Footprint based Retrieval for a CBR system employed in a RoboSoccer domain

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Outline

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Problem Statement

CBR for defensive robosoccer agent

- Consider only 1 opponent attacker, 2 defenders and our goalie
- Action selection for coordinated defense behaviors
  - block the goal, steal the ball - no parameters
  - clear, tackle the opponent - parameters
- Episodic knowledge for improving rule based approach

The focus is on analysing *Footprint cases* using the concept of Competance Groups.

Our Contribution

- Finding a derived feature space which covers the problem space and has intuitive and relevant features
- Defined the notion of *Solves* which is crucial towards using Footprint based Retrieval
- Acquired case data of features and actions for defenders and goalie through rules designed by domain experts
- Developed a CBR engine for decision making
- Developed tools for visualizing and analysing data
- Analysed the relative coverage of cases based on the adopted similarity measures

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State space $\rightarrow$ Feature space

- State Space: observations from simulator (pos,vel,ang) for each robot and the ball
- Feature Space: transformed space which also covers the whole problem/state space.
- Features are relevant for decision making using the CBR system

Decision making is non-linearly related to state space. Transformation to feature space helps remove non-linearity, and simplify similarity measure definitions

Features Used

- Ball position and velocity w.r.t goal
- Position of two nearest defenders and attacker w.r.t ball
- Angle of ball w.r.t bots direction
- goalie position w.r.t ball

16 features in total

Output of the CBR system

The output is described as an action for each robot.

- Actions are abstract tasks
- The game state is used to decide how to go about an action.
- There are 2 kinds of actions
  - Non-Parameterized - Uses only game state data to execute action e.g Block ypos, spin clear
  - Parameterized - Uses additional information, provided by CBR system e.g Block line, intercept the ball

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Similarity Measures

We use a difference / ratio distance function, and an approximate sigmoid function defined as

$$f(d) = \frac{1}{2}\left(1 - \frac{k}{1+|k|}\right); \quad k = \frac{d-\theta}{\alpha} \tag{1}$$

where θ is the point of similarity 0.5, and α gives the rate of decay of the sigmoid.
We use a preference order and a weighted sum for global similarity.

Retrival and Adaptation

- Retrieval - We use priority queue to get closest k cases
- Adaptation - Since the output is an abstract action which uses the problem's game state to execute action, there is little need for adaptation.
- For parameterized actions, we can use weighted sum of parameters of retrieved cases.

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Solves

Def 1: RetrievalSpace(t) $= \{c \in C$: c is retrieved for t$\}$

- The RetrievalSpace of a case is controlled by the Similarity Measures.

Def 2: AdaptationSpace(t) $= \{c \in C$: c can be adapted for t$\}$

Def 3: Solves(c,t) iff $c \in$ [RetrievalSpace(t) $\cap$ AdaptationSpace(t)]

Coverage

Def 4: CoverageSet(c) = {c' ∈ C:Solves(c,c')}

Def 5: ReachabilitySet(c)={ c' ∈ C:Solves(c',c)}

Def 6: RelativeCoverage(c) =

$$\sum_{c' \in CoverageSet(c)} \frac{1}{|ReachabilitySet(c')|}$$

Coverage

RelatedSet(c) = CoverageSet(c) $\cup$ ReachabilitySet(c)
SharedCoverage(c1,c2) iff RelatedSet(c1) $\cap$ RelatedSet(c2)

- We can then define a Competence Group (maximal sets of independent cases with shared coverage)
- In every competence group, we can find the cases with highest relative coverage that solve all cases in group. This gives the footprint set.

Computation

- RetrievalSpace is governed by retrieved k cases for every case
- AdaptationSpace is determined if the solution actually solves the problem
- A directional graph is generated based on solves
- The in degrees and out degrees of a node give the Coverage and Reachability Set sizes

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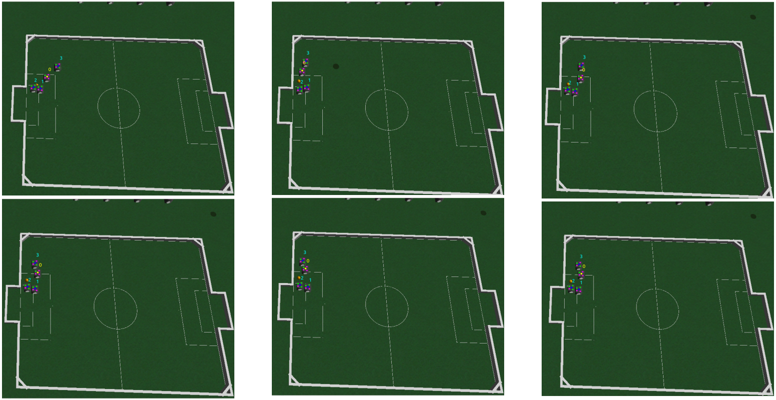
Data collection

A sample strategy used for collecting data from the system

- **Goalie**
  - If *OurBall* and *goalie_is_closer*, then *goalie_clear_ball* else *goalie_defend_ball_ypos*
  - if *not OurBall* and *on_goal*, then *goalie_defend_ball_extrapolated_position*, else *goalie_defend_ball_ypos*
- **Defenders**
  - If *OurSide* and *not OurBall*, then *defender_steal* else *defender_pass_clear*
  - If *not OurSide*, then *defender_sine*
- **Attacker**
  - If *TheirSide*, then *move_ball_to_goal*

Data Visualization



Training

There are two aspects to training the system:

- Random restarts from different initial configurations
- Running different strategies for attacker and defender
  - If the different strategies produce contradicting behaviours, the conflicts need to be resolved

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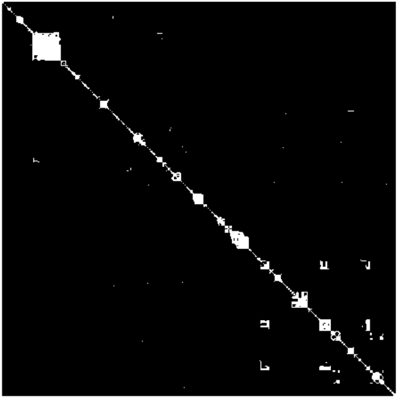
Case Base

- We ran 2 strategies and sampled every 0.5 seconds to gather 663 cases.
- These were chosen to be non conflicting in action

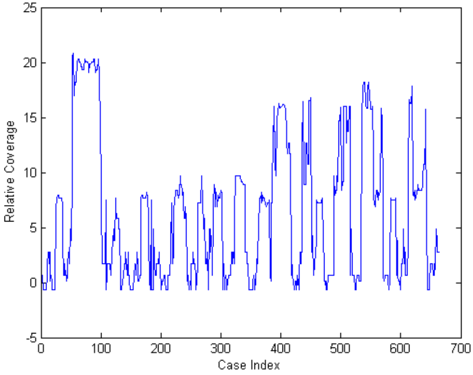
Case Base as Image

Using the notion of *Solves*, we generated a graph of which cases help solve others. The image for the graph is shown below



Relative Coverage

We then computed the relative coverage and shared coverage for each case.



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Inferences from Heatmap

- Sparse matrix. Only 8055 edges in a 663×663 graph
- Solid Squares along diagonal. Similar cases are adjacent in the temporal space
- 4 corner squares. These correspond to recurrence of a scenario at different time instances
- Can be used to analyse casebase alignment using Case Base as an Image Metaphor
- High relative coverage corresponds to the squares in the heatmap

Ack: Case base as an Image Metaphor, Sutanu et. al

Limitations

- Dataset is biased to single strategy. Aggregating data from multiple strategies would give new insights
- Few behaviours (i.e. small solution space). Adding more specialized actions would let the game evolve differently
- Adding adaptation knowledge will help in discovering new competance groups

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Conclusion

- Implemented CBR Engine for a defensive AI agent. Defined feature space, similarity measures, behaviours (inherently capturing adaptation).
- Data collection using rule based approaches for imparting human domain expert knowledge
- Used notion of *Solves* to obtain a heatmap which gives useful insights
- Used relative coverage to detect competence groups
- Analysed the major limitations of our work and pointed out various possible extensions

Questions

Questions?