Identifying and Utilizing Subgroup Coordination Patterns in Team Adversarial Games

(Extended Abstract)

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ABSTRACT

This paper addresses the problem of identifying player coordination patterns in multi-player adversarial games. In the Rush 2008 football simulator, we observe that each play relies on the efforts of different subgroups within the main team to score team touchdowns. We present a method to automatically identify these subgroups from historical play data based on: 1) mutual information between the offensive player, defensive blocker, and ball location 2) the observed ball work flow. After extracting these subgroups, we demonstrate how subgroups can be used to create new plays by performing play adaptations of existing offensive plays tuned to counter specific defensive plays.

Categories and Subject Descriptors

I.2.1 [**Applications and Expert Systems**]: Games

General Terms

Experimentation

Keywords

opponent modeling, multi-player games, mutual information, play adaptation

1. INTRODUCTION

Effective player coordination has been shown to be an important predictor of team success in adversarial games such as Robocup soccer [9]. Much work has centered on the problem of role allocation, correctly allocating players to roles appropriate for their capabilities and smoothly switching players between roles [7]. However, in complex team tasks, roles cannot always be accomplished by a single player. In this case, the team must divide into subgroups to simultaneously handle multiple complex tasks. In the worst case, determining which players to group together to accomplish a task requires searching over the partition set of potential team assignments (the Bell number) [8]. In this paper, we demonstrate a novel method for discovering which agents will make effective subgroups based on an analysis of game data from successful team plays. We evaluate our subgroup extraction method using the Rush 2008 American football simulator.

To succeed at football, a team must be able to successfully execute closely-coordinated physical behavior. To achieve this tight physical coordination, teams rely on a pre-existing playbook of offensive maneuvers to move the ball down the field and defensive strategies to counter the opposing team's attempts to make yardage gains. There are three types of cues used to identify subgroups: spatial, temporal, and coordination dependencies. Our subgroup extraction method uses all three to build a candidate set of subgroups. By examining mutual information between the offensive player, defensive blocker, and ball location along with the observed ball workflow, we can determine which players frequently coordinate in previously observed plays. Although automatic subgroup identification could be useful for applications such as opponent modeling or game commentary, in this paper we demonstrate how extracted subgroups can be used to create new multi-agent plays by adaptation of existing plays.

Prior work on finding coordination patterns from an automated analysis of historical play data in team adversarial games falls into four general categories: 1) formation matching based on static spatial patterns, 2) data mining approaches, 3) classification-based play recognizers, and 4) coaching systems. Research on formation matching focuses on matching noisy game data to existing formation templates. Formations are typically known a priori, rather than automatically extracted, and the techniques robustly identify correspondences between the template patterns and the data.

Automatically devising counters to specific opponent actions has been generally addressed by competitors in the Robocup coach league. In previous versions of the coach league, the agent had to improve the performance of Robocup teams by suggesting online modifications to ongoing plays. Techniques have been developed to extract specific information, such as home areas [6], opponent positions during set-plays [5], and adversarial models [2]. This data is later used by the coach agent to improve the team's scoring performance. This work used relatively simple heuristics to identify salient features, whereas we present a general method based on mutual information between players to extract subgroup patterns.

2. METHOD AND RESULTS

For the purposes of this paper, we focus on yardage gained over a single play, independent of the team's down or other plays that the team has executed in the past. The idea behind our approach is to identify subgroups of coordinated players by observing a large number of football plays. Earlier work, such as [4], showed appropriately changing behavior of a critical subgroup (e.g., QB, RB, FB) during an offensive play, in response to a recognized defensive strategy, significantly improves yardage. Identifying these key players in previous work has relied entirely on domain knowledge. In contrast, our work automatically determines the critical sub-

groups of players (for each play) by an empirical analysis of play statistics. Once a candidate subgroup has been identified, we can perform dynamic play adaptation [4] in response to the recognized defensive play to improve the team's performance.

To find which players should be grouped, dependencies among the eight players for each formation must be understood. All players coordinate to some extent but some players' actions are so tightly coupled that they form a *subgroup* during game play. Changing commands for an athlete in a subgroup without adjusting the others causes the play to lose cohesion. We identify subgroups using a combination of two methods; statistical analysis of player trajectories and workflow.

Our method for identifying subgroups attempts to quantify the degree to which the trajectories of players are coupled based on a set of observed instances of the given play. For each offensive player, the trajectory of the defensive player assigned to block him is determined. Since this assigned defensive player is typically the closest opponent during the course of the play, we determine the assigned defender to be the one whose average distance to the given player is the least. So, for a given offensive player, $o \in \{o_1, \ldots, o_8\}$, the assigned defender, $d \in \{d_1, \ldots, d_8\}$ is: $d = \underset{d_i}{\mathrm{argmax}} \sum_{t=1}^{T} ||o(t) - d_i(t)||_2$, where $o(t)$ and $d_i(t)$ denote the 2D positions of the given players at time t. Our feature $f(t)$ is simply the centroid (average) of $o(t)$, $d(t)$ and the ball position $b(t)$: $f(t) = \frac{1}{3}[o(t) + d(t) + b(t)]$. We now compute sets of features $\{f_i\}$ and $\{f_j\}$ from the collection of observed plays for a given pair of offensive players o_i and o_j, treating observations through time simply as independent measurements. We model the distributions F_i and F_j of each of these features as 2D Gaussian distributions with diagonal covariance.

To quantify the independence between these feature distributions we use the symmetricized Kullback-Leibler [3] divergence: $S(o_i, o_j) = D_{KL}(F_i||F_j) + D_{KL}(F_j||F_i)$, where $D_{KL}(F_i, F_j) = \sum_k F_i(k) \log(F_i(k)/F_j(k))$. Pairs of athletes with low $S(.)$ are those whose movements during a given play are closely coupled. We compute the average $S(.)$ score over all pairs (o_i, o_j) in the team and identify as candidate subgroups those pairs whose score falls in the lowest quartile.

In addition to finding the mutual information between player we must also determine relationships formed based on possession of the football. When the quarterback hands the ball off to the running back or fullback their movements are coordinated for only a brief span of time before the ball is transferred to the next player and so we also find groups formed by transference of the ball between players and add them to the group list. At the time of this paper we devised a simple sorting mechanism where groups are ranked based the number of ball receptions players in a subgroup made in addition to group sizes. Statistical evidence indicated a correspondence to the importance of a group for a given type of offensive formation.

To adapt the current offensive play we employ a straightforward form of dynamic play adaptation. Based upon our estimate of the most likely defensive formation sensed early in the play (at t=3), we switch the key subgroup to the play that has the best a priori chance of countering the opponent's strategy. To recognize the defensive play in progress we trained a set of support vector machines (SVMs) based on observed player trajectories. We rely upon these to recognize the opponent's strategy at an early stage in the play and we identify the strongest counter based on the yardage history of the offensive playbook against the recognized defense.

An analysis of test results clearly indicated the detected best subgroup switch using the proposed method produced greater yardage gains than when switching the domain knowledge key group across all formations. The subgroup proposed by our method outperforms both the random and the domain knowledge based method on all scenarios. Overall the proposed method produced about a 20% gain over the domain knowledge key group from [4] and about 39% better than the randomly-generated groups.

3. CONCLUSION AND FUTURE WORK

In this paper, we present an unsupervised method for extracting subgroup coordination patterns from historical play data. We demonstrate our method in the Rush 2008 football simulator and believe that it can easily generalize to other team adversarial games, such as basketball and soccer. We use two techniques to focus our search over the space of play adaptations. First, by recognizing the opponent's play, we can eliminate poor play adaptations, based on historical yardage data. Second, by identifying key groups of players we can limit our search to the modifying the most effective players, without exhaustively searching the set partition of player subgroups. Our candidate group generation method is solely on spatio-temporal movement traces, but the sorting algorithm incorporates play yardage information by generating and testing the effects of different play combinations. In future work, we will explore the usage of our candidate subgroups at limiting other types of multi-agent search problems within the Rush simulator such as multi-agent reinforcement learning and Monte Carlo planning (e.g.,[1]).

4. ACKNOWLEDGMENTS

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