

# The Brainstormers - Learning on the Tactical Level



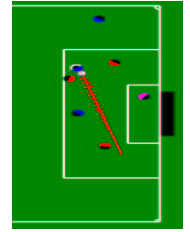
GOAL: LEARN TO USE THE BASIC SKILLS BY SUCCESS OR FAILURE

## Tactics

- actions: basic skills with varying length (kick, intercept, go2pos, ...)
- need for cooperation  $\Rightarrow$  multi-agent reinforcement learning
- clearly defined goal: score!!!



Tactics: cooperative team play



Tactics: cooperative team play

## AI used in **competition team**

- estimation of success probabilities (used in 1999; (Buck, Riedmiller, 2000))
- Depth-limited search for with-ball tactical decisions (since 2000)
- Neural network based cooperative attack positioning (since 2001)
- Neural network based complete cooperative attack behaviour (since 2002)

## Realized, but in **research stage**

- Feature-Q-learning based attack (double-passes! (Ehrmann, Riedmiller))

## Research Issues

- Reinforcement learning in cooperative multi-agent systems
- MAS-RL with features
- learning to communicate (Moore, Schneider, Riedmiller, 2001)
- incorporation of prior knowledge (constraints, special actions (homepositions), partially fixed policies (goalshot))
- theory: MAS-q algorithm for deterministic domains (Lauer, Riedmiller, 2000)
- theory: MAS-q algorithm for stochastic domains (Lauer, Riedmiller, 2001)
- theory: MAS-RL under varying conditions (e.g. exchange of information during learning): NAI, FAI, PSI, FSI, ...

## Learning 7 vs 8 Attack

- individual decisions;
- actions: no-ball: 8 directions, default position  
with-ball: pass, dribble, hold-ball
- prior knowledge: intercept and goalshot are decided otherwise with priority
- cooperate (central) learning and distribution of value function
- $\Rightarrow$  theoretically justified: optimal cooperate policy can be found
- practical compromises: model based instead of Q-learning
- use of an approximate model
- raw coding of positions:  $(7 + 8) \times 2 + 4 = 34$  inputs

## MAS learning algorithm

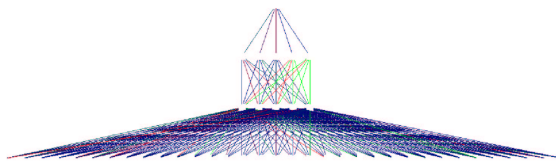
```

FOR all Situations s repeat n times{
  set_situation;
  play_and_record();
  /* until sequence terminates
}
evaluate&generate_training_patterns();
train_NN_by_Rprop();
distribute_NN();
REPEAT playing
    
```

## Results - example: positioning

Policy type	Average Seq.Length	Success
random value function	139.8	0.16 (0.10)
attack 2000 (handcoded)	129.4	0.18 (0.12)
Neuro Positioning (2001)	118.0	0.29 (0.18)

improved by 1.7 over vice-world champion team 2000!



Neural Network for Positioning

## Individual action selection

```

GenerateActionSet();
FOR all actions{
  AbstractModel(s,a,s');
  evaluate(s');
  determine_best_action();
}

GENERATEACTIONSET(): depends on situation
(w. ball, no. ball);
estimation of success

ABSTRACT MODEL(): Rough estimation
of successor state
    
```

