Probabilistic Decision Making in Robot Soccer*

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Abstract. Decision making is an important issue in robot soccer, which has not been investigated deeply enough by the RoboCup research community. This paper proposes a probabilistic approach to decision making. The proposed methodology is based on the maximization of a game situation score function, which generalizes the concept of accomplishing different game objectives as: passing, scoring a goal, clearing the ball, etc. The methodology includes a quantitative method for evaluating the game situation score. Experimental results in a high-level strategy simulator, which runs our four-legged code in simulated AIBOs' robots, show a noticeable improvement in the scoring effectiveness achieved by a team that uses the proposed approach for making decisions.

1 Introduction

The aim of this paper is to propose a general methodology for taking decisions probabilistically in robot soccer. In a robotic soccer match, a player needs to take several decisions as for example: (i) where to position itself in the field when not having the ball, (ii) when to approach the ball, (iii) when to act as a support player, either supporting an attacker or a defender, (iv) what movements to do with the ball when having it, and (v) when and (vi) to which position to kick the ball. The decisions must take into account the role of the robot (defender, attacker, etc), the state of the game (score), the robot surround (position of teammates, opponents and the ball), and the teammates actions. In addition, decisions should be taken as fast as possible.

Most of the existent work related with decision making in robot soccer has focused in resolving specific tasks such as pass selection, and has not taken enough care of the big picture. The few approaches that consider several tasks at the same time, start their reasoning by considering a lot of reasonable decision criterions, and finally trying to mix them as best as possible. On the contrary, we believe that any strategy must start by defining a clear and general objective to be accomplished. Then, this general objective may be decomposed in more specific ones. In soccer, the general objective is to win the match, which can be also said as: "to score more goals than the opponent". Thus, instead of making a detailed list of possible risks, gains and costs, and then trying to take them all into account in the best way, we are proposing to reason in the opposite way: to clearly define the general objective to achieve, and then

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to find the more relevant criterions that can lead us to right decisions in order to accomplish this objective.

When the problem is faced in this fashion, it is clear how to balance the specific objectives as passing the ball, shooting to the goal, etc., and a wide spectrum of decisions' classes can be performed. Probabilities are nice to define such an approach, because in a probabilistic framework the natural uncertainties found in the process can be easily considered. The here-proposed methodology considers a score function of a given game situation. Decisions are taken in order to maximize the expected value of this score function. To make the kick decisions probabilistically, Montecarlo-based algorithms are used to integrate the PDFs (Probability Density Functions) of the available kicks over the field space. Another particularity of the proposed system is the way it takes opponents into account: they are not merely seen as possible blockers of the intended actions. Instead, we consider that the opposite team is intending, as much as the own, to score goals. Thus, we evaluate their possibilities with the same deepness that we do with the own: all of our analysis is symmetric for both teams. As a result, the presented approach is able to naturally balance defensive and offensive behaviors, and furthermore, it is able to change this balance according to the present situation. As human players do, robots following our approach will be more averse to risk when facing a defensive situation, and will gradually become more prone to take risks as the situation gets more offensive. Finally, the proposed methodology provides a quantitative method for evaluating the game situation score.

The advantages of the proposed system are the following: (i) the method relays only on the expected scored goal difference, and not in others conventionally taken into account such as pass success or ball possession time length; (ii) as stated in [8], when the space of the possible decisions is explored with a grid, it is possible to balance the accuracy of the decision and the computational cost; (iii) the uncertainty in the kicks result is considered; and (iv) the symmetric analysis of the situations allows a natural balancing between offensive and defensive behaviors. One disadvantage of the proposed method is the assumption of arbitrary models for the calculation of several of the probabilities. However, we believe this disadvantage may be corrected, by redefining if necessary the model of these probabilities, without affecting the core of the proposed system.

This paper is organized as follows. In section 2 is presented some related work. The proposed probabilistic methodology for decision making is described in section 3. In section 4, experimental results are presented. Finally, in section 5 conclusions of this work are given.

2 Related work

For simulated soccer there have been proposed several interesting approaches that take into account several factors to make decisions ([4][7][8] to name a few). Some of them are based in reward functions, but finally, they use heuristics to mix probabilities (for example it is not clear how to compare the reward of a successful pass with the one of a successful shoot to the goal). Besides, they do not consider the uncertainty in the kicks' result.

When choosing an appropriate kick for an objective, most of the teams consider the time that it takes to be realized, the ball departure angle, and the shoot power, which is reflected on the ball speed after the kick (see for example the Team Description Papers in [2]). This information is usually acquired using statistics of data obtained from the repetition of a particular kick, and calculating the mean values of the distance and the angle of the final ball position for each available punch. There are different ways to choose the kick as a function of these parameters. From the strategic point of view there are differences at the moment of choosing a kick. For instance, the method implemented by the German Team [5] to pass the ball does not only use the information provided by its team partners; it uses in addition some visual information about the position of the receiver. Then it chooses the pass so that the objective is exactly the position of the receiving robot, which has to be warned right on that moment to react, and go back to the initial position for a better control of the ball.

In [1], it is proposed an interesting approach to deal with kicks uncertainty, based on a MonteCarlo sampling. The probabilities of accomplishing some prioritized objectives (passing, self-passing, shooting, and clearing) were estimated for each kick. We have incorporated the idea of the MonteCarlo sampling to our work, but instead of using a prioritized list of objectives for the objective and kick selection, we are proposing the use of a generalized objective which takes into account simultaneously all the listed objectives considered in [1], plus other possible objectives which are very difficult to consider in such an approach, as for example leading passing (passing not directly to the teammate but to a point ahead).

3 Proposed Approach

3.1 Game Segment

A RoboCup soccer match may be split into *game segments*. A game segment is the interval between two kick offs (kick offs occur when the match starts, and after a goal is scored). Every game segment may end in two ways: time out or goal. We can then define the score obtained in the current game segment as:

$$\beta = \begin{cases} -1 & \omega^{g'} \\ 0 & \omega^{t} \\ 1 & \omega^{g} \end{cases} \tag{1}$$

Where $\omega^{g'}$, ω^{t} and ω^{g} are respectively the events: “the opposite team scores”, “time is out before anyone scores” and “the own team scores”.

3.2 Ball Control Action

A *ball control action* (*BCA*) is what a robot does after catching the ball, and it consists in a relative displacement $\Delta\mathbf{x} = (\Delta x, \Delta y)^T$ and rotation $\Delta\theta$ of the robot holding the ball, and a kick $\mathbf{k}$ of the ball:

$$a = (\mathbf{d}, \mathbf{k})^T;\ \mathbf{d} = (\Delta\mathbf{x}, \Delta\theta)^T \tag{2}$$

Each game segment may be seen as a succession of BCA's $\{a_k\}$. We have a limited set of kicks $\mathbf{\Omega} = \{\mathbf{k}_l\}$. Let (r_l, θ_l) be the polar coordinates, relative to the kicking robot, to what the ball will arrive, if it is allowed to roll freely, after the kick $\mathbf{k}_l$ is performed. We assume that r_l and θ_l are independent Gaussian random variables with respective means $\mu_{r,l}$ and $\mu_{\theta,l}$, and variances $\sigma^2_{r,l}$ and $\sigma^2_{\theta,l}$. Then, the kick $\mathbf{k}_l$ can be parameterized using: $\mathbf{\Pi}_l = (\mu_{r,l}, \mu_{\theta,l}, \sigma^2_{r,l}, \sigma^2_{\theta,l})$. The parameters $\mathbf{\Pi}_l$ have to be calculated previously for each of the available kicks. Figure 1.a shows our current available set of kicks and their parameters.

3.3 Score Function

Let us define a *game situation* as a vector $\mathbf{S} = (\mathbf{R}, \mathbf{b})^T$ where $\mathbf{b}$ is the estimated position of the ball and $\mathbf{R} = (\mathbf{x}_1, ..., \mathbf{x}_{N_R}, \mathbf{x}'_1, ..., \mathbf{x}'_{N_R})^T$ is a vector containing the estimated poses of all robots, being N_R the number of robots per team. In particular, each robot may have an estimation of $\mathbf{S}$. In our implementation, teammate robots share their own estimated positions, the observations of the ball and of the other robots, and each robot tracks all the mobile objects using an EKF based approach. We propose that any situation of the game may be evaluated in terms of how advantageous it is. We will call this measurement the *Game Situation Score (GSS)*. The *GSS* is defined as:

$$GSS(\mathbf{S}) = E(\beta|\mathbf{S}) = P(\omega^g|\mathbf{S}) - P(\omega^{g'}|\mathbf{S}) \tag{3}$$

We are especially interested in situations when the ball just arrived to a new position, after a BCA. We define $\mathbf{S}_k = (\mathbf{R}_k, \mathbf{b}_k)^T$ as the situation produced by a_k, in the moment when the ball stops rolling. The event "a goal is scored by means of a_k" is defined as ω^g_k or $\omega^{g'}_k$, depending on which team scored. The events ω^g_{k+} and $\omega^{g'}_{k+}$ correspond to a goal scored, by means of a later BCA than a_k, by respectively the own team and the opposite team. Then $P(\omega^g|\mathbf{S}_k)$ is calculated as (the calculation of $P(\omega^{g'}|\mathbf{S})$ is symmetrical):

$$P\left(\omega^{g}\left|\mathbf{S}_{k}\right.\right)=P\left(\omega_{k}^{g}\left|\mathbf{S}_{k}\right.\right)+\left(1-P\left(\omega_{k}^{g}\left|\mathbf{S}_{k}\right.\right)\right)P\left(\omega_{k+}^{g}\left|\mathbf{S}_{k}\right.\right) \tag{4}$$

It is straightforward from the previous definitions that the *immediate goal probability* $P\left(\omega_{k}^{g}\left|\mathbf{S}_{k}\right.\right)$ is 1 or 0 depending on whether $\mathbf{b}_{k}$ is inside or outside the opposite goal.

The *future scoring probability* of the own team may be calculated in a recursive form:

$$P\left(\omega_{k+}^{g}\left|\mathbf{S}_{k}\right.\right)=\int P\left(\omega_{k+}^{g}\left|\mathbf{S}_{k+1}\right.\right)P\left(\mathbf{S}_{k+1}\left|\mathbf{S}_{k}\right.\right)d\mathbf{S}_{k+1} \tag{5}$$

It is impractical to calculate the former integral, so we make some simplifications: (i) after the ball arrives to $\mathbf{b}_{k}$, the closest robot of each team, will lead to $\mathbf{b}_{k}$ until one of them catches the ball, (ii) as the pose of the rest of the robots at k+1 is unpredictable, we will assume they will remain static, and (iii) a_{k+1}, and thus $\mathbf{b}_{k+1}$, are totally determined by the team of the robot which will perform a_{k+1} and by all the robots' poses. Therefore, $\mathbf{S}_{k+1}$ is only a function of which robot will capture the ball and consequently perform a_{k+1}. Two events are defined: "the closest robot of the own team will catch the ball", called ω_{k+1}^{c}, and "the closest robot of the opposite team will catch the ball", called $\omega_{k+1}^{c'}$. Then, equation (5) can be rewritten as:

$$P\left(\omega_{k+}^{g}\left|\mathbf{S}_{k}\right.\right)\approx P\left(\omega_{k+}^{g}\left|\omega_{k+1}^{c},\mathbf{S}_{k}\right.\right)P\left(\omega_{k+1}^{c}\left|\mathbf{S}_{k}\right.\right)+P\left(\omega_{k+}^{g}\left|\omega_{k+1}^{c'},\mathbf{S}_{k}\right.\right)P\left(\omega_{k+1}^{c'}\left|\mathbf{S}_{k}\right.\right) \tag{6}$$

The *catching probabilities* $P\left(\omega_{k+1}^{c(c')}\left|\mathbf{S}_{k}\right.\right)$ are approximated as (analogous for $\omega_{k+1}^{c'}$):

$$P\left(\omega_{k+1}^{c}\left|\mathbf{S}_{k}\right.\right)=\frac{t_{c}'\left(\mathbf{S}_{k}\right)}{t_{c}'\left(\mathbf{S}_{k}\right)+t_{c}\left(\mathbf{S}_{k}\right)} \tag{7}$$

Where $t_{c}\left(\mathbf{S}_{k}\right)$ and $t_{c}'\left(\mathbf{S}_{k}\right)$ are the amounts of time required to arrive to $\mathbf{b}_{k}$ for the closest robot of respectively the own team and the opposite team:

$$t_{c}\left(\mathbf{S}_{k}\right)=\frac{\left|\mathbf{x}_{i,k}-\mathbf{b}_{k}\right|}{v_{R}}+\frac{\left|\theta_{i,k}-\measuredangle\left(\mathbf{b}_{k}-\mathbf{x}_{i,k}\right)\right|}{\omega_{R}} \tag{8}$$

Where $\mathbf{x}_{i,k}$ and $\theta_{i,k}$ are respectively the position and orientation of the robot of the own team closest to the ball at time k. Note that the time required for displacing and for rotating are considered in terms of the estimated robot linear speed v_{R} (=40cm/sec) and angular speed ω_{R} (=120°/sec) (these values correspond to AIBO ERS7 robots). The calculation of $t_{c}'\left(\mathbf{S}_{k}\right)$ is analogous.

The *future scoring probabilities* $P\left(\omega_{k+}^{g}\left|\omega_{k+1}^{c(c')},\mathbf{S}_{k}\right.\right)$ can be calculated using (4):

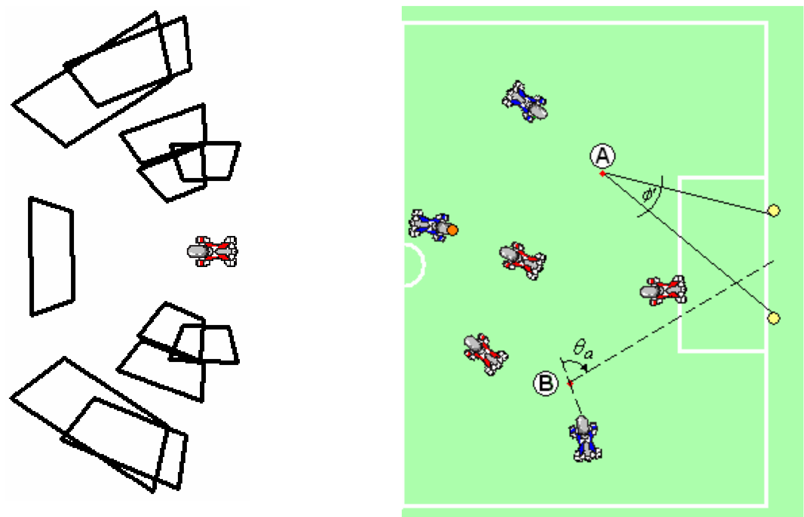
$$P\left(\omega_{k+}^{g}\left|\omega_{k+1}^{c(c')},\mathbf{S}_k\right.\right)=P\left(\omega_{k+1}^{g}\left|\omega_{k+1}^{c(c')},\mathbf{S}_k\right.\right)+\left(1-P\left(\omega_{k+1}^{g}\left|\omega_{k+1}^{c(c')},\mathbf{S}_k\right.\right)\right)P\left(\omega_{k+1+}^{g}\left|\omega_{k+1}^{c(c')},\mathbf{S}_k\right.\right) \tag{9}$$

This leads to a possibly infinite recursion, therefore we will approximate all the remaining probabilities as a function of some coarse indicators of how advantageous the resulting situations are. We introduce the *expected free time* (t_f or t'_f) of the robot that catches the ball, as the amount of time that the robot will be able to hold the ball without the direct presence of a rival, and is calculated as (analogous for t'_f):

$$t_f = bnd\left(0;t'(\mathbf{S}_k)-t(\mathbf{S}_k);\infty\right) \tag{10}$$

With $bnd(c;d;e)$ defined as the quantity d lower bounded by c and upper bounded by e. We also define the *aligning time* (t_a or t'_a) of the robot that catches the ball as the amount of time that it will need for aligning to its opposite goal. If $\mathbf{g}'$ is the position of the opposite goal , t_a is calculated as (analogous for t'_a):

$$t_a = \frac{\theta_a}{\omega_R} = \frac{\left|\measuredangle\left(\mathbf{b}_k-\mathbf{x}_{i,k}\right)-\measuredangle\left(\mathbf{g}'-\mathbf{b}_k\right)\right|}{\omega_R} \tag{11}$$



(a) (b)

Fig. 1. (a) Set of available kicks with their relative means and variances, each plotted polar rectangle is bounded by $\left(\mu_{r,l}\pm\sigma_{r,l},\mu_{\theta,l}\pm\sigma_{\theta,l}\right)$. (b) illustration of ϕ' and θ_a for two objective points (A and B, respectively).

We approximate $P\left(\omega_{k+1}^{g}\left|\omega_{k+1}^{c},\mathbf{S}_k\right.\right)$ as a function of the *opening angle* ϕ', which is the angle difference between the two posts of the goal from the point of the ball.

$$P\left(\omega_{k+1}^{g}\left|\omega_{k+1}^{c},\mathbf{S}_{k}\right.\right)=bnd\left(0;\frac{t_{f}-t_{a}}{\sec};3\right)bnd\left(0;\frac{\phi'}{\bar{\sigma}_{\theta}};1\right)u\left(\max_{j}\left(\mu_{r_{j}}\right)-\left|\mathbf{b}_{k}-\mathbf{g}'\right|\right) \tag{12}$$

Where $\bar{\sigma}_{\theta}$ is the mean of the angle variances of the available kicks, and u is the step function, which will become 1 if it is possible to reach the goal, considering the maximum mean distance reached by an available kick.

The remaining probabilities are even fuzzier, therefore we make use of coarser indicators. We approximate $P\left(\omega_{k+1+}^{g}\left|\omega_{k+1}^{c},\mathbf{S}_{k}\right.\right)$ as:

$$P\left(\omega_{k+1+}^{g}\left|\omega_{k+1}^{c},\mathbf{S}_{k}\right.\right)=\nu_{1}\left(t_{f}-t_{a}\right)\frac{\max\left(\mu_{r_{i}}\right)}{\left|\mathbf{b}_{k}-\mathbf{g}'\right|} \tag{13}$$

With a selected value of $\nu_{1}=0.3Hz$. For the calculation of $P\left(\omega_{k+}^{g}\left|\omega_{k+1}^{c'},\mathbf{S}_{k}\right.\right)$, we assume that a robot will not score in its own goal. Thus,

$$P\left(\omega_{k+1}^{g}\left|\omega_{k+1}^{c'},\mathbf{S}_{k}\right.\right)=0 \tag{14}$$

$$\Rightarrow P\left(\omega_{k+}^{g}\left|\omega_{k+1}^{c'},\mathbf{S}_{k}\right.\right)=P\left(\omega_{k+1+}^{g}\left|\omega_{k+1}^{c'},\mathbf{S}_{k}\right.\right) \tag{15}$$

The *future crossed score probability* $P\left(\omega_{k+1+}^{g}\left|\omega_{k+1}^{c'},\mathbf{S}_{k}\right.\right)$ is approximated as:

$$P\left(\omega_{k+1+}^{g}\left|\omega_{k+1}^{c'},\mathbf{S}_{k}\right.\right)\approx\frac{\tau}{t_{f}'}\frac{\max\left(\mu_{r_{i}}\right)}{\left|\mathbf{b}_{k}-\mathbf{g}'\right|} \tag{16}$$

Where a value of $\tau=0.3\sec$ is found to yield satisfactory results. Summarizing, $GSS\left(\mathbf{S}_{k}\right)$ may be calculated using equations (3), (4), (6), (7), (8), (9), (10), (11), (12), (13), (15), (16). Figure 1.b illustrates some of the variables used in the calculation of the *GSS*.

3.4 Decision Map

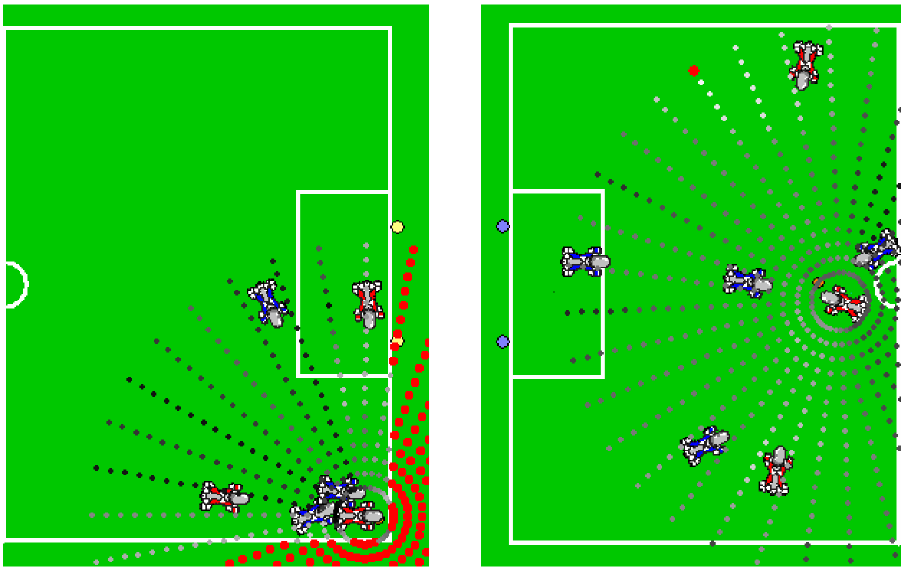
In the moment where a robot holds the ball, it has infinite possible BCA's that should be evaluated in order to decide for the best. We make a discretization of this space to be able to explore it. The discretization consists in a polar grid, where the distance is limited by the maximum distance that the ball can be kicked considering the available kicks, and the amount of time that the ball can be held. This grid is called *decision map* and consists in *M objective points* $\mathbf{p}_{m}$. Figure 2 shows some examples of decision maps. Accomplishing the generalized objective is defined as maximizing the expected *GSS* of the final position of the ball. The decision map is used to explore the space of feasible final positions of the ball after a BCA.

3.5 Objective and Ball Control Action Selection

If we leave $\mathbf{R}$ fixed, *GSS* may be seen as a function of the ball position $\mathbf{b}$, $GSS_{\mathbf{R}}(\mathbf{b})$. Then, for each objective point $\mathbf{p}_m$ in the decision map, its *ideal score* π_m is calculated as:

$$\tilde{\pi}_m = GSS_{\mathbf{R}}\left(rep\left(\mathbf{p}_m\right)\right) \tag{17}$$

If $\mathbf{p}_m$ is out of the field, the ball will be replaced by a human referee in an arbitrary point (see [3] for details). Thus $rep\left(\mathbf{p}_m\right)$ is the expected ball replacement position if $\mathbf{p}_m$ is out of the field, and in other case it is equal to $\mathbf{p}_m$.



(a) (b)

Fig. 2. Examples of decision maps and taken decisions, using the developed high-level strategy's simulator. The polar grid is around the red robot that holds the ball. Lighter points correspond to higher scores in the decision map. The big red points correspond to the selected points. (a) Defensive situation, the red robot holding the ball is blocked by two blue robots, thus points out of the field are selected (even preferring them over a possible but risky pass to the goalie), because its partner will be very close to the ball after the referee replace it. (b) Offensive situation, where a leading pass is selected, preferring it over a direct pass.

Taking into account objective points out of the field, the *rep* function has the nice effect, often observed in human players, that in some situations the robot may decide to kick the ball out of the field (see a simulated example en figure 2.a). Let us define the *filtered score* of the objective point $\mathbf{p}_m$ as:

$$\bar{\pi}_m = E\left(GSS_{\mathbf{R}}\left(rep\left(\mathbf{b}\right)\right)\middle|\mathbf{p}_m\right) \tag{18}$$

Note that $\bar{\pi}_m \neq \tilde{\pi}_m$ since there is an uncertainty in the final position of the ball after performing any kick. To consider this uncertainty, $\bar{\pi}_m$ is calculated as the result of applying a Gaussian low-pass filter over each polar coordinate to $\tilde{\pi}_m$. Consequently, smooth maxima of $\tilde{\pi}_m$ are preferred over sharp ones.

For the sake of simplicity, to calculate $\tilde{\pi}_m$ and $\bar{\pi}_m$ we use **R** as the estimation of the poses of all the robots in the moment when the decision is taken. However, **R** will probably vary from the moment when the robot makes de decision of where to kick the ball, to the moment when the ball finally arrives to its final position **b**. We assume that the variation of **R** when time passes will always diminish the maxima of $\bar{\pi}_m$, which is a reasonable assumption since as time passes by, other robots may block the way from the robot holding the ball to any given objective point. Thus, for each objective point $\mathbf{p}_m$ in the decision map, we select the index $l(\mathbf{p}_m)$ of the required kick $\mathbf{k}_{l(\mathbf{p}_m)}$ as:

$$l(\mathbf{p}_m) = \arg\min_l \left(t_d \left(\mathbf{k}_l, \mathbf{p}_m, \mathbf{R} \right) \right) \tag{19}$$

Where $t_d(\mathbf{k}_l, \mathbf{p}_m, \mathbf{R})$ is the *required dribbling time* for kicking to the objective point $\mathbf{p}_m$, using the kick $\mathbf{k}_l$, and given the robots (teammates and opponents) poses $\mathbf{R}$, and is calculated as:

$$t_d(\mathbf{k}_l, \mathbf{p}_m, \mathbf{R}) = \frac{|\Delta \mathbf{x}_{m,l}|}{v_R} + \frac{|\Delta \theta_{m,l}|}{\omega_R} \tag{20}$$

With $\Delta \mathbf{x}_{m,l}$ and $\Delta \theta_{m,l}$ being respectively the required displacement and rotation of the robot to perform $\mathbf{k}_l$ and reach $\mathbf{p}_m$, if the kick results in its expected values $\mu_{r,l}$, $\mu_{\theta,l}$. If the way from the robot to $\mathbf{p}_m$ is free, $\Delta \mathbf{x}_{m,l}$ just aims to adjust the distance to $\mathbf{p}_m$ (the robot moves in the axis between it and $\mathbf{p}_m$). If the way to $\mathbf{p}_m$ is blocked, $\Delta \mathbf{x}_{m,l}$ also considers an obstacle-avoiding component, which means that the robot will move to the closer free axis to $\mathbf{p}_m$, to the point at a distance $\mu_{r,l}$ of $\mathbf{p}_m$. In both cases, $\Delta \theta_{m,l}$ is calculated to align the robot with the needed angle to kick to $\mathbf{p}_m$ using $\mathbf{k}_l$. Once $l(\mathbf{p}_m)$ is selected, the minimum dribbling time, $t_d\left(\mathbf{k}_{l(\mathbf{p}_m)}, \mathbf{p}_m, \mathbf{R}\right)$, is used to punish the *final score* π_m of the objective point $\mathbf{p}_m$.

$$\pi_m = \begin{cases} \bar{\pi}_m - \nu_2 t_d\left(\mathbf{k}_{l(\mathbf{p}_m)}, \mathbf{p}_m, \mathbf{R}\right) & t_d\left(\mathbf{k}_{l(\mathbf{p}_m)}, \mathbf{p}_m, \mathbf{R}\right) < 3 \\ -1 & \sim \end{cases} \tag{21}$$

With a selected value of $\nu_2 = 0.12Hz$. The condition in (21) ensures that only feasible points are considered (the robot is allowed to hold the ball for a maximum of

3 seconds [3]). The selected objective point $\mathbf{p}_m$ is selected as the one that maximizes π_m. Figure 2 shows some examples of the calculation of π_m in determined situations.

4 Results

As we have defined the decision making problem –in terms of maximizing the expected score advantage obtained– results should show that a team using the presented decision making framework is able to beat, getting as much score advantage as possible, another team using another decision making framework. The complete benefits of the system should be noticeable in a standard 4 versus 4 robots match. To test the system and to be able to present comprehensive results, we have developed a high-level strategy simulator, *UChile HL-SIM*, which runs our four-legged code in simulated AIBO's robots. Differing from our realistic simulator, UChilSim [6], UChile HL-SIM is not focused in realistic 3D visualization of scenes, neither in realistic dynamic interactions simulation, but it is intended for debugging specifically high-level strategy and behaviors. For that purpose, each simulated robot runs our strategy and actuation code, and the simulator brings them error-free perception and world modeling information. The result of the intended displacements of the robot is also simulated as error-free. Dynamic interactions between objects (ball, robots, and goals) are modeled in an idealized but comprehensive fashion (simplified 2D geometry). In order to provide a normal game flow, refereeing is also simulated, taking into account the RoboCup 2006 Four Legged League Competition Rules [3]. Figure 3 shows a screenshot of UChile HL-SIM.

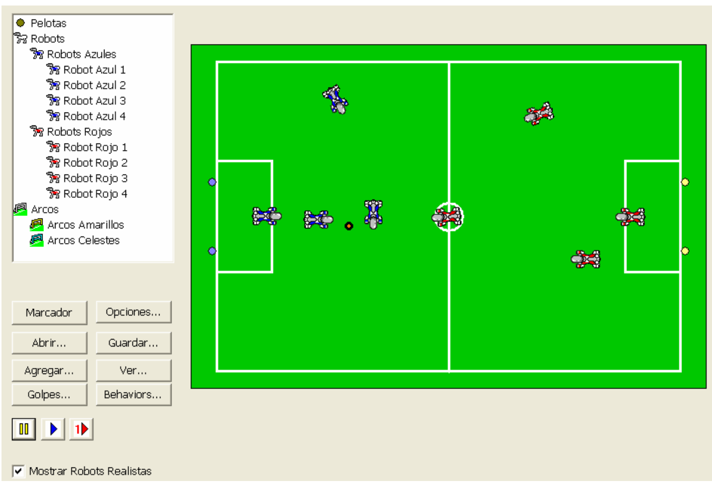


Fig. 3. UChile HL-SIM: High Level simulator used for testing the proposed strategy.

For testing and validation purposes, we tested the described probabilistic-based decision making strategy, in 10 simulated matches between a team which uses this new strategy against a team which uses the decision making system proposed in [1] (probabilistic kick selection). The matches were always won by the proposed approach with an average goal difference of 8.5 (see Table 1 for details on the results). In the simulated matches, it was evident how some of the described improvements, as leading passes and clearing outside the field, appeared.

Table 1. Detailed results of the simulated matches. The proposed strategy score goes first.

Match	Score	Goal Difference
1	12 - 5	7
2	14 - 3	11
3	6 - 4	2
4	7 - 3	4
5	9 - 2	7
6	15 - 2	13
7	14 - 1	13
8	16 - 3	13
9	9 - 3	6
10	10 - 1	9
Average	**11.2 - 2.7**	**8.5**

5 Conclusions

We have presented a novel approach for general decision making in robot soccer, based on the definition of a game situation score function, and the consequent discrimination of more specific objectives as passing and shooting to the goal.

The main advantage of the proposed system is that it relays only on the scored goals probability, and not in others conventionally taken into account such as pass success or ball possession time length. Additional advantages are the possibility of balancing the accuracy of the decision and the computational cost, by modifying the decision map resolution, and the consideration of the kicks' result uncertainty. The assumption of arbitrary models for the calculation of some of the probabilities should be corrected in future works, for example by using a machine learning approach.

The presented approach takes into account the uncertainty in the actions' results (kicks PDF's), but it does not take into account the uncertainty in the perception of the situations (vision, objects tracking and localization). We are planning to extend our work to make it able to consider the perceptual uncertainty.

The presented high-level strategy simulator is very well suited for testing high-level strategy and behaviors. We are planning to extend its capabilities in order to learn the parameters and morphology of the decision-making's algorithms inside the behaviors of different levels.

The preliminary results encourage us to continue developing our system. In particular, more factors may be included to better estimate some probabilities, but always keeping the conceptually hierarchized approach. On the other hand, some of the parameters used for calculating probabilities may be learned during a game, in order to adapt the strategy to the opponent characteristics.

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