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# Positioning to Win: A Dynamic Role Assignment and Formation Positioning System

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### Abstract

This paper presents a dynamic role assignment and formation positioning system used by the 2011 RoboCup 3D simulation league champion UT Austin Villa. This positioning system was a key component in allowing the team to win all 24 games it played at the competition during which the team scored 136 goals and conceded none. The positioning system was designed to allow for decentralized coordination among physically realistic simulated humanoid soccer playing robots in the partially observable, non-deterministic, noisy, dynamic, and limited communication setting of the RoboCup 3D simulation league simulator. Although the positioning system is discussed in the context of the RoboCup 3D simulation environment, it is not domain specific and can readily be employed in other RoboCup leagues as it generalizes well to many realistic and real-world multiagent systems.

## 1 Introduction

Coordinated movement among autonomous mobile robots is an important research area with many applications such as search and rescue (Kitano et al. 1999) and warehouse operations (Wurman, D'Andrea, and Mountz 2008). The RoboCup 3D simulation competition provides an excellent testbed for this line of research as it requires coordination among autonomous agents in a physically realistic environment that is partially observable, non-deterministic, noisy, and dynamic. While low level skills such as walking and kicking are vitally important for having a successful soccer playing agent, the agents must work together as a team in order to maximize their game performance.

One often thinks of the soccer teamwork challenge as being about where the player with the ball should pass or dribble, but at least as important is where the agents position themselves when they *do not* have the ball (Kalyanakrishnan and Stone 2010). Positioning the players in a formation requires the agents to coordinate with each other and determine where each agent should position itself on the field. While there has been considerable research done in the 2D soccer simulation domain (for example by Stone et al. (Stone and Veloso 1999) and Reis et al. (Reis, Lau, and Oliveira 2001)), relatively little outside of (Chen and Chen 2011) has been published on this topic in the more physically realistic 3D soccer simulation environment. (Chen and Chen 2011), as well as related work in the RoboCup middle size league (MSL) (Lau et al. 2009), rank positions on the field in order of importance and then iteratively assign the closest available agent to the most important currently unassigned position until every agent is mapped to a target location. The work presented in this paper differs from the mentioned previous work in the 2D and 3D simulation and MSL RoboCup domains as it takes into account real-world concerns and movement dynamics such as the need for avoiding collisions of robots.

In UT Austin Villa's positioning system players' positions are determined in three steps. First, a full team formation is computed (Section 3); second, each player computes the best assignment of players to role positions in this formation according to its own view of the world (Section 4); and third, a coordination mechanism is used to choose among all players' suggestions (Section 4.4). In this paper, we use the terms (player) position and (player) role interchangeably.

The remainder of the paper is organized as follows. Section 2 provides a description of the RoboCup 3D simulation domain. The formation used by UT Austin Villa is given in Section 3. Section 4 explains how role positions are dynamically assigned to players. Collision avoidance is discussed in Section 5. An evaluation of the different parts of the positioning system is given in Section 6, and Section 7 summarizes.

## 2 Domain Description

The RoboCup 3D simulation environment is based on SimSpark,[1] a generic physical multiagent system simulator. SimSpark uses the Open Dynamics Engine[2] (ODE) library for its realistic simulation of rigid body dynamics with collision detection and friction. ODE also provides support for the modeling of advanced motorized hinge joints used in the humanoid agents.

The robot agents in the simulation are homogeneous and are modeled after the Aldebaran Nao robot,[3] which has a height of about 57 cm, and a mass of 4.5 kg. The agents in-

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[1] http://simspark.sourceforge.net/
[2] http://www.ode.org/
[3] http://www.aldebaran-robotics.com/eng/

teract with the simulator by sending torque commands and receiving perceptual information. Each robot has 22 degrees of freedom: six in each leg, four in each arm, and two in the neck. In order to monitor and control its hinge joints, an agent is equipped with joint perceptors and effectors. Joint perceptors provide the agent with noise-free angular measurements every simulation cycle (20 ms), while joint effectors allow the agent to specify the torque and direction in which to move a joint. Although there is no intentional noise in actuation, there is slight actuation noise that results from approximations in the physics engine and the need to constrain computations to be performed in real-time. Visual information about the environment is given to an agent every third simulation cycle (60 ms) through noisy measurements of the distance and angle to objects within a restricted vision cone (120°). Agents are also outfitted with noisy accelerometer and gyroscope perceptors, as well as force resistance perceptors on the sole of each foot. Additionally, agents can communicate with each other every other simulation cycle (40 ms) by sending messages limited to 20 bytes.

## 3 Formation

This section presents the formation used by UT Austin Villa during the 2011 RoboCup competition. The formation itself is not a main contribution of this paper, but serves to set up the role assignment function discussed in Section 4 for which a precomputed formation is required.

In general, the team formation is determined by the ball position on the field. As an example, Figure 1 depicts the different role positions of the formation and their relative offsets when the ball is at the center of the field. The formation can be broken up into two separate groups, an offensive and a defensive group. Within the offensive group, the role positions on the field are determined by adding a specific offset to the ball's coordinates. The *onBall* role, assigned to the player closest to the ball, is always based on where the ball is and is therefore never given an offset. On either side of the ball are two forward roles, *forwardRight* and *forwardLeft*. Directly behind the ball is a *stopper* role as well as two additional roles, *wingLeft* and *wingRight*, located behind and to either side of the ball. When the ball is near the edge of the field some of the roles' offsets from the ball are adjusted so as to prevent them from moving outside the field of play.

Within the defensive group there are two roles, *backLeft* and *backRight*. To determine their positions on the field a line is calculated between the center of the team's own goal and the ball. Both backs are placed along this line at specific offsets from the end line. The goalie positions itself independently of its teammates in order to always be in the best position to dive and stop a shot on goal. If the goalie assumes the *onBall* role, however, a third role is included within the defensive group, the *goalieReplacement* role. A field player assigned to the *goalieReplacement* role is told to stand in front of the center of the goal to cover for the goalie going to the ball.

During the course of a game there are occasional stoppages in play for events such as kickoffs, goal kicks, corner kicks, and kick-ins. When one of these events occur UT

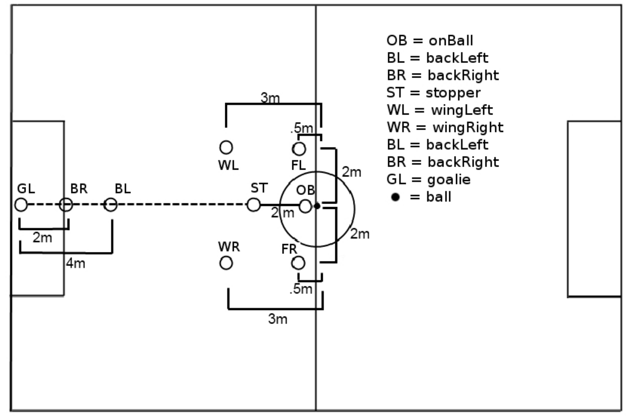


Figure 1: Formation role positions.

Austin Villa adjusts its team formation and behavior to assume situational set plays which are detailed in a technical report (MacAlpine et al. 2011).

Kicking and passing have yet to be incorporated into the team's formation. Instead the *onBall* role always dribbles the ball toward the opponent's goal.

## 4 Assignment of Agents to Role Positions

Given a desired team formation, we need to map players to roles (target positions on the field). Human soccer players specialize in different positions as they have different bodies and abilities, however, for us, the agents are all homogeneous, and so it is unnecessary to limit agents to constant specific roles. A naïve mapping having each player permanently mapped to one of the roles performs poorly due to the dynamic nature of the game. With such static roles an agent assigned to a defensive role may end up out of position and, without being able to switch roles with a teammate in a better position to defend, allow for the opponent to have a clear path to the goal. In this section, we present a dynamic role assignment algorithm. A role assignment algorithm can be thought of as implementing a role assignment *function*, which takes as input the state of the world, and outputs a one-to-one mapping of players to roles. We start by defining three properties that a role assignment function must satisfy (Section 4.1). We then construct a role assignment function that satisfies these properties (Section 4.2). Finally, we present a dynamic programming algorithm implementing this function (Section 4.3).

### 4.1 Desired Properties of a Valid Role Assignment Function

Before listing desired properties of a role assignment function we make a couple of assumptions. The first of these is that no two agents and no two role positions occupy the same position on the field. Secondly we assume that all agents move toward fixed role positions along a straight line at the same constant speed. While this assumption is not always completely accurate, the omnidirectional walk used by the agent, and described in (MacAlpine et al. 2012), gives a fair approximation of constant speed movement along a straight line.

We call a role assignment function *valid* if it satisfies the following three properties:

1. *Minimizing longest distance* - it minimizes the maximum distance from a player to target, with respect to all possible mappings.
2. *Avoiding collisions* - agents do not collide with each other as they move to their assigned positions.
3. *Dynamically consistent* - a role assignment function $f$ is dynamically consistent if, given a *fixed* set of target positions, if $f$ outputs a mapping $m$ of players to targets at time $T$, and the players are moving toward these targets, $f$ would output $m$ for every time $t > T$.

The first two properties are related to the output of the role assignment function, namely the mapping between players and positions. We would like such a mapping to minimize the time until all players have reached their target positions because quickly doing so is important for strategy execution. As we assume all players move at the same speed, we start by requiring a mapping to minimize the maximum distance any player needs to travel. However, paths to positions might cross each other, therefore we additionally require a mapping to guarantee that when following it, there are no collisions. The third property guarantees that once a role assignment function $f$ outputs a mapping, $f$ is committed to it as long as there is no change in the target positions. This guarantee is necessary as otherwise agents might unduly thrash between roles thus impeding progress. In the following section we construct a valid role assignment function.

## 4.2 Constructing a Valid Role Assignment Function

Let $M$ be the set of all one-to-one mappings between players and roles. If the number of players is $n$, then there are $n!$ possible such mappings. Given a state of the world, specifically $n$ player positions and $n$ target positions, let the *cost* of a mapping $m$ be the $n$-tuple of distances from each player to its target, sorted in decreasing order. We can then sort all the $n!$ possible mappings based on their costs, where comparing two costs is done lexicographically. Sorted costs of mappings from agents to role positions for a small example are shown in Figure 2.

Denote the role assignment function that always outputs the mapping with the lexicographically smallest cost as $f_v$. Here we provide an informal proof sketch that $f_v$ is a valid role assignment; we provide a longer, more thorough derivation in Appendix A.

**Theorem 1.** *$f_v$ is a valid role assignment function.*

It is trivial to see that $f_v$ minimizes the longest distance traveled by any agent (Property 1) as the lexicographical ordering of distance tuples sorted in descending order ensures this. If two agents in a mapping are to collide (Property 2) it can be shown, through the triangle inequality, that $f_v$ will find a lower cost mapping as switching the two agents' targets reduces the maximum distance either must travel. Finally, as we assume all agents move toward their targets

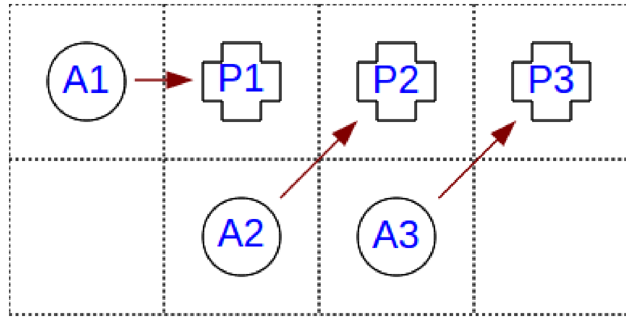


Figure 2: Lowest lexicographical cost (shown with arrows) to highest cost ordering of mappings from agents (A1,A2,A3) to role positions (P1,P2,P3). Each row represents the cost of a single mapping.

| | | | |
|---|---|---|---|
| 1: | $\sqrt{2}$ (A2→P2), | $\sqrt{2}$ (A3→P3), | 1 (A1→P1) |
| 2: | 2 (A1→P2), | $\sqrt{2}$ (A3→P3), | 1 (A2→P1) |
| 3: | $\sqrt{5}$ (A2→P3), | 1 (A1→P1), | 1 (A3→P2) |
| 4: | $\sqrt{5}$ (A2→P3), | 2 (A1→P2), | $\sqrt{2}$ (A3→P1) |
| 5: | 3 (A1→P3), | 1 (A2→P1), | 1 (A3→P2) |
| 6: | 3 (A1→P3), | $\sqrt{2}$ (A2→P2), | $\sqrt{2}$ (A3→P1) |

at the same constant rate, the distance between any agent and target will not decrease any faster than the distance between an agent and the target it is assigned to. This observation serves to preserve the lowest cost lexicographical ordering of the chosen mapping by $f_v$ across all timesteps thereby providing dynamic consistency (Property 3). Section 4.3 presents an algorithm that implements $f_v$.

## 4.3 Dynamic Programming Algorithm for Role Assignment

In UT Austin Villa's basic formation, presented in Section 3, there are nine different roles for each of the nine agents on the field. The goalie always fills the *goalie* role and the *onBall* role is assigned to the player closest to the ball. The other seven roles must be mapped to the agents by $f_v$. Additionally, when the goalie is closest to the ball, the goalie takes on both the *goalie* and *onBall* roles causing us to create an extra *goalieReplacement* role positioned right in front of the team's goal. When this occurs the size of the mapping increases to eight agents mapped to eight roles. As the total number of mapping permutations is $n!$, this creates the possibility of needing to evaluate $8!$ different mappings.

Clearly $f_v$ could be implemented using a brute force method to compare all possible mappings. This implementation would require creating up to $8! = 40,320$ mappings, then computing the cost of each of the mappings, and finally sorting them lexicographically to choose the smallest one. However, as our agent acts in real time, and $f_v$ needs to be computed during a decision cycle (20 ms), a brute force method is too computationally expensive. Therefore, we present a dynamic programming implementation shown in Algorithm 1 that is able to compute $f_v$ within the time constraints imposed by the decision cycle's length.

**Theorem 2.** *Let $A$ and $P$ be sets of $n$ agents and positions respectively. Denote the mapping $m := f_v(A, P)$. Let $m_0$ be a subset of $m$ that maps a subset of agents $A_0 \subset A$ to a*

**Algorithm 1** Dynamic programming implementation

1: HashMap $bestRoleMap = \varnothing$
2: $Agents = \{a_1, ..., a_n\}$
3: $Positions = \{p_1, ..., p_n\}$
4: **for** $k = 1$ to $n$ **do**
5:     **for all** $a$ in $Agents$ **do**
6:         $S = \binom{n-1}{k-1}$ sets of $k-1$ agents from $Agents - \{a\}$
7:         **for all** $s$ in $S$ **do**
8:             Mapping $m_0 = bestRoleMap[s]$
9:             Mapping $m = (a \rightarrow p_k) \cup m_o$
10:            $bestRoleMap[a \cup s] = mincost(m, bestRoleMap[a \cup s])$
11: **return** $bestRoleMap[Agents]$

| {P1} | {P2,P1} | {P3,P2,P1} |
|---|---|---|
| A1→P1 | A1→P2, $f_v$(A2→P1) | A1→P3, $f_v$({A2,A3}→{P1,P2}) |
| A2→P1 | A1→P2, $f_v$(A3→P1) | A2→P3, $f_v$({A1,A3}→{P1,P2}) |
| A3→P1 | A2→P2, $f_v$(A1→P1) | A3→P3, $f_v$({A1,A2}→{P1,P2}) |
| | A2→P2, $f_v$(A3→P1) | |
| | A3→P2, $f_v$(A1→P1) | |
| | A3→P2, $f_v$(A2→P1) | |

Table 1: All mappings evaluated during dynamic programming using Algorithm 1 when computing an optimal mapping of agents A1, A2, and A3 to positions P1, P2, and P3. Each column contains the mappings evaluated for the set of positions listed at the top of the column.

*subset of positions $P_0 \subset P$. Then $m_0$ is also the mapping returned by $f_v(A_0, P_0)$.*

A key recursive property of $f_v$ that allows us to exploit dynamic programming is expressed in Theorem 2. This property stems from the fact that if within any subset of a mapping a lower cost mapping is found, then the cost of the complete mapping can be reduced by augmenting the complete mapping with that of the subset's lower cost mapping. The savings from using dynamic programming comes from only evaluating mappings whose subset mappings are returned by $f_v$. This is accomplished in Algorithm 1 by iteratively building up optimal mappings for position sets from $\{p_1\}$ to $\{p_1, ..., p_n\}$, and using optimal mappings of $k-1$ agents to positions $\{p_1, ..., p_{k-1}\}$ (line 8) as a base when constructing each new mapping of $k$ agents to positions $\{p_1, ..., p_k\}$ (line 9), before saving the lowest cost mapping for the current set of $k$ agents to positions $\{p_1, ..., p_k\}$ (line 10).

An example of the mapping combinations evaluated in finding the optimal mapping for three agents through the dynamic programming approach of Algorithm 1 can be seen in Table 1. In this example we begin by computing the distance of each agent to our first role position. Next we compute the cost of all possible mappings of agents to both the first and second role positions and save off the lowest cost mapping of every pair of agents to the the first two positions. We then proceed by sequentially assigning every agent to the third position and compute the lowest cost mapping of all agents mapped to all three positions. As all subsets of an optimal (lowest cost) mapping will themselves be optimal, we need only evaluate mappings to all three positions which include the previously calculated optimal mapping agent combinations for the first two positions.

Recall that during the $kth$ iteration of the dynamic programming process to find a mapping for $n$ agents, where $k$ is the current number of positions that agents are being mapped to, each agent is sequentially assigned to the $kth$ position and then all possible subsets of the other $n-1$ agents are assigned to positions 1 to $k-1$ based on computed optimal mappings to the first $k-1$ positions from the previous iteration of the algorithm. These assignments result in a total of $\binom{n-1}{k-1}$ agent subset mapping combinations to be evaluated for mappings of each agent assigned to the $kth$ position. The total number of mappings computed for each of the $n$ agents across all $n$ iterations of dynamic programming is thus equivalent to the sum of the $n-1$ binomial coefficients. That is,

$$\sum_{k=1}^{n} \binom{n-1}{k-1} = \sum_{k=0}^{n-1} \binom{n-1}{k} = 2^{n-1}$$

Therefore the total number of mappings that must be evaluated using our dynamic programming approach is $n2^{n-1}$. For $n = 8$ we thus only have to evaluate 1024 mappings which takes about 3.3 ms for each agent to compute compared to upwards of 50 ms using a brute force approach to evaluate all possible mappings.[4] For future competitions it is projected that teams will increase to 11 agents to match that of actual soccer. In this case, where $n = 10$, the number of mappings to evaluate will only increase to 5120 which is drastically less than the brute force method of evaluating all possible $10! = 3,628,800$ mappings.

## 4.4 Voting Coordination System

In order for agents on a team to assume correct positions on the field they all must coordinate and agree on which mapping of agents to roles to use. If every agent had perfect information of the locations of the ball and its teammates this would not be a problem as each could independently calculate the optimal mapping to use. Agents do not have perfect information, however, and are limited to noisy measurements of the distance and angle to objects within a restricted vision cone (120°). Fortunately agents can share information with each other every other simulation cycle (40 ms). The bandwidth of this communication channel is very limited, however, as only one agent may send a message at a time and messages are limited to 20 bytes.

We utilize the agents' limited communication bandwidth in order to coordinate role mappings as follows. Each agent is given a rotating time slice to communicate information, as in (Stone and Veloso 1999), which is based on the uniform number of an agent. When it is an agent's turn to send a message it broadcasts to its teammates its current position, the position of the ball, and also what it believes the optimal mapping should be. By sending its own position and the position of the ball, the agent provides necessary information for computing the optimal mapping to those of its teammates for which these objects are outside of their view cones. Sharing the optimal mapping of agents to role positions enables synchronization between the agents, as follows.

First note that just using the last mapping received is dangerous, as it is possible for an agent to report inconsistent

[4]As measured on an Intel Core 2 Duo CPU E8500 @3.16GHz.

mappings due to its noisy view of the world. This can easily occur when an agent falls over and accumulates error in its own localization. Additionally, messages from the server are occasionally dropped or received at different times by the agents preventing accurate synchronization. To help account for inconsistent information, a sliding window of received mappings from the last $n$ time-slots is kept by each agent where $n$ is the total number of agents on a team. Each of these kept messages represents a single vote by each of the agents as to which mapping to use. The mapping chosen is the one with the most votes or, in the case of a tie, the mapping tied for the most votes with the most recent vote cast for it. By using a voting system, the agents on a team are able to synchronize the mapping of agents to role positions in the presence of occasional dropped messages or an agent reporting erroneous data. As a test of the voting system the number of cycles all nine agents shared a synchronized mapping of agents to roles was measured during 5 minutes of gameplay (15,000 cycles). The agents were synchronized 100% of the time when using the voting system compared to only 36% of the time when not using the voting system.

## 5 Collision Avoidance

Although the positioning system discussed in Section 4 is designed to avoid assigning agents to positions that might cause them to collide, external factors outside of the system's control, such as falls and the movement of the opposing team's agents, still result in occasional collisions. To minimize the potential for these collisions the agents employ an active collision avoidance system. When an obstacle, such as a teammate, is detected in an agent's path the agent will attempt to adjust its path to its target in order to maneuver around the obstacle. This adjustment is accomplished by defining two thresholds around obstacles: a *proximity* threshold at 1.25 meters and a *collision* threshold at .5 meters from an obstacle. If an agent enters the *proximity* threshold of an obstacle it will adjust its course to be tangent to the obstacle thereby choosing to circle around to the right or left of said obstacle depending on which direction will move the agent closer to its desired target. Should the agent get so close as to enter the *collision* proximity of an obstacle it must take decisive action to prevent an otherwise imminent collision from occurring. In this case the agent combines the corrective movement brought about by being in the *proximity* threshold with an additional movement vector directly away from the obstacle. Figure 3 illustrates the adjusted movement of an agent when avoiding a collsion.

## 6 Formation Evaluation

To test how our formation and role positioning system[5] affects the team's performance we created a number of teams to play against by modifying the base positioning system and formation of UT Austin Villa.

[5]Video demonstrating our positioning system can be found online at
http://www.cs.utexas.edu/~AustinVilla/sim/3dsimulation/AustinVilla3DSimulationFiles/2011/html/positioning.html

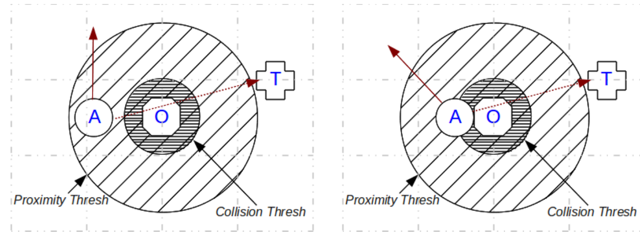


Figure 3: Collision avoidance examples where agent A is traveling to target T but wants to avoid colliding with obstacle O. The left diagram shows how the agent's path is adjusted if it enters the *proximity* threshold of the obstacle while the right diagram depicts the agent's movement when entering the *collision* threshold. The dotted arrow is the agent's desired path while the solid arrow is the agent's corrected path to avoid a collision.

**UT Austin Villa** Base agent using the dynamic role positioning system described in Section 4 and formation in Section 3.

**NoCollAvoid** No collision avoidance.

**AllBall** No formations and every agent except for the goalie goes to the ball.

**NoTeamwork** Similar to AllBall except that collision avoidance is also turned off such that agents disregard their teammates when going for the ball.

**NoCommunication** Agents do not communicate with each other.

**Static** Each role is statically assigned to an agent based on its uniform number.

**Defensive** Defensive formation in which only two agents are in the offensive group (one on the ball and the other directly behind the ball).

**Offensive** Offensive formation in which all agents except for the goalie are positioned in a close symmetric formation behind the ball.

**Boxes** Field is divided into fixed boxes and each agent is dynamically assigned to a home position in one of the boxes. Similar to system used in (Stone and Veloso 1999).

**NearestStopper** The *stopper* role position is mapped to nearest agent.

**PathCost** Agents add in the cost of needing to walk around known obstacles (using collision avoidance from Section 5), such as the ball and agent assuming the *onBall* role, when computing distances of agents to role positions.

**PositiveCombo** Combination of *Offensive*, *PathCost*, and *NearestStopper* attributes.

Results of UT Austin Villa playing against these modified versions of itself are shown in Table 2. The UT Austin Villa agent is the same agent used in the 2011 competition, except for a bug fix,[6] and so the data shown does not directly match with earlier released data in (MacAlpine et al. 2012). Also shown in Table 2 are results of the modified agents playing against the champion (Apollo3D) and runner-up (CIT3D) of the 2011 RoboCup China Open. These agents were chosen as reference points as they are two of the best teams available with CIT3D and Apollo3D taking second and third place respectively at the main RoboCup 2011 competition. The

[6]A bug in collision avoidance present in the 2011 competition agent where it always moved in the direction away from the ball to avoid collisions was fixed.

Table 2: Full game results, averaged over 100 games. Each row corresponds to an agent with varying formation and positioning systems as described in Section 6. Entries show the goal difference (row − column) from 10 minute games versus our base agent, using the dynamic role positioning system described in Section 4 and formation in Section 3, as well as the Apollo3D and CIT3D agents from the 2011 RoboCup China Open. Values in parentheses are the standard error.

| | UTAustinVilla | Apollo3D | CIT3D |
|---|---|---|---|
| PositiveCombo | 0.33 (.07) | 2.16 (.11) | 4.09 (.12) |
| Offensive | 0.21 (.09) | 1.80 (.12) | 3.89 (.12) |
| AllBall | 0.09 (.08) | 1.69 (.13) | 3.56 (.13) |
| PathCost | 0.07 (.07) | 1.27 (.11) | 3.25 (.11) |
| NearestStopper | 0.01 (.07) | 1.26 (.11) | 3.21 (.11) |
| UTAustinVilla | — | 1.05 (.12) | 3.10 (.12) |
| Defensive | -0.05 (.05) | 0.42 (.10) | 1.71 (.11) |
| Static | -0.19 (.07) | 0.81 (.13) | 2.87 (.11) |
| NoCollAvoid | -0.21 (.08) | 0.82 (.12) | 2.84 (.12) |
| NoCommunication | -0.30 (.06) | 0.41 (.11) | 1.94 (.10) |
| NoTeamwork | -1.10 (.11) | 0.33 (.15) | 2.43 (.12) |
| Boxes | -1.38 (.11) | -0.82 (.13) | 1.52 (.11) |

China Open occurred after the main RoboCup event during which time both teams improved (Apollo3D went from losing by an average of 1.83 to 1.05 goals and CIT3D went from losing by 3.75 to 3.1 goals on average when playing 100 games against our base agent).

Several conclusions can be made from the game data in Table 2. The first of these is that it is really important to be aggressive and always have agents near the ball. This finding is shown in the strong performance of the *Offensive* agent. In contrast to an offensive formation, we see that a very defensive formation used by the *Defensive* agent hurts performance likely because, as the saying goes, the best defense is a good offense. The poor performance of the *Boxes* agent, in which the positions on the field are somewhat static and not calculated as relative offsets to the ball, underscores the importance of being around the ball and adjusting positions on the field based on the current state of the game. The likely reason for the success of offensive and aggressive formations grouped close to the ball is because few teams in the league have managed to successfully implement advanced passing strategies, and thus most teams primarily rely on dribbling the ball. Should a team develop good passing skills then a spread out formation might become useful.

The *NearestStopper* agent was created after noticing that the *stopper* role is a very important position on the field so as to always have an agent right behind the ball to prevent breakaways and block kicks toward the goal. Ensuring that the *stopper* role is filled as quickly as possible improved performance slightly. This result is another example of added aggression improving game performance.

Another factor in team performance that shows up in the data from Table 2 is the importance of collision avoidance. Interestingly the *AllBall* agent did almost as well as the *Offensive* agent even though it does not have a set formation. While this result might come as a bit of surprise, collision avoidance causes the *AllBall* agent to form a clumped up mass around the ball which is somewhat similar to that of the *Offensive* agent's formation. For the strategy of all the agents running to the ball to work well it is imperative to have good collision avoidance. This conclusion is evident from the poor performance of the *NoTeamwork* agent where collision avoidance is turned off with everyone running to the ball, as well as from a result in (MacAlpine et al. 2012) where the *AllBall* agent lost to the base agent by an average of .43 goals when both agents had a bug in their collision avoidance systems. Turning off collision avoidance, but still using formations, hurts performance as seen in the results of the *NoCollAvoid* agent. Additionally the *PathCost* agent showed an improvement in gameplay by factoring in known obstacles that need to be avoided when computing the distance required to walk to each target.

Another noteworthy observation from the data in Table 2 is that dynamically assigning roles is better than statically fixing them. This finding is clear in the degradation in performance of the *Static* agent. It is important that the agents are synchronized in their decision as to which mapping of agents to roles to use, however, as is noticeable by the dip in performance of the *NoCommunication* agent which does not use the voting system presented in Section 4.4 to synchronize mappings. The best performing agent, that being the *PositiveCombo* agent, demonstrates that the most successful agent is one which employs an aggressive formation coupled with synchronized dynamic role switching, path planning, and good collision avoidance. While not shown in Table 2, the *PositiveCombo* agent beat the *AllBall* agent (which only employs collision avoidance and does not use formations or positioning) by an average of .31 goals across 100 games with a standard error of .09. This resulted in a record of 43 wins, 20 losses, and 37 ties for the *PositiveCombo* agent against the *AllBall* agent.

## 7 Summary and Discussion

We have presented a dynamic role assignment and formation positioning system for use with autonomous mobile robots in the RoboCup 3D simulation domain — a physically realistic environment that is partially observable, non-deterministic, noisy, and dynamic. This positioning system was a key component in UT Austin Villa[7] winning the 2011 RoboCup 3D simulation league competition.

For future work we hope to add passing to our strategy and then develop formations for passing, possibly through the use of machine learning. Additionally we intend to look into ways to compute $f_v$ more efficiently as well as explore other potential functions for mapping agents to role positions.

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[7]More information about the UT Austin Villa team, as well as video highlights from the 2011 competition, can be found at the team's website:
http://www.cs.utexas.edu/~AustinVilla/sim/3dsimulation/

ONR (N00014-09-1-0658), and the Federal Highway Administration (DTFH61-07-H-00030). Patrick MacAlpine is supported by a NDSEG fellowship.

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# Appendix

## A Role Assignment Function $f_v$

The following is a more in depth analysis of the the role assignment function $f_v$ described in Section 4.2.

### A.1 Minimizing Longest Distance

Having all agents quickly reach the target destinations of a formation is important for proper strategy execution, particularly that of set plays for game stoppages discussed in (MacAlpine et al. 2011) where there is a set time limit of 15 seconds before play resumes. It is trivial to determine that $f_v$ selects a mapping of agents to role positions that minimizes the time for all agents to have reached their target destinations. The total time it takes for all agents to move to their desired positions is determined by the time it takes for the last agent to reach its target position. As the first comparison between mapping costs is the maximum distance that any single agent in a mapping must travel, and it is assumed that all agents move toward their targets at the same constant rate, the property of minimizing the longest distance holds for $f_v$.

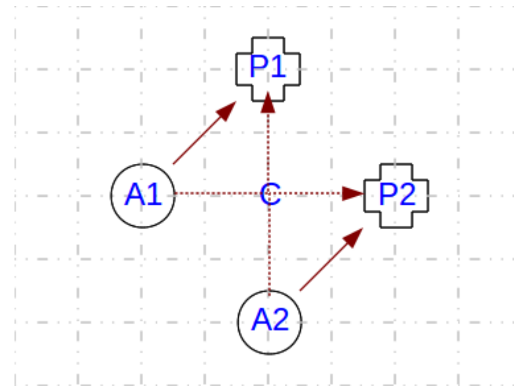


Figure 4: Example collision scenario. If the mapping (A1→P2,A2→P1) is chosen the agents will follow the dotted paths and collide at the point marked with a C. Instead $f_v$ will choose the mapping (A1→P1,A2→P2), as this minimizes maximum path distances, and the agents will follow the path denoted by the solid arrows thereby avoiding the collision.

### A.2 Avoiding Collisions

Given the assumptions that no two agents and no two role positions occupy the same position on the field, and that all agents move toward role positions along a straight line at the same constant speed, if two agents collide it means that they both started moving from positions that are the same distance away from the collision point. Furthermore if either agent were to move to the collision point, and then move to the target of the other agent, its total path distance to reach that target would be the same as the path distance of the other agent to that same target. Considering that we are working in a Euclidean space, by the triangle inequality we know that the straight path from the first agent to the second agent's target will be less than the path distance of the first agent moving to the collision point and then moving on to the second agent's target (which is equal to the distance of the second agent moving on a straight line to its target). Thus if the two colliding agents were to switch targets the maximum distance either is traveling will be reduced, thereby reducing the cost of the mapping, and the collision will be avoided. Figure 4 illustrates an example of this scenario.

The following is a proof sketch related to Figure 4 that no collisions will occur.

**Assumption.** *Agents A1 and A2 move at constant velocity $v$ on straight line paths to static positions P2 and P1 respectively. A1 $\neq$ A2 and P1 $\neq$ P2. Agents collide at point C at time $t$.*

**Claim.** *A1→P2 and A2→P1 is an optimal mapping returned by $f_v$.*

**Case 1.** *P1 and P2 $\neq$ C.*
*By assumption:*
$\overline{A_1C} = \overline{A_2C} = vt$
$\overline{A_1P_2} = \overline{A_1C} + \overline{CP_2} = \overline{A_2C} + \overline{CP_2}$
$\overline{A_2P_1} = \overline{A_2C} + \overline{CP_1} = \overline{A_1C} + \overline{CP_1}$

*By triangle inequality:*
$\overline{A_1P_1} < \overline{A_1C} + \overline{CP_1} = \overline{A_2P_1}$
$\overline{A_2P_2} < \overline{A_2C} + \overline{CP_2} = \overline{A_1P_2}$

$max(\overline{A_1P_1}, \overline{A_2P_2}) < max(\overline{A_1P_2}, \overline{A_2P_1})$
$\therefore cost(A1 \rightarrow P1, A2 \rightarrow P2) < cost(A1 \rightarrow P2, A2 \rightarrow P1)$
*and claim is False.*

**Case 2.** *P1 = C, P2 $\neq$ C.*
*By assumption:*
$\overline{CP_2} > \overline{CP_1} = 0$
$\overline{A_2C} \leq \overline{A_1C} = vt$
$\overline{A_1P_1} = \overline{A_1C} < \overline{A_1C} + \overline{CP_2} = \overline{A_1P_2}$

*By triangle inequality:*
*if* $\overline{A_1C} = \overline{A_2C}$
$\quad \overline{A_2P_2} < \overline{A_2C} + \overline{CP_2} = \overline{A_1C} + \overline{CP_2} = \overline{A_1P_2}$
*otherwise* $\overline{A_2C} < \overline{A_1C}$
$\quad \overline{A_2P_2} \leq \overline{A_2C} + \overline{CP_2} < \overline{A_1C} + \overline{CP_2} = \overline{A_1P_2}$

$max(\overline{A_1P_1}, \overline{A_2P_2}) < max(\overline{A_1P_2}, \overline{A_2P_1})$
$\therefore cost(A1 \rightarrow P1, A2 \rightarrow P2) < cost(A1 \rightarrow P2, A2 \rightarrow P1)$
*and claim is False*

**Case 3.** *P2 = C, P1 $\neq$ C.*
*Claim False by corollary to Case 2.*

**Case 4.** *P1, P2 = C.*
*Claim False by assumption.*

As claim is False for all cases $f_v$ does not return mappings with collisions. □

## A.3 Dynamic Consistency

Dynamic consistency is important such that as agents move toward fixed target role positions they do not continually switch or thrash between roles and never reach their target positions. Given the assumption that all agents move toward target positions at the same constant rate, all distances to targets in a mapping of agents to role positions will decrease at the same constant rate as the agents move until becoming 0 when an agent reaches its destination. Considering that agents move toward their target positions on straight line paths, it is not possible for the distance between any agent and any role position to decrease faster than the distance between an agent and the role position it is assigned to move toward. This means that the cost of any mapping can not improve over time any faster than the lowest cost mapping being followed, and thus dynamic consistency is preserved. Note that it is possible for two mappings of agents to role positions to have the same cost as the case of two agents being equidistant to two role positions. In this case one of the mappings may be arbitrarily selected and followed by the agents. As soon as the agents start moving the selected mapping will acquire and maintain a lower cost than the unselected mapping. The only way that the mappings could continue to have the same cost would be if the two role positions occupy the same place on the field, however, as stated in the given assumptions for $f_v$, this is not allowed.

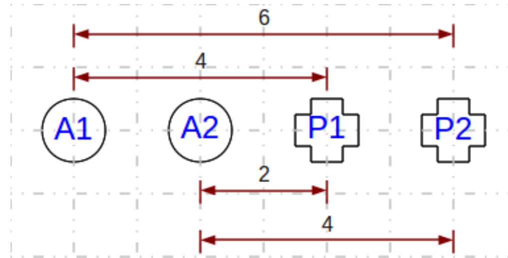


Figure 5: Example where minimizing the sum of path distances fails to hold desired properties. Both mappings of (A1→P1,A2→P2) and (A1→P2,A2→P1) have a sum of distances value of 8. The mapping (A1→P2,A2→P1) will result in a collision and has a longer maximum distance of 6 than the mapping (A1→P1,A2→P2) whose maximum distance is 4. Once a mapping is chosen and the agents start moving the sum of distances of the two mappings will remain equal which could result in thrashing between the two.

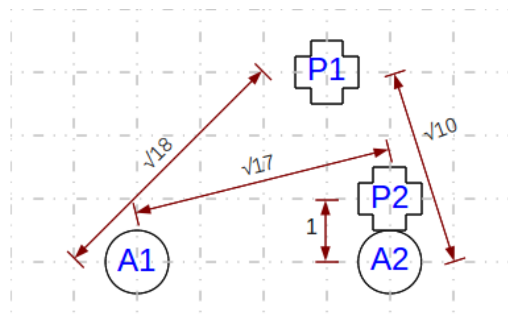


Figure 6: Example where minimizing the sum of path distances squared fails to hold desired property of minimizing the time for all agents to have reached their target destinations. The mapping (A1→P1,A2→P2) has a path distance squared sum of 19 which is less than the mapping (A1→P2,A2→P1) for which this sum is 27. $f_v$ will choose the mapping with the greater sum as its maximum path distance (proportional to the time for all agents to have reached their targets) is $\sqrt{17}$ which is less than the other mapping's maximum path distance of $\sqrt{18}$.

## A.4 Other Role Assignment Functions

Other potential ordering heuristics for mappings of agents to target positions include both minimizing the sum of all distances traveled and also minimizing the sum of all path distances squared. Neither of these heuristics preserve all the desired properties which are true for $f_v$. As can be seen in the example given in Figure 5, none of the three properties hold when minimizing the sum of all path distances. The third property of all agents having reached their target destinations is not true when minimizing the sum of path distances squared as shown in the example in Figure 6.