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Positioning in Robots Soccer

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1. Introduction

In this chapter, the focus is on an important issue of robots' decision making process which is positioning. Positioning involves making the best decision for the agents who do not possess the ball regarding the team strategy and consequently finding the best target for them. Current section would express some evidences to prove the positioning criticality.

Multi-agent frameworks usually restrict the agents' communications; therefore understanding the game state and collaborators' situation is based on the information provided by the world model. Regards to this information the agent must decide about game state and his action.

In robot soccer competition, separate tasks need to be defined for the agent defending the goal (the goalie) and the agent intercepting the ball (the active agent). The other agents are *strategic agents* who need to do positioning, i.e. getting distributed in the field regarding the team strategy. The positions of these strategic players have impressive effects on decision making process of both teammate and opponent agents. In the following paragraphs we explain the effects of good positioning on teammates tasks.

- The collaboration between goalie and goal defenders is of crucial importance for saving the goal. A simple kind of this collaboration occurs when defenders' positions cover some parts of the goal coordinates; this enables goalie to take care of a small part of the goal area rather than whole of it.
- The importance of collaboration between active agent and strategic agents is important as well. To see that, we need some knowledge about active agent tasks and decision making process. Active agent can kick the ball by different velocities and (in some soccer frameworks) different kicking angles. Applying these options, different actions can be defined for active agent. For example, a kick with small velocity is a dribble action and a kick by higher velocity can be a pass action. Assume the active agent wants to pass the ball to a teammate. The teammate receiving the pass should be close enough to the active agent (to avoid world-model's noise affects) and also far from opponent agents (to reduce the probability of losing the ball). If the active agent concerns just these factors, the positioning process can be defined as distributing the

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agents in the way of increasing the number of eligible agents. Provided with more eligible agents, the active agent can perform its action with higher accuracy.

To see the effect of good positioning on opponents decision making process, assume that the opponent's active agent wants to select one of his teammates to pass the ball. By blocking, i.e. following and sticking to the other opponents, the opponent's active agent can not find free teammate and its decision making process would be corrupted. Also through blocking, the probability of seizing the ball would be increased and the opponents' attacks would be counteracted. As it is clear blocking should be defined as a part of positioning process.

We come to conclusion that a perfect positioning methodology is an important issue for a team. As described above a good positioning of strategic agents improves the performance of goalie and active agent. Moreover a good positioning is vital for blocking opponents in a defensive situation. 'Offside trap' is another plan that can be applied through a good positioning method to keep the goal area safe.

After describing the benefits of perfect positioning methodologies, we will see some obstacles of developing such methods; during the competition, regards to the ball position, strategic agents have to traverse long paths to reach suitable position and driving to the destination, needs agent's stamina. Whereas robots (like humans) have restricted stamina, saving the stamina is vital and developing positioning methods in which agents spend minimum stamina is another challenge in positioning process. Another aspect for developing beneficial positioning process is determining effective parameters for positioning process. Some of these parameters could be the attraction vectors to the ball, teammates, opponents and aggressiveness vector to the opponent goal.

Positioning decision making is based on the information received from agent's environment. Analyzing this information enables agent to decide about its further position. After processing the information the agent does not need more interactions to exterior components. It means that the positioning process is independent of robot's class (simulated in 2 or 3 dimensions, middle size, humanoid, etc.) and the protocol of gathering information. Here we illustrate the positioning methodologies implemented in Robocup soccer simulation framework; however they can be extended to other robot soccer frameworks.

Different approaches are presented in Robocup soccer simulation framework. The common approach is Dynamic Positioning which is considered in this chapter. There are two popular dynamic positioning methods in Robocup soccer simulation framework. Each of them has some advantages and disadvantages. The first approach is Situation Base Strategic Positioning (SBSP) presented by FC Portugal soccer simulation team (Reis et al., 2001(a)), and the second is Dynamic Positioning based on Voronoi Cells (DPVC) which presented by UTUtd soccer simulation team (Dashti et al., 2006).

The SBSP method defines target position for strategic agents; an agent's target position is calculated regarding the agent's role and the current formation of teammates. Also some home positions are assigned to agents such that each agent is allowed to move just in the specific area defined around its home position. These home positions are used for assigning roles to agents. The target position is calculated based on agents' home positions. Formation is arrangement of agents in the game field and involves agents' roles. Regarding the game situation different formations and respectively different home positions are defined. These home positions are one of the restrictions of the SBSP method. DPVC solves this problem and introduces a methodology in which no home position and formation is defined.

In section 2 we have an overview on present positioning methods in Robocup soccer framework. Centroidal Voronoi Diagrams would be discussed in sections 3. DPVC as a

dynamic positioning approach of positioning is presented in section 4. Section 5 contains the results of some experiments in which DPVC and SPSB are compared.

2. Previous Works

2.1 Strategic Positioning

Generally at a certain moment, the positioning destination of an agent is called its strategic position. Strategic positioning method discusses about problems of choosing the strategic position and way of driving to there. There is always one player who is associated with the ball and obeys a different decision method based on the strategy; other agents should move toward their best position in the field. So positioning should be carefully implemented in the team strategy. The most popular strategic method for positioning in Robocup Soccer Simulation is SBSP (Situation Based Strategic Positioning) (Reis et al., 2001[a]) which is presented by FC Portugal team (Reis et al., 2001[b]). This method defines specific target positions for agents who do not possess the ball; these target positions are calculated with regard to the current formation of the team and roles of agents in this formation. For active situations, the agent position on the field is calculated using specific ball possession, ball recovery or playoff decision mechanisms. To calculate its strategic positioning, the agent analyses which is the game situation, tactic and formation in use and its positioning (and corresponding player type). Using the tactic, formation and positioning the agent calculates its base strategic position in the field in that formation.

This position is then adjusted according to the ball position and velocity, situation (attack, defense, scoring opportunity, etc.) and player type strategic information. The agent then issues a command that moves it towards that strategic adjusted positioning. This behavior enables the team to move similarly to a real soccer team, keeping the ball well covered while the team remains distributed along the field. Fig. 1 (Comes from Reis et al., 2001(a)) illustrates the graphical schematic of strategic positioning which described in SBSP method.

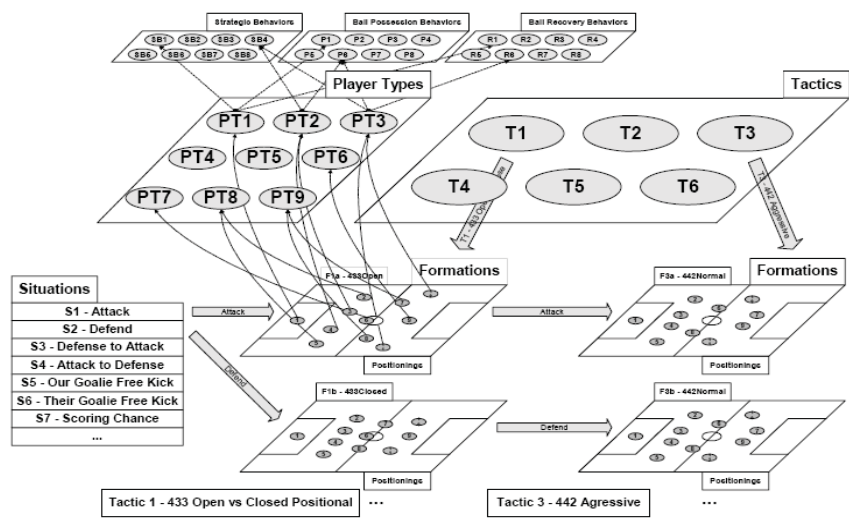


Fig. 1. Team strategy definition example

2.2 Dynamic Positioning

The goal of dynamic positioning is to let the agents to switch their positioning inside a given tactic and formation whenever that action leads to an improvement of the team global utility. Each agent has an allocated position inside the current formation that changes dynamically with the competition specific situation. Due to the dynamic positioning Situation Based Strategic Positioning for Coordinating Homogeneous Agents and role exchange mechanism agents do not have fixed positioning inside the formation.

For example, agent 2 can be at positioning 2 at a given time and at positioning 9 a few moments later.

There are many different implementations of Dynamic Positioning including the approach of FCPORTUGAL which was based on SBSP but here we will discuss the newest approach of Dynamically Positioning presented by ZJUBase team in Robocup2005 (Hao et al., 2006).

ZJUBase dynamic positioning method used NURB curves (Schneider 1996) to describe the strategic movement of players at a certain moment. In this method a parametric function on the balls position is defined to calculate the players' position. Here an important motivation for employing the NURB curves is the ability to control smoothness and the convenience. For example, Some spots B^i arbitrarily placed as control points, and the curve drawn with a NURB function, as shown in Fig. 2-a. Then in Fig. 2-b, The point B7 moves which its motion makes changes on curvature. So in order to get the required curve we only need to place and adjust the control points. This feature enables us to build a graphical editor and get much easier to adopt the positioning strategy. The applied function can be expressed by equation 1.

$$Q(u) = \frac{\sum B_i \omega_i N_{i,k}(u)}{\sum \omega_i N_{i,k}(u)} \quad (1)$$

Where B^i is the projection of one of four-dimensional control point and the ω^i is its weight. Equation 2 shows the $N(u)$ function.

$$N_{i,0}(u) = \begin{cases} 1 & t_{i \leq u < t_{i+1}} \\ 0 & otherwise \end{cases} \quad (2)$$

$$N_{i,k}(u) = \frac{(u - t_i)N_{i,k-1}(u)}{t_{i+k} - t_i} + \frac{(t_{i+k+1} - u)N_{i+1,k-1}(u)}{t_{i+k+1} - t_{i+1}}$$

Here it is the conventional notation for the i 'th knot in the knots vector [Fig. 2] and k is the order of the curve. In this function these parameters are determinate. The three equations are based on a NURB curve. To learn more about the NURB curves, please refer to some related books or papers, such as (Schneider 1996).

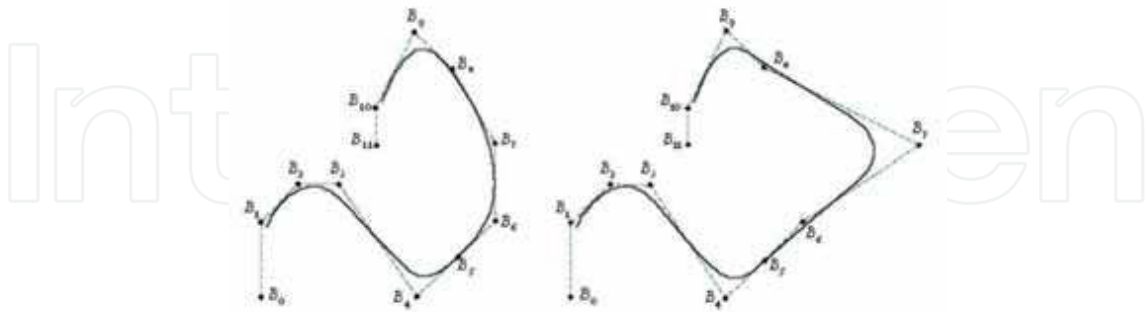


Fig. 2. Defining a curve with control points (Comes from (Schneider 1996))

2.3 Positioning using machine learning

For everyone with a background in artificial intelligence it is not a surprise to see that machine learning approaches are able to get good results in different complex aspects of robot soccer. Here we will describe a reinforcement learning approach which implemented by the BrainStormers team (Riedmiller et al., 2005) at 2D league of robocup2005 competition:

The key idea behind this approach is to learn a central value function $V(s)$ for all players that describe how is a desirable situation. In other words, $V(s)$ is a mapping from a state s to a value in $[-1, 1]$. A value close to 1.0 indicate that this situation is close to success (goal), a value near -1.0 means that it is very probable to loose the ball in that situation.

In this approach a situation consists of ball position and velocity plus the position of all attacking teammates and all defending opponents. The number of teammates and opponents that are used in the state representation for the value function has to be fixed beforehand.

The learning is done in epochs. In the beginning, the value function is initialized randomly so the players pursue a random strategy. Now the players play according to that strategy until five successful trajectories have been collected. If a trajectory was unsuccessful (e.g. loss of the ball) it is also stored. An example set E consisting of situations and rewards is generated from these five successful plus maximal five unsuccessful trajectories. The terminal state S_n of a trajectory gets a reward of 1.0 ($V(S_n) = 1.0$) if it is a successful terminal state and a reward of -1.0 ($V(S_n) = -1.0$) otherwise. The reward of the other states in the trajectory depends on the distance from the terminal state. Let $[S_1, S_2, S_3, \dots, S_n]$ be the states encountered on a trajectory. The equation 3 computes these states' value.

$$V(s_i) = \text{decay}^{(n-i)} * V(s_n) \quad i=1, \dots, n-1 \quad (3)$$

The action set for a player without the ball is very simple and consists only of moving to different positions relative to the current player position.

It is clear that such players' arrangement yield to players arbitrary moving, to handle this condition Riedmiller et al. like SBSP used the concept of home position.

A player without ball can choose an action from the following actions types (Actions that moves the player out of his home area is not allowed):

- go in one of eight directions from current position.

- go to one of eight positions around the players' home position.
- go to home position.

3. Centroidal Voronoi Diagrams

Since 1908 when Voronoi Tessellations were formally defined and studied by Russian Mathematician Georgy Voronoi, these diagrams have found numerous applications in various fields of study including Physics, Biology, Chemistry, etc. To see a list of application, see (de Berg et al., 2000) .

One of the applications of Voronoi Tessellations can be in Robocup Positioning.

Consider that you are given the positions of a set of agents and these agents are to cover the field in order to have some sort of control on whole the field. This control can be defined as a reasonable distance to the ball if the ball is put randomly on some point. To handle this situation, it is useful to partition the field into areas of influence in a way that each agent is responsible to cover one area. The area assigned to each agents can be defined as the set of the points to whom the agent is the nearest agent. This leads to the formal definition of Voronoi Diagram:

Defenition 1:

Given a set of points $\{S_1, S_2, \dots, S_n\}$, the Voronoi cell V_i corresponding to the point S_i is defined as the set: $V_i = \{X \mid |X - S_i| < |X - S_j| \text{ for } j = 1, \dots, n, j \neq i\}$. The points $\{S_i\}_{i=1}^n$ are called generators or sites and the resulted tessleation is called Voronoi Tessellation or Voronoi Diagram.

Modeling the agent's positions as the Voronoi Sites has some advantages that would be discussed later. First we review some easy facts about Voronoi Diagrams. You can find most of the proofs in (de Berg et al., 2000).

Observation 1:

V_i (Voronoi Cell corresponding to the i 'th site) is the intersection of $n-1$ lines and hence, an open convex polygon region bounded by at most $n-1$ vertices called *Voronoi Vertices* and at most $n-1$ edges called *Voronoi Edges*.

Observation 2:

Since Voronoi Tessellation applies on whole the plane, some Voronoi Cells would be unbounded, however in most of the applications it is usefule to define a *bounding box* containig all sites and Voronoi Vertices. (Fig. 3)

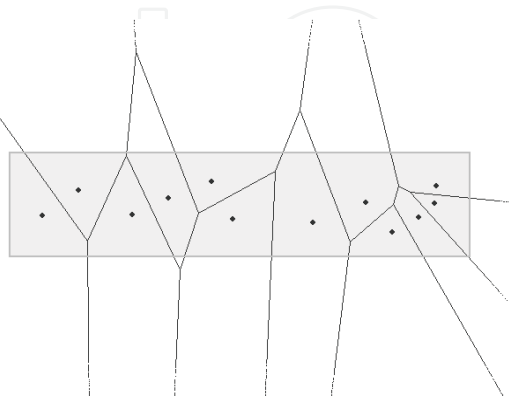


Fig. 3. a bounding box for the Voronoi Diagram

Observation 3:

$\Omega(n \log n)$ is a lower bound for computing the Voronoi Diagrams. This can be shown by reducing the problem of sorting to the problem of computing Voronoi Diagrams. Also there are some algorithm achieving this bound, among them the most popular is *Fortune Algorithm*. Fortune Algorithm uses a sweep line method for computing Voronoi Diagram. However for the problem of positioning in Robocup, since there are just a small number of sites, the time complexity is not a matter and a simpler algorithm can be more effective.

Observation 1 provides a very simple method for computing the voronoi diagram in a bounded box. For computing the cell of agent i , It is enough to start with the entire box and cut it $n-1$ times with bisectors of site i with $n-1$ other sites. (Fig. 4)

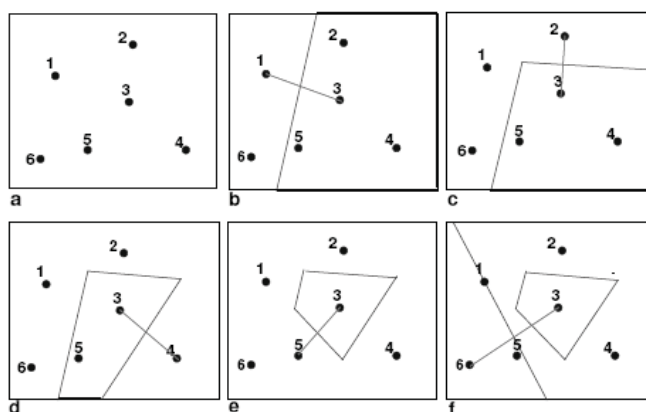


Fig. 4. A simple Algorithm for Computing Voronoi Diagram

3.1 Centroidal Voronoi Diagrams

Centroidal Voronoi Diagram are an interesting type of Voronoi Diagrams having several applications in to problems in image compression, finite difference methods, distribution of resources, cellular biology, statistics, and even the territorial behavior of animals. For a detailed discussion of these applications See (Du et al., 1999).

In this section we study Centroidal Voronoi Diagram as a rather ideal dynamic formation of agents in the field.

The *centroid* of an object X in 2-dimensional space is the intersection of all lines that divide X into two parts of equal moment about the line. Informally, it is the "average" of all points of X . The x -coordinate of the centroid of an object can be calculated as the integral $\int x \cdot f(x) dx / \int f(x) dx$, where $f(x)$ is the vertical extent of the object at abscissa x . In this way it is rather easy to find the centroid of an object.

The geometric centroid of a physical object coincides with its *center of mass* if the object has uniform density. So some times we refer the 'centroid' as the 'center of mass' or shortly 'center'.

A *centroidal Voronoi diagram* is a Voronoi tessellation whose generating points (sites) are the centroids (centers of mass) of the corresponding Voronoi regions. Note that to define centroids for Voronoi Cells, all of them need to be bounded. As a result Centroidal Voronoi Diagrams are defined on bounded boxes.

Fig. 5 shows two samples of Centroidal Voronoi Diagram (from Du et al., 1999).

As the core property of the centroid, we can say that the centroid of an area as a set of points minimizes the weighted sum of the Euclidean distances from the points to any point in the plane. (Abdi. 2007)

As a result, the centroid of the Voronoi Cell is a good position that an agent can take. In this way it can have better control on its cell. For example, putting the ball in a random position in the cell, the expected value of the distance to ball is minimized in the centroid. So trying to achieve a Centroidal Voronoi Diagram can be a good idea for the positioning of agents.

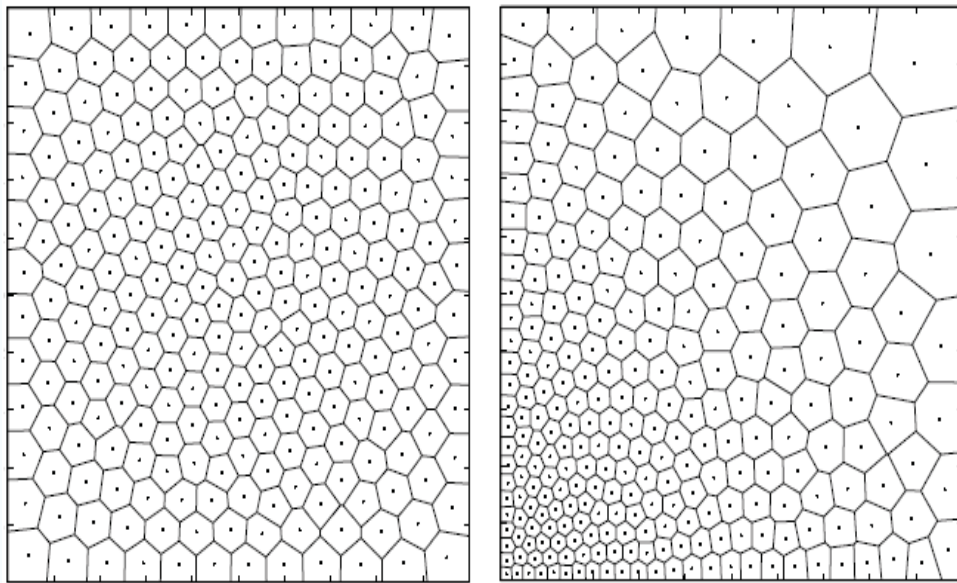


Fig. 5. Two samples of Centroidal Voronoi Diagrams (with 256 sites)

3.2- Lloyd's Method

There exist both probabilistic and deterministic approaches for achieving Centroidal Voronoi Diagram. One of the deterministic methods is *Lloyd's Method*. [See (Du et al., 1999) for probabilistic approaches]. This method was first presented by Stuart Lloyd in (Lloyd. 1982). There are some variations on Lloyd's method; However generally it can be described as follow:

0. Select an initial set of n points (Voronoi Sites).
1. Construct the Voronoi Diagram associated with the points.
2. Compute the mass centroids of the Voronoi regions found in step 1; these centroids are the new set of sites.
3. If this new set of sites meets some convergence criterion, terminate; otherwise, return to step 1.

The termination procedure in step 3 is very dependent on the specific application.

Fig. 6 show the behaviour of Lloyd's methods¹. As you can see, this method can be described as a set of *relaxations rounds*. After each round, the points are left in a slightly more even distribution: closely spaced points move further apart, and widely spaced points move closer together. Although the final shape of the diagram is a function of initial formation of points, the result has always an even distribution.

Note that defining a termination procedure is important since after each round the method convergence rate decreases². (See Fig. 6)

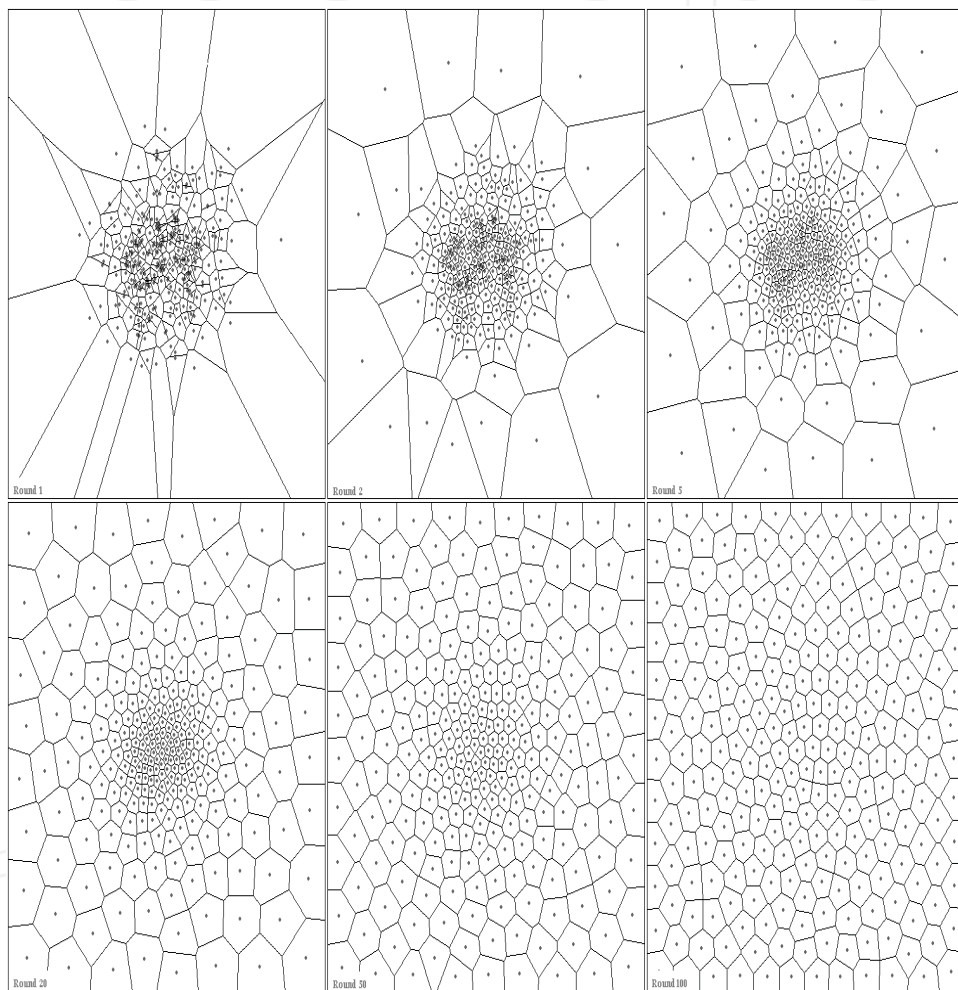


Fig. 6. Applying Lloyd's method on a set of 256 points. You see rounds 1, 2, 5, 20, 50, 100. The points are initially distributed normally in range $[0..1]$ with $\text{mean}=0.5$ and $\text{variance}=0.1$

¹ The code for generating these slides is available upon request.

² The 1-dimension version of the Lloyd's method is proved to converge. The 2-dimension version is also conjectured to converge but no proof exists yet.

4. Dynamic Positioning based on Voronoi Cells (DPVC)

As mentioned before Dynamic Positioning based on Voronoi Cells is a Positioning method which models the agents (team mates) as the Voronoi Sites and uses a variation of Lloyd's method³ to slightly distribute them in the field. Such modeling has the advantages of a dynamic positioning; for example there is no need for defining home positions for agents. Also as we will see it is very easy to apply futures of the soccer world to this model.

In DPVC, like the original version of Lloyd's method, in each sense (relaxation round), agents construct their Voronoi Cells and the center of such cell. Then, each agent should be replaced by the center of its cell, however since the agents movement is continuous they may not be able to get their center in one sense. So rather than 'putting' the agent into its center, we force the agent toward the center of its cell. Such force would be applied to the agent through a force vector called *Voronoi Vector*.

Fig. 7 shows the movement of agents (following a set of senses) while applying Voronoi Vectors. Like the original version of Lloyd's algorithm, applying Voronoi Vectors on agents causes them to repulse their team mates and cover the free spaces in the field. Also as you can compare Fig. 6 and Fig. 7, the convergence rate of this method is not worst than the original version of Lloyd's method⁴.

It is believed that this variation of Lloyd's method, i.e. relaxing the diagram by approximating sites (agents) toward their cells' centers, converges to a centroidal Voronoi Diagram. Here we can define the convergence criterion to be a threshold on the size of Voronoi Vector, i.e. we stop the algorithm if the size of Voronoi Vector of all agents gets smaller than a constant value ϵ .

Fig. 8 show the convergence of agents in Robocup soccer simulation.

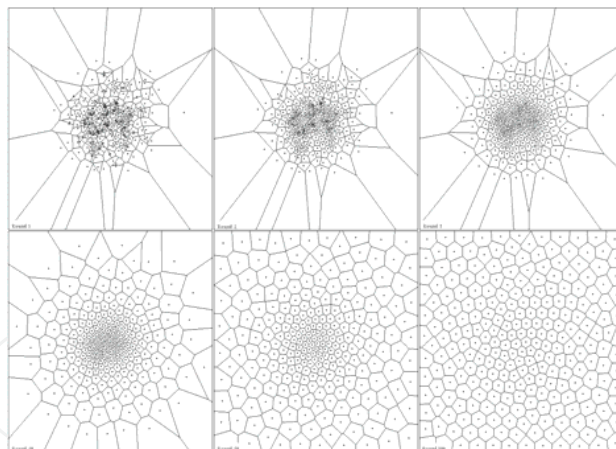


Fig. 7. applying DPVC on the same set of points of Fig. 6. The points have continuous movement. You see rounds 1, 2, 5, 20, 50, 100. The agents' velocity is 0.01 per round

³ For the first time that DPVC was appeared in (Dashti. 2006) the authors were not aware of Lloyd's Method. However because of the similarities between two methods, it is better to regard the backbone of DPVC as a variation of Lloyd's method.

⁴ Obviously the convergence rate of DPVC deeply depends on the (maximum) velocity of agents per round.

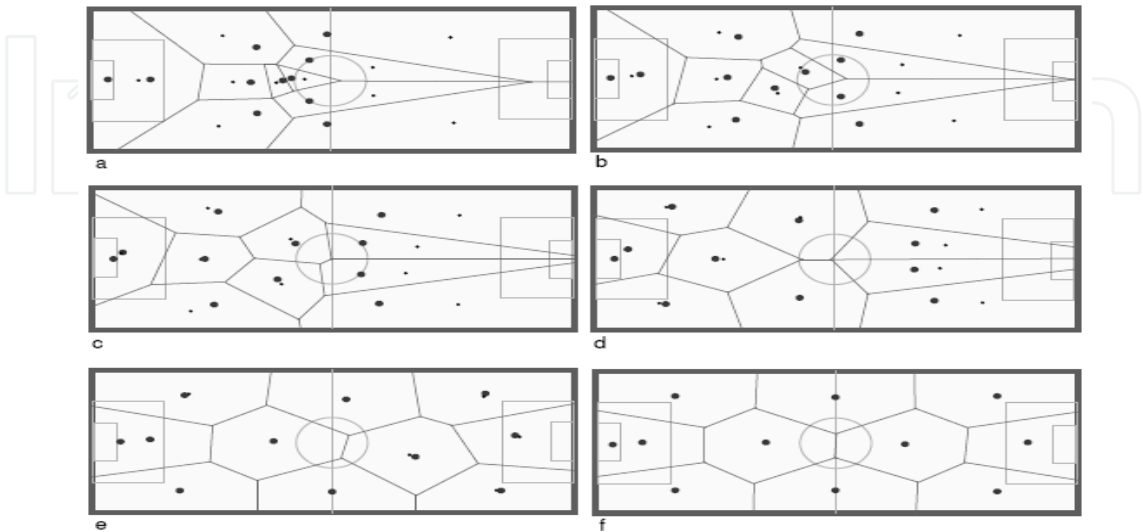


Fig. 8. Applying DPVC (without strategy) in Robocup Soccer Simulator Server 3D

4.1. Applying Strategy

Up to now what studied was a *plain* version of DPVC (Fig. 8) in which the Voronoi Vectors are just functions of the positions of team mate agents. We can easily apply other futures like opponents' positions, agents' batteries, team strategy, etc. to implement the team's strategy:

Opponents' positions

Considering game situation, it is wise to distribute some agents in the open spaces between opponents to make passes more successful. Adding opponents' positions to the Voronoi sites, the Voronoi Vectors would be constructed in the way of making agents move toward opponent team's openings. In this way agents would have a kind of repulsion to both opponents and teammates. (Fig. 9)

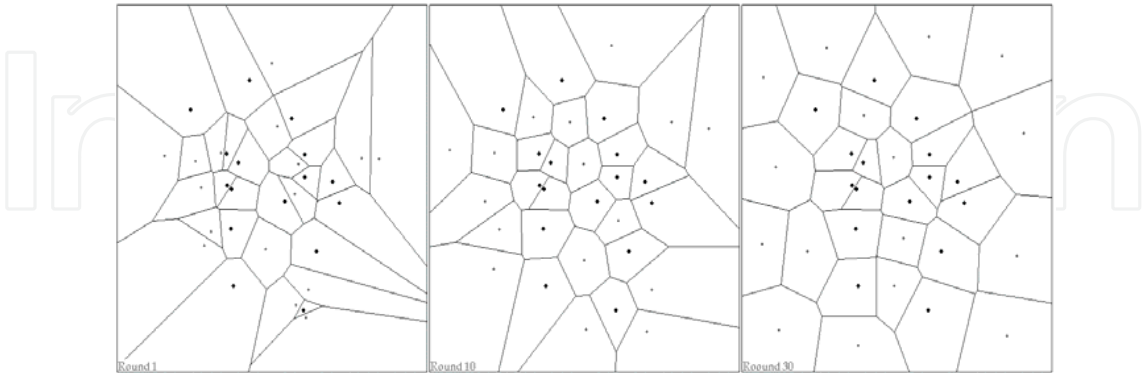


Fig. 9. Applying Opponents positions in DPVC. Opponent sites are bolded and fixed during the relaxation rounds. You see rounds 1, 10, 30. The team mates get positions in the openings between opponents

Agents' Stamina:

The *additively weighted Voronoi Diagram*⁵ is a generalization of Voronoi Diagram in which a *weight* is assigned to each Voronoi site and while measuring distances to a site, the weight of the site is added to the usual Euclidian distance. Fig. 10 shows a sample of additively Voronoi Diagram. As you can see the sites with smaller weights would have smaller cells. Also note that the boundaries between cells are segments of circles rather than straight lines.

Since the agents with smaller cells would have smaller Voronoi Vector, we can model the agents' stamina by the weight of Voronoi sites, in this way agents with lower battery would have smaller Voronoi Vectors and can save stamina in this way.

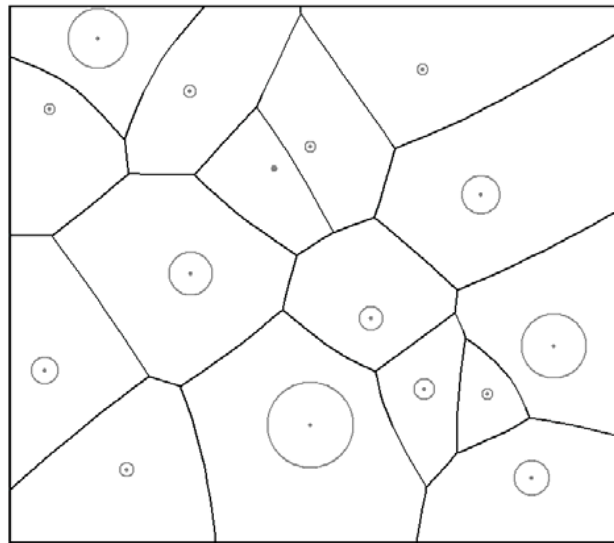


Fig. 10. weighted Voronoi diagram for a set of 16 sites. The radius of disks shows the weight of the sites

Concentration of agents

The Voronoi Bounding box is mainly defined as the whole field. However Considering the game situation, it is wise to shrink this box to concentrate agents in an appropriate area. For example as Fig. 11 shows restriction on the width of box causes agents concentrate in an extreme side of the field which can be interperated as a more defensive (or offensive) formation⁶. Also it is easy to see how this restricting on the width of box can be applied to form an Offside trap.

Note that if we use the same algorithm of section 3 for computing Voronoi Cells, the cells of all agents, even those that are out of the bounding box, would lie inside the box. So after several rounds all agents get into the box.

⁵ There exist some other types of weighted Voronoi diagram such as "multiplicatively weighted Voronoi diagram", "additively weighted power Voronoi Diagram". See (Okabe et al., 2000) for more details.

⁶ Getting an offensive or defensive formations can be a matter of ball position or other factors set by game strategy.

Other factors

It is desirable to apply all key factors of team strategy exclusively through Voronoi vectors (As we did about opponent's position, agents' batteries, Offside trap, and ball position). In this way the agent's movement would be much more stable and extra movements would be reduced. However it is not that easy to apply more complicated strategies just by Voronoi Vectors (for example in the case of collaborating with goalie or blocking opponents). To handle these types of strategies, we need to define some extra force vectors called *Attraction Vectors*. These vectors are set by the team strategy considering the game situation and involve attractions to specific positions in the field. In this case the final force vector would be applied to the agent as a combination of the Voronoi Vector and Attraction Vectors⁷.

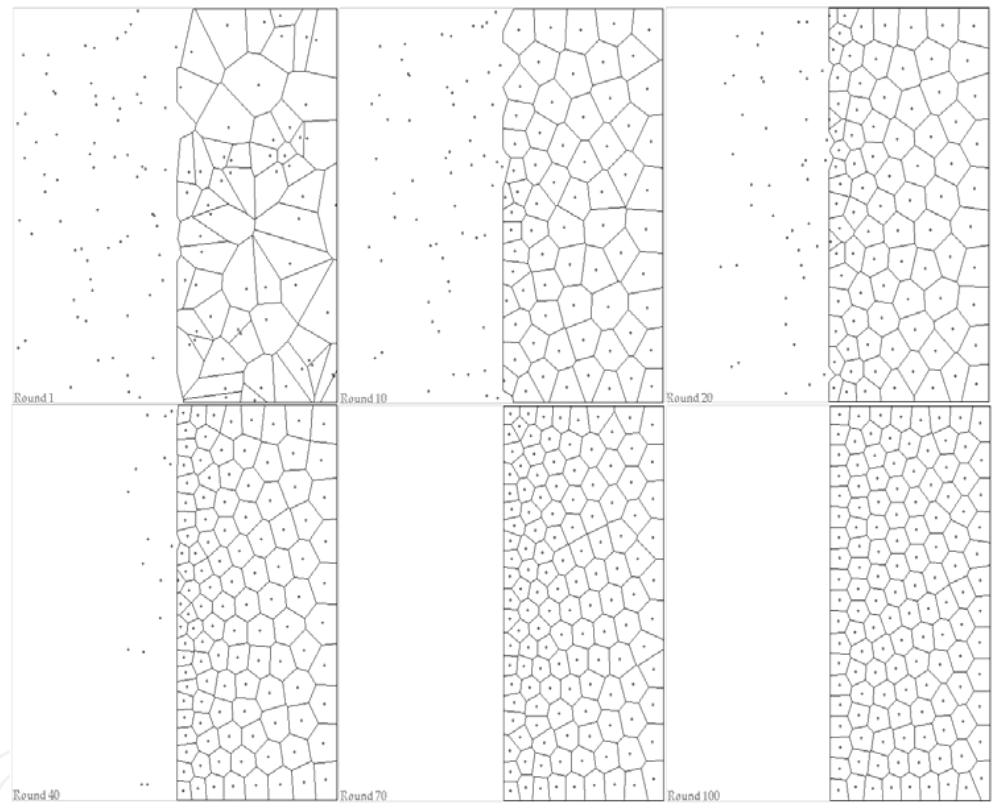


Fig. 11. Concentrating agents to one side of the field by restricting the Voronoi Bounding Box. You can see rounds 1, 10, 20, 40, 70, 100. In the beginning, there are 128 agents uniformly distributed in $[0..1] \times [0..1]$. The bounding box is a $[0..5] \times [0..1]$ rectangle and the agents velocity is 0.01

⁷ Here we do not go deep to the concept of attraction Vectors since they are very much dependant on the specific team strategy

5. Experimental Results

5.1- Statistical Experiments

Performance of a team not only depends on its positioning method but also depends on other decision modules and efficiency in implementation of agents skills. Accordingly it is difficult to define an appropriate criterion to evaluate the positioning method. In order to survey the applied positioning, we compared two similar teams using different positioning methods in Robocup soccer simulation 3-D. One of these teams uses SBSP as positioning method and the other uses DPVC. Since there is usually little density of players near corners of the field, we improved DPVC by restricting the initial Voronoi Cells of agents to a hexagonal surrounded by the entire field rectangle.

To compare these two positioning methods we prepared two experiments. In these experiments both teams play against Aria team the champion of Robocup 2004 3D competitions. In the first experiment the number of passable players around the ball when the ball is in possession of the testing team is measured.

Passable player is a player who has the opportunity to get the ball if it is passed. So being a passable player is a matter of player’s distance from the ball. In our experiment a player is defined to be passable if its distance from ball is less than 20 meters. Figure 12 is a statistical diagram of passable players of the team. In Figure 12-a DPVC is used as the positioning method, whereas in Figure 12-b the positioning is based on SBSP.

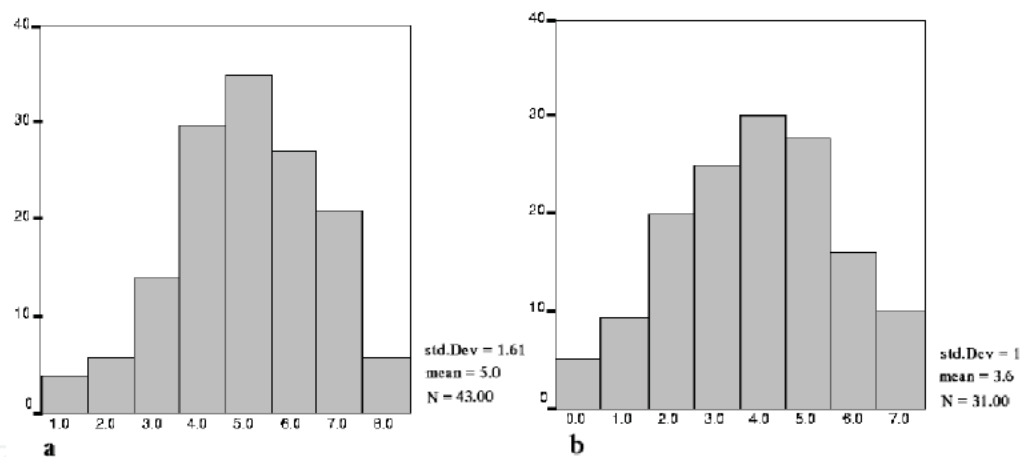


Fig. 12. The figure shows statistical distribution for average number of passable players of the team against Aria, using DPVC and SBSP methods for positioning. N is number of the team opportunities to pass the ball. Numbers in x-axis show number of passable players where numbers in y-axis show the times that these numbers occur. As it is shown while using DPVC in average there are five passable players whereas by using SBSP there are 3.6 passable players

In the second experiment both the team using DPVC and the team using SBSP are ran against Aria 10 times. Table 1 reports results of these two series of tests. Records of this table show parameters defined to compare the influence of each method of positioning on success of the team.

	DPVC	SBSP
Average number of passable players	4.09	3.36
Ball in control of the team	58.31%	56.92%
Ball in own half	18.80%	22.15%
Ball in own penalty area	1.47%	1.26%
Ball in opponent penalty area	23.02%	19.98%

Table 1. Results when two similar teams using different positioning methods (DPVC and SBSP) play against Aria team

5.2 Experiments at Robocup World Championship

For the first time DPVC was implemented by UTUtd (Dashti et al., 2006) at Robocup world championship 2005 at Osaka. UTUtd after playing 21 matches with 13 wins 6 draws and 2 losses reached the 5th place among 32 teams in the 3D simulation league. Next year at Robocup world championship in Bremen DPVC was implemented by Virtual Werder (Lattner et al., 2006). In this implementation of DPVC players had little attraction to ball and had a defensive Formation. Virtual Werder team could rank up to 8 between 32 teams after 5 wins, 17 draws and only 1 loss. As it is seen below the number of losses in VW team is much lower than the second and third team.

Rank	Team Name	Won	Draw	Lost
1	FCPortugal3D	19	2	0
2	WrightEagle	10	7	4
3	ZJUBase	12	6	3
8	VW3D	5	17	1

Table 2. Results from Robocup world championship 2006

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Robotic Soccer

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Many papers in the book concern advanced research on (multi-)robot subsystems, naturally motivated by the challenges posed by robot soccer, but certainly applicable to other domains: reasoning, multi-criteria decision-making, behavior and team coordination, cooperative perception, localization, mobility systems (namely omnidirectional wheeled motion, as well as quadruped and biped locomotion, all strongly developed within RoboCup), and even a couple of papers on a topic apparently solved before Soccer Robotics - color segmentation - but for which several new algorithms were introduced since the mid-nineties by researchers on the field, to solve dynamic illumination and fast color segmentation problems, among others. This book is certainly a small sample of the research activity on Soccer Robotics going on around the globe as you read it, but it surely covers a good deal of what has been done in the field recently, and as such it works as a valuable source for researchers interested in the involved subjects, whether they are currently "soccer roboticists" or not.

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