have a clear shot at goal in situations without significant opponent's pressure.

Some metrics (duration of the plan, number of steps, number of participants involved, ball traveled distance) were calculated for the goal plans in order to understand their overall complexity and are summarized in Table III.

TABLE III: Complexity of the goal plans

Metric	Duration	Steps	Participants	Traveled distance
CK	47.3 ± 17.8	7.5 ± 1	3.9 ± 2.4	90.9 ± 30.1
FK	64.2 ± 67	7.1 ± 1.4	3.3 ± 4.8	94.2 ± 70
GK	140.4 ± 29.9	10.6 ± 1.2	5.3 ± 3.3	161.7 ± 21.8
KI	82.7 ± 56.1	8.8 ± 1.4	4.2 ± 5	114.7 ± 61.8
KO	104.6 ± 35.6	10.3 ± 1.3	4.3 ± 4.3	135.1 ± 38.4

Corner-Kick (CK), Free-Kick (FK), Goal-Kick (GK), Kick-In (KI), Kick-Off (KO)

In general, the goal plans were complex since they consisted on the execution of 8 to 10 steps, involving 3 to 5 participants and taking around 80 cycles to complete. The simplest extracted goal plan was a free-kick in the opponent goalie area with 3 steps that took 2 participants and 7 cycles (simple pass and direct shoot at goal). Contrarily to what could be expected, the most complex extracted goal plan had 37 steps and started from a kick-in in the opponent middle instead of a goal-kick for being further away from the opponent's goal. Also contrarily to what could be expected for having the highest number of steps, it did not not involve the highest number of participants (5 instead of 8). However, it was the one which took the most cycles (416) to complete.

The goal plans that took the longest to complete were in general the ones that started furthest away from the opponent's goal. The number of participants required for the execution of a goal plan tends to increase with the distance to the goal, although some exceptions were observed, particularly in matches opposing stronger to much weaker teams.

The number of participants that took part in the extracted goal plans per play mode is described in Table IV.

The majority of the extracted goal plans originated from kick-ins (45%) and involved 3 to 4 players (26%). From these kick-ins, WrightEagle was the team with the most (25%).

The start zones and transition zones for all games and the team with the highest number of extracted goal plans (WrightEagle) are depicted in Fig. 3.

TABLE IV: Goal plans per participants and play mode

Participants	CK	FK	GK	KI	KO	Total
2 players	1	19	0	5	2	27
3 players	5	5	0	18	2	30
4 players	4	5	2	21	7	39
5 players	5	10	4	12	4	35
6 players	0	2	2	6	2	12
7 players	0	0	0	4	1	5
8 players	0	0	1	1	0	2
Total	15	41	9	67	18	150

Corner-Kick (CK), Free-Kick (FK), Goal-Kick (GK), Kick-In (KI), Kick-Off (KO)

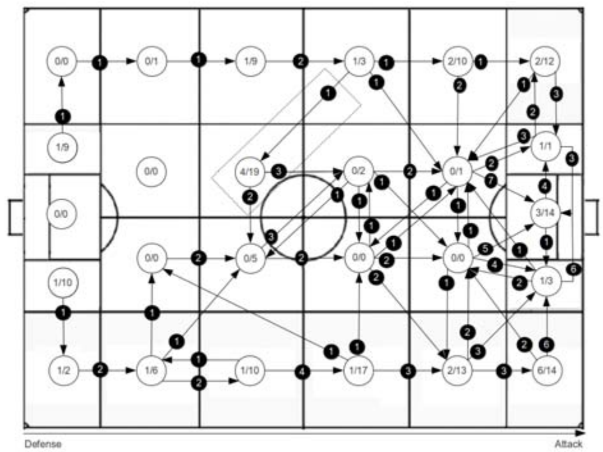

Fig. 3: Start execution zones and zone transitions of extracted goal plans from all games and from WrigthEagle. The left and right numbers in the white circles separated by a slash represent the number of goal plans for all games and for WrightEagle that started from the underlying zone respectively. The number in the black circles is the number of transitions that occurred between two zones for WrightEagle. The sum of zone transitions that enter a given zone is equal to the number goal plans that start and exit from that zone.

By taking a closer look at the dashed polygon it can be concluded that the highest number of extracted goal plans for WrightEagle from that zone was 4 out of a total of 19. Moreover, from this zone the goal plans continue downwards and rightwards for 2 and 3 times respectively. When interpreting this zone exit transitions 1 entry transition from another zone must be considered. The extracted goal plans are distributed unevenly over 17 distinct starting zones and followed 131 distinct execution paths (linked transitions between zones). The zone from which the most goal plans (19) started is near the midfield and it includes kick-offs (18). From these, the most started from the opponent side wings (69), in particular from the right side (44). Other results obtained allowed us to conclude that 97% of the goal plans ended with a shot at goal inside the opponent penalty area performed by players #11 (43%), #10 (26%) and #9 (21%). However, it was a surprise to see that some goals (5) were scored from outside the opponent penalty area, since the distance to goal is quite high and should give a good goalie enough time to make a save. The majority of WrightEagle goal plans started from the opponent side wings near their penalty area. A bird's eye view over the start zones and transitions followed reveals that they tend to start in the wings and converge to the inner sides and center of the opponent's penalty area.

The number of extracted goal plans per game period and play mode are depicted in Table V.

TABLE V: Goal plans per game quarters and play-mode

Game Quarter	CK	FK	GK	KI	KO	Total
First	3	9	0	19	6	37
Second	3	12	4	12	2	33
Third	2	12	2	17	10	43
Fourth	7	8	3	19	0	37
Total	15	41	9	67	18	150

Corner-Kick (CK), Free-Kick (FK), Goal-Kick (GK), Kick-In (KI), Kick-Off (KO)

The 3^{rd} quarter was the period in which the most goal plans (43) were extracted, although their distribution was more or less balanced throughout the game periods. From this data, it can also be inferred that corner-kicks and kick-offs tend to be more effective in the 3^{rd} and 4^{th} quarters respectively, possibly due to teams exhaustion.

The most effective type of extracted goal plans were kick-ins (67) followed by free-kicks (41). The most kick-ins started near the opponents penalty area (50%) and near the midfield zones (28%). Since kick-ins are the events that occur most frequently in a match, this suggests that more goal plans should be devised for these situations.

In order to check if the participation of certain groups of players was favored in the extracted goal plans a cluster analysis was performed for each distinguished number of initial participants and the results are depicted in Table VI.

For instance, in the 5 goal plans that involved 7 players there were only 2 relevant subgroups that emerged with 3 and 4 players respectively. By taking a closer look at subgroup {7,10,11} it should be interpreted that in the smaller subgroups those specific players could be combined in all possible manners and would maintain the same coverage.

From Table VI it can be concluded that the player, pair of players, threesome of players and foursome of players that were most used in the extracted goal plans are {11}, {10,11}, {7,10,11} and {6,7,10,11} respectively. These results can be used to infer which particular players should be payed more attention when a goal plan is about to be triggered, particularly if there are too many from which to choose from.

VII. CONCLUSIONS

The developed set-play extraction process revealed an optimal accuracy for identifying possible goal plans that start from a set-piece after corroboration by a visual inspection.

The results of the 2^{nd} experiment support the relevance of performing this kind of analysis since a significant amount of goals (25%) originated from set-pieces. This also suggests more strongly that the focus of this study should be shifted to the analysis of goal plans that result from play-on situations. Moreover, these results can be used to aid the preparation of a team against specific opponents and derive several guidelines for the definition of goal plans in the future. For instance the extracted goal plans could be used to gain a competitive advantage over an opponent against which they were successful possibly with some minor optimizations.

TABLE VI: Representative groups of players that participated in extracted goal plans. The start and end brackets identify a particular group which can contain one or more player identifiers separated by a comma. Several groups of players with the same coverage are also separated by a comma. The coverage is the percentage of times a group of players participated in goal plans relative to the underlying number of participants depicted in Table IV. Groups of players of smaller sizes were omitted if their coverage was equal to the next largest group described and their composition is equal to all the possible combinations of players of that group.

Participants	Groups of players	Coverage
2 players	{11}	53.33%
2 players	{8,10}	13.33%
3 players	{11}	66.67%
3 players	{10,11},{9,10},{9,11}	30.00%
3 players	{9,10,11}	13.33%
4 players	{11}	82.05%
4 players	{10,11}	53.85%
4 players	{8,10,11}, {7,6,11}	23.08%
4 players	{6,7,10,11}	5.41%
5 players	{9},{10}	75.71%
5 players	{9,10}	54.29%
5 players	{7,9,10},{9,10,11}	34.29%
5 players	{6,7,10,11}	22.86%
5 players	{6,7,8,9,10}	8.57%
6 players	{6}, {10},{11}	83.33%
6 players	{6,7,9,10,11}	25.00%
7 players	{7,10,11}	100.00%
7 players	{6,7,10,11},{9,7,10,11},{5,7,10,11},{5,6,10,11}	80.00%
8 players	{2,6,7,8,9,10,11}	100.0%

The complexity associated with some of the extracted goal-plans (e.g. many participants, steps and/or time to execute) suggests that perhaps these were not planned and thus it will be unlikely for them to succeed repeatedly. There can be no certainty on whether the extracted goal plans were deliberately executed by a team or if they simply emerged as a combination of players simple behaviors. In particular, goal plans that use many players are more likely to be unplanned and pose higher risks if the opponent team recovers the ball since more players might be further from their tactical positions.

Another relevant conclusion that can be drawn from these results is that goal plans that start from kick-ins were the most representative. Thus, since kick-ins occur most frequently in a match more attention should be given to them.

Based on the analysis of the results of the 2^{nd} experiment several guidelines can be inferred to guide the future definition of goal plans set-plays. A set-play should involve up to 5 participants as observed in 87% of the goal plans. A set-play should comprise from 3 to 10 steps as observed in 77% of the goal plans, of which the most had 4 steps (18%).

In the future there are several developments that are worth pursuing to improve the usefulness of the developed framework. One such development consists on extending the analysis for behaviors that occur during play-on and that do not lead to a goal but create an advantage for the team. For instance, it can be useful to extract behaviors that allow a team to preserve ball possession for long periods when it is winning or quickly advance to the opponent team area.

Also, the usefulness of the extracted goal plans can be improved by adding more clever methods for the selection of participants (e.g. consider opponents and passive teammates behaviors) and decide upon the triggering conditions. Robustness could also be added to the extracted set-plays by trying to define virtual transitions between real steps that account for unexpected events (e.g. instead of moving linearly from step 1 to step 2 of a goal plan, a direct leap could be made to a subsequent step).

The development of a fuzzy recognition system that is capable of identifying the extracted set-plays as a complete or partial specification of others that were previously saved in a repository can also be useful to identify the offensive or defensive strategies being used by an opponent in a match.

The extracted set-plays that indite good results could be applied to try to improve the performance of a team (defensively or offensively). To measure the success of these set-plays an automatic procedure should be developed that in conjunction with the previously mentioned fuzzy recognition system will be able to score their impact. Moreover, the ad-hoc set-plays defined by the user could also be automatically checked for their effectiveness by figuring out if they are contributing to an increase in the team's performance.

ACKNOWLEDGMENTS

The first author' was supported with a PROFAD scholarship from IPV. We thank the support of "INTELLWHEELS - Intelligent Wheelchair with Flexible Multimodal Interface" (FCT/RIPD/ADA/109636/2009).

REFERENCES

[1] C. Carling, A. Williams, and T. Reilly, *Handbook of Soccer Match Analysis - A Systematic Approach to Improving Performance*. Routledge, 2nd Edition, 2007.

[2] P. Abreu, V. Vinhas, P. Mendes, L. P. Reis, and J. Garganta, "Real-Time Wireless Location and Tracking System with Motion Pattern Detection," H. Yussof, Ed. InTech, 2010, ch. Robot Localization and Map Building, pp. 467–492.

[3] P. Abreu, J. Moreira, I. Costa, D. Castelão, L. P. Reis, and J. Garganta, "Human versus virtual robotics soccer: A technical analysis," *European Journal of Sport Science*, vol. 12, no. 1, pp. 26–35, 2012.

[4] L. Mota, N. Lau, and L. P. Reis, "Co-ordination in RoboCup's 2D simulation league: Setplays as flexible, multi-robot plans," in *Robotics Automation and Mechatronics (RAM), 2010 IEEE Conference on*, June 2010, pp. 362 –367.

[5] I. Noda, H. Matsubara, K. Hiraki, and I. Frank, "Soccer Server: A tool for research on multiagent systems," *Applied Artificial Intelligence*, vol. 12, no. 2-3, pp. 233–250, 1998.

[6] P. Riley and M. Veloso, "Coaching a simulated soccer team by opponent model recognition," in *Proceedings of the 5th International Conference on Autonomous Agents*, ser. AGENTS '01. New York, NY, USA: ACM, 2001, pp. 155–156.

[7] P. Riley, M. Veloso, and G. Kaminka, "Towards any-team coaching in adversarial domains," in *Proceedings of the 1st International Joint Conference on Autonomous Agents and Multiagent Systems: part 3*, ser. AAMAS '02. New York, NY, USA: ACM, 2002, pp. 1145–1146.

[8] G. Kaminka, M. Fidanboylu, A. Chang, and M. Veloso, "Learning the Sequential Coordinated Behavior of Teams from Observations," in *RoboCup 2002: Robot Soccer World Cup VI*, G. A. Kaminka, P. U. Lima, and R. Rojas, Eds. Springer Berlin / Heidelberg, 2003, vol. 2752, pp. 111–125.

[9] T. Steffens, "Feature-Based Declarative Opponent-Modelling," in *RoboCup 2003: Robot Soccer World Cup VII*, ser. LNCS, D. Polani, B. Browning, A. Bonarini, and K. Yoshida, Eds. Springer Berlin / Heidelberg, 2004, vol. 3020, pp. 125–136.

[10] ——, "Adapting Similarity-Measures to Agent-Types in Opponent-Modelling," in *Workshop on Modeling Other Agents from Observations at AAMAS*, M. Bauer, P. Gmytrasiewicz, G. A. Kaminka, and D. V. Pynadath, Eds., 2004, pp. 125–128.

[11] ——, "Knowledge-Intensive Similarity-Based Opponent Modelling," in *Proceedings of the IJCAI Workshop on Representation, Reasoning, and Learning in Computer Games*, D. W. Aha, Ed., 2005.

[12] R. de Dios Bulos, C. Dulalia, P. Go, P. Tan, and M. Uy, "A Data Mining Approach in Opponent Modeling," in *AI 2005: Advances in Artificial Intelligence*, ser. LNCS, S. Zhang and R. Jarvis, Eds. Springer Berlin / Heidelberg, 2005, vol. 3809, pp. 993–996.

[13] P. Riley and M. Veloso, "Coach planning with opponent models for distributed execution," *Autonomous Agents and Multi-Agent Systems*, vol. 13, pp. 293–325, 2006.

[14] R. Fathzadeh, V. Mokhtari, M. Mousakhani, and F. Mahmoudi, "Mining Opponent Behavior: A Champion of RoboCup Coach Competition," in *Robotics Symposium, 2006. LARS '06. IEEE 3rd Latin American*, 2006, pp. 80–83.

[15] R. Fathzadeh, V. Mokhtari, and M. R. Kangavari, "RoboCup 2007: Robot Soccer World Cup XI," U. Visser, F. Ribeiro, T. Ohashi, and F. Dellaert, Eds. Berlin, Heidelberg: Springer-Verlag, 2008, ch. Opponent Provocation and Behavior Classification: A Machine Learning Approach, pp. 540–547.

[16] J. A. Iglesias, J. A. Fernández, I. R. Villena, A. Ledezma, and A. Sanchis, "The winning advantage: using opponent models in robot soccer," in *Proceedings of the 10th International Conference on Intelligent Data Engineering and Automated Learning*, ser. IDEAL'09. Berlin, Heidelberg: Springer-Verlag, 2009, pp. 485–493.

[17] A. Ledezma, R. Aler, A. Sanchis, and D. Borrajo, "OMBO: An Opponent Modeling Approach," *AI Community*, vol. 22, no. 1, pp. 21–35, January 2009.

[18] J. A. Iglesias, A. Ledezma, and A. Sanchis, "CAOS Coach 2006 Simulation Team: An opponent modelling approach," *Computing and Informatics*, vol. 28, no. 1, pp. 57–80, 2009.

[19] C. Bauckhage, C. Thurau, and G. Sagerer, "Learning Human-Like Opponent Behavior for Interactive Computer Games," in *DAGM Symposium Symposium for Pattern Recognition*, 2003, pp. 148–155.

[20] R. Aler, J. M. Valls, D. Camacho, and A. Lopez, "Programming Robosoccer agents by modeling human behavior," *Expert Systems with Applications*, vol. 36, no. 2, Part 1, pp. 1850–1859, 2009.

[21] G. Kuhlmann, P. Stone, and J. Lallinger, "The UT Austin Villa 2003 Champion Simulator Coach: A Machine Learning Approach," in *RoboCup 2004: Robot Soccer World Cup VIII*, ser. LNCS, D. Nardi, M. Riedmiller, C. Sammut, and J. Santos-Victor, Eds. Springer Berlin / Heidelberg, 2005, vol. 3276, pp. 636–644.

[22] P. Abreu, J. Moura, D. Silva, L. P. Reis, and J. Garganta, "Performance analysis in soccer: a Cartesian coordinates based approach using RoboCup data," *Soft Computing - A Fusion of Foundations, Methodologies and Applications*, pp. 1–15, 2012.

[23] P. Stone, P. Riley, and M. Veloso, "Defining and Using Ideal Teammate and Opponent Agent Models," in *Proceedings of the 17th National Conference on Artificial Intelligence and 12th Conference on Innovative Applications of Artificial Intelligence*. San Francisco, USA: AAAI Press, 2000, pp. 1040–1045.

[24] A. Ledezma, R. Aler, A. Sanchis, and D. Borrajo, "Predicting Opponent Actions by Observation," in *RoboCup 2004: Robot Soccer World Cup VIII*, ser. LNCS, D. Nardi, M. Riedmiller, C. Sammut, and J. Santos-Victor, Eds., vol. 3276, The RoboCup Federation. Lisbon, Portugal: Springer Verlag, July 2005, pp. 286–296.

[25] C. Druecker, S. Huebner, H. Neumann, E. Schmidt, U. Visser, , and H. Weland, "Virtualweder: Using the online-coach to change team formations," University of Bremen, Tech. Rep., 2000.

[26] P. Stone, P. Riley, and M. Veloso, "The CMUnited-99 Champion Simulator Team," in *RoboCup-99: Robot Soccer World Cup III*, M. Veloso, E. Pagello, and H. Kitano, Eds. Springer Berlin / Heidelberg, 2000, vol. 1856, pp. 79–95.

[27] P. Riley and M. Veloso, "Recognizing Probabilistic Opponent Movement Models," in *RoboCup-2001: Robot Soccer World Cup V*, A. Birk, S. Coradeschi, and S. Tadokoro, Eds. Berlin: Springer Verlag, 2002, no. 2377, pp. 453–458.