Using a Competitive Approach to Improve Military Simulation Artificial Intelligence Design

Dr. Sevdalin Stoykov and Dr. Christian Darken
Rakovski Defense and Staff College
82 Evlogi Georgiev blvd., Sofia, Bulgaria
Naval Postgraduate School
1 University Circle, Monterey, California, USA

sevdalin_stoykov@yahoo.com / cjdarken@nps.edu

ABSTRACT

The research presented in this paper attempts to show how using a competitive approach to artificial intelligence (AI) design can lead to improvement of the AI solutions used in military simulations. To demonstrate the potential of the competitive approach, ORTS, a real-time strategy game engine is used. The idea is to setup a tournament of virtual battles between base case AIs and new test AIs, and by using the information from these battles to advance the test AIs. The analysis of the results from the experimental tournament shows possible advantages and applications of the competitive approach. At the end of the paper, some conclusions and recommendations for future work are made.

1.0 INTRODUCTION

In recent years, the focus of military operational analysis has been switching from massive conflicts, dominant in the Cold War, to local conflicts and local fighting, shaping the post 9/11 world. In the process of exploring this new type of warfare, the modeling and simulation community is using more and more the solution suggested by Lauren (1999) by treating the complexities of warfare as a complex adaptive system (CAS). This idea is very close to the idea presented in the research of Ilachinski (2000) on Irreducible Semi-Autonomous Adaptive Combat (ISAAC)/EINStein models. His idea is to use a bottom-up approach, where the individual combatants are modeled, and their interaction in a battlefield produces desired data for combat analysis. This allows researches to address important components of asymmetrical warfare such as spatial layout of the forces, tactical movement or target acquisition and assessment, which are not addressed by traditional models.

To present advanced features of combat using the principles of CAS, in many cases the designers employ solutions from the domain of artificial intelligence (AI) (Pawloski, 2001, Reece, Kraus, & Dumanoir 2000). The main usage of AI solutions in military simulations is to model different tactics and behaviors of forces. This is done by using AI as a control system for forces in the simulation, which are sometimes called synthetic forces. This allows the synthetic forces in the simulation to mimic the reactions and behavior of the real forces in the battle.

The evaluation of success of these solutions is normally made by subject matter experts who subjectively compare the expected entity behaviors to those shown in the military simulations. Although this approach is proven to lead to improvements, it does not provide enough information to answer questions such as: Is there possibly a better strategy or set of tactics for solving the same problem? Do additional factors exist that can be used to produce AI solutions that can demonstrate more realistic or more natural behaviors? In the search for alternative approaches, which may answer some of these questions, this paper is focused on exploring how a competitive approach in AI design can be used to produce better AI solutions for use in military simulations.

2.0 ESSENCE OF THE COMPETITIVE APPROACH IN AI DESIGN

The idea behind the competitive approach is to treat the development of new AI designs for military simulations as an optimization in an abstract hyperspace. The objective function is represented as a set of measurements of effectiveness (MOE), used for quantitative evaluation of each AI design. The feasible region consists of AI solutions, which are able to achieve its goal and are free of errors. The optimization then can be explained as an interactive process, with the following steps:

- Create or choose an AI solution for the base case.
- Create or choose a test AI solution for comparison with the base case.
- Compare these two AI solutions by putting them in a competitive environment.
- Analyze the results from the competition and use them to create a new test AI solution for the next iteration.

There must be a clear distinction between a simulation of a battle run in a military simulation and a simulation of a battle used in competitive approach. Although they both represent force-on-force conflicts, the configuration of forces are significantly different. In the military simulations, forces have the same AI driving designs and the winning side is determined by differences in additional parameters such as ability to move or weapons fire range. In simulations of battles using the competitive approach, the parameters of forces are the same, and the driving AI design makes the difference in the battle. In this way, the competitive approach allows designing of experiments, in which the AI design is the independent variable, and the response is to be measured by selecting MOEs.

3.0 ANALYSIS OF ORTS GAME ENGINE AS A COMPETITIVE ENVIRONMENT

The first step of the research was to find an appropriate environment for the testing of the competitive approach in AI designs. By analyzing and comparing available military simulations and products similar to military simulations, the Open Real-Time Strategy (ORTS) game engine project attracted authors' attention. ORTS has been developed by the University of Alberta, Canada (Buro, 2002; Buro & Furtak, 2003; Buro & Furtak, 2004). The ORTS game engine has a client-server architecture. The server is responsible for managing the state of the "world" of the game, and the clients are responsible for analyzing the current situation in the game and responding adequately by sending commands back to the server. To enforce fairness in the game, the ORTS server executes received commands in random order. Some of the reasons for choosing ORTS as a research platform are:

- ORTS was built mainly as a research project for studying real-time AI problems such as pathfinding, scheduling, planning and dealing in situations with imperfect information.
- ORTS is free software distributed under General Public License (GPL).
- ORTS is written in C++ and all the code and protocol descriptions are freely available. This allows full freedom to implement different AI solutions.
- The client-server architecture of ORTS allows a single non-controversial state of the world for the game at a single time with almost unlimited player sides, human or AI driven.
- The ability to choose from different graphic clients, such as 2D or 3D, can significantly reduce polygon rendering without losing important information.
- Some additional advantages of ORTS as a competitive environment are:

- ORTS has a built-in tournament manager, which significantly reduces time for the design of experiments and analysis of results.
- ORTS has pre-built game scenarios, which are rich enough for exploring AI designs demonstrating complex behavior.
- The designers of ORTS encourage development of AI solutions for tournament participation in a broad community, including industry, academics, and just hobbyists.

The main concern for ORTS, as it relates to this research, is that it cannot be treated as a deterministic simulation. Mainly it is because ORTS does not provide exclusive mechanism for resolving concurrency and because ORTS is based on the network distributed architecture, this introduces an additional randomness in the ORTS event execution mechanism. Although these limitations can be minimized in statistical analysis, the problem with manipulation of the seed in a simulation remains. In an ORTS simulation, the same simulation seed does not produce the same result. By setting the simulation seed, identical conditions can be reproduced for the terrain or for the initial layout of resources, but because of its inherited randomness, ORTS will produce different results each time. Therefore, the manipulation of the simulation seed cannot be used as a replay mechanism for behavior analysis in ORTS. All these drawbacks are relatively easy to overcome, and they have no significant impact on the results of the research.

4.0 DESIGN OF EXPERIMENT

The next step of research was design the elements of the experimental setup. The ORTS TM was set up to run each battle a hundred times with a different simulation seed each time.

4.1 Choosing a Scenario for the Competition

From all built-in games in ORTS, the game number four — "Small-Scale Combat" — was selected as the best representation of generic combat. For this game, the setup of the scenario is as follows:

- There are two opponent sides.
- Each side starts with fifty randomly positioned soldiers ("marines").
- The terrain is without obstacles, spread over sixty-four by forty-eight tiles. The "marines" can be positioned on a finer grain than a single tile, which means that a couple of "marines" can occupy a single tile.
- Each side has perfect information for position and status of its opponent's soldiers.
- Some small mobile obstacles ("sheep") are moving randomly. They cannot be moved or destroyed by the soldiers.

The objective of the game is to destroy as many opponent "marines" as possible within a five-minute time limit.

The goal for the AI design is to create an ORTS client that shows complex behavior and implements winning tactics. Challenges for the AI design in this scenario are the tactics used in small-scale combat, cooperation in goal achievement and unit management. In addition, all other challenges that a RTS game can offer for AI research are present, including the real-time phenomenon.

4.2 Design of MOEs for the Experimental Competition

The main MOE, which measures the efficiency of each AI design, is the percentage of wins. It can be calculated using the following formula:

$$\%wins = \frac{number\_of\_wins}{number\_of\_games\_play} \quad (1)$$

Although this MOE has great expressive power, it is not sensitive enough. Therefore, two new, more sensitive MOEs are added: the number of casualties at the end of the battle and the duration of the battle. This set of MOEs allows each AI design to be positioned according its performance, and at the same time gives enough information about possible advantages or weaknesses of each AI design.

To collect the data for these MOEs, the Tournament Manager (TM) was used. This is a built-in feature in ORTS, which allows a tournament of battles to be conducted, where the AI designs fight with each other in a full factorial combination. Each battle can be repeated an unlimited number of times with different simulation seeds. The ORTS TM is capable of recording the time when a battle ends and the casualties for both sides. The output from the ORTS TM is a text file, which makes the reported data available for processing with almost all statistical packages.

4.3 Setting the Base Cases

The design of the first version of an ORTS AI client was based on results from the ORTS 2007 tournament (ORTS, 2007). At the time when the thesis research had started, only two AI designs for the ORTS game four were available. These were the NPS entrant in the tournament, developed by Patrick Jungkunz, and the design developed by the University of Alberta. For convenience, each tested AI design was assigned a codename (and is referenced by its codename later in the paper). The codename for the AI design for the NPS entrance in the ORTS 2007 tournament is “Circle,” and the codename for the AI design developed by University of Alberta is “UofA.”

4.4 Setting the Test Cases

The next step in the competitive approach is to create a competitive AI design that will hopefully be, or become, better than the base cases. The challenge for the chosen scenario is in two categories. The first part is movement. The soldiers must be in the right place, and in the right time, when they fire on the opposing forces. Therefore, the AI design must provide an advanced tactical movement. The second part is another optimization problem. The problem is to decide when the soldiers are in a firing position, and with which opponent to engage, so the salvo will have maximum effect. In its essence, the problem is a fire allocation problem, and solving it is not a trivial task. In this case, heuristic algorithms are used with an emphasis on quick results.

The research was focused on improving soldier’s tactics through improvements in movement only. To achieve “marine” tactical movement, the test design was separated into two pieces with codenames “g4a” and “g4b.” The goal was to create two AI designs with different architectures and by using the competitive approach to distinguish which one is capable of better accomplishing the task in the ORTS game four.

4.4.1 Creating a Competitive AI Design Based on Finite State Machine

The idea of AI design for “g4a” was to create more “advanced” soldiers, by using the principles in CAS and Ilachinski’s work, which will create new emergent behavior, and this collective behavior will bring the victory. One way to model soldier’s behavior is to use Finite State Machine (FSM); the design of such an FSM modeling a “marine” behavior for “g4a” is shown in Figure 1.

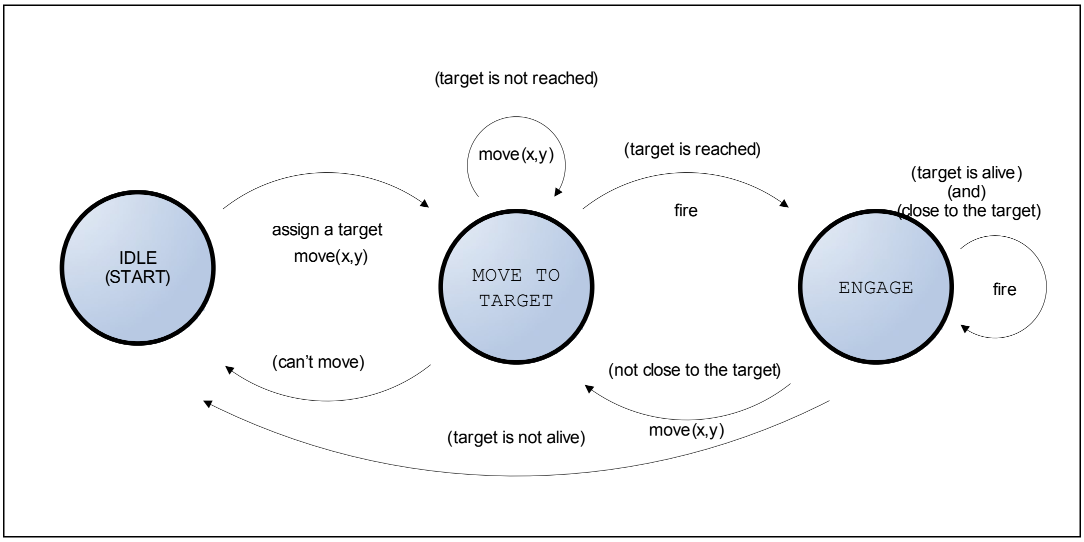


Figure 1: FSM modeling a "marine" behavior

The overall coordination of the "marine" force is achieved by the information provided to individual "marines." Because the ORTS game four is a game of perfect information, each "marine" can make own decision with which opponent and when to engage. Another advantage of using FSM is that it allows the "marines" easily to escape "sheep" or a friendly "marine" standing in their way. The AI design for the "marine" can be classified as model-based reflex agent (Russell & Norvig, 2003).

4.4.2 Creating a Competitive AI Design Based on Force Propulsion

Contrary to the bottom-up approach used in "g4a," an artificial component, a "commander," was introduced in the design for "g4b." The purpose of this "commander" is to get the picture of the battlefield and to send commands to each "marine." At the same time, this was implemented indirectly. "Marines" are still individual agents, but it is the "commander" who controls the driving forces for each agent. This can be classified as more of a hybrid approach than the "g4a" design. The principles of CAS are still in place, but in a more controlled and predictable way.

To achieve "force concentration," the design of "g4b" employs principles similar to those used in the "flocking" algorithms developed by Reynolds (1987). In "g4b," each "marine" is a reflex agent with a set of impact forces shown in Figure 3. The top two arrows are representative of the attractive forces, and the bottom two arrows are representative of the repulsing forces.

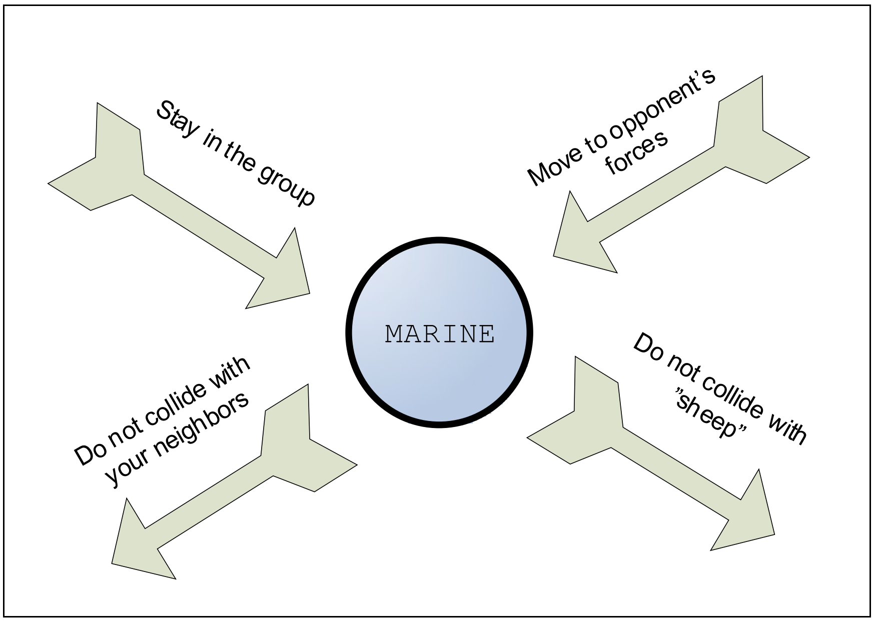


Figure 2: Forces influencing a "marine's" behavior

As opposed to the "Circle" formation, the "marines" in "g4b" are in a dynamic and more flexible formation. In this way, they do not have to wait for formation to be built, but rather are in formation all the time.

5.0 RESULTS FORM THE FIRST RUN OF THE COMPETITION

The first set of experiments ran a set of battles between the base case, "Circle," and test cases, "g4a" and "g4b." The corresponding results for the main MOE, the percentage of wins, from the battles between "Circle" and "g4a" and between "Circle" and "g4b" are presented in Table 1. On the same table are presented the results from the same experiment but with base case "UofA" and test cases again "g4a" and "g4b."

	"g4a"	"g4b"
"Circle"	44% ~~56%~~	100% ~~0%~~
"UofA"	0% ~~100%~~	0% ~~100%~~

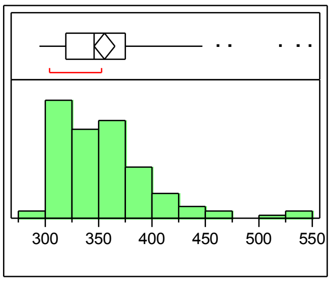
Table 1. The results from form the first run of the competition (% of wins)

The results on Table 1 show that the design of "g4a" didn't fulfill the desired goal. It has forty-four percent of the wins against "Circle", and it didn't score a win against "UofA". On the other hand, "g4b" had total dominance over "Circle," but again it didn't score a single win against "UofA."

The next step of the research was to conduct a deeper analysis of competition results and to reveal some of the reasons for the total dominance of "UofA" as it is demonstrated on Table 1. At this stage, there were two key sources of information: the set of MOEs and the built-in capability of ORTS for 2D visualization.

The MOE percentage of wins demonstrates the dominance of the design for "g4b" over "Circle," but it does not have the power to show why "g4a" and "g4b" performed so badly against "UofA." On the other hand, the other two MOEs are used for analysis of possible problems. The results for these MOEs are shown in Figure 3, Figure 4, Figure 5, and Figure 6. Figure 3 and Figure 4 represent the distribution of the duration of each battle in the battles against "UofA."

Battle time



Quantiles

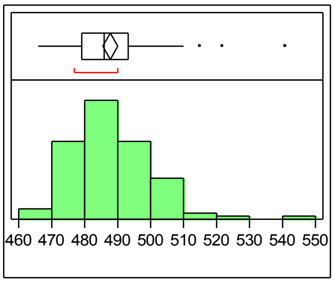
100.0%	maximum	549.00
99.5%		549.00
97.5%		529.60
90.0%		413.90
75.0%	quartile	375.00
50.0%	median	346.50
25.0%	quartile	319.75
10.0%		305.30
2.5%		300.57
0.5%		294.00
0.0%	minimum	294.00

Moments

Mean	355.98
Std Dev	49.818657
Std Err Mean	4.9818657
upper 95% Mean	365.8651
lower 95% Mean	346.0949
N	100

Figure 3: Distribution of the time of battle in the battle between "UofA" and "g4a"

Battle time



Quantiles

100.0%	maximum	541.00
99.5%		541.00
97.5%		518.33
90.0%		501.90
75.0%	quartile	493.00
50.0%	median	486.00
25.0%	quartile	479.00
10.0%		475.00
2.5%		466.52
0.5%		466.00
0.0%	minimum	466.00

Moments

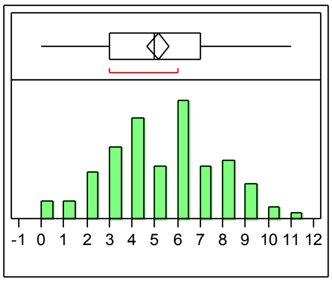
Mean	487.66
Std Dev	11.860485
Std Err Mean	1.1860485
upper 95% Mean	490.01338
lower 95% Mean	485.30662
N	100

Figure 4: Distribution of the time of battle in the battle between "UofA" and "g4b"

These figures show that the battles between "UofA" and "g4a" take on average 355.98 seconds. In comparison the battles between "UofA" and "g4b" have on average of 487.66 seconds. This is evidence that "g4b" has better staying power than "g4a." At the same time, the standard deviation of the duration of the battle for "g4a" is 49.82 seconds versus 11.86 seconds for "g4b," which can be an indicator that the tactic of "g4a" is more unpredictable.

Figure 5 and Figure 6 represent the distribution of the casualties of the "marines" controlled by "UofA" at the end of corresponding battles.

Casualties (UofA)



Quantiles

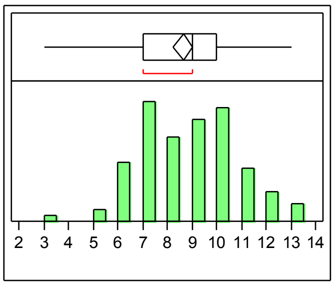
100.0%	maximum	11.000
99.5%		11.000
97.5%		10.000
90.0%		8.000
75.0%	quartile	7.000
50.0%	median	5.000
25.0%	quartile	3.000
10.0%		2.000
2.5%		0.000
0.5%		0.000
0.0%	minimum	0.000

Moments

Mean	5.16
Std Dev	2.4317762
Std Err Mean	0.2431776
upper 95% Mean	5.6425172
lower 95% Mean	4.6774828
N	100

Figure 5: Distribution of the casualties of "UofA" in the battle between "UofA" and "g4a"

Casualties (UofA)



Quantiles

100.0%	maximum	13.000
99.5%		13.000
97.5%		13.000
90.0%		11.000
75.0%	quartile	10.000
50.0%	median	9.000
25.0%	quartile	7.000
10.0%		6.000
2.5%		5.000
0.5%		3.000
0.0%	minimum	3.000

Moments

Mean	8.66
Std Dev	1.9808171
Std Err Mean	0.1980817
upper 95% Mean	9.0530371
lower 95% Mean	8.2669629
N	100

Figure 6: Distribution of the casualties of "UofA" in the battle between "UofA" and "g4b"

By comparing these two figures, it is clear that "g4b" has better lethality. On average at the end of the battle, "g4b" managed to eliminate 8.66 soldiers against 5.16 eliminated soldiers by "g4a."

Using the built-in visualization capabilities in ORTS, Figure 7 and Figure 8 were produced. Figure 7 presents a snapshot of a battle between the designs of "UofA" and "g4a."

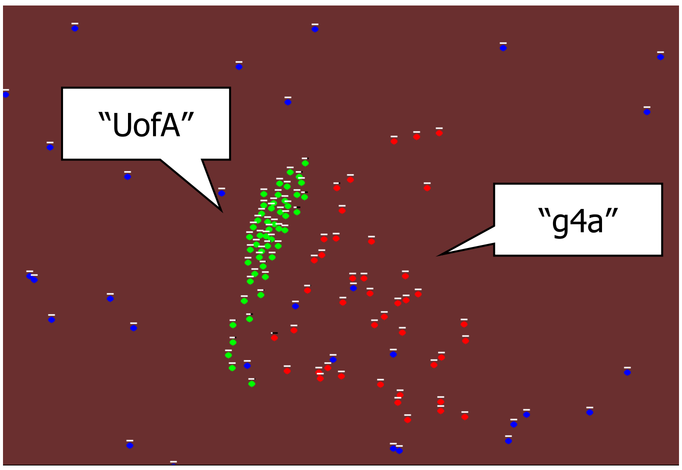


Figure 7: A battle between "UofA" and "g4a" designs

This shows the main problem with the AI design for "g4a:" the forces are too dispersed on the battlefield. They are facing the opponent's forces one by one, and the overall concentration of forces is missing. At the same time this dispersion does not allow "UofA" to make a proper flanking formation, which is confirmed by the tail of the distribution for the duration of the battle on Figure 7.

Figure 8 presents a snapshot of a battle between the "UofA" and "g4b" designs. It demonstrates that the "marines" controlled by "g4b" are in a good condensed formation, approaching the opponent's forces. The problem is that not all of them are in a position to fire. Only the left edge of the formation is facing the opponent forces, and the right edge is out of fire range. This means, that despite the fact that the "marines" of "g4b" are in condensed formation, their firing power is dispersed. Therefore, once again Lanchester's principle of force concentration is missing. This lack of force concentration is not as bad as in the design of "g4a," but sill it is the main factor for poor performance against "UofA."

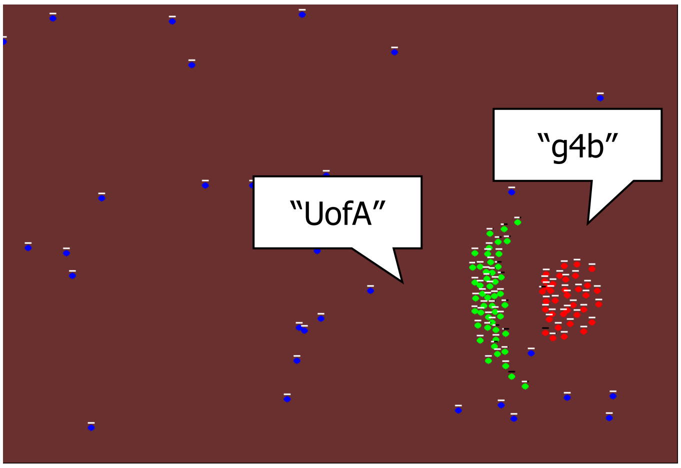


Figure 8: A battle between "UofA" and "g4b" designs

6.0 MODIFICATIONS IN THE TEST AI DESIGN

The next part of this research was to try to improve the test AI designs. The decision was to build a new AI design based on "g4b." The codename for this new design was "g4c." The design of "g4b" was force driven, so the question was, can the driving forces be modified so that "g4c" can obtain a winning strategy?

The analysis for the results from the experimental competition demonstrates three properties of AI designs that have the potential to lead to winning strategy. First, the "marines" should face the opponent's forces in condensed formation. Second, this formation must be flexible enough to place a maximum number of "marines" in firing range. Third, the tactics of "marines" should include outflanking maneuvers demonstrated by "UofA."

Translation of these desired properties to force manipulation is not a trivial task. Usually, the reverse tasks are solved in CAS simulations. The agents are influenced by a set of predefined forces, and in reaction to these forces, the agents demonstrate emergent behavior. In other words, the set of forces is known and the behavior is unknown. In this case, the task is opposite, the desired behavior is known, but the set of forces leading to this behavior are unknown.

To address these problems in the design of "g4c," the behavior of "marines" was separated into three stages:

- First, "marines" must make a condensed formation.

- Second, when the “marines” are in the range of fire, they must start firing, and conduct outflanking tactics.
- Third, if the opponent’s forces are out of firing range, the “marines” must pursue them.

Applying these three stages to the behavior demonstrated by the “marines” in the “g4b” design, it was clear that for the first and the last stage there was no need to change the tactics. The problem was the second stage and the modifications were focused on that stage.

The new suggested set of forces influencing the “marine’s” behavior in the stage of exchange of fire is shown in Figure 13.

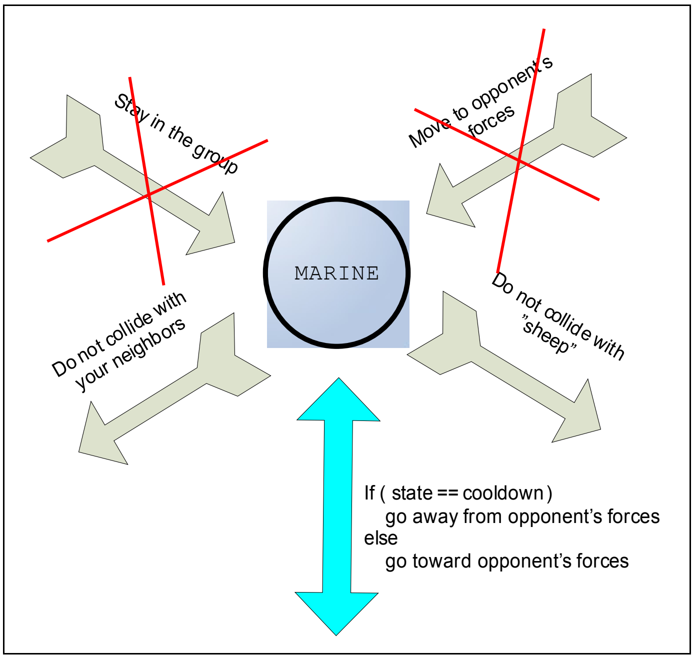


Figure 9: Forces influencing a “marine’s” behavior for the “g4c” design

The difference between Figure 9 and Figure 2 is that the force “Move to opponent’s forces” was replaced with a new force, the direction of which depends on the state of the “marine’s” weapon. At the same time, the force “Stay in the group” was eliminated, which allowed “marines” to make more dispersed outflanking formations.

The conditions for switching between different behaviors were:

- After the ORTS game starts, for a certain amount of time, the “marines” are reacting to the forces shown in Figure 2.
- When the “marines” are in a firing range with the opponent’s formation, they start to react to the forces shown in Figure 9.
- Finally, if the opponent’s forces retreat, and are out of firing range, again the “marines” will start to react to the forces shown in Figure 2.

6.0 RESULTS FORM THE SECOND RUN OF THE COMPETITION

The experimental competition was executed again for test cases “g4c” and the base cases “Circle” and “UofA.” The results for the main MOE, the percentage of wins, are presented on Table 2.

	“g4c”
“Circle”	100% 0%
“UofA”	89% 11%

Table 2. The results from form the second run of the competition

As expected, because “g4c” is a continuation of “g4b,” it has total dominance over the design of “Circle,” and at the same time they demonstrate significant improvement in the tactics shown by “g4c” in comparison to “g4b.” The “marines” controlled by the design of “g4c” managed to win almost ninety percent the battles against “UofA.”. This can be explained by the new formation demonstrated by the “marines” from “g4c,” presented in a snapshot shown on Figure 10. In Figure 10, the “marines” controlled by the “UofA” are on the left side and the “marines” controlled by “g4c” are on the right side.

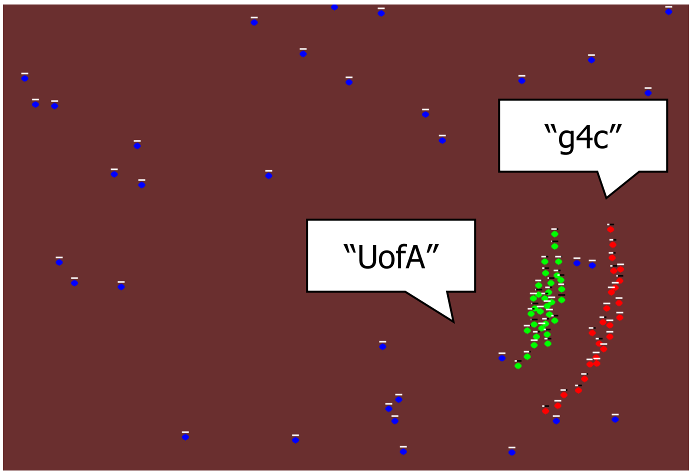
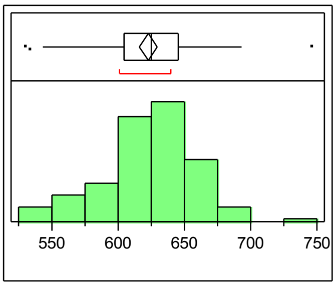


Figure 10: A battle between “UofA” and “g4c” designs

Figure 10 shows that “g4c” had a better outflanking strategy than “UofA.” This strategy is better because the design of “g4c” managed to put more “marines” in the front edge of the formation. In some cases, “g4c” even achieved putting all the “marines” in a curve surrounding the opponent’s formation within firing distance. This is the best solution from the perspective of force concentration. This allows the “marines” to advance, fire, and then wait for the weapon’s cooldown at a safe distance. This increases “marines” survivability, which is indicated in Figure 11.

Battle time



Quantiles

100.0%	maximum	747.00
99.5%		747.00
97.5%		691.95
90.0%		665.50
75.0%	quartile	645.25
50.0%	median	625.50
25.0%	quartile	604.00
10.0%		565.90
2.5%		539.20
0.5%		531.00
0.0%	minimum	531.00

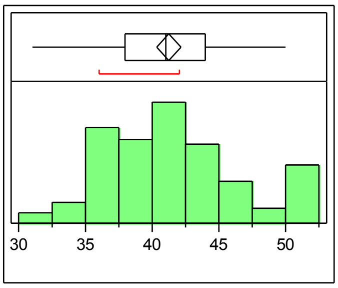
Moments

Mean	622.71
Std Dev	36.321042
Std Err Mean	3.6321042
upper 95% Mean	629.91688
lower 95% Mean	615.50312
N	100

Figure 11: Distribution of the time of battle in the battle between "UofA" and "g4c"

Figure 11 represents the distribution of the MOE for the duration of the battle. It shows that on average the battles lasts for 622.71 seconds longer than the 487.66 seconds registered in the battles between "UofA" and "g4b." This is clear evidence of the increased staying power of "g4c." At the same time, the next MOE for casualties at the end of the battle reveals some additional information about the design of "g4c." The distributions of the MOE for opponent casualties at the end of the battle between "UofA" and "g4c" are presented in Figure 12.

Casualties (g4c)



Quantiles

100.0%	maximum	50.000
99.5%		50.000
97.5%		50.000
90.0%		50.000
75.0%	quartile	44.000
50.0%	median	41.000
25.0%	quartile	38.000
10.0%		36.000
2.5%		32.525
0.5%		31.000
0.0%	minimum	31.000

Moments

Mean	41.25
Std Dev	4.785025
Std Err Mean	0.4785025
upper 95% Mean	42.199453
lower 95% Mean	40.300547
N	100

Figure 12: Distribution of "g4c" casualties in the battles between "UofA" and "g4c"

From Figure 12, it is interesting to note that on average the casualties of "g4c" at the end of the battle are 41.25 solders. This means that the battle is very tight and "g4c" wins by approximately eight "marines" on average. The fact that the advantage of "g4c" is so tiny is supported by the standard deviation of the distribution, which is 4.78. These results show that the design of "g4c" has evolved by employing tactics similar to the complex tactics used by "UofA," but at the same time it has achieved only a slight advantage.

7.0 CONCLUSIONS

The research succeeded in the development of a framework and methodology to apply the competitive approach. In addition, the results presented in the paper demonstrated the advantages of the competitive approach in AI designs used in military simulations. These advantages can be summarized in the following aspects. First, the ORTS engine was tested and it was found to be a suitable platform for exploring new AI designs with application to military simulations. Second, the research results show that the competitive approach leads to improvements of AI designs for ORTS, and this can reasonably be expected to extend to those used in military simulations. Third, and most important, the advantage of the competitive approach for AI designs is that it gives valuable inside information about the problem, which is almost impossible to obtain otherwise.

This research clearly implies that the competitive approach has more universal application. It can be used not only for battles between two AI designs, but also for competitions between AI designs of any kind. For example, in ORTS game one, the main goal is to collect "minerals" in a certain time. The competition here is testing which AI design would do a better job by collecting more minerals in that time. This small example shows that the competitive approach has great potential for improving not only military simulation, but also AI designs for other problem domains, such as development of more advanced algorithms for driving autonomous vehicles in collaborative environments.

8.0 REFERENCES

[1] 2007 ORTS RTS Game AI Competition. Available at http://www.cs.ualberta.ca/~mburo/orts/AIIDE07/index.html, Accessed March 2008.

[2] Buro, M., & Furtak, T. (2003). RTS Games as Test-Bed for Real-Time Research, *Invited Paper at the Workshop on Game AI*, JCIS, 481-484.

[3] Buro, M., & Furtak, T. (2004). RTS Games and Real-Time AI Research, *Proceedings of the Behavior Representation in Modeling and Simulation Conference*, 34-41.

[4] Buro, M. (2002). ORTS: A Hack-Free RTS Game Environment, *Proceedings of the International Computers and Games Conference*, 280-291.

[5] Ilachinski, A. (2000). Irreducible Semi-Autonomous Adaptive Combat (ISAAC): An Artificial-Life Approach to Land Combat, Military Operations Research, 5(3), 29-46.

[6] Lauren, M., & Stephen, R. (2002). Mana: Map-aware non-uniform automata: A New Zealand approach to scenario modeling, Journal of Battlefield Technology 5, 27-31.

[7] Lauren, M. (1999). Characterising the Difference Between Complex Adaptive and Conventional Combat Models, Defence Operational Technology Support Establishment, Auckland, New Zealand.

[8] Moffat, J. (September 2003). Complexity Theory and Network Centric Warfare US DoD Command and Control Research Program. Available at http://www.dodccrp.org/files/Moffat_Complexity.pdf, Accessed March 2008.

[9] Pawloski, J. (2001). Modeling tactical level combat using a multi-agent system design paradigm (GI Agent), (Master's thesis, Naval Postgraduate School, 2001).

[10] Reece, D. A., Kraus, M., & Dumanoir, P. (2000). Tactical Movement Planning for Individual Combatants, *9th Conference on Computer Generated Forces and Behavioral Representation*. Available at http://www.sisostds.org/index.php?tg=fileman&idx=get&id=2&gr=Y&path=CGF-BR%2F9th+CGF-BR%2F9TH+Abstracts%2C+Papers+and+Presentations&file=9TH-CGF-045.doc, Accessed November 2007.

[11] Taylor, J. G. (1983). Lanchester models of warfare, Operations Research Society of America, Military Applications Section, Arlington, VA.