Learning Complementary Multiagent Behaviors: A Case Study

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ABSTRACT

As the reach of multiagent reinforcement learning extends to more and more complex tasks, it is likely that the diverse challenges posed by some of these tasks can only be addressed by combining the strengths of different learning methods. While this important aspect of learning is yet to receive theoretical analysis, useful insights can be gained from its applications to concrete tasks. This paper presents one such case study grounded in the robot soccer context. The task we consider is Keepaway, a popular benchmark for multiagent reinforcement learning. Whereas previous successful results in this domain have limited learning to an isolated, infrequent decision that amounts to a turn-taking behavior (passing), we expand the agents' learning capability to also include a much more ubiquitous action (moving without the ball, or getting open), such that at any given time, multiple agents are executing learned behaviors simultaneously. We introduce a policy search method for learning "GetOpen" to complement the temporal difference learning approach employed for learning "Pass". Empirical results indicate that the learned GetOpen policy matches the best hand-coded policy for this task, and outperforms the best policy found when Pass is learned. We demonstrate that Pass and GetOpen can be learned together, and indeed that these learned behaviors specialize towards the counterpart behaviors with which they are trained. Our formulation of GetOpen as a learning problem multiplies the opportunities for multiagent learning research within the Keepaway test-bed.

1. INTRODUCTION

Multiagent sequential decision making is traditionally studied using general frameworks such as Dec-POMDPs. In a typical setting, each agent has a set of actions available from every state. The agent gets a reward for choosing an action; crucially, this reward depends on the actions taken in step by other agents. While lending the problem a high degree of generality, models such as Dec-POMDPs are tractable to solve only under limiting assumptions of discrete state and observability of the global state [6]. Multiagent systems that occur in practice seldom meet these assumptions; yet often they possess characteristics that can simplify reasoning. For example, agents may perform implicit and explicit coordination of their actions, assume roles in different parts of the state space, or act in temporally distinct phases.

In the context of multiagent reinforcement learning, a number of models have been proposed to exploit task-specific regularities such as coordination of actions [7], state abstraction [5], and shared information [19]. While such measures all pave the way towards learning increasingly complex tasks, they still assume that the task being considered is simple enough to be learned using a *single* learning algorithm. Yet complex multiagent tasks often comprise multiple overlapping behaviors, whose diverse demands can only be met by combining the strengths of qualitatively different learning approaches. Identifying this as a crucial direction for future research, we present a detailed case study of one such task, which is grounded in the context of robot soccer.

The task we consider is Keepaway [18], which has become a popular test-bed for multiagent reinforcement learning [12, 13]. Keepaway is a realistic, continuous, high-dimensional, stochastic task, and is significantly more complex than synthetic, discrete tasks such as Predator-Prey [1] that have been used in the past for studying both agent cooperation [10] and competition [9]. However to date, all the learning in Keepaway has focused on just one aspect of the problem, in which the learned decision is made on a turn-taking basis among teammates. Specifically, these studies have all focused on the "Pass" behavior of the player with possession of the ball in deciding whether (and to which teammate) to pass. They assume that its teammates, when moving to positions on the field likely to induce successful passes, execute fixed, hand-coded "GetOpen" strategies.

In contrast, we formulate GetOpen as a multiagent learning problem, thereby extending learning in Keepaway from Pass to Pass+GetOpen. Consequently, Keepaway becomes an instance of a learning problem composed of highly interdependent behaviors executing simultaneously. Each player executes multiple behaviors (Pass and GetOpen) that affect the outcome of its teammates' behaviors, and in the long run, also interact with one another. Such a scenario poses a significant challenge for designing a credit assignment scheme that both reflects the intended objectives in the underlying task and guides learning in a natural, incremental manner.

We present a novel solution for learning GetOpen using policy search, which contrasts with the temporal difference learning method used for Pass. Results show that the learned GetOpen policy matches the best performing hand-coded policy for this task. Further experiments illustrate that learning these complementary behaviors results in a tight coupling between them, and indeed that Pass and

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GetOpen can be learned together. These results demonstrate the effectiveness of applying separate learning algorithms to distinct components of a significantly complex task. We provide detailed analyses to guide the design and evaluation of similar solutions developed in the future, and hope that this exploratory research will also motivate theoretical advances towards combining separately learned behaviors. Numerous opportunities for conducting research in multiagent systems arise as a direct consequence of our formulation of GetOpen for learning.

This paper is organized as follows. In Section 2 we review the standard Pass task and formalize GetOpen similarly. In Section 3 we describe algorithms for learning Pass and GetOpen, both individually and together. Experimental results are discussed in Section 4, which is followed by a presentation of related and future work in Section 5. Our conclusions are summarized in Section 6.

2. KEEPAWAY Pass AND GetOpen

The simulated RoboCup soccer domain [3] models several difficulties that agents must cope with in the real world. Soccer is necessarily a multiagent enterprise, in which agents have both teammates and opponents. In the RoboCup simulation, they are only provided partial and noisy perceptions, and have imperfect actuators. Their sensing and acting routines are not synchronized, and in the interest of keeping real time, do not admit extensive deliberation. The atomic actions available to an agent are Turn, Turn-Neck, Dash, Kick, and Catch; skills such as passing to a teammate or going to a point must be composed of a string of these low-level actions executed sequentially. For all these reasons, simulated RoboCup soccer becomes a challenging domain for machine learning.

Keepaway [18] is a subtask of soccer in which a team of 3 *keepers* aims to keep possession of the ball[1] away from the opposing team of 2 *takers*. The game is played within a square region of side $20m$.[2] Each episode begins with some keeper having the ball, and ends when some taker claims possession or the ball overshoots the region of play. It is the objective of the keepers to maximize the length of the episode, referred to as the episodic **hold time**. The keepers must cooperate with each other in order to realize this objective; they compete with the team of takers that seeks to minimize the hold time. Figure 1(a) shows a snapshot of a Keepaway episode in progress.

In order to make the task amenable to learning, it becomes necessary to constrain the scope of decision making by the keepers. Figure 2 outlines the policy followed by *each* keeper in the scheme employed by Stone *et al.* [18]. The keeper closest to the ball intercepts the ball until it has possession. Once it has possession, it must execute the Pass behavior (not to be confused with a pass action), by way of which it may retain ball possession or pass to a teammate. Keepers other than the one closest to the ball move to a position conducive for receiving a pass by executing GetOpen behavior.

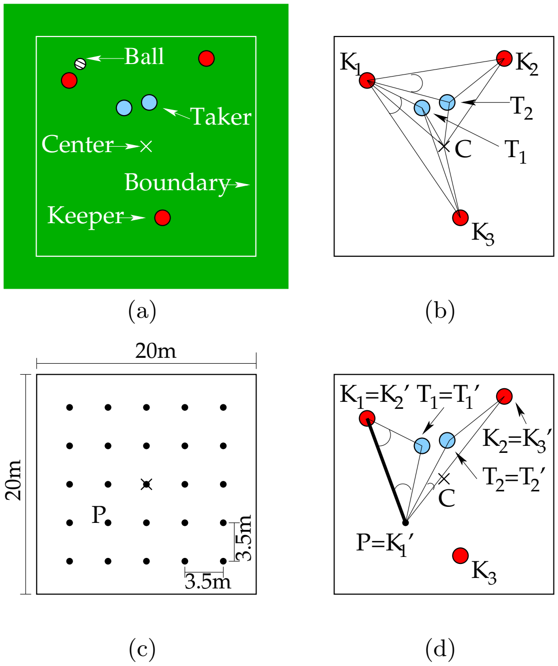


Figure 1: (a) A snapshot of Keepaway. (b) Corresponding Pass state variables. (c) Target points for GetOpen, among them P. (d) Corresponding GetOpen state variables. $dist(K_1', K_2')$ **and** $dist(K_1, K_1')$ **(darkened) overlap.**

Pass and GetOpen, by offering a *choice* of high-level actions based on the keeper's state, are candidates for the application of learning. Most prior work assumes GetOpen, and indeed the behavior followed by the takers, to follow fixed, hand-coded strategies. In other words, the teammates and opponents of the keeper with the ball do not *adapt* to the specific characteristics of that keeper, as they do in real soccer. As a step in the direction of furthering team adaptation, we extend the frontier of learning in Keepaway to include GetOpen. Thus, we treat Keepaway as a composite of two distinct behaviors to be learned: Pass and GetOpen. As in previous work [18], we consider the takers to follow the fixed policy of moving towards the ball.[3]

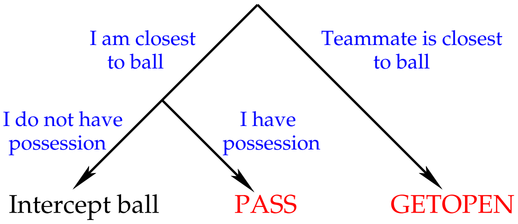


Figure 2: Policy followed by each keeper.

2.1 Keepaway Pass

Here we revisit the problem of Pass defined by Stone *et al.* [18]. The keepers and takers assume roles that are indexed based on their distances to the ball: K_i is the i^{th} closest keeper to the ball, and T_j the j^{th} closest taker. From Figure 2, we see that the keeper executing Pass must be K_1.

[1] A player is deemed to have *possession* of the ball if it is close enough to be kicked.

[2] Keepaway can be generalized to varying numbers of keepers and takers, as well as different field sizes [18].

[3] In recent work, Iscen and Erogul [11] explore learning taker behavior, which we discuss briefly in Section 5. This aspect of Keepaway complements the work in our paper.

The high-level actions available to K_1 are HoldBall, which is composed of a series of kicks close to itself, but away from approaching takers; and PassBall-i, $i \in 2,3$, a direct pass to K_i. In this work, we assume that the high-level actions are fixed, i.e., they are not learned. Each player processes its low-level perceptual information to construct a world model, which constitutes a continuous state space. This space is represented through a vector of 13 state variables, comprising distances and angles among the players and the center C of the field. These are marked in Figure 1(b), and enumerated in Table 1. A policy for PASS maps a 13-dimensional vector representing the state variables to one of the high-level actions: HoldBall, PassBall-2, and PassBall-3. An example of such a policy is PASS:HAND-CODED (Algorithm 1), which implements a well-tuned manually programmed strategy [18]. Under this policy, K_1 executes HoldBall until the takers get within a certain distance, after which distances and angles involving its teammates and opponents are used to decide whether (and to which teammate) to pass. Yet another policy for PASS is PASS:RANDOM, under which K_1 chooses one of the three available actions with equal likelihood. PASS:LEARNED denotes a learned PASS policy, which is described in Section 3.

Algorithm 1 PASS:HAND-CODED

```
input PASS state variables (13)
output Action ∈ {HoldBall, PassBall-2, PassBall-3}
  if $dist(K_1, T_1) > C_1$ then
    Return HoldBall.
  for $i \in 2,3$ do
    $valAng_i \leftarrow \min_{j \in 1,2} ang(K_i, K_1, T_j)$.
    $valDist_i \leftarrow \min_{j \in 1,2} dist(K_i, T_j)$.
    $val_i \leftarrow C_2 \cdot valAng_i + valDist_i$.
  if $\max_{i \in 2,3} val_i > C_3$ then
    $passIndex \leftarrow \text{argmax}_{i \in 2,3} val_i$.
    Return PassBall-passIndex.
  else
    Return HoldBall.
  {$C_1 = 5.0, C_2 = 0.25, C_3 = 22.5$; distances are taken to be in meters and angles in degrees.}
```

2.2 Keepaway GETOPEN

Whereas learning the PASS behavior has been studied extensively in the literature [12, 13], to the best of our knowledge, all previous work has used the hand-coded GETOPEN policy originally defined by Stone *et al.* [18], which we refer to here as GETOPEN:HAND-CODED. Thus, while previous work on this task has considered multiple agents learning, they have never been executing their learned behaviors concurrently (only one player executes PASS at any given time). This paper introduces a learned GETOPEN behavior, thereby expanding the scope of multiagent learning in Keepaway significantly. Below we describe our formulation of GETOPEN.

In principle, there are infinitely many positions that K_2 and K_3 can occupy on the square playing field, However, they only get a small amount of time to pick a target. Since nearby points are likely to be of similar value, an effective strategy is to evaluate only a small, finite set of points spread out across the field and choose the most promising. Figure 1(c) shows a uniform grid of 25 points overlaid on the field, with a 15% margin on the sides. GETOPEN is implemented by evaluating each point P and moving to the one with the highest value. The GETOPEN learning problem is defined to be finding an evaluation function that assigns a value to every target point P, given the field configuration.

Table 1: Pass and GetOpen state variables.

PASS	GETOPEN
$dist(K_1, K_2)$	$dist(K'_1, K'_2)$
$dist(K_1, K_3)$	$dist(K'_1, K'_3)$
$dist(K_1, T_1)$	$dist(K'_1, T'_1)$
$dist(K_2, T_2)$	$dist(K'_2, T'_2)$
$\min_{j \in 1,2} dist(K_2, T_j)$	$\min_{j \in 1,2} dist(K'_2, T'_j)$
$\min_{j \in 1,2} ang(K_2, K_1, T_j)$	$\min_{j \in 1,2} ang(K'_2, K'_1, T'_j)$
$\min_{j \in 1,2} dist(K_3, T_j)$	$\min_{j \in 1,2} dist(K'_3, T'_j)$
$\min_{j \in 1,2} ang(K_3, K_1, T_j)$	$\min_{j \in 1,2} ang(K'_3, K'_1, T'_j)$
$dist(K_1, C)$	$dist(K_1, K'_1)$
$dist(K_2, C)$	$\min_{j \in 1,2 ang(K'_1, K_1, T_j)}$
$dist(K_3, C)$	
$dist(T_1, C)$	
$dist(T_2, C)$	

As with PASS, it becomes necessary to define a set of state variables for learning GETOPEN. In Figure 1(d), K_3 is shown seeking to evaluate the point P at some time t. The distances and angles marked correspond to the GETOPEN state variables used for the purpose, which we identify based on informal experimentation. None of the state variables involve K_3, as K_3 is examining a situation at time t' in the future when it would itself be at P. At time t', K_3 expects to have possession of the ball, and re-orders the other players based on their distances to it. Thus K_3 becomes K'_1, and in the state from Figure 1(d), K_1 becomes K'_2, T_1 becomes T'_1, and so on.

Conceptually, the evaluation of the target point P should consider both the likelihood of receiving a pass at P, and the value of being at P with the ball afterwards. This leads to two logical groups within the state variables. One group contains 2 variables that influence the success of a pass from K_1 to K'_1, the latter being at P. These are the distance between K_1 and K'_1, and the minimum angle between K_1, K'_1 and any taker. The other group of state variables bear direct correspondences with those used for learning PASS, but computed under the re-ordering at t'. Of the 13 state variables used for PASS, we leave out the 5 distances between the players and the center of the field, as they do not seem to benefit the learning of GETOPEN. This results in a total of 10 state variables for GETOPEN, which are listed in Table 1.

In defining the state variables for GETOPEN, it is implicitly assumed that players other than K'_1 do not change their positions between t and t'. This clearly imperfect assumption does not have too adverse an impact since GETOPEN is executed *every* cycle, always with the *current* positions of all players. Revising the target point every cycle, however, has an interesting effect on a random GETOPEN policy. In order to get from point A to point B, a player must first turn towards B, which takes 1-2 cycles. When a random target point is chosen each cycle, K'_1 constantly keeps turning, achieving little or no net displacement. To redress this effect, our implementation of GETOPEN:RANDOM only allows K'_1 to revise its target point when it reaches its current target. Such a measure is not necessary when the targets remain reasonably stable, as they do for GETOPEN:LEARNED, the learned policy, and GETOPEN:HAND-CODED [18]. Under GETOPEN:HAND-CODED (Algorithm 2), the value of a point P is inversely related to its *congestion*, a measure of its distances to the keepers and takers. Assuming that K_1 will pass the ball from *predictedBallPos*, P is deemed an inadmissible target (given a value of $-\infty$) if any taker comes within a threshold angle with the line joining *predictedBallPos* and

P. Thus, GetOpen:Hand-coded is a sophisticated policy using complex entities such as congestion and the ball's predicted position, which are not captured by the set of state variables we define for learning GetOpen. In Section 4, we compare GetOpen:Hand-coded with GetOpen:Learned to verify if distances and angles alone can describe competent GetOpen behavior.

Algorithm 2 GetOpen:Hand-coded

```
input Evaluation point $P$, World State
output Value at $P$
  $teamCongestion \leftarrow \sum_{i \in 1,2,3, i \neq myIndex} \frac{1}{dist(K_i, P)}$.
  $oppCongestion \leftarrow \sum_{j \in 1,2} \frac{1}{dist(T_j, P)}$.
  $congestion \leftarrow teamCongestion + oppCongestion$.
  $value \leftarrow -congestion$.
  $safety \leftarrow \min_{j \in 1,2} ang(P, predictedBallPos, T_j)$.
  if $safety < C_1$ then
    $value \leftarrow -\infty$.
  Return $value$.
  {$C_1 = 18.4$; angles are taken to be in degrees.}
```

2.3 Keepaway Pass+GetOpen

Pass and GetOpen are separate behaviors of the keepers, which together may be viewed as "distinct populations with coupled fitness landscapes" [16]. At any instant of time, there are always two keepers executing GetOpen; their teammate, if it has intercepted the ball, executes Pass. More specifically, each keeper executes GetOpen when it assumes the role of K_2 or K_3, and executes Pass when it has possession of the ball, as K_1. The extended sequence of actions that results as a combination each keeper's Pass and GetOpen policies determines the team's performance. The episodic hold time is the temporal length of that sequence.

Pass has been the subject of many previous studies, in which it is modeled as a (semi) Markov Decision Problem (MDP) and solved through temporal difference learning (TD learning). In Pass, each action (HoldBall, PassBall-1, PassBall-2) is taken by exactly one keeper; hence only the keeper that takes an action needs to get rewarded for it. When this reward is the time elapsed until the keeper takes its next action (or the episode ends), the episodic hold time gets maximized if each keeper maximizes its own long-term reward.

Unfortunately, GetOpen does not admit a similar credit assignment scheme, because at any instant, two keepers (K_2 and K_3) take GetOpen actions to move to target points. If K_1 executes the HoldBall action, none of them will reeceive a pass; if K_1 passes to K_2 (K_3), it is not clear how K_3 (K_2) should be rewarded. In principle, the sequence of *joint actions* taken by K_2 and K_3 up to the successful Pass must be rewarded. Yet, such a joint action is taken *every* cycle (in contrast with Pass actions, which last 4-5 cycles on average), and the large number of atomic GetOpen actions (25, compared to 3 for Pass) leads to a very large joint action space. In short, GetOpen induces a far more complex MDP than Pass. An additional obstacle to be surmounted while learning Pass and GetOpen together is non-stationarity introduced by each into the other's environment. All these reasons, combined with the inherent complexity of simulated RoboCup soccer, make Pass+GetOpen a demanding problem for machine learning.

3. LEARNING FRAMEWORK

Each of the 3 keepers must learn one Pass and one GetOpen policy; an array of choices exists in deciding whether the keepers learn separate policies or learn them in common. Thus, the total number of policies learned may range from 2 (1 Pass, 1 GetOpen) to 6 (3 Pass, 3 GetOpen). Different configurations have different advantages in terms of the size of the overall search space, constraints for communication, the ability to learn specialized behaviors, etc. It falls beyond the scope of this paper to systematically comb the space of solutions for learning Pass and GetOpen. As an exploratory study, our emphasis in this work is rather on verifying the *feasibility* of learning these complementary behaviors, which are qualitatively distinct. In the learning scheme we adopt, based on informal experimentation, each keeper learns a unique Pass policy, while all of them share a common GetOpen policy. This amounts to learning 4 policies in total (3 Pass, 1 GetOpen). Below we provide descriptions of the methods we use for learning Pass and GetOpen. As in Section 2, we furnish pseudo-code and parameter settings to ensure that our presentation is complete and our experiments reproducible.

3.1 Learning Pass

We apply the same algorithm and parameter values employed by Stone *et al.* for learning Pass [18], under which each keeper uses Sarsa to make TD learning updates. The reward for a keeper's action is the time elapsed until the next action is taken from the next state by that keeper (or the episode ends). Assuming that the keepers follow stationary GetOpen policies, this scheme seeks to directly maximize the episodic hold time by separately improving each keeper's Pass policy. A one-dimensional tile coding scheme is used for function approximation; tile widths are 3.0m along state variable corresponding to distances, and 10° along those representing angles. The exploration parameter ϵ is set to 0.01, and the learning rate α to 0.125.

3.2 Learning GetOpen

The solution to be learned under GetOpen is an evaluation function over its 10 state variables, by applying which the keepers maximize the hold time of the episode. The difficulties in credit assignment under GetOpen, as outlined in Section 2.3, make direct optimization of the policy parameters, or "policy search", a more promising alternative than TD learning. Thus, we represent the evaluation function as a parameterized function and search for parameter values that lead to the highest episodic hold time.

Our learned GetOpen policy is implicitly represented through a neural network that computes a value for a target location given the 10-dimensional input state. The player executing GetOpen compares the values at different target points on the field, and moves to the point with the highest value. Note that unlike with Pass, these values do not have the same semantics as action values computed through TD learning; rather, they merely serve as *action preferences*, whose relative order determines which action is chosen. We achieve the best results using a 10-5-5-1 network, with a total of 91 parameters (including biases at each hidden node). The parameters are initialized to random values drawn uniformly from $[-0.5, 0.5]$; hidden nodes implement the sigmoid function $f(x) = 1.7159 \cdot tanh(\frac{2}{3}x)$, suggested by Haykin [8].

A variety of policy search methods are applicable for optimizing the 91-dimensional policy, and we verify informally that methods such as hill climbing, genetic algorithms, and policy gradient methods all achieve qualitatively similar results. The experiments reported in this paper are carried out using the cross-entropy method [4], which evaluates a population of candidate solutions drawn from a distribution, and progressively refines the distribution based on a selection of the fittest candidates. In our experiments, we use a population size of 20 drawn initially from $N(0,1)^{91}$, picking the best 5 after each evaluation of the population to recompute the distribution. Each keeper follows a fixed, stationary Pass policy across all evaluations in a generation; within each evaluation, all keepers share the same GetOpen policy, which is the one being evaluated. The fitness function used is the average hold time over 125 episodes, which negates the high stochasticity of the Keepaway task.

3.3 Learning Pass+GetOpen

Algorithm 3 outlines our method for learning Pass+GetOpen. Learning is bootstrapped by optimizing a GetOpen policy for a random Pass policy. The best GetOpen policy found after two iterations (a total of $2 \times 20 \times 125 = 5000$ episodes) is fixed, and followed while learning Pass using Sarsa for the next 5000 episodes. The Pass policy is now frozen, and GetOpen is once again improved. Thus, inside the outermost loop, either Pass or GetOpen is fixed and stationary, while the other is improved, starting from its current value. In Section 4.1, we observe that several approaches for learning Pass and Get-Open simultaneously are not successful. Note that π_{Pass} and π_{GetOpen} are still *executed* concurrently during each Keepaway episode as part of *learnPass*() and *learnGetOpen*().

Algorithm 3 Learning Pass+GetOpen

```
output Policies $\pi_{\text{Pass}}$ and $\pi_{\text{GetOpen}}$
  $\pi_{\text{Pass}} \leftarrow$ Pass:Random.
  $\pi_{\text{GetOpen}} \leftarrow$ GetOpen:Random.
  repeat
    $\pi_{\text{GetOpen}} \leftarrow learnGetOpen(\pi_{\text{Pass}}, \pi_{\text{GetOpen}})$.
    $\pi_{\text{Pass}} \leftarrow learnPass(\pi_{\text{Pass}}, \pi_{\text{GetOpen}})$.
  until convergence
  Return $\pi_{\text{Pass}}, \pi_{\text{GetOpen}}$.
```

Whereas Algorithm 3 describes a general learning routine for each keeper to follow, in our specific implementation, the keepers execute it in phase, and indeed share the same π_{GetOpen}. Also, we obtain slightly better performance in learning Pass+GetOpen by spending more episodes on learning GetOpen than on learning Pass, which we report in the next section.

4. RESULTS AND DISCUSSION

In this section, we report the results of a systematic study pairing three Pass policies (Pass:Random, Pass:Hand-coded, and Pass:Learned) with three GetOpen policies (GetOpen:Random, GetOpen:Hand-coded, and GetOpen:Learned). For the sake of notational convenience, we use abbreviations: thus, Pass:Random is denoted P:R, GetOpen:Learned is denoted GO:L, and their conjunction P:R-GO:L. Nine configurations arise in total. Figure 3 shows the performance of each Pass policy when paired with three different GetOpen policies, and vice versa. Policies in which both Pass and GetOpen are either random or hand-coded are static, while the others show learning.

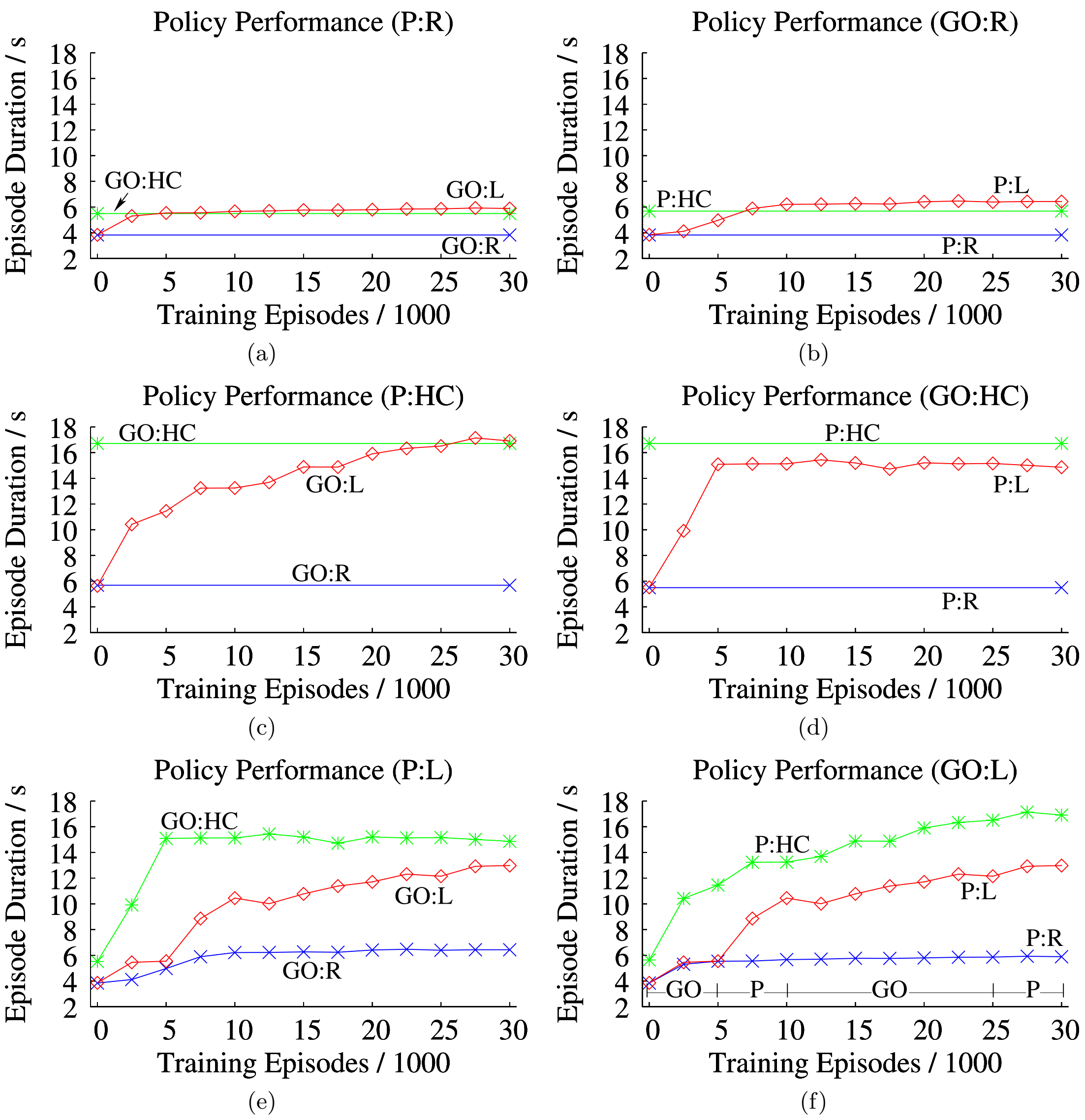
4.1 Performance of Learning

Figure 3(e) shows the performance of P:L. P:L-GO:HC corresponds to the experiment conducted by Stone *et al.* [18], and yields similar results. After 30,000 episodes of training, the hold time achieved is 14.9 seconds, which falls well short of the 16.7 seconds registered by the static P:HC-GO:HC policy (Figure 3(c)). Although P:L-GO:HC is trained in these experiments with a constant learning rate of $\alpha = 0.125$, we posit that annealing α will improve its performance by avoiding the gradual dip in hold time we observe between episodes 12,500 and 30,000. In the absence of any guarantees about convergence to optimality, we consider the well-tuned P:HC-GO:HC policy to serve as a near-optimal benchmark for the learning methods. Interestingly, under the random GetOpen policy, GO:R (Figure 3(b)), P:HC is overtaken by P:L at 30,000 episodes ($p < 0.0001$). This result highlights the ability of learning methods to adapt to different settings, for which hand-coded approaches may demand tedious manual attention.

Figure 3(f) confirms the viability of our policy search method for learning GetOpen, and its robustness in adapting to different Pass policies. Practical considerations force us to terminate experiments after 30,000 episodes of learning, which corresponds roughly to one day of training time. After 30,000 episodes, P:HC-GO:L achieves a hold time of 16.9 seconds, which indeed exceeds the hold time of P:HC-GO:HC (Figure 3(c)); yet despite running 20 independent trials of each, this result is not statistically significant. Thus, we only conclude that when coupled with P:HC, learning GetOpen, a novel contribution of this work, matches the hand-coded Getopen policy that has been used in all previous studies on the Keepaway task. This result also highlights that well-crafted state variables such as *congestion* and *predictedBallPos*, which are used by P:HC-GO:HC, are not necessary for describing good GetOpen behavior. Interestingly, the hold time of P:HC-GO:L is significantly higher than that of P:L-GO:HC ($p < 0.001$). In other words, our GetOpen learning approach outperforms the previously studied Pass learning when each is paired with a hand-coded counterpart, underscoring the relevance of treating GetOpen as a problem for learning.

An important result we observe from Figures 3(e) and 3(f) is that not only can Pass and GetOpen be learned when paired with static policies, they can indeed be learned in tandem. In our implementation of Algorithm 3, we achieve the best results by first learning GetOpen using policy search for 5000 episodes, followed by 5000 episodes of learning Pass using Sarsa. Subsequently, we conduct 6 generations of learning GetOpen (episodes 10,000 to 25,000), followed by another 5000 episodes of Sarsa, as depicted along the x axis in Figure 3(f). The hold time of P-L:GO-L (13.0 seconds after 30,000 episodes) is significantly lower than P:L-GO:HC, P:HC-GO:L, and P:HC-GO:HC ($p < 0.001$), reflecting the additional challenges encountered while learning Pass and GetOpen together.

We notice several *negative* results with other variant methods for learning Pass+GetOpen. In one approach, we represent both Pass and GetOpen as parameterized policies and evolve their weights concurrently to maximize hold time. In another approach, GetOpen uses the value function being learned by Pass as the evaluation function for target points. In both these cases, and indeed in schemes in which Pass and GetOpen are learned simultaneously, i.e., both are learned on every episode, the performance never rises significantly above random. Thus, while the reported P:L-GO:L results confirm that Pass and GetOpen can indeed



(a) (b) (c) (d) (e) (f)

Figure 3: Learning curves corresponding to conjunctions of various Pass and GetOpen policies. Each curve represents an average over at least 20 independent trials. Each reported point corresponds to an evaluation (non-learning) for 500 episodes; points are reported every 2500 episodes. Note that each of the nine experiments is reported once in the left column, where experiments are grouped by common Pass policies, and once in the right column, where they are grouped by GetOpen.

be learned in tandem (note that the learning curve in Figure 3(f) is still rising after 30,000 episodes), there appears to be dramatic scope for improving this result. In Section 5, we consider multiple channels of related work which may apply.

4.2 Specialization of Learned Policies

We conduct a further experiment in order to ascertain the degree of specialization achieved by learned Pass and GetOpen policies, i.e., whether it is beneficial to learn Pass specifically for a given GetOpen policy (and vice versa). In Table 2, we summarize the performances of learned Pass and GetOpen policies trained and tested with different counterparts. Each column corresponds to a test pairing. We notice that the best performing Pass policy for a given GetOpen policy is one that was trained with the same GetOpen policy (and vice versa); the maximal sample mean in each column coincides with the diagonal. It must be noted, however, that despite conducting at least 20 trials of each experiment, some comparisons are not statistically significant. A possible reason for this is the high variance caused by the stochasticity of the domain. Yet, it is predominantly the case that learned behaviors adapt to work best with the counterpart behavior with which they are playing. Several practical problems demand specialized solutions for specific situations; by automatically gravitating towards tightly-coupled behaviors that maximize performance, learning can offer a significant advantage.[4]

[4] The results presented here are supplemented by a collection of videos in which different Pass and GetOpen policies can be compared. This is available at the following web page: `http://www.cs.utexas.edu/~AustinVilla/sim/keepaway-getopen/`.

Table 2: In the table on the left, Pass learned while trained with different GetOpen policies is tested against different GetOpen policies. Each entry shows the mean hold time and one standard error of at least 20 independent runs, conducted for 500 episodes. Each *column* corresponds to a test GetOpen policy. The largest entry in each column is in boldface; entries in the same column are marked with "-" if not significantly lower ($p < 0.05$). The cell GO:L-GO:L shows two entries: when the learned Pass policy is tested against the same ("s") learned GetOpen policy as used in training, and when tested against a different ("d") learned GetOpen policy. The table on the right is constructed similarly for GetOpen, and uses the same experiments as Pass for the cell P:L-P:L.

Pass:Learned			
Train	Test		
	GO:R	GO:HC	GO:L
GO:R	**6.37** ± 0.05	11.73 ± 0.25	10.54 ± 0.26
GO:HC	6.34 ± 0.06$^-$	**15.27** ± 0.26	12.25 ± 0.32
GO:L	5.96 ± 0.07	13.39 ± 0.35	**13.08** ± 0.26 (s)
			12.32 ± 0.32 (d)$^-$

GetOpen:Learned			
Train	Test		
	P:R	P:HC	P:L
P:R	**5.89** ± 0.05	10.40 ± 0.39	11.15 ± 0.43
P:HC	5.48 ± 0.04	**16.89** ± 0.39	12.99 ± 0.43$^-$
P:L	5.57 ± 0.06	11.78 ± 0.56	**13.08** ± 0.26 (s)
			12.32 ± 0.32 (d)$^-$

5. RELATED AND FUTURE WORK

Multiple learning methods are used in the layered learning architecture developed by Stone [17] for simulated soccer. These include neural networks for learning to intercept the ball, decision trees for evaluating passes, and TPOT-RL, a TD learning method for high-level strategy learning. Our work shares the motivation that different sub-problems in a complex multiagent learning problem can benefit from specialized solutions. Yet a key difference is that in Stone's architecture, skills learned using supervised learning are employed in higher-level sequential decision making, to which reinforcement learning is applied; in our work, the two learning problems we consider are themselves both sequential decision making problems. Whereas we employ qualitatively different methods for learning Pass and GetOpen in a cooperative setting, Rosin and Belew [16] consider evolving opponents in *competitive* scenarios using a genetic algorithm. On games such as Tic-Tac-Toe and Nim, they demonstrate that coupled fitness functions present opportunities for members of the opposing populations to share evaluations, thereby expediting learning. By aiming to maximize the same objective function, Pass and GetOpen too are candidates for simultaneous co-evolution.

In their survey, Panait and Luke [14] divide cooperative multiagent learning into two broad categories: under *team learning*, a single learner develops the behavior for the entire team; under *concurrent learning*, each agent follows a separate learning processes. Interestingly, our learning method for Pass+GetOpen occupies both categories: GetOpen uses team learning, while Pass uses concurrent learning. Further, these two processes are themselves interleaved. The policy search approach we use for GetOpen is similar to the method used by Haynes *et al.* [10] for evolving cooperative behavior among four predators that must collude in order to catch a prey. The predators share a common policy, represented as a strongly-typed LISP S-expression, in contrast with the neural representation we engage for computing a real-valued evaluation function. The Predator-Prey domain [1], which is discrete and non-stochastic, is much simpler compared to Keepaway.

By decomposing Keepaway into Pass and GetOpen, our work enriches the multiagent nature of the problem and spawns numerous avenues for future work. For example, a new promising dimension is agent communication. Consider K_1 "yelling" to K_2 where it is about to pass, as is common in real soccer. K_1's Pass and K_2's GetOpen behaviors could conceivably exploit such information to further team performance. A similar situation arises while evolving quadrupedal wall-climbing [2], in which different legs must act in phase for the robot to move. Several learning methods that have been applied to Keepaway Pass also find relevance in the context of GetOpen. For instance, Metzen *et al.* [13] introduce EANT, a method to evolve *both* the structure and the weights of a neural network representing a policy for Pass. While we use a fixed neural network topology in this work for representing the GetOpen policy, EANT can potentially evolve topologies that yield higher performance. Keepaway can be extended to more keepers and takers: Taylor *et al.* [20] study transferring knowledge obtained in simpler configurations to more complex ones. While the experiments in this paper all involve 3 keepers and 2 takers, a promising area of future work is to implement GetOpen with more players, possibly incorporating the knowledge transfer methods developed by Taylor *et al.*

The Brainstormers RoboCup team [15] has applied reinforcement learning for learning attacking team behavior. In their work, the actions available to the player with the ball include several variants of passing and dribbling. Its teammates can move in different directions or head to a home position. Assuming the availability of an environmental model, TD learning is used to estimate a value function over the possible states. The team attack is shown to increase its goal-scoring percentage. Recently, Iscen and Erogul [11] have considered applying TD learning to the behavior of the takers. The actions available to the takers are ball interception and player marking. Whereas Pass+GetOpen models cooperation, extending Keepaway to include taker behavior would also incorporate competition.

6. CONCLUSION

This paper presents exploratory research intended to guide the effort of scaling multiagent learning to tackle complex, realistic domains. We advance the case for applying different learning algorithms to qualitativly distinct behaviors present in a multiagent system. We demonstrate the effectiveness of combining temporal difference and policy search reinforcement learning through a specific case study that encapsulates the challenges faced in such domains: sequential decision making, high-dimensional state spaces, noisy perceptions and actions, and real-time constraints. In particular, we introduce Keepaway GetOpen as a multiagent learning problem that complements Keepaway Pass, the well-studied reinforcement learning test-bed problem from the simulated RoboCup soccer domain. Pass is turn-taking in nature, while GetOpen is executed by multiple players every cycle. Yet, these qualitatively distinct behaviors both aim to achieve the same objective of maximizing episodic hold time.

We provide a policy search method for learning GetOpen, which compares on par with the well-tuned hand-coded GetOpen policy used previously, and indeed performs better when paired with a random Pass policy. Learning GetOpen with a hand-coded Pass policy outperforms the earlier result in which Pass is learned and GetOpen is hand-coded. These results show that policy search methods can be effective on complex MDPs defined over multiple agents, for which traditional TD learning is not well-suited. Our algorithm for learning both Pass and GetOpen in an interleaved manner confirms the feasibility of learning them together, but also shows significant scope for improvement. We discuss several ideas from related work that may aid progress in this direction. Our further experiments investigate the interdependence between learned Pass and GetOpen policies, and expose their tightly-coupled nature. Our presentation includes videos of the various policies being executed.

Our demonstration of the autonomous learning of such a significant fraction of a complex task extends the reach of machine learning in practical applications. While this work showcases the richness of the Pass+GetOpen learning problem, it takes the step of putting together distinct learning techniques that apply to sequential decision making, which we identify as a crucial element in scaling to even more complex multiagent learning problems.

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