5-4-2022

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Recommended Citation

Wilson, R., King, D., & Peterson, G. (2022). Evolution of Combined Arms Tactics in Heterogeneous Multi-Agent Teams. The International FLAIRS Conference Proceedings, 35. https://doi.org/10.32473/flairs.v35i.130577

Evolution of Combined Arms Tactics in Heterogeneous Multi-Agent Teams

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Abstract

Multi-agent systems research is concerned with the emergence of system-level behaviors from relatively simple agent interactions. Multi-agent systems research to date is primarily concerned with systems of homogeneous agents, with member agents both physically and behaviorally identical. Systems of heterogeneous agents with differing physical or behavioral characteristics may be able to accomplish tasks more efficiently than homogeneous teams, via cooperation between mutually complementary agent types. In this article, we compare the performance of homogeneous and heterogeneous teams in combined arms situations. Combined arms theory proposes that the application of heterogeneous forces, en masse, can generate effects far greater than outcomes achieved by homogeneous forces or the serial use of individual arms. Results from experiments show that combined arms tactics can emerge from simple agent interactions.

1 Introduction

The field of multi-agent systems research seeks to develop methods and algorithms for developing individual agents so as to produce desirable system behaviors. The field has yielded famous algorithms such as Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), but has focused primarily on systems of identical, *homogeneous*, agents. Recent work has begun to explore the potential of *heterogeneous* systems, or systems of agents with differing behaviors or physical forms. Of particular interest to us, is the application of such systems to the development and validation of combined arms theory.

The military theory of combined arms combines different types of armaments to achieve effects greater than could be attained if the same armaments were applied singly or in sequence (Army 2019). It combines complementary arms in such a way that to avoid one, the enemy must expose itself to another (Corps 1997a). A combined arms unit is therefore *heterogeneous*, since the arms or agents it comprises differ from each other. Since a combined arms force is a heterogeneous multi-agent system, the study of multi-agent systems may bear fruit for the military study of combined arms. This paper presents a set of experiments designed to explore the emergence of combined arms tactics in systems of *heterogeneous* agents, i.e. agents which differ in behavior or physical form.

Experiments were conducted in a two-dimensional (2D) battle simulation in which teams of agents competed to achieve set objectives. A genetic algorithm was used to evolve effective teams for each scenario, and the behavior of each evolved team was compared with definitions of combined arms behavior from existing military doctrine. The hypothesis, proven correct, was that combined arms tactics can emerge from the interactions of simple heterogeneous agents.

The rest of this work is divided into sections by subject. Section 2 reviews existing research in homogeneous and heterogeneous multi-agent systems. Section 3 describes the platform and measures used during experimentation. Section 4 outlines the test scenarios, and Section 5 discusses the outcome of each experiment. Section 6 provides closing remarks and suggestions for future work.

2 Background

In 2013 Dorigo, et al. lamented the almost exclusive focus of multi-agent systems research on systems of homogeneous agents (Dorigo 2013). Homogeneous agents share the same physical and behavioral characteristics, while heterogeneous agents differ in either behavior or physical makeup (Kengyel et al. 2015). Following Kengyel's usage, this paper refers to differentiation of behavior as behavioral heterogeneity, while physical differences are called morphological heterogeneity.

Several experiments with behavioral heterogeneity have been performed since Dorigo, et al. made their complaint. Deka, et al. (Deka and Sycara 2021) demonstrated the development of heterogeneous behaviors by teams of morphologically homogeneous agents in a pursuit-evasion game. Over time, multi-agent teams developed strategies requiring heterogeneous behaviors from member agents. Agents approached a target zone from multiple directions, or acted as decoys to allow team members to reach the objective.

In another set of pursuit-evasion experiments, King, et al. showed that the ability to select actions from a set of heterogeneous behaviors improved the performance of morphologically homogeneous agents in a swarm (King, Bindewald, and Peterson 2018). Their Iterative Team Assignment Algorithm (ITAA) divided agents on the pursuing team into *patrol*, *circle*, and *pursuit* roles, each with its own behavioral logic. The pursuing team was tasked with capturing members of an evading team before they could reach a defended zone. Results showed that behavioral adaptation via the ITAA improved the pursuers performance.

Dorigo, et al. developed a multi-agent system called Swarmanoid, made up of morphologically and behaviorally heterogeneous robots which cooperate to accomplish tasks (Dorigo 2013). 'Eye-bots' capable of flight gather information about the environment from the air and relay it to other robots. 'Hand-bots' use manipulators to grasp objects, climb surfaces, or connect with other robots. 'Foot-bots' possess tracks and wheels, and provide transportation for the hand-bots. Working together, the Swarmanoid robots can perform cooperative tasks like fetching a book from a shelf in another room, a task requiring cooperation between each of the distinct agent morphologies. Each morphology has a *niche*, or a particular role defined by its characteristics.

To understand the effect of agent niches on a system, King examined the impact of behavioral and morphological differentiation on task performance in the K coverage problem (King 2018). He noted that morphological differentiation limits the ways agents in a system can adapt. In a morphologically homogeneous system, any agent is capable of performing the same task as any other agent, if it changes its behavior to match. In a morphologically heterogeneous system, an agent in one niche may be physically incapable of performing another's task.

In King's experiments, swarms of *observer* and *tracker* agents with differing morphologies cooperated to identify and monitor random targets. Compared with morphologically homogeneous swarms, the morphologically heterogeneous teams had worse detection rates but better agent distributions. He concluded that morphological differentiation can improve a system's performance, but that it can also reduce the system's adaptability by placing strict constraints on an agent's possible roles (King 2018). For example, one of King's *tracker* agents could fill in for another *tracker*, but not for an *observer*.

The same principle is evident in military tactics. Artillery and infantry units are mutually supporting but not interchangeable. Their roles in a larger military organization are based on their morphologies: artillery delivers supporting fire for infantry, and infantry provides artillery with protection (Corps 1997b). Combined arms warfare entails the simultaneous application of different types of arms in order to achieve an effect greater than could be attained by their separate or sequential application (Army 2019). "Different types of arms" refers to morphologically distinct military agents, such as artillery and infantry. A combined arms force is therefore a morphologically heterogeneous multi-agent system, in which agents develop behavioral and morphological niches comparable to those in King's and Dorigo's experiments.

Many military problems consequently reveal themselves to be multi-agent systems engineering problems. Commanding Marines in Vietnam, Lt Col John Studt successfully thwarted ambushes by incorporating dogs with patrolling units (Shulimson et al. 1997). The combination of dogs with Marines created a morphologically heterogeneous system with dog and Marine agents, the dog specialized for detection of enemies, Marines for combat and decision-making.

In Studt's case the combination of dog and Marine was a product of costly trial and error. Dogs were used because the Marines had already suffered casualties. If multi-agent systems research could simulate combined arms forces and evaluate them by some measure of fitness, one might be able to devise more effective unit compositions and tactics without the commensurate cost in blood. The simulator described in Section 3 is a first step in that direction, and though the environment it simulates is simple and not particularly realistic, it serves to demonstrate that from such experiments may yield effective unit combinations and tactics.

3 Simulator

A novel simulator based on the popular RoboCode program was developed to run these experiments. RoboCode is a two-dimensional battle simulator with tank-like robots as combatants (Nelson, Larsen, and Savara 2022). A good test bed for robotic control algorithms, RoboCode is often used to teach AI concepts, with students writing controllers to guide their robots to victory. The software frequently appears in research on robotics and multi-agent systems. Woolley and Peterson (Woolley and Peterson 2009) used RoboCode to develop the Unified Behavior Framework (UBF), a modular framework of reactive robot control in which an arbiter draws on a collection of possible behaviors to select the best action for a given state. Recchia, et al. and Rebelo, et al. used RoboCode to prototype behaviorally heterogeneous multi-agent teams with behaviors based on psychological theories of personality (Recchia, Chung, and Pochiraju 2014; Rebelo et al. 2015). In spite of RoboCode's extensive documentation and existing research, the platform is not suitable for testing morphologically heterogeneous teams of agents because it supports only one robot morphology.

Simulations for this paper were conducted in RoboCodePlus, a RoboCode-like simulator written in C++.[1] Like RoboCode it simulates battling robots in a two-dimensional plane, but adds morphologically heterogeneous robot types and objective-based scenarios. RoboCodePlus agents are composed of a behavior and a morphology.

A RoboCodePlus morphology can be understood as a collection of components. A typical *Tank* morphology, for example, comprises four main components: a chassis that controls movement, a turret that provides a platform for a weapon and sensor, and the weapon and sensor themselves. Every time the physics engine updates the simulated environment[2], each component receives a control signal from the robot's behavior, which tells it how to act. The sensor might rotate clockwise while the weapon fires some designated munition, for example.

Each agent's behavior generates those control signals based on the agent's perceived state. Behaviors are simple

[1] RoboCodePlus source code is available on request.

[2] The Box2d physics engine is used, and updates the simulation 60 times per second of game time.

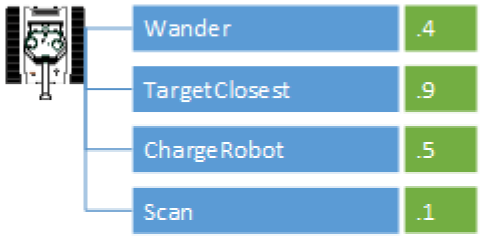

Figure 1: A composite robot behavior in RoboCodePlus. Each behavior (blue rectangle) is associated with a weight (green rectangle) which determines its precedence in the Priority Fusion arbiter.

	Tank	**Scout**	**Artillery**
Energy	100	80	100
Max Velocity (m/s)	15	25	15
Rate of Fire (rounds/s)	3	n/a	1.2
Weapon Damage	12.5	n/a	5.0 x 32 rays
Weapon Range (m)	100	n/a	200
Sensor Range (m)	100	150	n/a

Table 1: Characteristics of agent morphologies

implementations of Woolley and Peterson's UBF. Each behavior is a composite of four *atomic* behaviors with an associated weight. Six times every second, each atomic behavior suggests an action. The composite uses a Priority Fusion arbiter to apply the highest-weight action for each component of the robot.

An example of a robot with such a behavior and arbiter is shown in Figure 1. The robot shown will follow the *Wander* behavior until it detects an adversary, moving randomly around the map. When an adversary is found, the *ChargeRobot* behavior's higher weight will override *Wander*. The robot will cease moving randomly and will instead accelerate towards the adversary.

Three morphologies are used in this paper (see Table 1). The *Tank* is comparable to a robot from the original RoboCode. It has a turret, a cannon, and a sensor. It is able to both find and destroy targets. A *Scout*, by contrast, has no weaponry, but boasts a longer-ranged sensor, a faster maximum speed, and a smaller profile, making it ideal for spotting adversaries but unable to engage them alone. The *Artillery* morphology is the opposite, with slower but more powerful munitions than the Tank, but no sensor of its own. Its munitions explode on impact, using the physics engine to cast 32 rays in a 5-meter circle, inflicting damage and applying force to every robot intersected by a ray. *Artillery* therefore is ideal for disrupting maneuvers or damaging tight formations of enemies, but must rely on allies with sensors to detect and relay target positions.[3]

[3]Video demonstrations of tactics evolved in these experiments are hosted at https://www.robocodeplus.com.

Algorithm 1 Run Experiment

function RUN(*Population* P, *Scenario* S, *int* I)
  for $i \leftarrow 1, \mathbf{I}$ **do**
    $\varepsilon \leftarrow \frac{\mathbf{I}-i}{2 \cdot \mathbf{I}}$ ▷ Update exploration variable
    EVOLVE(P)
    RESETSCORES(P) ▷ Clear old fitness
    for $p \in P$ **do** ▷ Iterate over population
      RESET(S)
      for $j \leftarrow 1, 10$ **do**
        PLAYROUND(S) ▷ Play 10 rounds/team
      end for
      ADDCREDIT(p) ▷ Calculate fitness
    end for
  end for
end function

Algorithm 2 Evolve Population

function EVOLVE(*Population* P)
  SORT(P) ▷ Sort population by fitness
  $n \leftarrow$ ELITES ▷ Set number of elites
  for $i \leftarrow n, P.count$ **do**
    $r \leftarrow$ RANDOM$(0, 1)$ ▷ Get random fraction
    if $r < \varepsilon$ **then**
      RANDOMIZE($P[i]$)
    else
      $p1, p2 \leftarrow$ GETRANDOMELITE()
      $P[i] \leftarrow$ CROSSOVER($p1, p2$)
    end if
  end for
end function

4 Evolution

Evolution was conducted on a population P of 100 teams, where each individual p in P was a team comprising several robots with their behaviors. During each run, the modified team completed 100 ten-round game sets, evolving after each set (see Algorithm 1). At each evolution the fittest 10 teams, elites, were preserved until the next generation. The rest of the population was filled with new teams produced via crossover between the elites or random generation. The ratio of teams produced by crossover versus random generation was controled by variable η. In early sets more teams were randomly generated, favoring exploration of the domain, while in later sets exploitation was favored, with most teams produced via crossover (see Algorithm 2). Random mutations were applied to robot morphologies and individual behaviors with a probability of 5% every iteration.

Teams were evolved in competition. At the start of each experiment, a population of 100 random teams was generated for both teams in the scenario. Teams were then evolved in eleven alternating runs, one team evolving on odd-numbered runs and the other on even. The evolved teams were then assessed for tactics matching the definitions of combined arms given in (Army 2019) and (Corps 1997a). Fitness scores were calculated as a composite of a team's win rate W and conservation C in each set of 10 games, as shown in Equation (1), Equation (2), and Equation (3). Conservation was based on the number of remaining robots out of the team's initial total, and the sum of all robots' remaining energy out of their maximum.

$$W = \frac{victories}{rounds} \tag{1}$$

$$C = .5\left(\frac{survivors}{totalRobots}\right) + .5\left(\frac{energy}{maxenergy}\right) \tag{2}$$

$$F = .6(W) + .4(C) \tag{3}$$

Coefficients for each equation were selected by trial and error, with no metaheuristic optimization. Equation (2) was written to weight survival rate equally with energy retention, while Equation (3) is influenced by a team's win rate slightly more than its conservation.

5 Experiments

Three scenarios were tested, each with a different objective. All scenarios took place on a 200 by 200 meter map with no obstacles or terrain features. Morphologies shown in the figures below changed as the teams evolved.

5.1 Zone Defense

In the Zone Defense scenario, the Southern team attempted to reach a target zone centered around the coordinates (100,200). The Northern team was meanwhile tasked with keeping the Southern team out of the target zone for at least 25 seconds of game time. The Southern team comprised two robots and the Northern team five.

5.2 Elimination

In Elimination, the Southern team's objective was to destroy a target robot on the Northern team, whose objective was to protect that robot for at least 25 seconds. The Northern, defensive team comprised five robots, including the target. The Southern team comprised four robots. While the attackers were given a target id, they received no special information about the target's location, so that they had to locate the target before it could be destroyed.

5.3 Last Team Standing

In the Last Team Standing scenario, each team was tasked with destroying the other. Teams started the game in random positions within 20 meters of the North or South edge of the map, respectively. If neither team attained victory within 84 seconds (5000 ticks of the physics engine), the game was declared a tie, and neither team was counted victorious.

6 Results

Each evolved team was assessed for the presence of combined arms tactics. A team behavior was deemed a combined arms tactic if it could be shown to fit the definitions of combined arms given by United States Army (USA) and Marine Corps (USMC) Doctrinal Publications. According to the Army, combined arms "is the synchronized and simultaneous application of arms to achieve and effect greater than

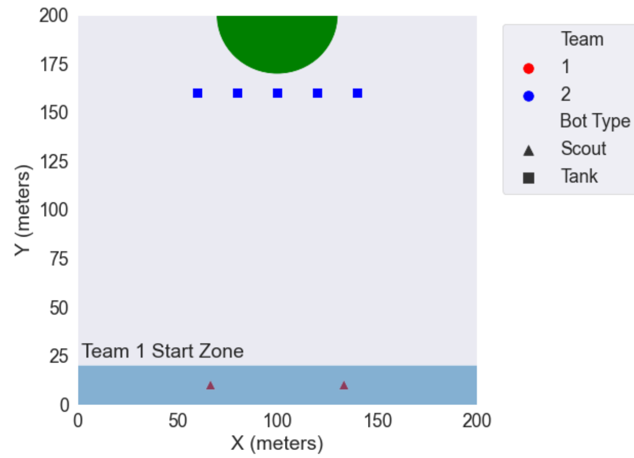

Figure 2: Zone Defense scenario map

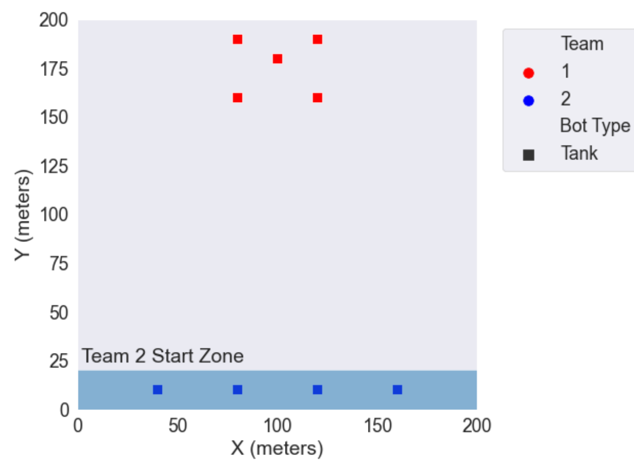

Figure 3: Elimination scenario map

if each element was used separately or sequentially" (Army 2019). According to the Marine Corps, it is "the full integration of arms in such a way that to counteract one, the enemy must become more vulnerable to another" (Corps 1997a).

Team tactics matching one or both definitions of combined arms were observed in all three test cases. Each tactic is described in this section, with an accompanying diagram of the team dispositions in each tactic.

6.1 Cooperative Scouting

In Zone Defense, the fittest defending teams consistently evolved to include a single scout and four artillery robots. The scout swept its sensor across the map and continually notified the artillery of the attackers' positions. The artillery focused their fire on the positions relayed by the scout. Such symbiotic teams of scout and artillery also emerged in the other two tested scenarios.

The scout and artillery morphologies are naturally symbiotic. The scout possesses superlative sensors but no armament, while the artillery possesses a powerful armament but

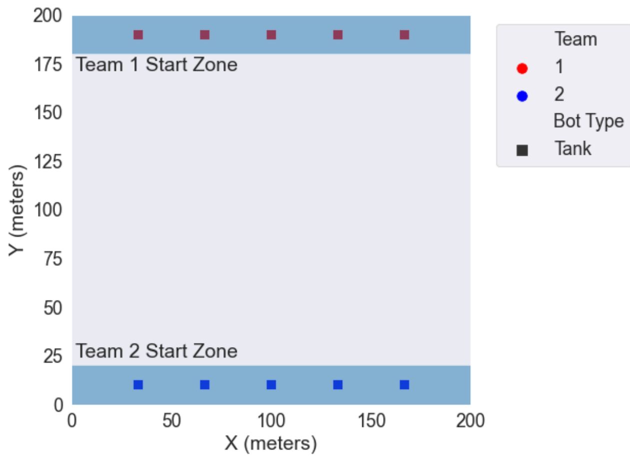

Figure 4: Last Team Standing scenario map

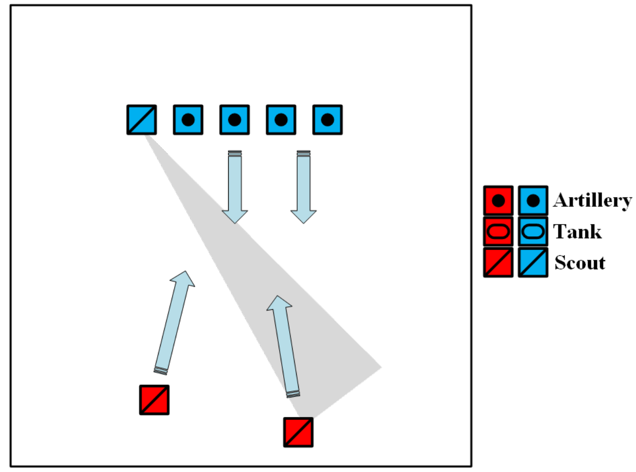

Figure 5: Cooperative scouting: the blue scout identifies targets for four blue artillery.

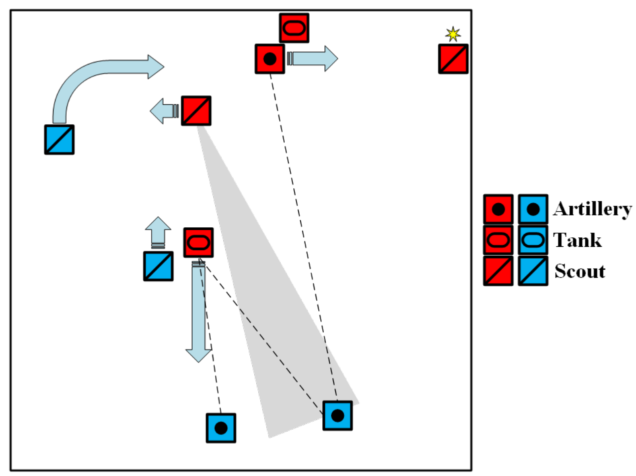

Figure 6: Decoy: One red tank advances to attack the blue artillery. The blue artillery fires on the red while they are distracted. The target robot is marked by a yellow star.

no sensors. Therefore neither morphology is capable of engaging an enemy without the other, making these teams an example of combined arms as defined in (Army 2019).

The pair are also an example of how the morphological forms of agents in a system can influence the roles those agents take in the overall system. The scout and the artillery each have a behavioral niche dictated by their physical makeup, which in turn constrains the tactical options of the larger team. The observation is important because it shows that behavior and morphology are not independent, and that the behavior of an emergent system might be engineered via the morphology of its constituent agents.

6.2 Decoy

The scout and artillery combination often arose in the Elimination scenarios. In one such instance, the attacking team used two scouts to identify the target robot for two artillery, which then destroyed the target from long range. To counter this strategy, the defending team evolved a decoy behavior incorporating the strengths of each morphology type. A tank charged the attacking artillery, damaging them and drawing their fire. The same tank and a scout scanned the battlefield and relayed enemy positions to a defending artillery unit, which began firing at the attackers while the attacking artillery was busy with the decoy tank. Meanwhile the defended robot fled to a corner to stay out of the way.

The attacking artillery face a dilemma. If they engage the decoy they come under fire from the defending artillery. If they ignore the decoy it can attack them itself. The defending team therefore fits the definition of combined arms in (Corps 1997a), integrating units such that by countering one, the enemy becomes vulnerable to another.

6.3 Multi-Pronged Attacks

Multi-pronged attacks occurred in both teams in the Elimination and Last Team Standing scenarios, and on the attacking side in the Zone Defense scenario. Several varieties of this tactic emerged, incorporating various combinations of robot morphologies. In such attacks, team members were distributed along different lines of approach to the target. One or two would flank East, for example, while another flanked West and two more advanced up the map center. These formations enabled teams to approach the target from multiple directions simultaneously and forced defenders to prioritize between different groups of attackers, once again recalling the definition of combined arms in (Corps 1997a).

One such instance occurred in the Last Team Standing scenario. The Northern team had just developed the tactic of sending robots in a pincer movement down the West and East flanks. In response, the Southern team evolved a two-pronged advance that sent three tanks down the West flank, where they overwhelmed that arm of the Northern pincer. The tanks used their sensors to identify targets for the second prong of the attack: two artillery robots which moved towards the map center. By using tanks rather than scouts to identify targets, the Southern team exchanged

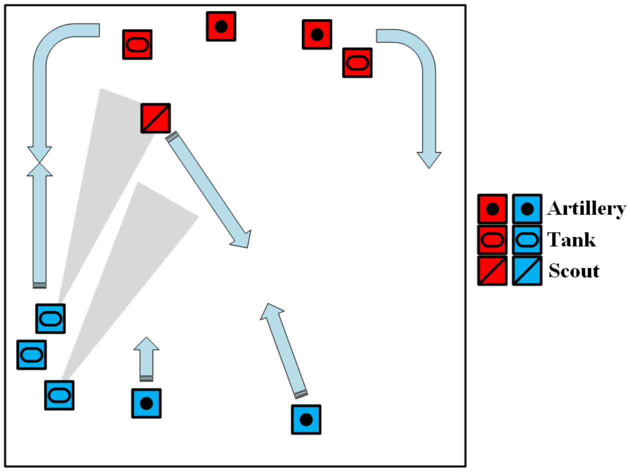

Figure 7: Multi-pronged attack: three blue tanks flank West while two blue artillery maneuver up the map center, firing on targets identified by the flanking tanks.

speed and sensor range for additional firepower, allowing them to strike heavily in the West while simultaneously spotting for the central artillery.

6.4 Summary of Findings

Three conclusions may be drawn from the team behaviors described above. First, cooperative team strategies may emerge from collections of simple agent behaviors. This finding is by no means novel, but merely confirms findings in (Holland 1995), (Dorigo and Di Caro 1999), and many other works. Second, heterogeneous morphologies can cooperate to produce team behaviors that would be impossible for a team comprising any single morphology. Once again the finding is not novel, but echoes the work of Dorigo, et al. in (Dorigo 2013) and of King in (King 2018). Third, systems of heterogeneous agents can exhibit combined arms tactics without centralized control. This last finding is a novel application multi-agent systems research to military theory, and suggests a new domain of study for students of both multi-agent systems and combined arms.

7 Conclusion

This paper examined combined arms tactics as a problem of multi-agent systems engineering. Experimental results demonstrated that combined arms tactics can emerge from simple agent interactions in a morphologically heterogeneous multi-agent system. Tactics involving the simultaneous application of multiple complementary unit types emerged in all three tested scenarios. All of these tactics developed from the decentralized behaviors of each team member, with no centralized controller. The results suggests that multi-agent simulations could be used to develop novel tactics, or to evaluate old ones.

Future work should expand the variety of morphologies and behaviors used for testing, and examine the impact of such factors as terrain features on unit behaviors and development. Historical battles could be used as set-piece scenarios in more realistic simulations. The relationship of morphological niches with emergent system behavior should be studied in more detail. Finally, conditional rule-based behaviors could be employed and evolved, perhaps in a Learning Classifier System (LCS) (Urbanowicz and Moore 2009), to allow the development of more complex agent behaviors.

References

Army, U. S. 2019. ADP 3-0: Operations.

Corps, U. S. M. 1997a. MCDP 1: Warfighting.

Corps, U. S. M. 1997b. MCDP 1.3: Tactics.

Deka, A., and Sycara, K. 2021. Natural Emergence of Heterogeneous Strategies in Artificially Intelligent Competitive Teams. 13–25.

Dorigo, M., and Di Caro, G. 1999. The Ant Colony Optimization meta-heuristic. In Corne, D.; Dorigo, M.; and Glover, F., eds., *New Ideas in Optimization*. London, UK: McGraw-Hill. chapter 2, 11–32.

Dorigo, Marco, e. a. 2013. Swarmanoid: A novel concept for the study of heterogeneous robotic swarms. *IEEE Robotics and Automation Magazine* 20(4):60–71.

Holland, J. 1995. *Hidden Order: How Adaptation Builds Complexity*. Reading, MA: Addison-Wesley Publishing Company.

Kengyel, D.; Hamann, H.; Zahadat, P.; Radspieler, G.; Wotawa, F.; and Schmickl, T. 2015. Potential of heterogeneity in collective behaviors: A case study on heterogeneous swarms. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* 9387:201–217.

King, D. W.; Bindewald, J. M.; and Peterson, G. L. 2018. Informal team assignment in a pursuit-evasion game. *Proceedings of the 31st International Florida Artificial Intelligence Research Society Conference, FLAIRS 2018* 32–37.

King, D. W. 2018. *Emergent Behavior Development and Control in Autonomous Swarms*. Ph.D. Dissertation.

Nelson, M.; Larsen, F.; and Savara, P. 2022. RoboCode.

Rebelo, A.; Catalão, F.; Alves, J.; and Marreiros, G. 2015. Prototyping Teams of Affective Agents in Robocode. 15(1).

Recchia, T.; Chung, J.; and Pochiraju, K. 2014. Performance of heterogeneous robot teams with personality adjusted learning. *Biologically Inspired Cognitive Architectures* 7:87–97.

Shulimson, J.; Blasiol, L. A.; Smith, C. R.; and Dawson, D. A. 1997. *US Marines in Vietnam: The Defining Year 1968*. Washington, DC: Headquarters, US Marine Corps.

Urbanowicz, R. J., and Moore, J. H. 2009. Learning Classifier Systems: A Complete Introduction, Review, and Roadmap. *Journal of Artificial Evolution and Applications* 2009:1–25.

Woolley, B. G., and Peterson, G. L. 2009. Unified behavior framework for reactive robot control. *Journal of Intelligent and Robotic Systems: Theory and Applications* 55(2-3):155–176.