Command and Control Training Centers: Computer Generated Forces Meet Classical Planning *

Carmel Domshlak
Industrial Engineering & Management,
Technion, Israel

Ziv Even-Zur and Yannai Golany
Elbit Systems, Ltd.
Israel

Erez Karpas
Industrial Engineering & Management,
Technion, Israel

Abstract

We describe SHOGUN, a fully automated system for controlling tactical agents, developed for integration within simulation-based command and control training centers produced by Elbit Systems Ltd. In particular, we focus on describing the action planning module of SHOGUN: while controlling tactical agents in military-style domains involves dealing with uncertainty and partial information in adversarial settings, the planning module of SHOGUN is based on classical, deterministic planning only, and employs a general-purpose classical planner. We describe our embedding of classical planners within the commercial command and control training center, and report on a recent evaluation of SHOGUN in operational scenarios, confronting subject matter experts as trainees.

Introduction

Comprehensive training of forces responsible to react in complex adversarial situations is critical for military high and low intensity conflicts as well as for homeland security scenarios of border control and smart city environments. Such a training should put together teams of trainees at various levels of command, and train them in realistic setups to improve their command and control (C2) capabilities. A vastly dominating portion of C2 training is delegated these days to software simulation systems in which commands of both role-playing trainees and adversary-playing instructors are accomplished by the respective computer generated forces (CGF). Following the paradigm of "train as you fight", the trainees are connected to the virtual battlefield through their operational C2 systems and combat-net radio, coupled by the overall training system to the simulation.

These days, commercial simulations for C2 training already achieve a sufficiently high level of realism in terms of modeling the physical properties of both the environment and forces. The outcome of the training, of course, depends a lot on the effectiveness of the instructors playing the role of the adversary, and this turns out to be an issue. Putting together a team of skilled and coordinated role-players needed for a large-scale simulated exercise requires months of costly preparations, availability of instructors for a long period of time, and a suitable venue. These limitations of relying on human instructors in simulation-based training suggest at least partly replacing them with artificial adversary-players implementing this or another action planning technology. Here we describe SHOGUN, a fully automated system for controlling tactical agents within a commercial military training simulation. SHOGUN has been developed in a joint effort of Elbit Systems Ltd. and the Technion for subsequent integration within the line of large-scale simulation-based training centers produced by Elbit. This system has been recently deployed to Elbit, and successfully passed a detailed performance evaluation.

An interesting property of SHOGUN is that the planner it embeds is not just inspired by the artifacts of academic AI research, but actually is such a direct artifact. Moreover, while in general controlling tactical agents in relevant domains involves decision making under uncertainty and partial information in adversarial settings, our experience provides yet more evidence that successful reasoning about real-world systems of active entities does not necessarily have to take explicitly into account all that complexity when choosing between alternative courses of action. While classical planning, capturing single-agent problems with deterministic actions and effectively full knowledge, has been repeatedly criticized for being unrealistic and thus irrelevant to real-world problems, here we demonstrate that this criticism should be taken with lots of caution: The decision making module of SHOGUN is based on classical, PDDL-based planning only, and employs a general-purpose (and thus fully replaceable) classical planner.

In what follows we describe our embedding of classical planners within the commercial C2 training system, as well as the way in which we divide-and-conquer the details of the physical system between the planning and the simulation modules. We then describe the aforementioned evaluation of SHOGUN in operational scenarios, confronting professional military personnel as trainees.

SHOGUN Architecture and Design Decisions

In this section we describe the overall architecture of SHOGUN, focusing on the adopted planning and execution formalism and its support within the system. At high level, SHOGUN comprises a standard architecture of iterative planning, depicted in Figure 1a. It consists of three major modules: (i) a *planning module*, (ii) a plan *execution monitor*,

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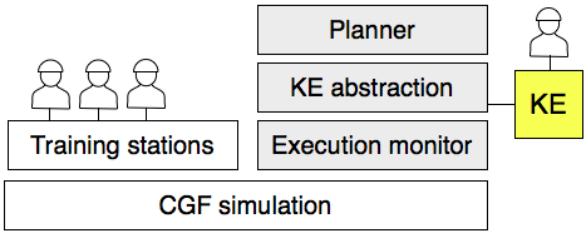

(a)

input: planning task stub $\Pi = \langle V, A, G \rangle$
local: partial-order plan ρ
forever:
  receive from EM the current state of knowledge σ and plan status $\{\rho_{\text{done}}, \rho_{\text{exe}}, \rho_{\text{next}}\}$
  s = TRANSLATE(σ, Π)
  s' = PROGRESSION(s, ρ_{exe})
  if VERIFY-PLAN(s', ρ_{next}) fails **then**
    ρ = MAKE-PLAN$(\langle V, A, s', G \rangle)$
    send ρ to EM

(b)

Figure 1: High-level (a) structure of the system, and (b) flow of the planner interacting with the KE abstraction mapping.

and (iii) a real-time high fidelity 3D tactical computer generated forces (CGF) *simulation* in which the actions selected by both trainees and instructors are actually simulated.

Planning, Execution simulation, and Monitoring

The CGF simulation maintains the entire battlefield arena, and supports an arbitrary number of force types (such as tanks, artillery, reconnaissance, etc.), as long as the simulation is provided with their respective physical models. The simulation runs a full 3D virtual environment of the terrain and physical models of sensors (such as line of sight and detection) and actuators (such as ballistics, path planning, and movement). The battlefield comprises two adversarial forces, blue force and red force, each comprising a, possibly heterogeneous, set of acting units. The trainees fully control the blue force troops and interact with the virtual arena via a training station using a high-level language of command. The planning module replacing the instructors fully controls the red force, and communicates with the simulation via effectively the same language of command. The control of the red force is achieved via a planning and execution loop that takes place during the entire training session. The overall loop is described below and the perspective of the planning module on that loop is pseudo-coded in Figure 1b.

- The execution monitor pulls from the CGF simulation all the data σ required to provide the planner with the current state of the red units (their locations, heading, ammunition, etc.), as well as with those parts of the state of the blue units that are considered by the simulation to be observable by the red units. Status of the blue units not detected by any red unit is not provided to the planner. Likewise, the execution monitor pulls from the CGF simulation a status of the currently executed plan ρ of the red force. Since the execution is continuous, at the moment of the query some of the actions of ρ have been already accomplished, some have started and are still executing, and some are yet to be started. Note that "accomplished" can stand here for both "successfully accomplished" and "failed". In any case, both the collected state of knowledge σ and the plan status $\{\rho_{\text{done}}, \rho_{\text{exe}}, \rho_{\text{next}}\}$ are passed to the planning module.
- The CGF simulation is the core of the virtual arena of Elbit's strategic and tactical training centers, designed to communicate with the training stations of human operators. Hence, the information σ about the current state of the (observable) world takes the form of a raw data. This raw data is then translated to a state of the world description s, corresponding to the abstraction of σ in terms of the planning problem operated by the planner. This translation is based on a knowledge engineering layer that is devoted to bridge between the physical view of the simulation and the symbolic view of the planner.
- Given state s and plan status $\{\rho_{\text{done}}, \rho_{\text{exe}}, \rho_{\text{next}}\}$, the planning module estimates whether the current plan ρ of the red force is still valid. In case the goal of reds turns out to be unachievable from s along the still unaccomplished part of ρ, a new plan is generated from the new initial state s, and passed to the execution monitor.

Classical planner: Why and How.

The heart of SHOGUN is its planning system. The first decision we had to make is whether to develop a special-purpose planner, or to adopt a generic, model-oriented planning system. The second, and in a sense, tangential decision we had to make was what details of the problem the planner should take into account and what details it could ignore without sacrificing the quality of the training.

While in principle special-purpose solutions can be more efficient and effective than generic ones, their development requires the enterprise to establish a development team in the respective area of expertise. Along with the fact that the development basically starts "from scratch", that adds numerous risks to the project. Generic planners obviously do not exhibit these risks by the virtue of being generic, having potential to be reused between various verticals. Of course, model-oriented generic planners come with their own risks such as capability of the respective model to capture the desired domain, the computational efficiency of the planner on the domain of interest, etc. However, in contrast to the risks associated with developing a brand new special-purpose system, these risks can be verified in very short time at the beginning of the project using an off-the-shelf planner.

Considering now the choice of the planning formalism, decision making in C2 environments of our interest always involves action non-determinism, partial information, and adversarial settings (Wilkins and Desimone 1992; Tate et al. 2000; Kott et al. 2005). A priori, this suggests that our planning tasks should be specified in terms of much more complicated action models than that of classical planning because the latter assumes deterministic actions, effectively full knowledge, and single-agent setting. Adopting complex planning formalisms, however, comes with a price: the performance of planning for such formalisms currently does not meet the requirements of large-

scale C2 training. On the other hand, the performance of classical planners has been dramatically improved over the last two decades, and today these are capable of generating in seconds plans of hundreds of steps in state models of more than 2^{1000} states. In addition, it is of growing understanding that successful reasoning about real-world systems of active entities does not necessarily have to explicitly take into account all the complexity of the reality while choosing between alternative courses of action. This property of many real-world domains has been exploited in the past both in experiments (Yoon, Fern, and Givan 2007; Yoon et al. 2008), as well as in ambitious applications of AI reasoning (Muscettola et al. 1998).

Departing from this matter of business, we have decided to start with a *fully off-the-shelf* satisficing classical planner, adapting it only when really needed and only via external wrappers. Specifically, in the experiments described later on, SHOGUN was using the very popular these days Fast Downward planner (Helmert 2006), using its greedy best first and WA* search engines, and the seminal FF heuristic (Hoffmann and Nebel 2001).

While Fast Downward is based on the SAS$^+$ language (Bäckström and Nebel 1995), which describes a fully deterministic, fully observable, single agent problem, the underlying physical simulation is much more complex. In what comes next we describe our abstraction mapping of planning tasks from the level of simulation to SAS$^+$.

- *Symbolic abstraction of the physical world.* The function TRANSLATE used by the planning module in Figure 1b to map a physical state σ to a SAS$^+$ state s is implemented via a knowledge engineering sub-module (KE). The latter comes to bridge between the general-purpose planner and the specifics of the simulated domain; as such, it is used twofold. First, KE allows a user to define various layers of information over the map. These layers describe strategic points, passable areas, ballistically dominating areas, etc., and for most, they can be derived automatically from the digital map used by the simulation. This processing can be performed once per map, and thus completely offline not only to a specific training session, but to the training in general. In addition, the subject matter expert (SME) in charge of the training session can use KE to further enrich this information by specifying, e.g., regions that he prefers not to be used for movements/positions of specific units. Based on the now defined information layers of the map, KE maps status messages received from the execution monitor to proper values of the respective SAS$^+$ variables. The abstraction of the geographic data such as unit locations and headings is archived via a, possibly non-uniform, grid overlaid on the map.
- *Non-determinism of actions.* While basically all actions of the units are simulated to have stochastic effects, the entropy of the underlying probability distributions is usually low, and typically they have single peaks that take most of the probability mass. A natural abstraction of such actions to fully deterministic SAS$^+$ actions simply ignores all but the most likely outcome of each action. SHOGUN uses precisely that simple abstraction, corresponding to a degenerate form of hindsight optimization, an "online anticipatory strategy" for control problems that has previously been successfully applied to problems of online scheduling (Wu, Chong, and Givan 2002) and probabilistic planning (Yoon, Fern, and Givan 2007; Yoon et al. 2008).
- *Partial observability.* Partial observability in the domain of battlefield training stems from the true modeling of reality in which the information that is available to the planner is only what the red force "sees": blue units which are not detected by any red units are not reported to the planner. We use "optimistic sensing" to get rid of this partial observability as follows: when a red unit performs a sensing action (that is, looks in some direction, trying to find blue units) the expected effects of that action are that no blue forces will be detected. If there are indeed no blue forces - the plan can proceed normally. If there are blue forces there, then the current plan is most likely no longer valid, and therefore re-planning is performed, this time accounting for the "new" blue forces.
- *Optimization objectives.* In most battlefield scenarios, the mission is to achieve some objective, while trying to minimize friendly losses. Since we use single-agent planning, we do not directly account for enemy actions, and specifically, we do not plan for friendly units to be destroyed. Therefore, we do not directly try to minimize friendly losses, but rather try to minimize *risk*. We associate a risk level with each action, by assigning higher costs to riskier actions. For example, maneuvering in a flat area at the base of an enemy-occupied hill is riskier than maneuvering on top of a hill, and is therefore more expensive. Although the planner we use is not an optimal planner, it does try to find a low-cost plan, which directly translates to a low-risk plan.

Domain Formulation

Several domain formulation choices affect the entire system. First, as stated before, we divide the map into locations, which are arranged on a grid, where each location can hold multiple friendly units, and multiple enemy units. Each grid location is represented by an object in the planning problem, and thus locations are used as parameters for operators and predicates. The translation of world knowledge to a planning state involves mapping units at specific coordinates to the corresponding grid locations.

Second, entities in operational domains often act in line with some standard operating procedures (SOP), and thus, in particular, act in *formations*. In maneuvering, for instance, a formation could be either a single entity moving by itself, 2 entities moving side-by-side, 3 entities moving in a single column, or any other arrangement. Types of formations are defined by the overall set of SOPs, and can be provided by a subject matter expert. We chose to formulate our domain so that all actions are performed by some formations of entities. For example, moving from one location on the grid to a neighboring location is done by using the *Move* action on a formation, which describes the entities to be moved, and their internal arrangement (side-by-side, column, etc.). Two special types of action, *Set-Formation* and *Break-Formation*, allow entities to rearrange themselves in

different (possibly larger or smaller) formations. Note that this is similar in spirit to the well-known Logistics planning benchmark from IPC-1998 and IPC-2000, where a formation can be thought of as a truck, and an entity can be thought of as a package loaded into the truck (aka joining formation). This engineering methodology appears to be quite useful in general; for instance a very similar technique has been used by Balla and Fern (2009) in their recent work on action selection for tactical assault, evaluated by the authors on Wargus computer games.

Third, we had to deal with enemy units on the battlefield, and their partial observability. We model enemy presence by creating a state variable for the number of enemy units at each grid location. The possible values for this range are either a number (between 0 and some bound) or *unknown* - a special value indicating that we have no knowledge about enemy presence in that grid location. Thus, the (expected) effect of performing a sensing action on a given grid location is that if the number of enemy units in that location was *unknown*, it becomes 0, and otherwise, there is no effect. This formulation also allows us to ignore the identities of enemy units, which are not part of the knowledge provided to the planner anyway.

Load Balancing and Parallelization

One addition to the standard classical planning setting that we found essential was load balancing between the red units. At high level, the load balancer in SHOGUN pre-assigns each sub-goal to a subset of units, decomposes the overall planning task into several smaller tasks that are planned for independently, and then combines their solutions into a plan for the overall task. This procedure is important for balancing the workload between different role-players, causing forces to act in a more "coordinated matter", and reduces the size of the individual planning tasks solved by the planner.

Similarly to all other system components, the load balancer in SHOGUN is completely domain independent. It starts by assigning to each goal a subset of units that can achieve it as cheaply as possible in the (easy to solve) delete-relaxed version of the planning task. Then, the rest of the units are assigned in proportion to the cost of the relaxed plan for each of the goals, so that goals that are riskier to achieve are assigned more units. Finally, the goals are grouped based on the transitive closure of the forces assigned to them, and each such group of goals is planned for using only the forces assigned to it. In the domain considered here, plan combination is trivial, since no two plans can interfere with each other.

One thing to note is that, although the load balancer might assign several units to a single goal, the planner might still not utilize all of these units (the plan found could involve just a single unit). In order to force SHOGUN to act more realistically, we artificially increase the cost of action repetitions. This puts a heavy bias toward using more than a single unit in each plan, resulting in plans allocating forces to goals in ad hoc proportion to the size of the goal.

Finally, though the quality metric for our plans is risk reduction, and thus we employ a cost-oriented, sequential planning, the actions of different units often can (and if so, should) be applied concurrently. While we do not plan for this second objective directly, we do convert our sequential plans into partial order plans allowing concurrent action execution. If our domain had been formulated in plain STRIPS, then simple Partial Order Causal Link (POCL) backward analysis of the plan would have given us a desired partial order. However, our domain formulation uses conditional effects, and this requires slight extension of the standard POCL analysis. To establish hypothetical causal relations between the actions, we first simulate sequential execution of the initial plan, determine which conditional effects of which action instances along the plan have been fired, compile the fired conditional effects into now unconditional effects of the respective actions, and then perform the standard POCL backward analysis of the plan. The resulting parallelization is sound and complete, and results in realistic schedule of plans for our multi-unit forces. Overall, the simultaneous acting effect, achieved in SHOGUN via the mixture of load balancing and plan parallelization, achieves the effect of a standard military C2 methodology called "mission-oriented C2", allowing for solving large-scale problems by wisely delegating its sub-parts to different planners.

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