Using Monte Carlo Search With Data Aggregation to Improve Robot Soccer Policies

Francesco Riccio[1]*, Roberto Capobianco[1]*, and Daniele Nardi[1]

Department of Computer, Control and Management Engineering "Antonio Ruberti",
Sapienza University of Rome, Rome, Italy
{riccio, capobianco, nardi}@dis.uniroma1.it

Abstract. RoboCup soccer competitions are considered among the most challenging multi-robot adversarial environments, due to their high dynamism and the partial observability of the environment. In this paper we introduce a method based on a combination of Monte Carlo search and data aggregation (MCSDA) to adapt discrete-action soccer policies for a defender robot to the strategy of the opponent team. By exploiting a simple representation of the domain, a supervised learning algorithm is trained over an initial collection of data consisting of several simulations of human expert policies. Monte Carlo policy rollouts are then generated and aggregated to previous data to improve the learned policy over multiple epochs and games. The proposed approach has been extensively tested both on a soccer-dedicated simulator and on real robots. Using this method, our learning robot soccer team achieves an improvement in ball interceptions, as well as a reduction in the number of opponents' goals. Together with a better performance, an overall more efficient positioning of the whole team within the field is achieved.

Keywords: Policy Learning; Reinforcement Learning; Humanoid Robots; Multi-Robot Systems.

1 INTRODUCTION

Machine learning methods have been increasingly used in robotics to deal with uncertain and unstructured environments. In such scenarios, directly learning from data a (sub-)optimal set of parameters to generate robot behaviors is often more robust than hard coding them from prior knowledge. However, the variety of the problems and the lack of big amount of data still refrain researchers from the application of standard learning approaches to challenging domains such as RoboCup soccer competitions [5]. Here, in fact, manifold problems must be faced by a multi-robot system, such as coordination and decision making under partial observability of an adversarial and dynamic environment.

RoboCup soccer teams typically tackle competitions by deploying static behaviors for their robots. Here, each programmed agent executes a single policy that takes into account the state of the robot teammates, but does not change at

---

* These two authors have contributed equally to the work.

Fig. 1. MCSDA generates effective robot policies in a highly dynamic environment.

run-time. However, during the game the partial observable environment discloses previously unavailable information, such as the strategy of the opponent team. On the one hand, predefined behavioral protocols cannot handle the newly available knowledge. Hence, the use of a learning approach to update each agent's current policy would be beneficial to the team performance. On the other hand, such information only consists of small portions of new data, that cannot be used without exploiting the structure of the domain and adequate machine learning methods.

In this paper, we specifically consider the setup proposed by the RoboCup Standard Platform League (SPL), where NAO robots compete in a 5-vs-5 soccer game (see Fig. 1). Our goal consists in generating a robot defender policy that adapts to the strategy of the opponent team. Such strategy is not known and, hence, makes the world dynamics unknown or difficult to model. The policy that we generate is composed of a discrete and limited set of actions, and it is at first instantiated to imitate an initial dataset of human (expert) deployed behaviors. To this end, we introduce Monte Carlo Search with Data Aggregation (MCSDA). Our algorithm uses a standard classifier to imitate expert actions given the current observation of a simplified representation of the game domain, modeled by the position and velocity of the ball in the field, as well as the player position. Since the classifier is trained over the distribution of observations and expert actions from multiple games, frequent patterns and main game areas can be exploited by the learned policy. Such policy is then improved by aggregating [11] the initial dataset with policy rollouts collected using simple Monte Carlo search [13]. While our algorithm strictly relates to state-of-the-art methods for reinforcement learning with unknown system dynamics [10] and recent applications to games like Go [12], the main novelty of this paper consists in the combination of these techniques, that allows to achieve good results on a partially observable, high dynamic robotic context. With this paper, in fact, we aim at showing that (1) the use of data aggregation together with Monte Carlo search is practical, effectively improves the learner's policy and preserves good

properties, and (2) by adopting a simplified representation of the domain a good policy improvement can be obtained on complex and challenging robotic scenarios. The obtained results show improvements in the overall team performance, where the percentage of recovered ball and the number of won games increase with the number of MCSDA iterations.

The reminder of this paper is organized as follows. Section 2 provides an overview on the literature about policy learning and improvement, as well as strategy adaptation in the RoboCup context; Section 3 describes in detail the proposed approach introducing the MCSDA algorithm (Section 3.2). Finally, Section 4 describes the robot platform and the experimental setup together with the obtained results, while Section 5 concludes the paper with final remarks and future work.

2   RELATED WORK

Policy learning is a very active area of research, due to its complexity and practical relevance. Reinforcement learning, Monte Carlo methods and imitation learning have been successfully applied in several contexts and domains. For example, in robotics Kober and Peters [6] use episodic reinforcement learning in order to improve motor primitives learned by imitation for a Ball-in-a-Cup task. Kormushev et al. [7], instead, encode movements with and extension of Dynamic Movement Primitives [4] initialized from imitation. Reinforcement learning is then used to learn the optimal parameters of the policy, thus improving the obtained performance. Differently, Ross et al. [11] propose a meta-algorithm for imitation learning (DAgger), which learns a stationary deterministic policy that is guaranteed to perform well under its induced distribution of states. Their method, which strictly relates to a no-regret online learning approach, is then applied to learn some policies that can steer a car in a 3D racing game and can play Super Mario Bros., given input image features and corresponding expert demonstrations. The idea of applying policy learning on video-games has been recently used also by Mnih et al. [8], that present a deep agent (deep Q-network), that can use reinforcement learning to generate policies directly from high-dimensional sensory inputs. The authors test their algorithm on classic Atari 2600 games, achieving a level comparable to that of a professional human player across a set of 49 games. Similarly, Silver et al. [12] use deep "value networks" and "policy networks" to respectively evaluate board positions and select moves for the challenging game of Go. These neural networks are trained by a combination of supervised learning from human expert games, reinforcement learning and Monte Carlo tree search. The resulting program showed to be able to beat human Go champions and to achieve a performance beyond any previous expectation.

Building on the idea of adopting a combination of techniques similar to [12], our work mostly relates to the AggreVate and NRPI algorithms by Ross and Bagnell [10]. The former leverages cost-to-go information – in addition to correct demonstration – and data aggregation; the latter extends the idea of no-regret

learners to Approximate Policy Iteration variants for reinforcement learning. However, differently from previous work our algorithm (MCSDA) uses shorter Monte Carlo roll-outs to evaluate policy improvements. By avoiding to always estimate the full cost-to-go of the policy MCSDA is more practical – and usable in robotics. Additionally, as explained in Section 3, the policy generated by our algorithm can be seen as a combination of expert and learned policies, allowing us to directly leverage results from [2].

Policy Adaptation in RoboCup

Policy classification and adaptation to the strategy of the opponent team is not a new idea in RoboCup competitions. For example, Han and Veloso [3] propose to employ Hidden Markov Models to detect opponents' behaviors, represented as game states. The authors first characterize the game state in terms of "behavioral-relevant state features" and then show how a cascade of HMMs is able to recognize different pre-defined robot behaviors. This idea has been further developed by Riley et al. [9], who propose a classification method for the opponents' behavior in a simulated environment. The authors first enable their agents to observe and classify the actions of the adversaries, and then to accordingly adapt their policy. More recently, Trevizan and Veloso [14] also address the problem of classifying opponents, and their strategies with respect to a set of behavioral components. Specifically, they are able to generalize and classify unknown opponents as combination of known ones. Yasui et al. [15] introduce a "dissimilarity function" to categorize opponent strategies via cluster analysis. The authors improve their team performance by analyzing logged data of previous matches and showing that team attacking strategies can be recognized and correctly classified. Finally, Biswas et al. [1] propose an opponent aware defensive strategies. In particular, once the state of the opponents is received, the robotic systems categorize the attacking robot as first and second level threats. Accordingly, the team displaces a variable number of defenders in order to prevent the opponent team to score.

It is worth remarking that all the aforementioned methods propose effective solutions to the problem of decision making in presence of adversaries. However, differently from our application of MCSDA on the RoboCup scenario – that uses only a small portion of the game-state and operates under unknown system dynamics, they operate in controlled environments, where full information is available. Additionally, while the MCSDA algorithm can be separately applied on each agent and automatically accounts for uncertainty, the described systems are usually centralized and do not consider uncertain outcomes. For these reasons, we consider our approach a valuable contribution also to the robotic and RoboCup community, where partially observable and highly dynamic scenarios need to be addressed.

3 APPROACH

The generation of our adaptive policy relies on standard machine learning methods. First, a classifier is used to imitate a sub-optimal expert policy and accordingly choose an action, given the current observation of the game domain. Then, the learned policy is improved by aggregating, in an online learning fashion, previous data with Monte Carlo policy rollouts. Throughout the learning process, the domain representation is simplified and it is reduced to the essential game elements – the position and velocity of the ball in the field.

3.1 Preliminaries

We present our learning problem using the Markov Decision Process notation, where S and A respectively represent a discrete set of states and actions, and $R(s)$ is the immediate reward obtained for being in state $s \in S$. R is assumed to be bounded in $[0, 1]$. In our learning setting not only we observe the reward function R, but also demonstrations of a sub-optimal policy π^* that aims at maximizing R and induces a state distribution d_{π^*}. Additionally, we assume the dynamics of the world to be unknown or to be accessible only through samples, due to its complexity. Those samples can be obtained by directly observing a policy executed in the world.

Our goal is to first find a policy $\hat{\pi}$ such that

$$\hat{\pi} = \arg\max_a \mathbb{E}_{s' \sim d_{\pi^*}}[s' \mid a, s], \tag{1}$$

and then to generate, at each iteration $i \in \{0, ..., N\}$, a new policy $\tilde{\pi}_i$ that improves $\tilde{\pi}_{i-1}$, with $\tilde{\pi}_0 = \hat{\pi}$. Such improvement is obtained by directly executing $\tilde{\pi}_{i-1}$ and aggregating the reward measured over several Monte Carlo simulations to the rewards at previous iterations. Note that, (1) as in previous work [11, 10, 2] we adopt a supervised learning approach to imitate and learn a policy, (2) since the chosen actions influence the distribution of states, our supervised learning problem is characterized by a non-i.i.d.[1] dataset.

3.2 Monte Carlo Search With Data Aggregation

We now present Monte Carlo Search with Data Aggregation – MCSDA, a modification of the AGGREVATE and NRPI algorithms by Ross and Bagnell [10] that (1) instead of the distribution of states induced by the expert, always uses the learned policy to roll-in and (2) rather than estimating the full cost-to-go of the policy, only uses shorter Monte Carlo roll-outs to evaluate policy improvements.

In its simplest form the algorithm takes as input a set $\mathcal{D}_e$ of state-action pairs obtained from expert demonstrations and proceeds as follows. First, MCSDA learns a classifier $\hat{\pi}$ by using $\mathcal{D}_e$ in order to imitate the expert. This is used to

---

[1] Independent and identically distributed

Algorithm 1: Monte Carlo Search with Data Aggregation (MCSDA).

Input: $\mathcal{D}_e$: dataset of state action pairs $\{s, a\}$ from expert demonstrations, N: number of iterations of the algorithm, K: number of Monte Carlo simulations, H: simulation steps.

Output: $\tilde{\pi}_N$: policy learned after N iterations of the algorithm.

1 begin
2   Train classifier $\hat{\pi}$ on $\mathcal{D}_e$ to imitate the expert.
3   Set $\tilde{\pi}_0 \leftarrow \hat{\pi}$.
4   Initialize $\mathcal{D} \leftarrow \mathcal{D}_e$.
5   **for** $i = 1$ **to** N **do**
6   Set s_0 in some state from the initial state distribution D.
7   **for** $t = 1$ **to** T **do**
8   Get state s_t by executing $\tilde{\pi}_{i-1}(s_{t-1})$.
9 $\mathcal{A} \leftarrow$ select or sub-sample (if needed) feasible actions in s_t.
10   **foreach** $a \in \mathcal{A}$ **do**
11   execute K Monte Carlo simulations of length H to estimate $V_p(s_t, a)$.
12   **end**
13   Set $a_t \leftarrow \arg\max_a V_p(s_t, a)$.
14   Set $\mathcal{D} \leftarrow \mathcal{D} \cup \{s_t, a_t\}$.
15   **end**
16   Train classifier $\tilde{\pi}_i$ on $\mathcal{D}$.
17   **end**
18   **return** $\tilde{\pi}_N$
19 end

initialize our policy $\tilde{\pi}$. Then, during each iteration, the algorithm extends its dataset by (1) executing the previous policy $\tilde{\pi}$ and generating a state s_t at each time-step, (2) selecting for each s_t an action a_t that maximizes the expected value $V_p(s_t, a)$ of performing action a at the given state, (3) aggregating the new state-action pairs – at each time-step – to the previous dataset. Finally, the aggregated dataset is used to train a new classifier $\tilde{\pi}$ that substitutes the policy used at the previous iteration. The details of MCSDA are provided in Algorithm 1.

By relying on data aggregation, MCSDA generates a sequence $\tilde{\pi}_1, \tilde{\pi}_2, ..., \tilde{\pi}_N$ of policies and preserves the main characteristics of algorithms like AGGREVATE – i.e., (1) it builds its dataset by exploring the states that the policy will probably encounter during its execution, (2) it can be interpreted as a Follow-The-Leader algorithm that tries to learn a good classifier over all previous data and (3) can be easily transformed to use an online learner by simply using the dataset in sequence. However, the implementation of MCSDA is more practical due to the reduced amounts of roll-outs generated from the Monte Carlo simulation. Additionally, our algorithm always performs the roll-in and the roll-out – after the one-step deviation – with the learned policy. Still, it is worth to notice that the learned policy is effectively generated from the mixture of sub-optimal expert

policies and learner's experience from Monte Carlo simulations. Hence, expert policy actions will be likely executed at the beginning, while their execution probability will reduce with the number of iterations of the algorithm. This can be interpreted as combining the sub-optimal policy of the expert and the learned policy with a varying mixing parameter β that initially is equal to 1 – always uses the expert – and decreases over subsequent iterations of MCSDA. Consequently, we can rely on performances analogous to those presented by Chang et al. [2].

3.3 Using MCSDA to Improve Robot Soccer Policies

The application of MCSDA to the RoboCup context is not straightforward, but requires an additional modeling effort. First, in order to reduce the size of the problem, only the two-dimensional position $p_r = (x_r, y_r)$ of the robot, the position $p_b = (x_b, y_b)$ and velocity $v_b = (v_{xb}, v_{yb})$ of the ball in the field have been adopted to represent the game state and, hence, to build our learning dataset. Additionally, we generated the state-action pairs by considering the following subset of actions: `stand` (the robot does not move), `move_up` (the robot moves forwards), `move_down` (the robot moves backwards), `move_left`, `move_right`.

Given this reduced domain representation, as well as the goal of generating a robot policy that adapts to the game adversaries, we applied MCSDA to the RoboCup scenario by using the opponent team as our expert. To this end, first we created a simple heuristic-based classifier to recognize the opponents' actions with respect to the ball (i.e., we collected their policy) and, then, learned such policy in order to perform imitation. Note that at execution time the learned policy is mapped to our robots by considering their relative position with respect to the ball. In this work, such a mapping has been manually defined. This resolves situations where the opponent (expert) robot and our (learner) agent face the ball from opposite directions and, for example, the opponent's `move_left` action maps to `move_right` on our robot. Finally, Monte Carlo roll-outs have been executed as illustrated in Fig. 2 and using a reward function shaped as:

$$R(s) = \frac{\texttt{MAX\_FIELD\_DISTANCE} - |p_r - p_b|}{\texttt{MAX\_FIELD\_DISTANCE}}, \tag{2}$$

where `MAX_FIELD_DISTANCE` corresponds to the game-field diagonal. To run our Monte Carlo simulations, we used both a simplified simulator and a more complex one, provided by the B-Human RoboCup Team[2].

4 EXPERIMENTAL EVALUATION

RoboCup is a dynamic adversarial environment where robots needs to adapt to the surroundings quickly and efficiently. For these reasons, the goal of this experimental section is to evaluate our learning approach in the short range after
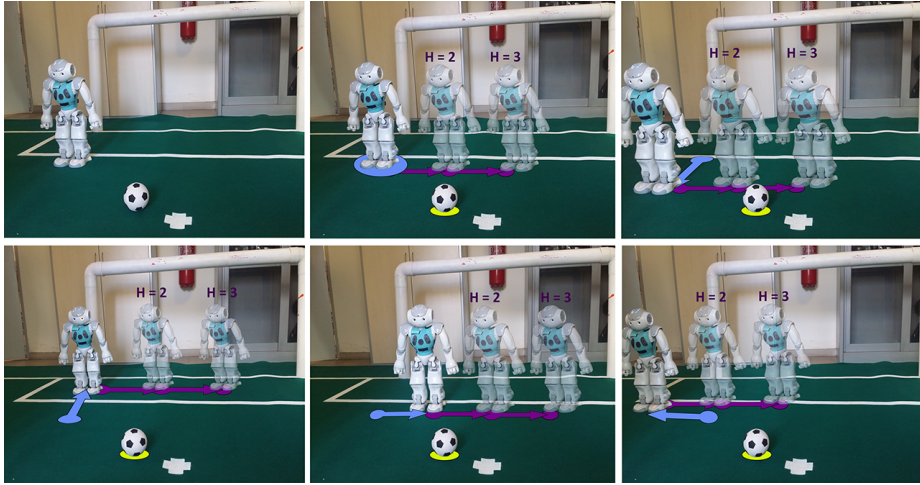
---

[2] https://www.b-human.de/

Fig. 2. Example of a full iteration of the Monte Carlo roll-outs: the robot evaluates all its actions, and selects the best one to maximize $V_p(s_t, a)$. In this example, the top-left sub-figure shows the world state at a given time t, and the current policy suggests the robot to execute `move_left`. Accordingly, the other sub-figures show the evolution of the world state after each roll-out extending the current policy until the horizon $H = 3$. The robot evaluates all the 5 actions: `stand` (top-center), `move_up` (top-right); `move_down` (bottom-left); `move_left` (bottom-center); `move_right` (bottom-right). In these figures, the blue arrow represents the chosen action for the current roll-out, while the purple arrows represent the movements of the robot according to the current policy. The yellow circle represents the point p_b used to compute the reward according to Eq. 2.

few number of simulation steps. The evaluation has been carried out through the B-Human soccer simulator entirely written in C++ with the middle-sized humanoid NAO robot. In this section, we test and validate the effectiveness of the two main phases of our approach: the continuous policy improvement via Monte Carlo roll-outs and the policy initialization via imitation learning. In our experiments we set the roll-out horizon $H = 3$. This value has been found to be a good trade-off between in-game performance improvement and usability of the approach. Extending the horizon, in fact, improves the player performance at the cost of more computational resources.

4.1 Policy Improvement

The goal of our learner is to improve its performance while playing against opponent robots and to decrease the number of opponent scores while intercepting as many balls as possible. According to Eq. 2, we can evaluate each action of our learner by considering the reward that the robot obtains during a match. Such a measurement expresses how good the learner is positioned within the field with respect to the ball. Therefore, we analyze the average reward of our agent as well as the number of ball interceptions and the final score of each match.
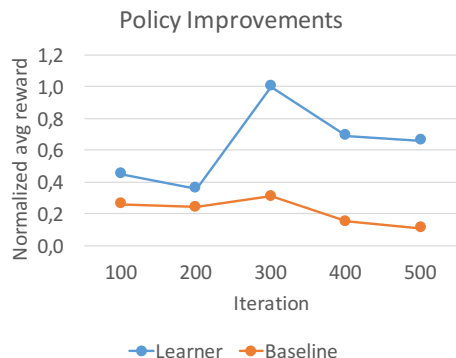
Fig. 3. Normalized average reward of the learner (*blue*) and baseline (*orange*) after different MCSDA iterations.

Fig. 3 reports the normalized average reward obtained by the learner during five regular games, after a different number of MCSDA iterations. On the y-axis is reported the obtained average reward.

Specifically, the learning defender features our MCSDA algorithm, while the non-learning defender has a fixed policy initialized at iteration zero. Such a baseline is a suitable comparison that allows us to quantify the improvements of our robot in terms of positioning with respect to its own initial policy. It is worth noticing that each reported match has been played with different policies generated at different iterations of MCSDA. Hence, each match represents a different configuration of the learner, where its actions are determined by a policy computed after 100, 200, 300, 400, 500 iterations of our algorithm. The plot shows a constant improvement with respect to our baseline and over previous configuration of its trained policy. It is worth remarking that the drop in performance between game 3 and 4 can be due to different factors affecting the game, such as player penalization and ball positioning rules. However, such drop has a marginal impact with respect to the previous improvements, and the performance of consequent matches remains constant.

Additionally, thanks to the nature of our testing environment, we are able to report more direct evaluation indices for our approach. To this end, we report the number of intercepted balls and the number of opponent scores. In particular, Fig. 4 shows the sum of intercepted balls of the two teams (learning and non-learning) on the same set of games as before, and Table 1 reports their final scores.

It is worth noticing that the number of intercepted balls of our learning agent (*green*) is more than twice the number of the opponent defender (*yellow*). Furthermore, the final results of the different matches promises an interesting profile: even though the learner does not win all of the matches, the number of opponent scores decreases as the learner refines its policy. Since MCSDA is applied only on defense robots, we do not achieve any improvement on the
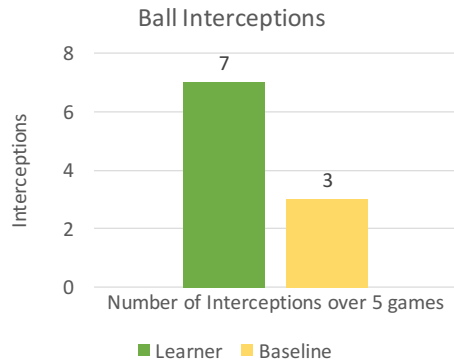
Fig. 4. Sum of intercepted ball over five matches after different MCSDA iterations.

Table 1. The table reports the final scores of five matches after different MCSDA iterations.

Teams	MCSDA iterations				
	100	200	300	400	500
Learning	2	3	0	1	1
Non-learning	3	2	1	1	1

number of goals of our team. However, as expected, by increasing the number of iterations of our algorithm, the number of goals of the opponent team decreases.

4.2 Imitation Influence

Since our robots operate in dynamic environments the policy training process cannot be too long. Therefore, we need to restrict the search space for our learning process as much as possible. To this end, we generate an initial policy by running 100 matches with the only purpose of analyzing most probable positions and velocities of the ball, as well as opponents' positions within the field as introduced in Section 3.3.

In this case, we setup an experimental evaluation with the aim of studying the influence of our policy initialization on the overall MCSDA approach. In the setting shown in Fig. 5, the blue team deploys a robot learner featuring an initialized policy, while the red team deploys a learner with a non-initialized policy. In this test, we let the two defenders train their policies for 300 iterations. Afterwards, we select the two different policy profiles in order to play a regular match. Fig. 5 shows the normalized averaged reward of the two learners: orange for the initialized policy, and purple for the not-initialized one. It is worth noticing that – as expected – an initialized policy significantly improves the learning process.
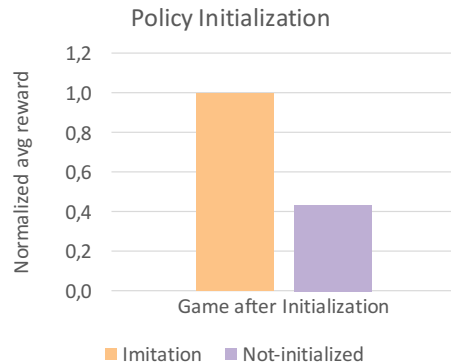
Fig. 5. Normalized average reward of the learner (*orange*) and the non-initialized policy learner (*purple*) during a match.

5   DISCUSSION AND FUTURE WORK

In this paper we presented MCSDA, an algorithm that strictly relates to recently developed approaches for policy improvement. We used and evaluated our method to generate better strategies for soccer defense in the RoboCup scenario. The application of MCSDA on this context allowed our robots to increase the number of ball interceptions, as well as to reduce the number of opponents' goals. Together with a better performance, an overall more efficient positioning of the defender player within the field has been achieved.

Contributions

The main contribution of this paper consists in the combination of data aggregation together with Monte Carlo search. The use of Monte Carlo search results in a practical algorithm, that allows a real-world implementation on a robot domain. By relying on data aggregation, instead, MCSDA preserves the main characteristics of algorithms like AGGREVATE and can be easily transformed to an online method. Finally, we also show that using MCSDA with a simplified representation of the domain a good policy improvement can be obtained on complex and challenging robotic scenarios.

Limitations and Future Work

Our algorithm still presents some limitations. In fact, even if Monte Carlo simulations make MCSDA practical, it requires expensive calls to a simulator and, hence, it has been applied to a single robot player. While simple simulators can be used, neither the online application of the algorithm, nor its use on a larger number of robots are straightforward. For this reason, as future work, we would like to adapt and test our algorithm to learn policies online and consequently

apply the algorithm to the whole robot soccer team. Furthermore, we plan to perform additional studies on the performance guarantees that MCSDA can achieve.

References

1. Biswas, J., Mendoza, J.P., Zhu, D., Choi, B., Klee, S., Veloso, M.: Opponent-driven planning and execution for pass, attack, and defense in a multi-robot soccer team. In: Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems. pp. 493–500. International Foundation for Autonomous Agents and Multiagent Systems (2014)
2. Chang, K.w., Krishnamurthy, A., Agarwal, A., Daume, H., Langford, J.: Learning to search better than your teacher. In: Proceedings of the 32nd International Conference on Machine Learning (ICML-15). pp. 2058–2066 (2015)
3. Han, K., Veloso, M.: Automated robot behavior recognition applied to robotic soccer. In: Hollerbach, J., Koditschek, D. (eds.) Robotics Research: the Ninth International Symposium, pp. 199–204. Springer-Verlag, London (2000), also in the Proceedings of IJCAI-99 Workshop on Team Behaviors and Plan Recognition
4. Ijspeert, A.J., Nakanishi, J., Schaal, S.: Trajectory formation for imitation with nonlinear dynamical systems. In: Intelligent Robots and Systems, 2001. Proceedings. 2001 IEEE/RSJ International Conference on. vol. 2, pp. 752–757. IEEE (2001)
5. Kitano, H., Asada, M., Kuniyoshi, Y., Noda, I., Osawa, E.: Robocup: The robot world cup initiative. In: Proceedings of the first international conference on Autonomous agents. pp. 340–347. ACM (1997)
6. Kober, J., Peters, J.R.: Policy search for motor primitives in robotics. In: Advances in neural information processing systems. pp. 849–856 (2009)
7. Kormushev, P., Calinon, S., Caldwell, D.G.: Robot motor skill coordination with em-based reinforcement learning. In: Intelligent Robots and Systems (IROS), 2010 IEEE/RSJ International Conference on. pp. 3232–3237. IEEE (2010)
8. Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.A., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G., et al.: Human-level control through deep reinforcement learning. Nature 518(7540), 529–533 (2015)
9. Riley, P., Veloso, M.: On behavior classification in adversarial environments. In: Distributed Autonomous Robotic Systems 4. pp. 371–380. Springer-Verlag (2000)
10. Ross, S., Bagnell, J.A.: Reinforcement and imitation learning via interactive no-regret learning. arXiv preprint arXiv:1406.5979 (2014)
11. Ross, S., Gordon, G.J., Bagnell, D.: A reduction of imitation learning and structured prediction to no-regret online learning. In: International Conference on Artificial Intelligence and Statistics. pp. 627–635 (2011)
12. Silver, D., Huang, A., Maddison, C.J., Guez, A., Sifre, L., van den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., et al.: Mastering the game of go with deep neural networks and tree search. Nature 529(7587), 484–489 (2016)
13. Tesauro, G., Galperin, G.R.: On-line policy improvement using monte-carlo search. In: NIPS. vol. 96, pp. 1068–1074 (1996)
14. Trevizan, F.W., Veloso, M.M.: Learning opponents strategies in the robocup small size league. In: Proc. AAMAS. vol. 10. Citeseer (2010)
15. Yasui, K., Kobayashi, K., Murakami, K., Naruse, T.: Analyzing and learning an opponents strategies in the robocup small size league. In: RoboCup 2013: Robot World Cup XVII, pp. 159–170. Springer (2013)