

Behavior-analysis and -prediction for agents in real-time and dynamic adversarial environments

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Abstract. We present an approach for recognition and subsequent prediction of spatio-temporal patterns in a physical real-time environment. The motivation is to provide a domain-independent approach for the analysis of agent's behavior in adversarial multi-agent scenarios. The goal is to create an opponent-specific model, which is used for behavior prediction. We develop a framework for representing a set of hierarchically structured facts, events and actions using temporal logic. Recognition, learning, and prediction is performed using a probabilistic approach utilizing Bayesian Networks. The system is applied to the domain of the RoboCup 3D Simulation League and evaluated with regard to the recognition-, prediction- and real-time capabilities.

1 INTRODUCTION

The paper is situated in the adversarial, multi-agent domain of robotic soccer. Here, representation of domain-specific concepts is vital for recognizing the current world-state and estimating the outcome of actions. This information is incorporated in the agent's planning and reasoning process, aiming at increasing its performance. We propose a domain-independent approach of creating a hierarchical, qualitative abstraction from temporal sequences. This representation is employed for the creation of probabilistic, team-specific behavior models used for predicting opponent's actions.

2 RELATED WORK

Dousson & Le Maigat [3] use chronicles, where hierarchical recognition is performed by selecting events and merge them with a factorization of common temporal scenarios. Miene et al. [7, 6] propose a comprehensive method for classification of quantitative time series data into spatio-temporal ground facts and a hierarchically organized formalization for motion situations. Wendler et al. [9] propose an approach for action detection geared towards an efficient object-oriented implementation in the context of a comprehensive behavior recognition and prediction framework. Intille and Bobick [5] developed a probabilistic framework for the classification of single, highly structured offensive plays in American football for performing game analysis. As none of the presented approaches for which a detailed survey can be found in [8] handles our complete set of requirements, we build upon Miene and Intille & Bobick's approaches and extend their preliminary work into the realm of real-time domains.

3 APPROACH

Our aim is to develop a domain-independent, human readable and extensible qualitative abstraction of a dynamic scene, which maintains temporal relations between recognized concepts. Utilizing these concepts as ground predicates, a probabilistic opponent behavior model is calculated by evaluating team-specific correlations between world-state predicates and observed opponent behavior. Due to the stochastic nature and partial observability of the domain both representation and recognition have to provide means for dealing with noise and uncertainty.

3.1 Modeling the domain

We adapted the generic representation formalism described in [7]. It provides a hierarchical domain representation where the chronological order of temporal sequences is maintained by utilizing subsets of the temporal relations proposed by [1] and [4]. It proposes three layers of abstract concepts: facts, events and actions. Facts are mostly domain-independent ground concepts and serve as a qualitative abstraction layer. Events are defined as conjugations of facts and represent significant domain-specific incidents. Actions are defined as conjugations of events and describe cooperative actions between agents. The selected subset consists of seven facts (*accelerating*, *decelerating*, *approaching*, *departing*, *contact*, *free*, *ball_control*), two events (*kick*, *receive*) and one action (*pass*). We focus on the *pass* action and supporting events, motivated by game analysis performed in [9], indicating that ball transfers account for the largest share of actions.

To incorporate noise and uncertainty, we adapted techniques proposed by [5] where hierarchical Bayesian Network (BN) classifiers, working on fuzzy logic assessments, are used to recognize concepts in dynamic domains and [2] who utilizes a technique to directly represent temporal relations in (dynamic) BNs. We convert the temporal descriptions from [7] into a set of BN classifiers where both the conceptual hierarchy and the temporal relations have to be preserved. Each fact, event and action is represented as a node, where connections indicated causal relationships thus directly mapping the hierarchical structure of the domain to the network topology. Based on the temporal intervals, an ordered sequence of the nodes is generated by merging all temporal relations down to three (*before*, *after* and *equals*). According to this sequence, the nodes are sorted into five time slots representing the abstract time concepts *past*, *just*, *now*, *soon* and *future*, which preserves information on temporal relations.

Application of these classifiers is performed by mapping the abstract time slots to concrete time-intervals of the domain, where segmentation granularity and projection range were arbitrarily selectable. Thus, facts serve as temporal abstraction nodes making the

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network independent to domain frequency. For each fact, the qualitative abstraction is calculated and assessed as fuzzy probability distribution to the appropriate node. Belief-updating for events and actions is performed by subsequently propagating of evidences through the classifier network.

3.2 Learning opponent behavior

The aim is to generate an opponent model feasible for predicting opponent pass target selection given current observations. The main hypothesis is that the deliberation process is both team specific and dependent on the current world state observation of the respective agent. Due to the fact that the opponent agent is a black box in terms of its internal world-state representation, assumptions on both selection and relevancy of dependent world state properties had to be made. We selected a number of seven properties (called *evidence facts*) based on the proposed game characteristics defined in [9].

Model generation is performed on a dataset consisting of team-internal ball transfers (bad passes were excluded) recognized based on previously recorded logfile data. In addition to the pass information the dataset contained the calculated evidence fact assessments. Following the assumption that the moment of deliberation on pass targets is performed just before pass execution, for each pass the state of a selection of evidence facts at the moment of pass initialization was stored. Based on these, a joined probability table is calculated which afterwards is transformed into a conditional probability table describing $P(\text{pass}|\text{evidence_facts})$.

4 EVALUATION

The described recognition and prediction concepts are implemented into a C++ software framework named OPAL (an abbreviation for opponent analysis), which provides two modes of operation. The offline mode, where data access was unrestricted, aims at providing augmented log-files for both post-game-analysis and visual debugging. The online mode enforces strict sequential data access by preventing access on *future* data and aims at evaluating both recognition and prediction performance. Evaluation was performed on 300 log-files, created in an all-play-all setup between the teams SEU (China), Brainstormers (Germany) and VW3D (Germany). We use 10-fold-cross-validation to evaluate team specificity of opponent models, prediction quality and run time performance.

5 RESULTS

For evaluation, a model was created for each team, which afterwards was used for predicting pass target selection for the team it was designed for as well as the two other teams. Table 1 shows the individual results for both cases, the average as well as the performance of *guessing* the pass target for each case. On average, the team-specific model performed better on the team it was trained for than on the other two. In both cases prediction performance was better than simple guessing. In a second step, we evaluate the performance of a model trained with example data from all teams. The performance of this model was 35,77% on average, thus between the case where the team matches the model and the opposite case. In a second evaluation step the recognition component was tested individually where 74.55% of all passes were recognized where the average time which elapsed before the correct most probable assumption was calculated was 37%. Average run-time for recognition (maintaining and updating 11 parallel hypotheses) is ≈ 3 ms. Average run-time when additionally performing prediction (on a subset of 3 *evidence facts*) is

≈ 6 ms. Comparing recognition performance of $\approx 75\%$ to [7] and [9] (both cases $> 90\%$) leaves room for improvement. However the run-time of 3 ms shows a general applicability to real-time domains. Regarding prediction performance [9] performs significantly better but shows drawbacks limited to perfect vision scenarios and having a run time of 23.9 ms to 40.2 ms in comparison to 6 ms.

Table 1. Mean prediction performance using team-specific models

$team_{model} = team_{predict}$		$team_{model} \neq team_{predict}$	
team	average	team	average
seu	42.48 %	seu	28.86 %
brainstormers	32.14 %	brainstormers	34.17 %
vw3d	36.52 %	vw3d	27.97 %
average	37.04 %		30.30 %
guessing		20.30 %	

6 CONCLUSION

We designed and implemented a system which provides suitable means for representing, recognizing and predicting situations in a dynamic real-time environment and the ability to learn and predict opponent behavior. We applied the approach to the RoboCup 3D domain, evaluated the performance on the *pass* target selection and have shown the team-specificity of the target selection. The run-time of the recognition component shows the applicability to real-time scenarios. Though other approaches show superior recognition and/or prediction quality, they are either limited to complete information scenarios or not usable in online situations. The domain independent structure provides transferability to other domains where next steps will be evaluating cases for applying the approach to other dynamic real-time scenarios.

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