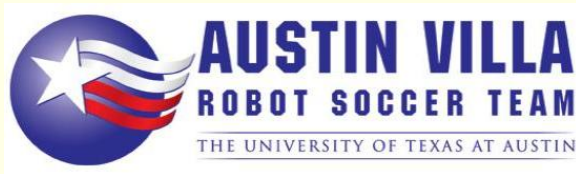


# Positioning to Win: A Dynamic Role Assignment and Formation Positioning System

Patrick MacAlpine, Francisco Barrera, and Peter Stone

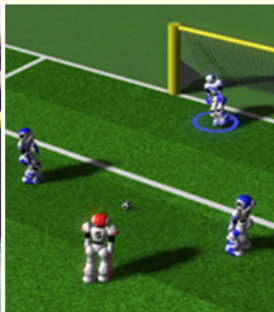
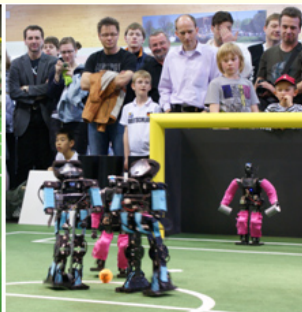
Department of Computer Science, The University of Texas at Austin

July 22, 2012



# What is RoboCup?

- International robotics competition founded in 1997
- Consists of many different robot soccer leagues
- Includes non-soccer robot competitions: RoboCup Rescue & RoboCup @Home





## RoboCup Goal

Have a team of fully autonomous humanoid robot soccer players beat the human World Cup champions by 2050

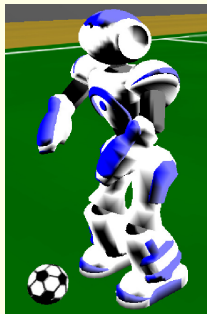


# Video

Humans vs Robots

## 2011 RoboCup 3D Simulation Domain

- Teams of 9 vs 9 autonomous agents play soccer
- Realistic physics using Open Dynamics Engine (ODE)
- Agents modeled after Aldebaran Nao robot
- Agent receives noisy visual information about environment
- Agents can communicate with each other over limited bandwidth channel

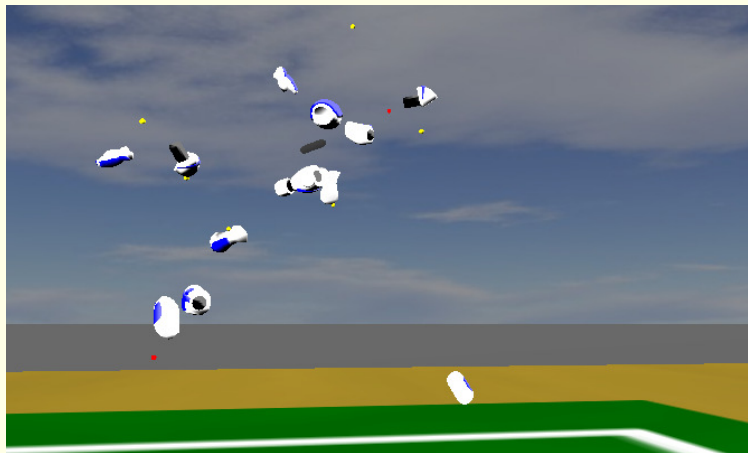


## Advantages of 3D Simulation

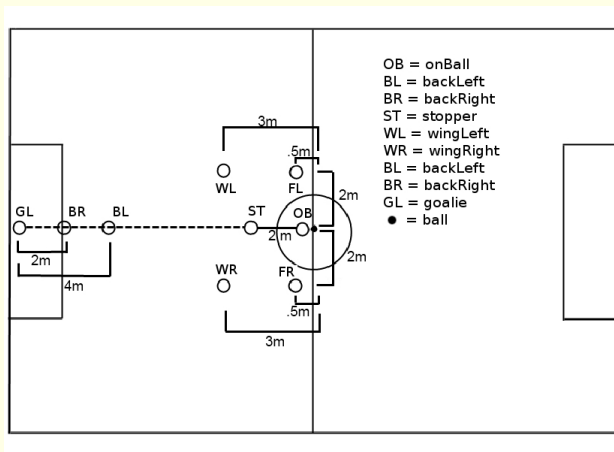
- Good for testing both low-level control and high-level processes
- Allows for quick prototyping of robot models and behavior
- Can do large scale machine learning
- Simulated robots don't break...

## Advantages of 3D Simulation

- Good for testing both low-level control and high-level processes
- Allows for quick prototyping of robot models and behavior
- Can do large scale machine learning
- Simulated robots don't break... well at least not usually!



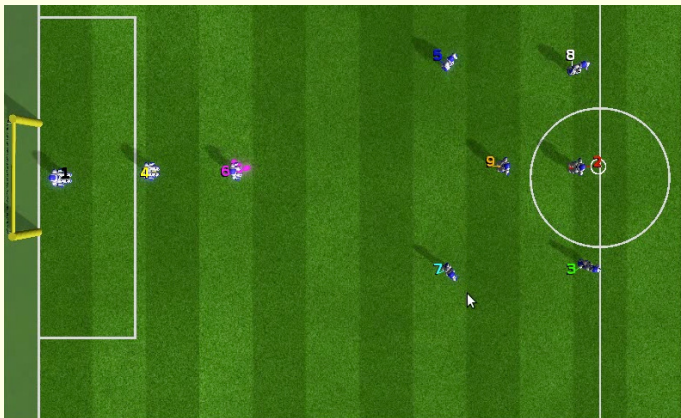
# Formation



- Every player assigned to a role (position) on the field
- Positions based on offsets from ball or endline
- *onBall* role assigned to the player closest to the ball
- Goalie positions itself independently

## Role Assignment Mapping and Assumptions

- One-to-one mapping of agents to positions
- Can be thought of as a role assignment *function*

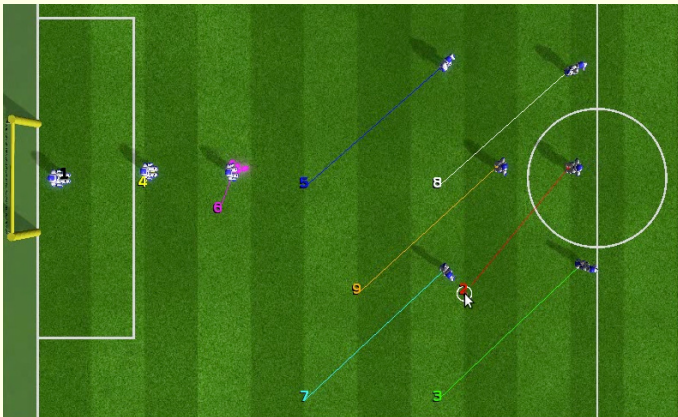


### Assumptions:

1. No two agents and no two roles occupy the same position
2. All agents move at constant speed along a straight line

## Role Assignment Mapping and Assumptions

- One-to-one mapping of agents to positions
- Can be thought of as a role assignment *function*



### Assumptions:

1. No two agents and no two roles occupy the same position
2. All agents move at constant speed along a straight line

# Desired Properties of a Role Assignment Function



## Desired Properties of a Role Assignment Function

1. *Minimizing longest distance* - it minimizes the maximum distance from a player to target, with respect to all possible mappings

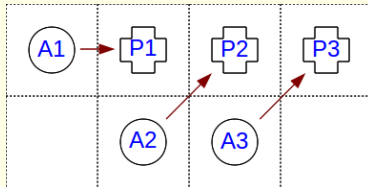
## Desired Properties of a Role Assignment Function

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

## Desired Properties of a Role Assignment Function

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
3. *Dynamically consistent* - role assignments don't change or switch as agents move toward target positions

## Role Assignment Function ( $f_v$ )



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)

- Mapping cost = vector of distances sorted in decreasing order
- Optimal mapping = lexicographically sorted lowest cost mapping

## Validation of Role Assignment Function $f_v$

- $f_v$  minimizes the longest distance traveled by any agent (Property 1) as lexicographical ordering of distance tuples sorted in descending order ensures this.
- Triangle inequality will prevent two agents in a mapping from colliding (Property 2) it can be shown, as switching the two agents' targets reduces the maximum distance either must travel.
- $f_v$  is dynamically consistent (Property 3) as, under assumption all agents move toward their targets at the same constant rate, lowest cost lexicographical ordering of chosen mapping is preserved because distances between any agent and target will not decrease any faster than the distance between an agent and the target it is assigned to.



- Brute force requires evaluating  $n!$  mappings, for  $n = 8$  is 40,320
- Must complete computation every 20ms (cycle time of server)

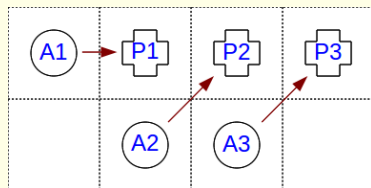
## Recursive Property of Role Assignment Function $f_v$

### Theorem

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

- **Translation:** Any subset of a lowest cost mapping is itself a lowest cost mapping
- 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

# Dynamic Programming Algorithm for Role Assignment

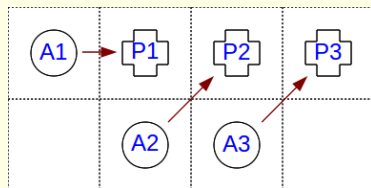


{P1}	{P2,P1}	{P3,P2,P1}

- Begin evaluating mappings of 1 agent and build up to  $n$  agents
- Only evaluate mappings built from subset mappings returned by  $f_v$
- Evaluates  $n2^{n-1}$  mappings, for  $n = 8$  is 1024 (brute force = 40,320)



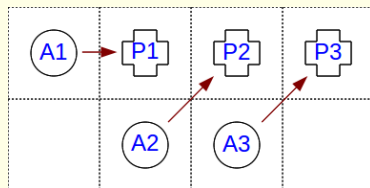
# Dynamic Programming Algorithm for Role Assignment



{P1}	{P2,P1}	{P3,P2,P1}
A1→P1 A2→P1 A3→P1		

- Begin evaluating mappings of 1 agent and build up to  $n$  agents
- Only evaluate mappings built from subset mappings returned by  $f_v$
- Evaluates  $n2^{n-1}$  mappings, for  $n = 8$  is 1024 (brute force = 40,320)

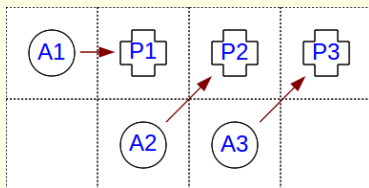
# Dynamic Programming Algorithm for Role Assignment



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

- Begin evaluating mappings of 1 agent and build up to  $n$  agents
- Only evaluate mappings built from subset mappings returned by  $f_v$
- Evaluates  $n2^{n-1}$  mappings, for  $n = 8$  is 1024 (brute force = 40,320)

## Dynamic Programming Algorithm for Role Assignment



$\{P1\}$	$\{P2, P1\}$	$\{P3, P2, P1\}$
$A1 \rightarrow P1$	$A1 \rightarrow P2, f_v(A2 \rightarrow P1)$	$A1 \rightarrow P3, f_v(\{A2, A3\} \rightarrow \{P1, P2\})$
$A2 \rightarrow P1$	$A1 \rightarrow P2, f_v(A3 \rightarrow P1)$	$A2 \rightarrow P3, f_v(\{A1, A3\} \rightarrow \{P1, P2\})$
$A3 \rightarrow P1$	$A2 \rightarrow P2, f_v(A1 \rightarrow P1)$	$A3 \rightarrow P3, f_v(\{A1, A2\} \rightarrow \{P1, P2\})$
	$A2 \rightarrow P2, f_v(A3 \rightarrow P1)$	
	$A3 \rightarrow P2, f_v(A1 \rightarrow P1)$	
	$A3 \rightarrow P2, f_v(A2 \rightarrow P1)$	

- Begin evaluating mappings of 1 agent and build up to  $n$  agents
- Only evaluate mappings built from subset mappings returned by  $f_v$
- Evaluates  $n2^{n-1}$  mappings, for  $n = 8$  is 1024 (brute force = 40,320)

## Positioning Video



Each position is shown as a color-coded number corresponding to the agent's uniform number assigned to that position. Agents update their role assignments and move to new positions as the ball or an agent is beamed (moved) to a new location.

# Voting Coordination System



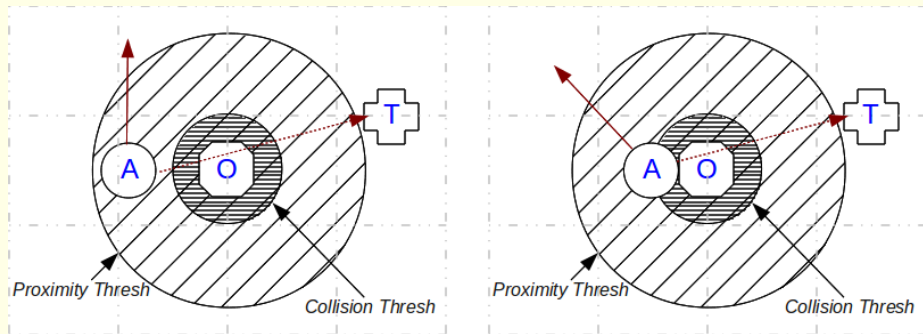
- Each agent broadcasts ball position, own position, and suggested role mapping during allotted time slot
- Sliding window stored of mappings received over last  $n$  time slots evaluated and mapping with the most number of votes is chosen
- If two mappings both have greatest number of votes then tie breaker goes to mapping with most recent vote received

# Voting Coordination System



- Each agent broadcasts ball position, own position, and suggested role mapping during allotted time slot
- Sliding window stored of mappings received over last  $n$  time slots evaluated and mapping with the most number of votes is chosen
- If two mappings both have greatest number of votes then tie breaker goes to mapping with most recent vote received
- **Synchronization: With voting system = 100%, without = 36%**

# Collision Avoidance



**Proximity Thresh** Move at angle tangent to obstacle

**Collision Thresh** Move along vector combination of angle tangent to and  $180^\circ$  from obstacle



# Video

**Clear Path** Unblocked path to target

**Blocked Path** Blocked path to target

**Corrected Path** Path to avoid obstacle

**Proximity Thresh** Proximity threshold around obstacle

**Collision Thresh** Collision threshold around obstacle



# Positioning System Evaluation Agents

**NoCollAvoid** No collision avoidance.

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

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

**Static** Role statically assigned to agents based on uniform number.

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

**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), such as the ball and agent assuming the *onBall* role, when computing distances of agents to role positions.

## Positioning System Evaluation

Average goal difference (row-column) across 100 games

	UTAustinVilla	Apollo3D	CIT3D
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)
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)

## Positioning System Evaluation

Average goal difference (row-column) across 100 games

	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)
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)

**PositiveCombo** *Offensive + PathCost + NearestStopper* agents

## Positioning System Evaluation

Average goal difference (row-column) across 100 games

	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)
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)

**PositiveCombo** *Offensive + PathCost + NearestStopper* agents

*PositiveCombo* agent beat *AllBall* agent by average of .31 goals.  
Record of 43 wins, 20 losses, 37 ties

# Positioning System Summary

## Positioning System Summary

- Minimizing longest distance any agent travels is effective function

## Positioning System Summary

- **Minimizing longest distance** any agent travels is effective function
- **Dynamic programming** provides considerable increase in computational efficiency

## Positioning System Summary

- **Minimizing longest distance** any agent travels is effective function
- **Dynamic programming** provides considerable increase in computational efficiency
- **Dynamic roles** with an **aggressive formation** does the best



# Positioning System Summary

- **Minimizing longest distance** any agent travels is effective function
- **Dynamic programming** provides considerable increase in computational efficiency
- **Dynamic roles** with an **aggressive formation** does the best
- **Communication**, **collision avoidance**, and **path planning** are important

## Related Work

- W. Chen and T. Chen. Multi-robot dynamic role assignment based on path cost, 2011.
- N. Lau, L. Lopes, G. Corrente, and N. Filipe. Multi-robot team coordination through roles, positionings and coordinated procedures, 2009.
- L. Reis, N. Lau, and E. Oliveira. Situation based strategic positioning for coordinating a team of homogeneous agents, 2001.
- P. Stone and M. Veloso. Task decomposition, dynamic role assignment, and low-bandwidth communication for real-time strategic teamwork, 1999.

## Future Work

- Implement passing and create formations to support this
- Attempt to learn better formations with machine learning
- Improve efficiency in calculating  $f_v$
- Explore other role assignment functions
- Extensions for heterogenous agents

## More Information

UT Austin Villa 3D Simulation Team homepage:  
[www.cs.utexas.edu/~AustinVilla/sim/3dsimulation/](http://www.cs.utexas.edu/~AustinVilla/sim/3dsimulation/)

Email: [patmac@cs.utexas.edu](mailto:patmac@cs.utexas.edu)



This work has taken place in the Learning Agents Research Group (LARG) at UT Austin. LARG research is supported in part by NSF (IIS-0917122), ONR (N00014-09-1-0658), and the FHWA (DTFH61-07-H-00030).

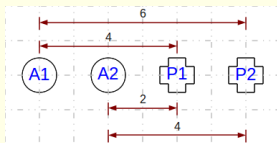
# Dynamic Programming Algorithm for Role Assignment

```
HashMap bestRoleMap =  $\emptyset$   
Agents =  $\{a_1, \dots, a_n\}$   
Positions =  $\{p_1, \dots, p_n\}$   
for  $k = 1$  to  $n$  do  
  for all  $a$  in Agents do  
     $S = \binom{n-1}{k-1}$  sets of  $k - 1$  agents from Agents -  $\{a\}$   
    for all  $s$  in  $S$  do  
      Mapping  $m_0 = \text{bestRoleMap}[s]$   
      Mapping  $m = (a \rightarrow p_k) \cup m_0$   
       $\text{bestRoleMap}[\{a\} \cup s] = \text{mincost}(m, \text{bestRoleMap}[\{a\} \cup s])$   
return bestRoleMap[Agents]
```

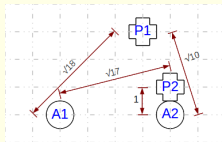
As  $\binom{n-1}{k-1}$  agent subset mapping combinations are evaluated for mappings of each agent assigned to the  $k$ th position, the total number of mappings computed for each of the  $n$  agents is thus equivalent to the sum of the  $n - 1$  binomial coefficients. That is,

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

## Other Role Assignment Functions



**Figure:** Example where minimizing the sum of path distances fails to hold desired properties. Both mappings of  $(A1 \rightarrow P1, A2 \rightarrow P2)$  and  $(A1 \rightarrow P2, A2 \rightarrow P1)$  have a sum of distances value of 8. The mapping  $(A1 \rightarrow P2, A2 \rightarrow P1)$  will result in a collision and has a longer maximum distance of 6 than the mapping  $(A1 \rightarrow P1, A2 \rightarrow P2)$  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:** 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  $(A1 \rightarrow P1, A2 \rightarrow P2)$  has a path distance squared sum of 19 which is less than the mapping  $(A1 \rightarrow P2, A2 \rightarrow P1)$  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  $\sqrt{18}$ .