

Deep Self-optimizing Artificial Intelligence for Tactical Analysis, Training and Optimization

Matthias Sommer

armasuisse Science and Technology
SWITZERLAND

matthias.sommer@armasuisse.ch

Michael Rügsegger

armasuisse Science and Technology
SWITZERLAND

michael.ruegsegger@armasuisse.ch

Oleg Szehr

Dalle Molle Institute for Artificial Intelligence (IDSIA) - SUPSI/USI
SWITZERLAND

oleg.szehr@idsia.ch

Giacomo Del Rio

Dalle Molle Institute for Artificial Intelligence (IDSIA) - SUPSI/USI
SWITZERLAND

giacomo.delrio@idsia.ch

ABSTRACT

The increasing complexity of modern multi-domain conflicts has made their tactical and strategic understanding and the identification of appropriate courses of action challenging endeavors. Modelling and simulation as part of concept development and experimentation (CD&E) provide new insight at higher speed and lower cost than what physical maneuvers can achieve. Amongst other, human-machine teaming through computer games provides a powerful means of simulating defense scenarios at various abstraction levels. However, conventional human-machine interaction is time-consuming and restricted to pre-designed scenarios, e.g., in terms of pre-programmed conditional computer actions. If one side of the game could be taken by Artificial Intelligence, this would increase the diversity of explored courses of actions and thus lead to a more robust and comprehensive analysis. If the AI plays both sides, this would allow employing the Data Farming methodology and thus creating and analyzing a database of a very large number of played games. To this goal, we employ combined Reinforcement Learning and Search algorithms, which have demonstrated super-human performance in various complex planning problems. Such Artificial Intelligence systems avoid the reliance on human experience and predictions by learning tactics and strategy through self-optimization in a large number of realistic scenarios. In this contribution, we present the benefits and challenges of applying a Neural-Network-based Monte Carlo Tree Search algorithm for strategic planning and training in air-defense scenarios and virtual war-gaming with systems that are available currently or potentially in the future to the Swiss Armed Forces.

1.0 INTRODUCTION

Today, wargaming is a widely applied and accepted tool within the military domain for planning, training and decision-making. However, traditional wargaming, where military planners, operators and decision makers play against Red Team operators, faces limitations [1]. Wargames are driven by player decisions and are therefore not reproducible. Objective tracking of cause and effect is difficult, and outcomes often depend on the subjective assessments of human players. Usually, Red Team operators rely upon long established techniques, tactics and procedures leading to over-constrained Courses of Action (CoA). Finally, the number of CoAs that can be explored by human operators is limited, both by the availability of financial and human resources. This is even more true given the complexity of continuous-time decision making and the large numbers of available options (high branching factors) that characterize real-world scenarios. In practice this results in a relatively small number of explored scenarios and a lack of strategic diversity in CoAs exploration, leading to biased and potentially vulnerable decision-making.

Recent developments in the Artificial Intelligence (AI) area and in particular Reinforcement Learning (RL), have demonstrated the ability of artificial agents to master commercial real-time strategy (RTS) video games of increasing complexity, reaching super-human performance in games such as StarCraft [2]. Artificial

agents have also proven super-human tactical and strategic capabilities in complex games such as Chess and Go [3]. Typically, modern RL systems learn ‘tabula rasa’, i.e., without relying on human experience, by exploring complex decision-spaces in a large number of scenarios and subsequent self-optimization. This avoids the bias towards human experience and perception in learning and leads to more robust, stronger, and non-emotional decisions in execution. While the learning process of AI systems often involves significant computational effort, their speed in execution is fast, often outperforming the ‘discussion-based’ human decision process.

In this work, we investigate AI systems, in particular Neural-Network-based Monte Carlo Tree Search algorithms, to support planning, training and decision-making in the field of Ground-Based Air Defence (GBAD). We apply the AI to the commercial of the shelf (COTS) wargame “Command: Modern Operations” (CMO) to explore complex decision-spaces, and to generate surprising new Red Force CoAs. This will challenge the preconception of Blue Force operators and stimulate the development of new techniques, tactics, and concepts.

2.0 METHODS

Two main software components are involved in the application described above. First, there is the model with rules and physical constraints of the scenario to be simulated (the so-called simulator), and second, an AI algorithm that controls one or both players in the conflict represented by the model. Both components and their integration are described in this section. In the current scenarios, one side of the game is played by an AI agent, while the other is controlled by the game engine itself, through pre-scripted, conditional actions. Specifically, the AI controls the attacking red fighter jet while the game engine controls the blue air defense batteries.

2.1 Model

The use of commercial over-the-shelf (COTS) games as simulation engines has a number of advantages: low cost, large user-base, high fidelity and good support to name just a few. Also, the gaming industry has been a driver for the development of realistic warfare scenarios, respective visualizations, and tailor-made hardware. Two central requirements for a model to be controlled by an external AI are:

1. faster than real-time simulations, this in turn requires in general to run the simulation without graphics;
2. interface to control and assess the state of the game externally.

The game “Command: Modern Operations” (CMO) fulfils these requirements in its professional version (Command Professional Edition) and additionally covers the domain of interest, namely air defense. It is a real-time strategy game mainly for air and sea combat that features a comprehensive and realistic database of past, current and future weapon systems.

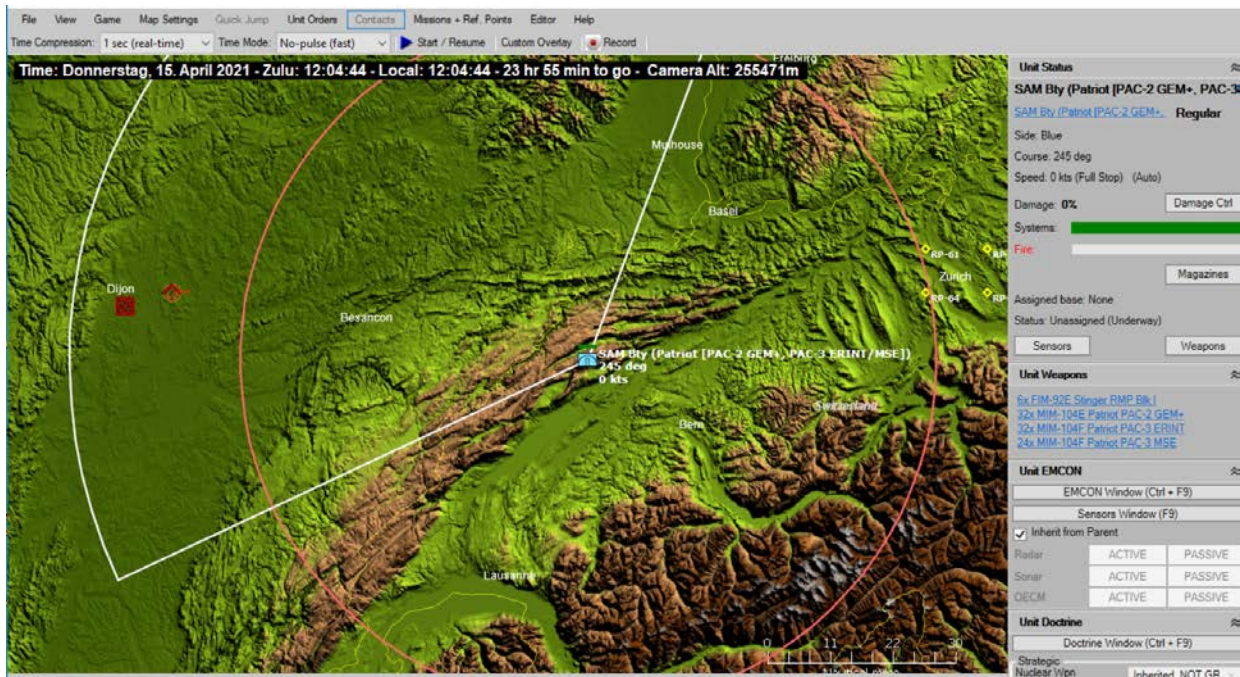


Figure 2-1: User interface of Command: Modern Operations

It comes with an API that allows interaction with the running simulation in batch mode, i.e., without graphics. In order to make the game more amendable to the AI, we introduced a turn-based mode for the real-time game. The game is paused and the AI can assess the scenario and select an action. Subsequently, the action is executed and the game is simulated for a given time window, here 10 seconds simulation time.

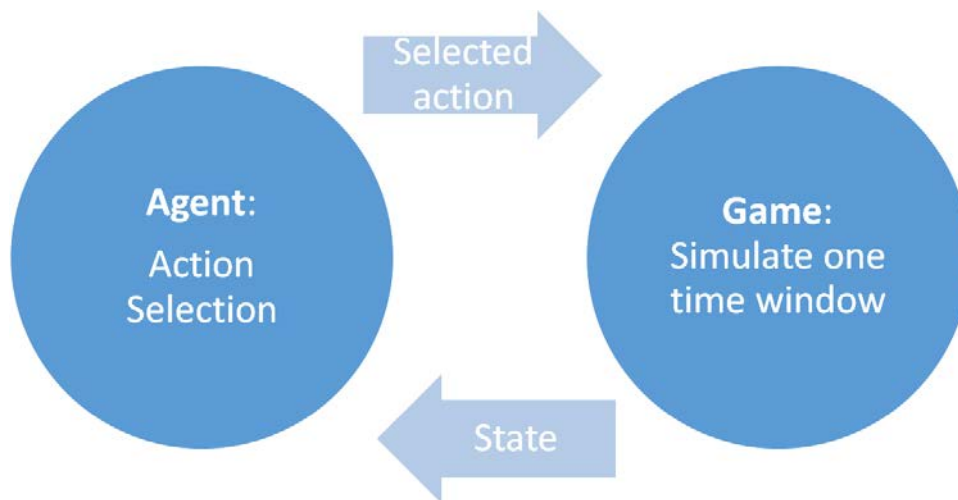


Figure 2-2: Turn-based game mode of Command: Modern Operations

In the design mode, one has the possibility to create a scenario with pre-defined or custom assets. In game mode, the simulation is then executed with the actions from either the players or the external AI.

2.1 AI

For complex game search problems, such as the CMO scenarios, the direct computation of optimal policies is intractable. The development of suitable approximation techniques has been an active area of research for many years leading to striking AI systems that outperform humans and classical tree search algorithms in strategic games such as Chess and Go [3]. At the core of the AI lies a sophisticated neural network-based Monte Carlo Tree Search algorithm (neural MCTS), whose performance is the result of a combination of techniques from diverse areas including Reinforcement Learning, Monte Carlo simulations and Deep Neural Networks. Traditionally search algorithms (such as alpha-beta search) are employed to study game play, but the search tree grows exponentially with its depth leading to large computational effort even for simple games. The tree's terminal nodes must be evaluated by a tailor-made valuation function, whose design involves significant human expertise. On the other hand, the choice of actions in a (Markovian) game can be viewed as a planning problem, with an agent whose goal it is to win, or, in other words, to maximize the total reward over the planning horizon. Such planning problems are footed on the theory of Markov decision processes [4]. The research area concerned with their solution has been commonly called Reinforcement Learning (RL) in recent years. In RL the Value/Policy iteration algorithms proceed by performing repeated Bellman updates over the state space and are guaranteed to yield the optimal policy if sufficient resources are granted. However, even for planning problems of moderate complexity the required resources tend to be immense because each Bellman update involves the entire state space. An important idea to improve the performance is to rely on Monte Carlo simulations to estimate state values [5]. In brief each state is evaluated by trying every possible action a certain number of times, and recursively, from each generated state every possible action the same number of times, too, until the depth of the planning horizon is reached [6]. Again, this yields the optimal course of actions in theory but in practice the width and depth of the Monte Carlo simulations are such that a near optimal solution becomes elusive. The key idea behind MCTS is to combine the iterative algorithms from RL with (the more traditional) tree search techniques [7]. Thus, instead of relying on 'brute force Monte Carlo' for state valuation, a problem-specific, restricted and asymmetric decision tree is built. The growth of the decision tree is controlled by a dedicated tree policy, whose purpose it is to trade-off the creation of new branches versus the execution of existing promising lines. The missing piece to engineer a world-champion AI are deep neural networks. The MCTS design is enhanced by deep neural networks [8] to guide the construction of the decision tree and to provide accurate evaluation of leaf-nodes. At the core of the neural MCTS algorithm lies an 'expert iteration' scheme, where the MCTS search and the neural networks mutually improve each other in an iterative process. In each iteration an instance of MCTS (the expert) delivers a list of strong actions and a neural network (the apprentice) is trained via supervised learning to imitate the MCTS tree policy. In the next iteration, the trained neural network, in turn, is used to bias the MCTS' tree construction towards stronger actions. The purpose of the expert is to accurately determine good actions. The purpose of the apprentice is to generalize those actions across states and to provide faster access to expert advice. Specifically, the apprentice policy π is trained on tree-policy targets by minimizing cross-entropy loss at state s

$$LOSS_{TreePolicy} = - \sum_{a \in \text{actions}} \frac{n(a)}{n} \log(\pi^A(a|s)).$$

Here, $n(a)$ is the number of times action a has been chosen so far and n is the total number of executed actions. The value network reduces search depth and avoids inaccurate rollout-based value estimation. It is trained to minimize the mean-squared error to the MCTS valuation z of the state

$$LOSS_{Value} = -(z - V^A(s))^2.$$

In turn the apprentice improves the expert by guiding tree search towards stronger actions. For this the standard MCTS tree policy (UCB1) is enhanced with an extra term

$$NUCB1(a) = UCB1(a) + w \frac{\pi^A(a|s)}{n(a) + 1}$$

where a hyper-parameter w weights the contributions of standard MCTS tree policy (UCB1) and the neural network. Neural MCTS branch selection proceeds by choosing the action a that maximizes $NUCB1$. To regularize value prediction and accelerate tree policy and valuation function are simultaneously covered by a multitask network with separate outputs. The loss for this network is the sum of losses from value and tree policy networks.

2.1.1 Training process

To achieve faster learning and higher stability the RL agent is pre-trained before operating on the game CMO directly. **In order to optimize the training process, a surrogate model was written in the language (Python) that was used for the AI algorithms. This allowed the agents to be pre-trained from scratch, later to be refined by training on the full game engine. Thus,** the process involves the training on a reduced but faster simulator, then transferring the pretrained agent to the CMO simulator for fine-tuning. This way the data-intensive (and therefore slow) initialization of the RL process can be handled efficiently, while there is no reduction in the agent’s performance due to training in a restricted setting.

3.0 SCENARIO

The reason armasuisse Science and Technology is interested in this technology, is the application to air defense training, concept development and experimentation (CD&E) as well as procurement projects. The main assets employed in the warfare scenarios are fighter jets, radars, and air defense missile systems. Ideally, an intelligent agent would be capable of identifying and executing a close-to-optimal strategy for all assets of one side simultaneously. Due to the complexity of fully realistic scenarios, developing and training of such an agent is beyond the goals of the current project stage. Instead, the aim is a feasibility study with reduced scenarios, where the RL agent controls a single asset. This scenario will be extended in a later stage of the project. The simple test scenarios are characterized in the above figure 2-1 and the following table 3-1:

Table 3-1: Scenario description

	Red Side	Blue Side
Assets	1 Fighter Jet	1 SAM Battery (Radar, missile system)
Mission	Penetrate blue Zurich airspace (yellow)	Defend blue Zurich airspace (yellow)
Red Scoring	+1 for attacker mission success -1 for loss of aircraft	-1 for defender mission success +1 for attacker mission success

4.0 RESULTS

The AI controlling red aircraft learns quickly that flying the direct path from its takeoff to the target will make it visible to the blue radar and therefore vulnerable to blue air defense. It thus chooses a more northern route to avoid the radar cone. In the following, we will work out what went well and where we see the challenges and bottlenecks for the transition to more interesting and complex scenarios.

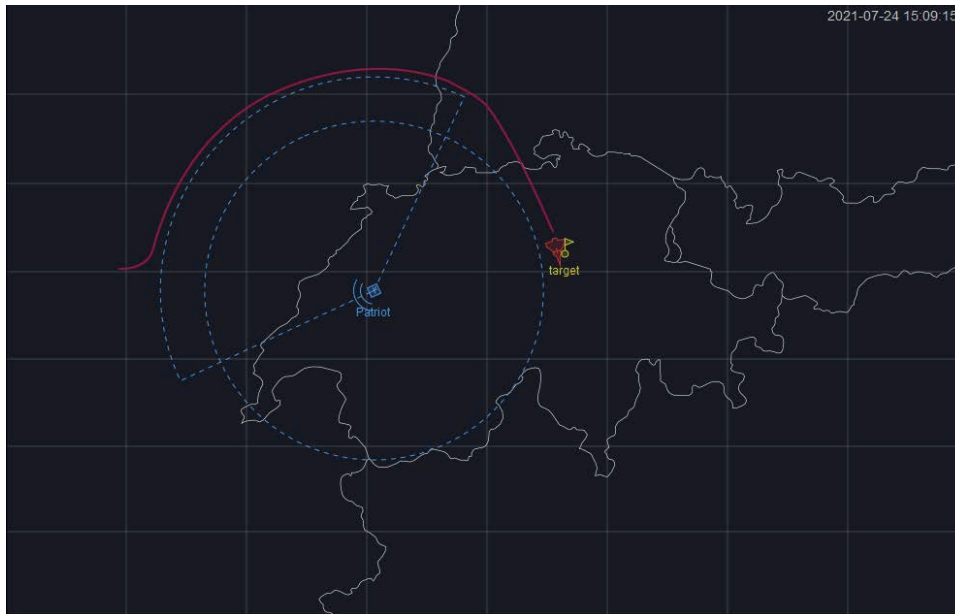


Figure 4-1: Example trajectory of trained red agent around the range of the blue air defense system

4.1 COTS Game as simulation engine and its interface

The use of a commercial over-the-shelf computer (COTS) games has a positive impact on the outcome for the reasons mentioned above. Additionally, the separation of AI, simulation engine and analytics tools make the application design more flexible and re-use of components possible. In particular, this approach avoids a large black-box simulation engine, where insight and extensibility are limited.

4.2 Application of neural MCTS to CMO scenarios

In all investigated scenarios the outlined training procedure led to neural MCTS finding the maximal theoretical reward after only a short number of learning cycles (5 neural training cycles, each based on 500 episodes and 100 MCTS samples per search step for all investigated scenarios). While this is somewhat expected given the relatively low complexity of the combat scenario and the proven ability of neural MCTS to solve sophisticated strategic problems, the presented work provides proof of concept that the practical implementation in the CMO context is successful. Connecting neural MCTS to CMO requires a dedicated API with fast access. In our experiments we have observed that access via the existing Lua API is too slow for MCTS to guide the behavior of CMO. To overcome this issue a dedicated surrogate simulator has been developed, which provides fast access in a simplified setting. The pretrained MCTS agents are subsequently handed to the full CMO setting for fine-tuning. As a result, we observe solidly increasing rewards on the simulator and the trained agent can be transferred to CMO successfully.

5.0 CONCLUSIONS AND OUTLOOK

Our results provide proof of concept of the application of RL and search techniques in the context of COTS wargames. In forthcoming research, the complexity of war game scenarios will be increased successively. The more complex setting is reflected by adaptations in the neural MCTS architecture. While simple linear, feed-forward networks are sufficient for the basic scenarios, we plan a deep convolutional architecture for the more complex setting. The additional computational burden of the complex scenarios is covered by code parallelization and cluster computing. We expect that MCTS will also be successful in complex scenarios as neural MCTS algorithms proved their superior performance in strategy games like Chess and Go. Overall, the value of an independent and innovative simulation application for training as well as CD&E seems larger than the prize to overcome the challenges in developing it.

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