Enabling Tactical Autonomy for Unmanned Surface Vehicles in Defensive Swarm Engagements

by

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Abstract

This research incorporates practical applications of marine vehicles with robotics control theory to reduce the vulnerability of allied assets to asymmetric warfare. This work utilizes distributed decentralized multi-objective optimization in the Mission Oriented Operating Suite with Interval Programming (MOOS-IvP) to enable a number of simulated unmanned surface vehicles (USV) to provide defense for a high value unit (HVU) against fast attack craft (FAC) aggressors. The primary objective is to enable a swarm of defending vehicles to protect the HVU and successfully counter a swarm of aggressors with the ability to adapt to changing situations. This research makes it possible for autonomous defenders to react according to variables such as number of defenders, number of aggressors, known kinematic capabilities of defenders, perceived kinematic capabilities of aggressors, and positional distribution of aggressors. A theoretical framework is first described for analyzing the engagements based on game theory by constructing the defense scenario as a three-party differential game. MATLAB is then utilized to demonstrate optimal solutions to this scenario as an application of game theoretical guidance, which was developed for use in missile guidance systems. Algorithms and behaviors are then presented to demonstrate that the multi-objective optimization in MOOS-IvP approaches the optimal solutions in the vehicles' autonomous response during engagements consistent with the three-party differential game. Finally this work presents MOOS-IvP simulation data to demonstrate autonomous tactical decision-making in more realistic engagement scenarios.

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Chapter 1

Introduction

In recent years unmanned systems have begun to receive increasing attention for military applications. Much of the focus has been on the development and employment of unmanned aircraft or underwater vehicles. Analysts and military planners have however identified applications for which surface vehicles are best suited, leading to an increased focus in technologies required to safely and effectively employ unmanned surface vehicles (USV), especially autonomous surface vehicles (ASV). This research focuses on the application of USVs in the defense of an allied vessel against threats posed by multiple hostile surface craft. Specifically, the overarching purpose is to provide USVs sufficient decision-making capability to function as ASVs in a tactical environment.[1] This chapter will present the motivations for this research as well as frame its contributions within the scope of existing work.

[1]In the context of this research the term USV will typically be used since, in accordance with U.S. Department of Defense nomenclature, it represents the broader vessel category. ASVs are therefore a subset of USVs with higher levels of autonomy consistent with Level 3 or Level 4 autonomy, defined in Appendix D from the DOD Unmanned Systems Integrated Roadmap [1]. This research seeks to enable USVs to reach Level 3 or 4 autonomy in a tactical environment.

1.1 Motivations for the Study of the Swarm Defense Problem

Military analysts as well as historic events have demonstrated the effectiveness of asymmetric warfare against the armed forces of the United States and its allies [2]. The central characteristic of asymmetric warfare is that a party with comparatively less advanced military technology or weaker strength of forces engages a more advanced or militarily stronger party. Typically this involves unconventional tactics that can include attacks en masse by large numbers of units against a single, often more heavily armed, unit. In naval warfare this method of attack is presented in large quantities of fast attack craft (FAC) engaging a larger vessel such as the carriers, cruisers, and destroyers in many nations' inventories [3].

In 2002, war games conducted by the Naval War College showed that asymmetric warfare against United States' and allied naval forces could result in significant losses by the stronger nations especially during early phases at the onset of hostilities [4]. To this end the United States and allied nations have revised tactics and focused on developing weapon technology to mitigate the effect of FAC swarms. While this work will not detail tactics in surface warfare due to the sensitivity of such information, one can look to the development of the Navy's laser weapon systems and testing utilizing High Speed Maneuvering Surface Target (HSMST) drones as evidence of this priority [5][6].

Despite this focus, technology and tactics have not completely removed the vulnerability of allied nations to the effect of FAC swarm attacks. Additionally, some adversarial nations which employ asymmetric warfare have historically shown that they will not refrain from attacking non-combatant vessels to include neutral shipping traffic [7]. Further developments in technology and tactics could enable naval forces to more successfully counter the FAC swarm threat while providing non-combatant vessels with some measure of defense.

1.2 Motivations for Unmanned Surface Vehicles in Swarm Defense

Unmanned vehicles, especially autonomous vehicles, are noted as highly desirable assets in situations where they can mitigate harm to allied personnel and offset a purely numerical advantage as in asymmetric warfare. Efforts to field unmanned vehicles by naval forces have primarily focused on underwater or aerial vehicles due respectively to their superior detection avoidance or superior sensor horizon compared to surface vehicles. Several missions, particularly the counter-FAC mission, have however been identified by military analysts for which surface vehicles are more ideally suited than other types of unmanned vehicles [8][9].

Compared to unmanned underwater vehicles, unmanned surface vehicles can communicate more frequently and at higher bandwidth with a mother ship and/or defended unit [8]. This communication enables engagement queuing from a command and control authority or engagement hand-off between units. Since the manned vessel will typically house superior sensors compared to unmanned vehicles, the unmanned craft can also cooperatively interact with the manned vessel to benefit from more accurate contact resolution. Additionally, cooperation between manned and unmanned vessels enables a far greater collaborative sensor horizon. This results from the combination of the increased sensor height-of-eye available on the manned vessel and the ability to position unmanned assets at the edge of line-of-sight communications range to thereby extend effective sensor range. Surface vehicles are also inherently better suited than underwater vehicles for employing the forms of electromagnetic systems most often used to detect and classify surface targets. These factors enable surface vehicles to provide a greater contribution as compared to underwater vehicles to the common tactical picture for surface threats.

Compared to unmanned aerial vehicles, unmanned surface vehicles can achieve greater persistence in a given area of operation [8]. Station-keeping on the ocean's surface generally requires less of a vehicle's fuel or energy reserves compared to sustained flight, enabling longer time on station and more energy available to support mission payloads. This makes surface vehicles ideal for sustained intelligence, surveillance, and reconnaissance (ISR), despite the shorter sensor horizon created by locating any onboard sensors only slightly above sea level. Unmanned surface vehicles can therefore maintain more continuous screening formations around defended assets in such a way as not possible by aerial vehicles.

When compared to both aerial and underwater vehicles, unmanned surface vehicles possess an advantage in that they are capable of carrying a larger payload capacity per unit volume or alternatively a higher ratio of payload weight to vehicle weight. This enables the flexibility to deploy the vehicles with additional sensors, extra fuel or batteries, or weapon systems to further enhance their capability to provide a defensive posture against FAC swarm threats.

1.3 Literature Review

Publications on unmanned surface vehicle guidance and control technology have demonstrated focus by researchers on fields such as navigation and path-planning, collision avoidance, maneuvering controllers for individual craft, sensor based guidance, and formation control algorithms. The aforementioned subjects can be seen as precursors for tactical applications of USV control by providing necessary underlying functionality, though literature in formation control algorithms with multiple simultaneous objectives is notably the most relevant for the context of this research. Additional works which frame the scope of this research are found in game theory. Specifically, comparable defensive scenarios have been evaluated as three-party differential games while the dynamics of swarm behaviors have seen significant focus in game theory research. Although direct tactical applications for the control of USVs may be largely absent from academic literature, articles concerning demonstrations by the Office of Naval Research provide insight into the state of USVs in the swarm defense problem.

1.3.1 Formation Control

While there have been many publications about techniques for improving various aspects of individual USV control, in recent years the predominant focus has come to include controlling formations of vehicles with some cases specifically taking swarm-based approaches under evaluation. Much of the work additionally focuses on inclusion of other objectives such as path planning and collision avoidance.

One approach, given by Hao et al., provided for control of formations with uncertainties and environmental disturbance perturbations by using a neural network based adapted controller at the unit level and then synchronizing the formation's course and speed with another feedback controller [10]. The dynamic surface control technique that they applied provided filtering to minimize control oscillation and improve the performance at the unit and formation levels. Another technique, presented by Peng et al., similarly utilized neural network based controllers to provide adaptive control with minimum oscillation despite environmental variations [11]. One distinction between this approach and the previous though is that it did not apply the same dynamic surface control technique and it focused primarily on low speed and station-keeping conditions, but it similarly achieved closed-loop control with minimal oscillation. Techniques which minimize excessive oscillatory motion are to be considered additionally relevant to discussion of the swarm defense problem in that steadier maneuvers are desirable in the event of weapons engagement by the unmanned defenders.

The approach to formation control presented by Liu and Bucknall provides another important consideration in that they simultaneously consider not only path planning and formation but also collision avoidance [12]. Using a fast marching square method, they emphasize a computationally efficient algorithm in order to consider the multiple objectives in a realistic environment with similar perturbations and uncertainties as the previous works. This method was enhanced to create the angle-guidance fast marching square method which incorporated heading constraints and vehicle maneuver restrictions into their guidance algorithms [13]. This provided further improvements to their formation maneuvering while balancing the objectives of path planning and collision avoidance.

Increasingly techniques for multiple vehicles have begun to emphasize decentralized decision-making in both cases with and without cooperative information sharing. An approach given by Liu, though not specifically applied to USVs, utilizes a task-based control system to enable control of a swarm of mobile robots [14]. The control system allowed a human operator to provide tasks for which the swarm would navigate while performing obstacle and collision avoidance. Another method presented by Qin et al. focuses on a hierarchical system in order to provide a human operator control of a swarm [15]. Specifically the hierarchy provided a layer for human interface, a layer for inter-vehicle coordination and control, and a layer for individual vehicle control functions.

1.3.2 Game Theory and Three-Party Differential Games

Game theory originated initially as a decision and analysis tool primarily for economics and as such it is still widely applied to business and economics. Shortly after its inception, publications by the RAND Corporation began demonstrating additional applications relevant to military strategy and operations analysis. A number of reports by Rufus Isaacs detailed the formulation and applications of differential game theory, which was later republished as a combined text that also provided a number of canonical scenarios [16]. The scenarios included games of evasion and pursuit such as aircraft dogfighting, cutters intercepting a fugitive ship, a bomber and anti-air battery, and other examples of two-party differential games.

Much of the successive work in game theory focused on these two-party games with various permutations of games of evasion and pursuit with varying degrees of information feedback. Notably though, research by Faruqi focused on the formulation of a three-party game scenario for the purpose of missile guidance [17]. His work is distinctly different from other game theoretic studies in missile guidance that had considered only two parties with an evader missile or aircraft and a pursuer missile. Rather he considered a defended aircraft with an allied missile defending the aircraft against an attacking missile which was simultaneously attacking the aircraft and evading the defender missile. He further expanded on his game theoretic guidance formulation, provided additional work with respect to incorporating artificial intelligence (AI) based enhancements to guidance, and detailed the formulation of demonstrative missile intercept scenarios [18]. These referenced works provide an analytic basis for which this research will frame the defense problem in order to provide a basis for optimality in later developing the MOOS-IvP formulation.

1.3.3 Game Theory of Swarms

As swarm intelligence began becoming a focus in other fields, so too did researchers in game theory begin formulating game theoretic models of swarms. Givigi and Schwartz presented an approach using a swarm of mobile robots and evaluated strategy selection in the context of a zero-sum game [19]. Their method included various traits of personality to define robot behaviors and included a reinforcement learning approach for trait selection. Givigi and Schwartz later presented another approach for modeling and simulating an autonomous swarm but instead focused specifically on modeling a multiple pursuer-evader game [20]. They utilized Markov chains with learning automata to show optimal solutions for decentralized decision-making with incomplete information. Another technique, developed by Duan et al., demonstrated the application of game theoretic techniques to unmanned combat air vehicle (UCAV) swarms [21]. The technique modeled UCAV dynamics using a predator-prey particle swarm optimization approach based on biological swarm behaviors, which they then applied to simulations of UCAV combat engagements. These publications provide examples of robot swarm simulations using discrete, non-differential games and alternative techniques to this research, but may eventually serve to inform future iterations of this research with a focus on adaptation and learning.

1.3.4 Demonstrations in Defense

In 2014 the Office of Naval Research demonstrated an autonomous boat swarm acting in defense of a high value unit [22]. The USVs used the Control Architecture for Robotic

Agent Command and Sensing (CARACaS) system to provide autonomous response in escorting an allied HVU and engaging an intruder vessel. Later tests in 2016 utilized the USV swarm in an area defense situation to identify and engage an intruder vessel to defend a harbor [23]. This test specifically demonstrated enhanced collaboration by the USV swarm by collectively deciding which vessels would react to the engagement in contrast to the earlier test where all vessels responded as a group of individual units. These tests give insight into the state of practical USV technology for defense applications and help contribute specific focus areas for this research such as motivating the inclusion of decision-making with multiple aggressors and autonomously adapting defensive formations.

1.4 Contributions of This Work

- This work presents a new application for the three-party differential game while presenting an analytic means to frame defense of an HVU surface vessel.
- Applications and behaviors are presented for modeling the three-party differential game in the MOOS-IvP autonomy software in order to demonstrate multi-objective optimization in MOOS-IvP approaches optimal game theoretic solutions.
- This work further demonstrates through simulation that swarm autonomy using distributed multi-objective optimization, exemplified here with MOOS-IvP enables effective tactical decision making in successfully defending an HVU surface vessel.

1.5 Thesis Overview

This thesis seeks to answer the primary question: can distributed, decentralized, multi-objective optimization, like that utilized in MOOS-IvP, approach the optimal (game theoretic) solution in a surface warfare defense scenario while providing autonomous tactical decision-making in a swarm scenario?

The primary objectives are:

- Frame the surface warfare scenario of defending a high value unit against an aggressor as a three-party differential game to determine an optimal solution.
- Demonstrate that distributed multi-objective optimization of behaviors in MOOS-IvP approaches the optimal (game theoretic) solution for a three-party game
- Demonstrate the scalability of the distributed decentralized multi-objective optimization approach by extending to experiments with seven vehicles, using the MOOS-IvP approach with additional modules developed in this work.

Chapter two describes the formulation of a game theoretical model that frames the HVU defense scenario in terms of the three-party defense game. The model is implemented in MATLAB, and key results are discussed.

Chapter three details the behavior algorithms and application programs utilized to implement this three-party HVU defense scenario in MOOS-IvP. Comparisons are drawn between the solutions obtained using MATLAB and the MOOS-IvP simulations of the AI augmented guidance laws.

Chapter four describes additional simulated engagement scenarios and results obtained using MOOS-IvP. Behaviors and applications are discussed which allow enhanced artificial intelligence (AI) logics and decision-making for expanding to larger and more realistic scenarios.

Chapter five discusses key conclusions of this work and identifies areas of future study in the swarm defense problem.

Chapter 2

Defense of the High Value Unit as a Three Party Game

Game theoretic models of relevant defense scenarios have generally followed one of two methodologies. The first is modeling the scenario as a differential game of two parties with an evader and pursuer or occasionally a pair simultaneously evading and pursuing one another. The alternative has largely been to consider pay-offs and strategies in a discrete game to include situations with more than two parties. For this thesis, discrete game theory was considered to be a poor representation of the dynamics of the swarm defense scenario, and thus differential game theory was investigated as the foundation for a theoretical model. Faruqi, in his research publications [17] and his text [18], framed the three-party differential game as a method to model a missile intercept scenario. Specifically in his model he considered an aircraft being targeted by an inbound missile. Upon detecting the attacking missile, the aircraft then fires a defensive interceptor missile. This scenario is then represented such that the aircraft, as the first party, evades the attacker missile. The defender missile, as the second party, pursues the attacker missile. The attacker missile as the third party is then both pursuing the aircraft and evading the defender missile. This formulation of the three-party game served as the fundamental guidance for formulating the HVU defense model used in this research.

2.1 Notable Assumptions

The game theoretic model used in this research does not incorporate environmental factors such as wind and current. Although such dynamics could be modeled as additional disturbance inputs, they are not the focus of this research and would therefore unnecessarily add layers of complexity to the model without providing additional insights into the key areas of interest.

The model does not simulate detection ranges and signal thresholds, thus all vehicles are aware of one another at all times in the simulation. Similarly, all vehicles are aware of the states of each other vehicle, but it is not specifically the intent of this research to evaluate this model in comparison to games with complete or perfect information. Rather the purpose of the game theoretic model is to facilitate comparative analysis of the formulations presented in Chapters 2 and 3.

Model simulations are run beyond initial intercept between defender and attacker. Although it would be likely in many situations that this initial intercept would destroy or disable the attacker, in most cases this work assumes the attacker survived in order to consider later dynamics between the attacker and HVU.

2.2 Model Formulation

In order to provide an analytic baseline for this research, a model was developed following Faruqi's equations [18] to frame the HVU defense scenario as a three-party differential game. In this model, the high value unit (HVU) as the first party evades an incoming fast attack craft (FAC) operated by hostile opposing forces (OPFOR). The second party represents an allied unmanned surface vehicle (USV), which defends the HVU and pursues the hostile craft. The hostile FAC as the third party both pursues the HVU and evades the USV.

The model is a linear system with Quadratic Performance Index (LQPI) for cost functions. The cost functions are first constructed for parties two with respect to three and parties three with respect to one. For clarity in the context of the HVU defense scenario, this work will typically use subscripts 'H' for the HVU as party 1, 'D' for the defender as party 2, and 'A' for the attacker as party 3. The cost functions are thus:

$$J_1 = \frac{1}{2} \cdot ||\vec{y}_{AH}(t_{f_1})||^2_{S_1} + \frac{1}{2} \cdot \int_{t_0}^{t_{f_1}} \left[||\vec{y}_{AH}||^2_{Q_1} + ||\vec{a}^p_A||^2_{R^p_A} + ||\vec{a}^e_H||^2_{R^e_H} \right] dt \tag{2.1}$$

$$J_2 = \frac{1}{2} \cdot ||\vec{y}_{DA}(t_{f_2})||^2_{S_2} + \frac{1}{2} \cdot \int_{t_0}^{t_{f_2}} \left[||\vec{y}_{DA}||^2_{Q_2} + ||\vec{a}^p_D||^2_{R^p_D} + ||\vec{a}^e_A||^2_{R^e_A} \right] dt \tag{2.2}$$

Where $\vec{y}_{AH}$ and $\vec{y}_{DA}$ are weighted distances between vehicles, $\vec{a}^p_A$ and $\vec{a}^p_D$ are control inputs for pursuit, and $\vec{a}^e_H$ and $\vec{a}^e_A$ are control inputs for evasion. The matrices $[R^e_H]$, $[R^p_D]$, $[R^p_A]$, and $[R^e_A]$ are weights on control inputs for the respective vehicles. The notation $||\vec{a}^p_A||^2_{R^p_A}$ denotes $\vec{a}^{p^T}_A [R^p_A]\vec{a}^p_A$ in each respective term as a manner of convenience[18].

Determine conditions for optimum solutions by minimizing cost functions.

$$J^*_1 = \underset{\vec{a}^p_A, \vec{a}^e_H}{Min}\, J_1 \tag{2.3}$$

$$J^*_2 = \underset{\vec{a}^p_D, \vec{a}^e_A}{Min}\, J_2 \tag{2.4}$$

The cost functions are optimized with regard to the above conditions by constructing the Hamiltonians using an Euler-Lagrangian multiplier vector.

$$H_1 = \frac{1}{2} \cdot \left\{ ||\vec{a}^p_A||^2_{R^p_A} - ||\vec{a}^e_H||^2_{R^e_H} \right\} + \vec{\lambda}^T_1 \left\{ [F]\vec{y}_{AH} + [G](\vec{a}^p_A - \vec{a}^e_H) - [G](-\vec{a}^e_A) \right\} \tag{2.5}$$

$$H_2 = \frac{1}{2} \cdot \left\{ ||\vec{a}^p_D||^2_{R^p_D} - ||\vec{a}^e_A||^2_{R^e_A} \right\} + \vec{\lambda}^T_2 \left\{ [F]\vec{y}_{DA} + [G](\vec{a}^p_D - \vec{a}^e_A) - [G](\vec{a}^p_A) \right\} \tag{2.6}$$

Where $[F]$ is the state coefficient matrix and $[G]$ is the input coefficient matrix.

Taking the first partial derivatives of the Hamiltonians with respect to the control inputs and setting them equal to zero yields:

$$\frac{\partial H_1}{\partial \vec{a}_H^e} = -[R_H^e]\vec{a}_H^e - [G]^T \vec{\lambda}_1 = \vec{0} \tag{2.7}$$

$$\frac{\partial H_1}{\partial \vec{a}_A^p} = [R_A^p]\vec{a}_A^p + [G]^T \vec{\lambda}_1 = \vec{0} \tag{2.8}$$

$$\frac{\partial H_1}{\partial \vec{a}_A^e} = [G]^T \vec{\lambda}_1 = \vec{0} \tag{2.9}$$

$$\frac{\partial H_2}{\partial \vec{a}_D^p} = [R_D^p]\vec{a}_D^p + [G]^T \vec{\lambda}_2 = \vec{0} \tag{2.10}$$

$$\frac{\partial H_2}{\partial \vec{a}_A^e} = -[R_A^e]\vec{a}_A^e - [G]^T \vec{\lambda}_2 = \vec{0} \tag{2.11}$$

$$\frac{\partial H_2}{\partial \vec{a}_A^p} = -[G]^T \vec{\lambda}_2 = \vec{0} \tag{2.12}$$

The boundary condition for distance between attacker and HVU at termination is defined by:

$$\vec{\lambda}_1(t_{f_1}) = [S_1]\vec{y}_{AH}(t_{f_1}) \tag{2.13}$$

And for termination between defender and attacker as:

$$\vec{\lambda}_2(t_{f_2}) = [S_2]\vec{y}_{DA}(t_{f_2}) \tag{2.14}$$

where the Euler-Langrange multipliers are defined by:

$$\vec{\lambda}_1 = [P_1]\vec{y}_{AH} + \vec{\xi}_1 \tag{2.15}$$

$$\vec{\lambda}_2 = [P_2]\vec{y}_{DA} + \vec{\xi}_2 \tag{2.16}$$

such that $\vec{\xi}_1$ and $\vec{\xi}_2$ are the Riccati vectors.

Applying the boundary conditions to the optimality criteria yields:

$$\vec{a}_H^e = -[R_H^e]^{-1}[G]^T([P_1]\vec{y}_{AH} + \vec{\xi}_1) \tag{2.17}$$

$$\vec{a}_A^p = -[R_A^p]^{-1}[G]^T([P_1]\vec{y}_{AH} + \vec{\xi}_1) \tag{2.18}$$

$$\vec{a}_D^p = -[R_D^p]^{-1}[G]^T([P_2]\vec{y}_{DA} + \vec{\xi}_2) \tag{2.19}$$

$$\vec{a}_A^e = -[R_A^e]^{-1}[G]^T([P_2]\vec{y}_{DA} + \vec{\xi}_2) \tag{2.20}$$

Defining the matrices:

$$[R_{AH}]^{-1} = \left([R_A^p]^{-1} - [R_H^e]^{-1}\right) \tag{2.21}$$

$$[R_{DA}]^{-1} = \left([R_D^p]^{-1} - [R_A^e]^{-1}\right) \tag{2.22}$$

and combining the series of preceding equations leads to the Matrix Riccati Differential Equations:

$$[\dot{P}_1] + [P_1][F] + [F]^T[P_1] - [P_1][G][R_{AH}]^{-1}[G]^T[P_1] = 0 \tag{2.23}$$

$$[\dot{P}_2] + [P_2][F] + [F]^T[P_2] - [P_2][G][R_{DA}]^{-1}[G]^T[P_2] = 0 \tag{2.24}$$

as well as the Vector Riccati Differential Equations:

$$\dot{\vec{\xi}}_1 + \left\{[F]^T - [P_1][G][R_{AH}][G]^T\right\}\vec{\xi}_1 - [P_1][G](-\vec{a}_A^e) = 0 \tag{2.25}$$

$$\dot{\vec{\xi}}_2 + \left\{[F]^T - [P_2][G][R_{DA}][G]^T\right\}\vec{\xi}_2 - [P_2][G](\vec{a}_A^p) = 0 \tag{2.26}$$

The Riccati equations were then implemented and solved in MATLAB to form the basis of the HVU defense model.

2.3 Verification of MATLAB Model

In order to verify the validity of the MATLAB model used in this work, it was compared to a demonstration presented by Faruqi [18]. Faruqi's model was first adapted to constrain degrees of freedom available for control input to those dominant in surface craft, notably surge and yaw. The kinematic limits for each party were then adjusted to values more typical to a support ship, security vessel, and fast attack craft for parties one, two, and three respectively. These parameters were then also input to the HVU defense model in order to compare the results. Initial conditions for the model verification test are provided in Table 2.1. A graphical representation of the comparative test case is shown in Figures 2-1 through 2-3.

$Vessel$	$Initial\ Position$	$Initial\ Speed$	$Initial\ Course$
HVU	(50,50)	15 knots	090
$Defender$	(55,55)	25 knots	090
$Attacker$	(700,500)	25 knots	180

Table 2.1: Initial Conditions for Model Verification

The metrics of interest for intercept between the defender and attacker and between the attacker and HVU are shown in Table 2.2. These metrics were verified to remain constant across successive executions. The close agreement between each measurement indicate that the HVU Defense Model is capable of providing comparable results to the optimal solutions obtained by modification of the model presented by Faruqi [17] [18].

$Model$	$D_{intercept}$ $Def-Att$ (m)	$T_{intercept}$ $Def-Att$ (s)	$D_{intercept}$ $Att-HVU$ (m)	$T_{intercept}$ $Att-HVU$ (s)
$Modified\ Faruqi$ $Model$	<0.01	17.879	<0.01	25.447
$HVU\ Defense$ $Thesis\ Model$	<0.01	17.880	<0.01	25.450

Table 2.2: Comparison of MATLAB Results for Model Verification

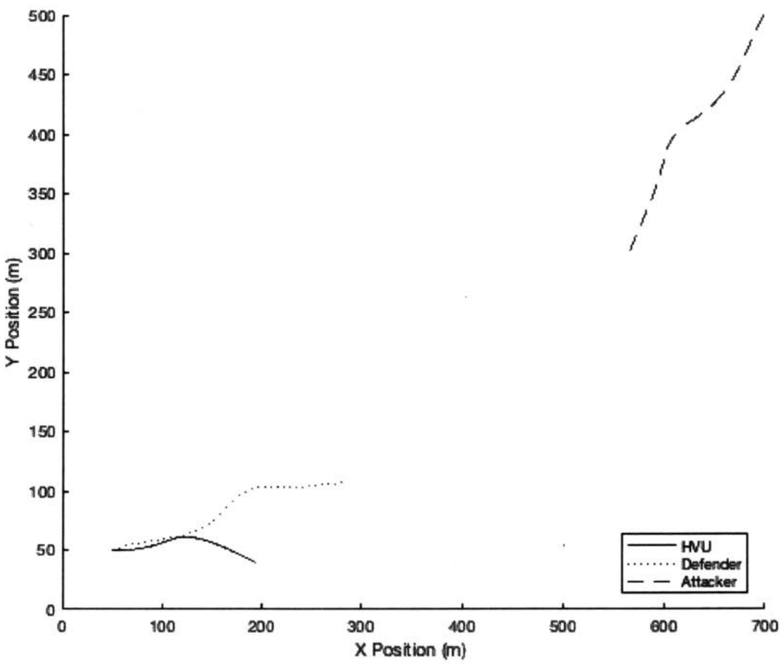


Figure 2-1: Example Test Case for Verification of MATLAB Model, Time Step 10s

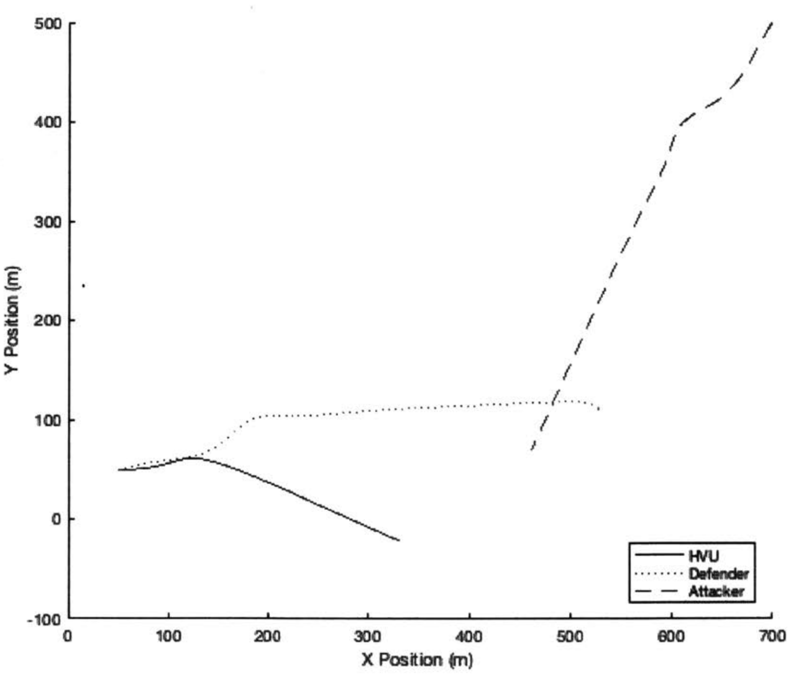


Figure 2-2: Example Test Case for Verification of MATLAB Model, Time Step 20s

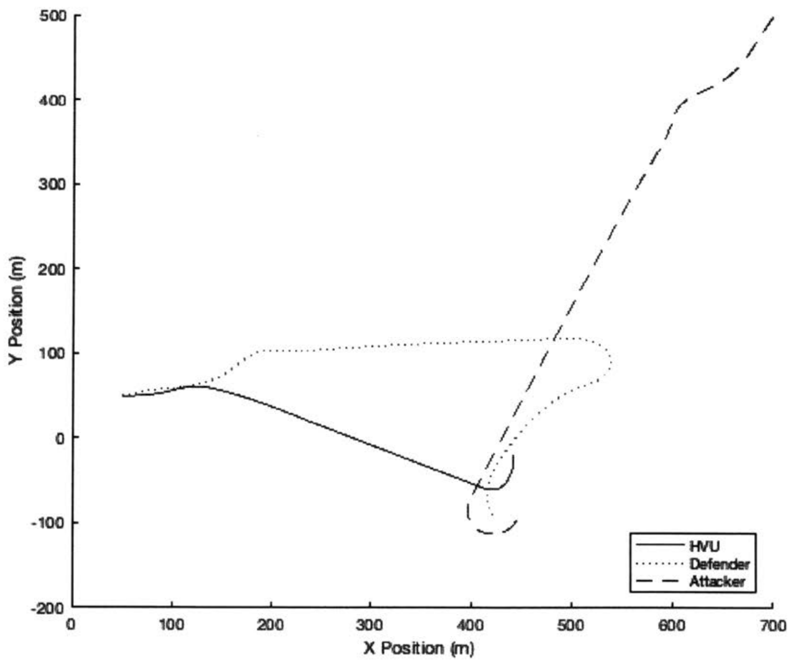


Figure 2-3: Example Test Case for Verification of MATLAB Model, Time Step 30s

2.4 Setup of Comparative Trials

Having verified the HVU Defense Model against the model modified from literature, the next focus of this research was to develop means of comparison between the MATLAB formulation and the simulations in successive stages of this research.

A series of trials were chosen in order to provide baselines for analyzing the MATLAB results with those to be obtained from later simulations. Twelve trials were generated based on varying initial engagement geometry. The HVU was positioned initially for each south, east, north, and west with the attacking vessel taking each of the three remaining positions. The defender in each case was initially offset from the HVU by five meters along the axis between the HVU and attacker. A schematic of the possible trial positions is shown in Figure 2-4.

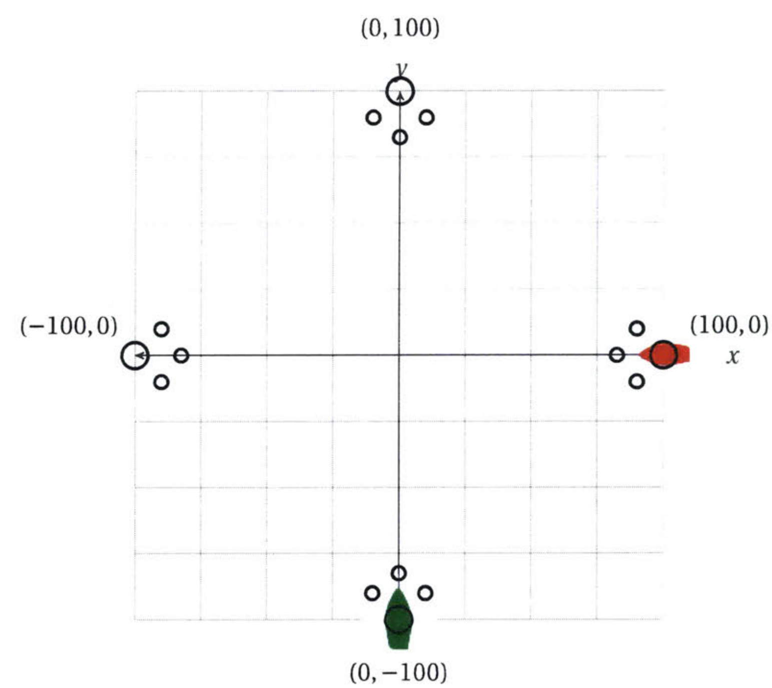


Figure 2-4: Representation of Possible Vehicle Positions for Comparison Trials.
Note: HVU (green) and attacker (red) shown for Trial 1; defender positions on small node between HVU and attacker in each trial. Distances in meters.

2.5 Results of Baseline Trials for Comparative Analysis

In each trial evaluated, the attacking vessel maneuvered to close with the HVU, prompting the HVU to maneuver away from the attacker. During the HVU's initial turn to retreat, the attacker counter-maneuvered in anticipation of the HVU's changing course, until the HVU's course became steadier and the attacker could solve for a steadier intercept course. The defender immediately moved to intercept the attacker as shown in Figure 2-5. The attacker attempted to evade as the defender closed, but due to the relative weighting of the attacker's pursuit and evasion, it did not prioritize evasion enough to completely avoid intercept by the defender as seen in Figure 2-6. Consistent with the assumptions expressed previously, this intercept was not used as a termination criteria despite intercept distances being close enough that the defender would realistically have destroyed or disabled the attacker.

After attempting evasion, the attacker continued to pursue the HVU, with the defender in pursuit, until it overtook the slower vessel as shown in Figure 2-7. This consistently resulted in the HVU continuously maneuvering to attempt escape while the attacker counter-maneuvered with the defender closely pursuing. At the onset of overtaking the HVU, the attacker closed within sufficient distance to successfully intercept the HVU assuming the attacker had survived previous intercept by the defender.

Quantitative results of each trial are given in Tables 2.3 and 2.4 while an example graphical depiction of one of the trials is provided in Figures 2-5 through 2-7. It should be noted that successive runs of a given trial scenario produced identical results and that variations were observed only when changing the initial geometry of the scenario.

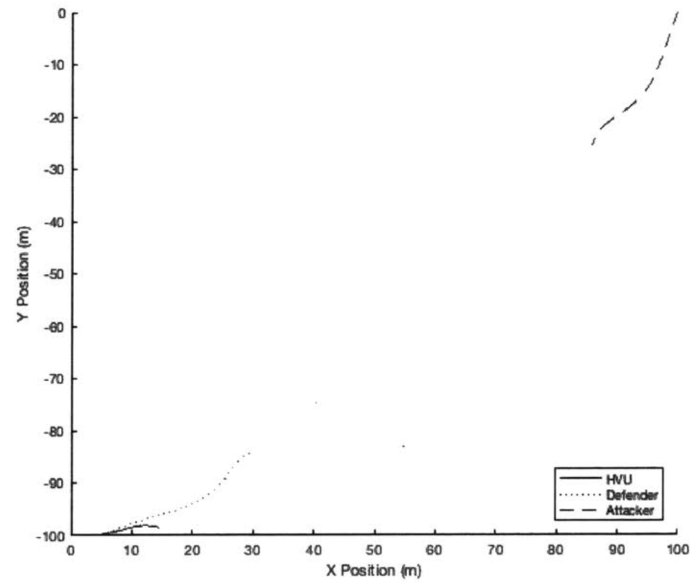


Figure 2-5: Graphical Results of HVU Defense Model, Trial Scenario 1 Positions, Time Step 5s

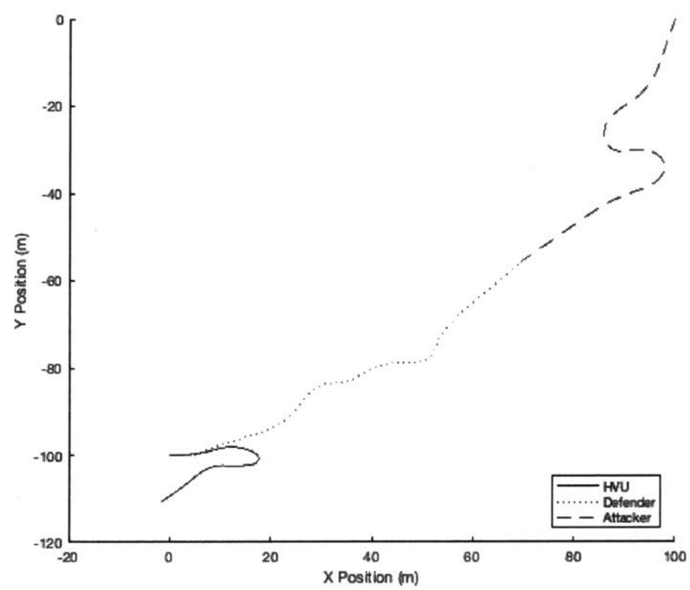


Figure 2-6: Graphical Results of HVU Defense Model, Trial Scenario 1 Positions, Time Step 14s

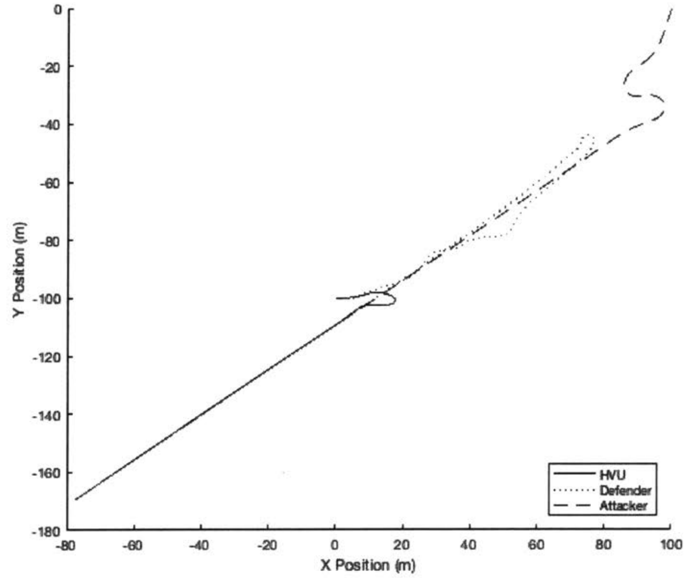


Figure 2-7: Graphical Results of HVU Defense Model, Trial Scenario 1 Positions, Time Step 45s

Trial Scenario	*HVU Start Position*	*Defender Start Position*	*Attacker Start Position*	$T_{intercept}$ $Def-Att$	$T_{intercept}$ $Att-HVU$
1	(0,-100)	(3.5,-96.5)	(100,0)	13.82	43.94
2	(0,-100)	(0,-95)	(0,100)	19.59	61.64
3	(0,-100)	(-3.5,-96.5)	(-100,0)	13.89	44.16
4	(100,0)	(96.5,3.5)	(0,100)	13.75	43.94
5	(100,0)	(95,0)	(-100,0)	19.39	61.64
6	(100,0)	(96.5,-3.5)	(0,-100)	13.75	44.16
7	(0,100)	(-3.5,96.5)	(-100,0)	13.89	43.72
8	(0,100)	(0,95)	(0,-100)	19.39	62.26
9	(0,100)	(3.5,96.5)	(100,0)	13.82	43.94
10	(-100,0)	(-96.5,-3.5)	(0,-100)	13.75	43.94
11	(-100,0)	(-95,0)	(100,0)	19.39	62.26
12	(-100,0)	(-96.5,3.5)	(0,100)	13.82	43.72

Table 2.3: Intercept Times for Baseline Trials

$Trial$ $Scenario$	HVU $Start$ $Position$	$Defender$ $Start$ $Position$	$Attacker$ $Start$ $Position$	$D_{intercept}$ $Def-Att$	$D_{intercept}$ $Att-HVU$
1	(0,-100)	(3.5,-96.5)	(100,0)	<0.01	<0.001
2	(0,-100)	(0,-95)	(0,100)	<0.01	<0.001
3	(0,-100)	(-3.5,-96.5)	(-100,0)	<0.01	<0.001
4	(100,0)	(96.5,3.5)	(0,100)	<0.01	<0.001
5	(100,0)	(95,0)	(-100,0)	<0.01	<0.001
6	(100,0)	(96.5,-3.5)	(0,-100)	<0.01	<0.001
7	(0,100)	(-3.5,96.5)	(-100,0)	<0.01	<0.001
8	(0,100)	(0,95)	(0,-100)	<0.01	<0.001
9	(0,100)	(3.5,96.5)	(100,0)	<0.01	<0.001
10	(-100,0)	(-96.5,-3.5)	(0,-100)	<0.01	<0.001
11	(-100,0)	(-95,0)	(100,0)	<0.01	<0.001
12	(-100,0)	(-96.5,3.5)	(0,100)	<0.01	<0.001

Table 2.4: Intercept Distances for Trials in MATLAB

Chapter 3

Implementing the Three Party Defense Game in MOOS-IvP

In order to provide a meaningful comparison between the game theoretic solution of the three-party differential game and the HVU defense scenario, a simulation of the three party game was developed in MOOS-IvP. MOOS is a middle-ware that uses a publish-and-subscribe architecture to host a number of applications. Each vehicle has a MOOS Database and runs a number of applications that are available in the current release of MOOS-IvP. One such application is the IvP Helm with a solver that uses interval programming to combine the objective functions for active behaviors using multi-objective optimization. The many years of development already conducted for MOOS-IvP meant that a plethora of useful calculation functions, utilities, and applications were already available in the public MOOS-IvP release [24] [25], thereby allowing more time for focusing on constructing the autonomy algorithms that represent the foundation of this work. For instance, waypoint and loiter behaviors provided in the MOOS-IvP release were used for orienting vehicles and transiting in the battle-space prior to commencing engagements while trail behaviors enabled trouble-free maintenance of vehicle formations. Similarly, multi-vehicle simulations, graphical displays of scenarios, post-simulation analysis, inter-vehicle communication and vehicle position, speed, and heading reporting were facilitated by applications available in the MOOS-IvP release. These fundamentals then allowed more focus in the development of critical works created for this research such as the Intercept Behavior, Evasion Behavior, and Tactical Decision Manager application as well as other supporting applications. MOOS-IvP also provided a simulation environment in which the scenarios could be formulated in such a way that would readily transition to testing with real vehicles in follow-on research based on this work.

3.1 Notable Assumptions

Environmental dynamics such as wind or current were not modeled in these simulations. Since such dynamics were not incorporated in the game theoretic model, they would represent a divergence between the models and would therefore not contribute to the comparative analysis. As such, vehicle course and heading coincide (sideslip angle equals zero) and the two may be used interchangeably in calculations.

The position, heading, and speed of each vehicle is known to all vehicles during simulations. This awareness approaches full information of states but does not necessarily lend itself to game theory models with complete or perfect information. In the context of the MOOS-IvP software, this data is shared through node reports generated by an application running on each vehicle. While some may argue against use of this information sharing as an unrealistic construct, this work assumes that such information would be obtained through an onboard radar system such as is readily available commercial-off-the-shelf.

In order to consider dynamics between the attacker and HVU, this work generally assumes that the attacker survives the initial intercept engagement with the defender. In reality this initial engagement would likely destroy, disable, or severely hinder the attacker. This assumption will be used during initial development of the model, but will be re-evaluated in later stages of this thesis when adding more realistic enhancements to the simulation model.

This work assumed that rules of engagement would not be applied to the three-party defense scenario. The details of such rules would be well beyond the scope of this research. Rather, in scenarios presented in following chapters the consideration of threat and danger ranges and determinations of hostile intent are included as rational means to govern engagements without formally enforcing rules of engagement.

Although there are behaviors in MOOS-IvP for collision avoidance between vehicles, these preexisting behaviors were not used in this formulation. The reason for this assumption is twofold: first collision avoidance was not modeled in the game theoretic formulation, and second collision avoidance might obscure the observation of the behaviors written in this work.

Vehicle maneuvering characteristics were not used in the decision algorithms for this research. Although turn-rate limits can be imposed in MOOS-IvP, default values were utilized and the decision-making processes did not consider turn-limits in determining actions. This assumption was considered reasonable in the context of highly maneuverable vessels such as the fast-attack craft and USV defenders. Additionally, even though the HVU is a slower, less agile vessel, it would not be seeking to make rapid, aggressive maneuvers which would create a divergence between desired maneuver and actual capability.

3.2 Intercept Behavior

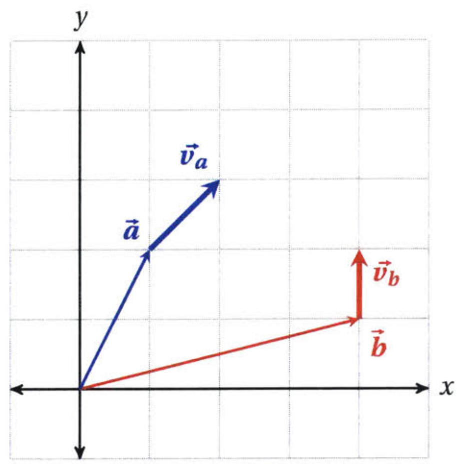
The Intercept Behavior was created to enable the attacking party to engage and pursue the HVU and to allow the defending party to engage the attacker in defense of the HVU. As such the behavior runs on the vehicles representing party 2 (defender) and party 3 (attacker) but not on party 1 (HVU). The run conditions for the behavior and relative priority weight with respect to other behaviors was controlled by the Tactical Decision Manager application, described in later sections.

The behavior uses vector calculations to determine an intercept course to a target as shown in Figure 3-1. On each behavior iteration loop, it pulls data for ownship position, course, and speed as well as target position, course, and speed. The maximum available speed for the vehicle is also pulled from the speed domain information in the IvP Helm buffer with the assumption that any propulsion limiting casualties that may be modeled in later development will be made to limit the max available speed through the speed domain parameters. Using this data, the behavior then considers the vectors which represent each vehicle's position and velocity. With these vectors, the behavior solves for a vector that represents the intercept point of the pursuer with its target. This is determined first by solving for an intercept time under the assumption that both vehicles are using max available speed. Once intercept time is determined, the behavior then solves for the course to intercept. Because the calculations are performed at each time iteration, the intercept course is re-evaluated such that the Intercept Behavior will update for a maneuvering target. The behavior did not apply a filter for information noise since the data was known exactly in the simulation and the iteration frequency was sufficient to provide smooth variation between steps.

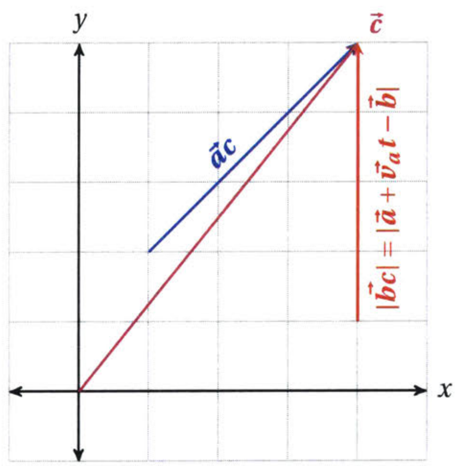
While the max-speed assumption may not hold under all circumstances, it is generally reasonable for most circumstances in the three-party engagement scenario. The HVU, while evading the attacker, will be using max available speed to attempt escape and thus the assumption generally holds for the attacker calculating the intercept. The attacker will be using max available speed to close with the HVU, so the assumption generally holds for the defender's calculation to intercept the attacker. When other behaviors are running simultaneously on the vehicle, such as perhaps collision avoidance between allied parties, it could be possible that maximum speed is not chosen.

After assigning the intercept course and speed, the Intercept Behavior constructs and publishes a report that provides a snapshot of the behavior's decision variables, specifically target name, target x and y position, desired vehicle course, and desired vehicles speed. This report, and the application it feeds, enabled continuous monitoring of decision variables mid-simulation for more rapid troubleshooting than would otherwise have been possible with only the post-simulation log files.

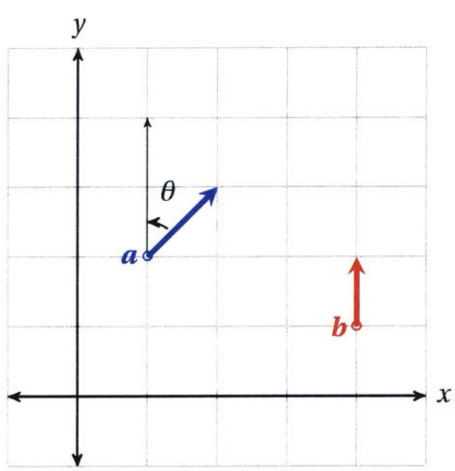
Once all decision variables were determined and appropriately reported, the behavior created an IvP objective function, shown in Figure 3-2, using the ZAIC toolkit described in the documentation by Benjamin et. al. [24] [25]. This function combines the course and speed solved for by the behavior and is then returned to the IvP Helm. The IvP Helm uses a weighted combination of objective functions generated by all active behaviors to determine the input course and speed for the vehicle.



(a) Determine position and velocity vectors

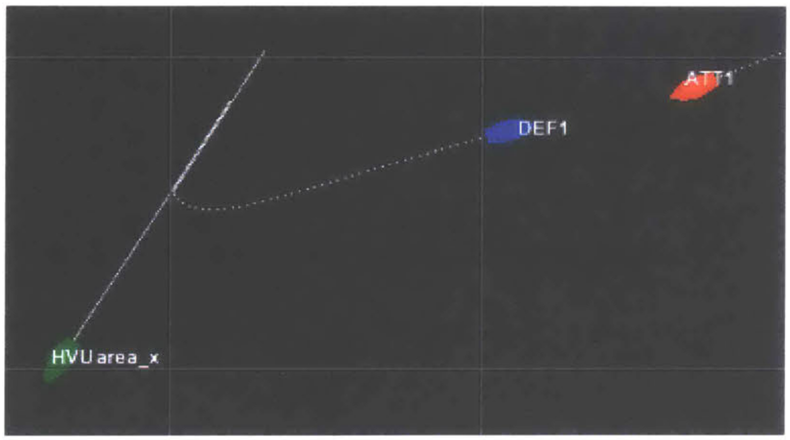


(b) Use vector magnitudes and distance to solve for intercept time. Solve for intercept location

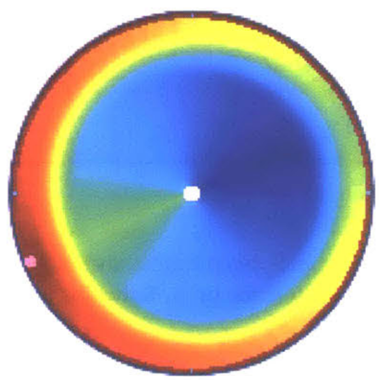


(c) Determine course to intercept location

Figure 3-1: Determining Course for Intercept



(a) Overhead View for Intercept Objective Function



(b) Graphical Representation of Intercept Objective Function

Figure 3-2: Intercept Behavior Objective Function
Note: Speed increases radially outward. Red regions of the objective function are desirable, blue are to be avoided. The peak of the function is shown as the purple dot.

3.3 Evasion Behavior

The Evasion Behavior was created to enable the HVU to maneuver away from threat vehicles and to allow the attacking party to maneuver to avoid the defender in order to continue attack on the HVU. As such the behavior runs on the vehicles representing party 1 (HVU) and party 3 (attacker) but not on party 2 (defender). Similar to the Intercept Behavior, behavior run conditions and relative priority weight were controlled by the Tactical Decision Manager application which is discussed in Section 3.4.

The Evasion Behavior utilizes a function to determine to what extent a vehicle should maneuver to evade its pursuer. Specifically this function is linear with respect to distance between the pursuer and the evading vessel such that the angular domain is variably bounded with respect to a specified response scaling parameter. The scaling parameter, known as the determination factor, is a configuration parameter which can be set in the behavior's configuration block. This provides a representation of the vehicle's degree of willingness to ignore its previous course determination in order to evade or alternatively to ignore the pursuer to continue on its desired course. It is initially assumed 50% unless otherwise defined.

The function for desired bearing can be represented as:

$$\theta_{desired} = \theta_{upper} - (r_{observed} - r_{innerthreshold})\frac{\theta_{upper} - \theta_{lower}}{r_{outerthreshold} - r_{innerthreshold}} \tag{3.1}$$

where for a given determination factor d between 0% and 100%

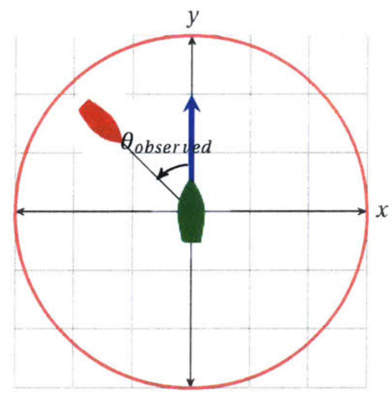
$$\begin{aligned} \theta_{upper}(d) = &\quad 180^\circ + 180^\circ \cdot (0.5 - \tfrac{d}{100}) \\ s.t. \quad \theta_{upper} \leq &\quad 180^\circ \end{aligned} \tag{3.2}$$

and

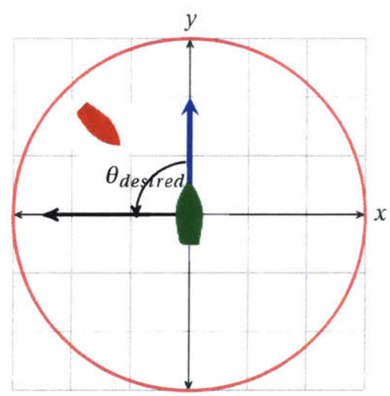
$$\begin{aligned} \theta_{lower}(d) = &\quad 180^\circ \cdot (0.5 - \tfrac{d}{100}) \\ s.t. \quad \theta_{lower} \geq &\quad 0^\circ \end{aligned} \tag{3.3}$$

The function provides a desired bearing offset such that the vehicle solves for a desired course to attain the bearing offset as shown through Figure 3-3. If the bearing offset to the pursuer is already greater than or equal to the desired bearing, or if the determination factor is such as to warrant no maneuver, the evader vehicle will maintain its current course.

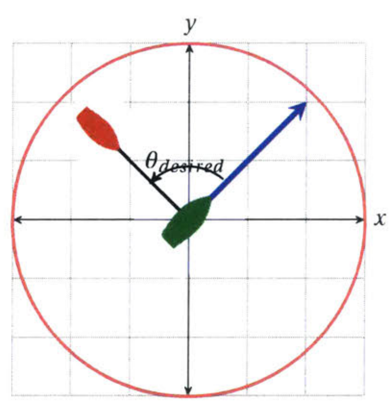
After determining and reporting decision variables, the behavior created an IvP objective function using the ZAIC toolkit described in the documentation by Benjamin et. al. [24] [25]. The IvP objective function, shown graphically in 3-4, combines the desired course and desired speed and is then returned to the IvP Helm for weighted combination with objective functions generated by other active behaviors.



(a) Determine bearing and range

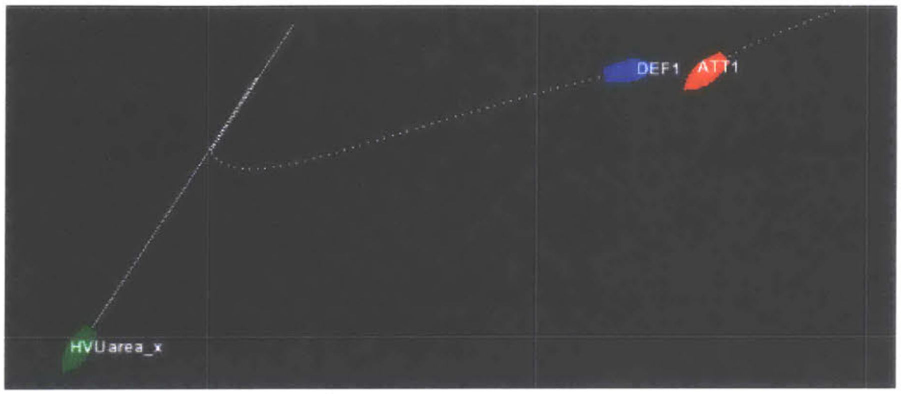


(b) Solve for desired bearing based on range and determination factor

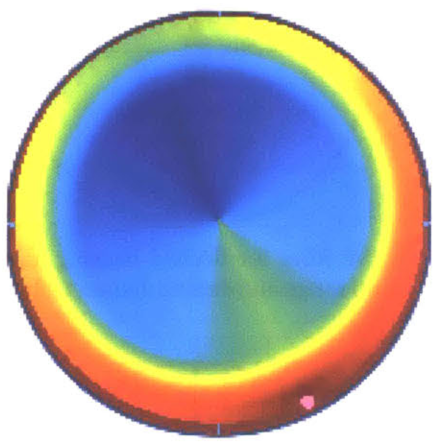


(c) Maneuver to place contact at desired bearing

Figure 3-3: Determining Evasion Course



(a) Overhead View for Evasion Objective Function



(b) Graphical Representation of Evasion Objective Function

Figure 3-4: Evasion Behavior Objective Function
Note: Speed increases radially outward. Red regions of the objective function are desirable, blue are to be avoided. The peak of the function is shown as the purple dot.

3.4 Tactical Decision Manager Application

The Tactical Decision Manager was created as an application running on each vehicle to govern responses by controlling behaviors. The first purpose that motivated its creation was to manage the interaction of behaviors on each vehicle by controlling run conditions and in some cases the priority weights of a vehicle's various behaviors. The application is presented in Algorithm 1 and is described throughout this section.

The Tactical Decision Manager was conceptually planned to represent the way in which a human tactical watchstander on a naval vessel would process and disseminate information in order to decide and act in the defensive engagement. Boolean switching was used to differentiate between simpler, more deterministic decisions in the baseline scenario and more complex decision algorithms in later scenarios.

The application received node reports from all units within reporting range. It checks whether the source of the report is a known ally or known enemy. At this stage of development, unknown vessels (neither known ally nor known enemy) were not modeled as the additional steps in determination of identity could have created a divergence from the game theoretic three-party solution. Later phases of this thesis considered vessel identities that were less predetermined, but additional improvements were noted for further study. The application initially set variables to specify the affiliations of all units, but was programmed to enable switching to more realistic methods such as through immediate friend or foe (IFF) transponders and codes. The relationship between the vehicle running the decision manager and the reporter from which the node report originated then determined how the data was applied and what successive decisions were evaluated.

3.4.1 Functionality for the HVU

On the HVU, reports from allied forces were not required in any decision-making process but were stored in case required in future algorithms. If the HVU received a report with data for an OPFOR vessel, the data was stored for later processing. On each time iteration of the decision manager, the HVU calculated the highest priority threat

Algorithm 1 Tactical Decision Manager - Three-Party Scenario

```
Require: Allies know Allies' identities; OPFOR know OPFOR identities
  {HVU and Defenders have "Allies" or "Allied" or "Allied Forces" affiliation}
  {Attackers have "OPFOR" affiliation}
Check for updated data
if Ownship is HVU then
   Algorithm 2: Threat to Ownship
else if Ownship is Defender then
   if Threat to HVU exists then
      for i = 1 to Number of OPFOR do
         Calculate distance from HVU to OPFOR_i
         Prioritize threats using distance
      end for
      Set Intercept Behavior run condition to true
   else
      Reset Intercept Behavior run condition to false
   end if
else
   {Ownship must be Attacker}
   if HVU located by ownship then
      Set Intercept Behavior run condition to true
   else
      Reset Intercept Behavior run condition to false
   end if
   Algorithm 2: Threat to Ownship
end if
```

as shown in Algorithm 2. Distance was used to determine the most immediate threats, while closest-point-of-approach and time were used to prioritize threats if there were none determined to be immediate.

One metric to quantify the threat determination was defined as a threat factor such that:

$$TF(r) = \begin{cases} 1 & r \le r_{danger} \\ 1 - \frac{r - r_{danger}}{r_{threat} - r_{danger}} & r_{danger} \le r \le r_{threat} \\ 0 & r \ge r_{threat} \end{cases} \qquad (3.4)$$

where the danger range, r_{danger}, was intended to represent a consideration of a vessel's weapons engagement range and threat range, r_{threat}, was used to tune when responses are initiated in this phase and also later phases of this work. The threat factor was used

Algorithm 2 Threat to Ownship

```
for i = 1 to Number of non-friendly vessel do
    if Ownship is attacker and Non-friendly vessel is HVU then
        Continue
    else
        Calculate range to vessel
        if Range < threat threshold then
            Threat to ownship exists
            Check if closer than any previous threat
            Calculate threat factor for priority: Equation 3.4
        end if
    end if
end for
if Threat to ownship exists then
    Post to Evasion Behavior report variable for closest threat
    Set Evasion Behavior run condition to true
else
    Reset Evasion Behavior run condition to false
end if
```

to prioritize immediate threats, while closest-point-of-approach was used in prioritizing vehicles outside threat range. Vessels inside the danger range would be prioritized in later phases when weapons were considered in decision-making algorithms. Since weapons engagement modeling was a function planned for later phases of this research, the danger and threat ranges were set such that the HVU always considered the attacker a threat in the three-party engagement.

The report for the highest threat was then fed to the Evasion Behavior such that the Evasion Behavior could then determine whether a maneuver was required and if so to what extent. Although this process of determining and prioritizing threats was trivial in the three-party defense scenario, it was applied on the HVU in order to facilitate transitioning to more complex scenarios later in this research.

3.4.2 Functionality for Attacking Vessel

On attacking vehicles, the decision manager served the purpose of controlling the Intercept Behavior and Evasion Behavior. Figure 3-5 shows a hierarchy model for the behavior modes on the attacker. Reports from OPFOR vessels are stored for use in later im-

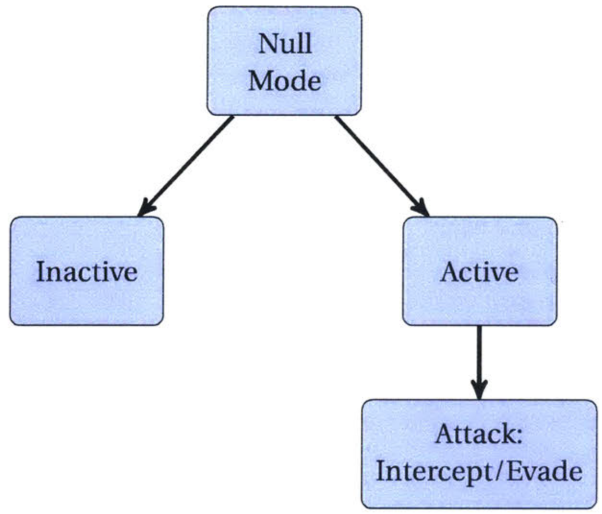


Figure 3-5: Behavior Hierarchy Model for Attacker

provements to enemy tactics but were not used for decision-making in the current scope of this research. Reports with the HVU's data were parsed and stored and were then used to feed the attacker's Intercept Behavior. Reports with the defender's data were parsed in order to determine the threat from a defender to an attacker. These threat determinations are provided by Algorithm 2. Just as with the HVU, distance calculations determined which threat was most immediate and closest-point-of approach calculations were used to prioritize non-immediate threats. Similarly a threat factor was calculated and a report for the highest threat was then generated to feed the attacking vehicle's Evasion Behavior which then determines necessary maneuvers. Also much like the HVU, prioritizing threats was trivial in the three-party engagements but was included to allow for scenarios considered later in the course of this work.

3.4.3 Functionality for Defending Vessel

On defending vehicles, the Tactical Decision Manager primarily served to switch between defending with the Trail Behavior and engaging attackers with the Intercept Behavior as well as to control the Intercept Behavior and feed it appropriate data . A hierarchy model for the defender's behavior modes is shown in Figure 3-6. Reports with the attacker's data as well as those with the HVU's data were parsed to maintain current state

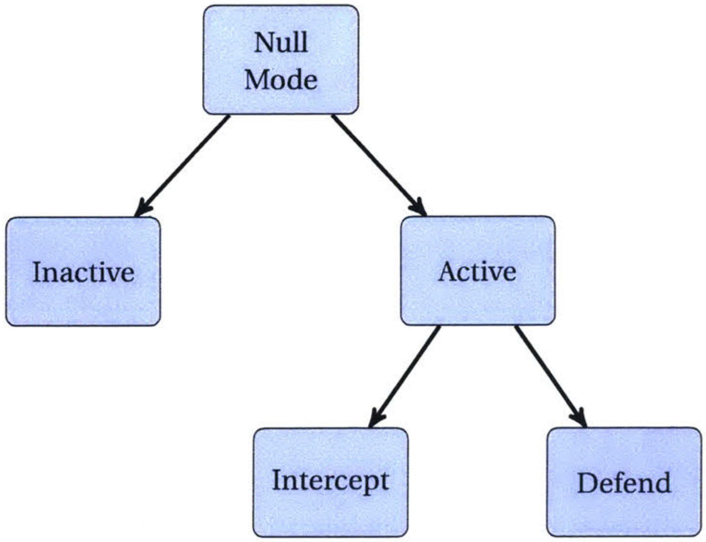


Figure 3-6: Behavior Hierarchy Model for Defender

knowledge. This information was then used to determine if a threat to the HVU existed and a threat factor was calculated comparable to the HVU's calculations for itself. At this stage in development, threats to the HVU were prioritized but decision variables were not specifically determined based on priority because of the triviality of threat priority in the three-party engagement. Once an attacker was determined to be a threat to the HVU, the decision manager passed the attacker's data to the Intercept Behavior and set the behavior to active state.

3.5 Engagement Metrics Application

During early stages of development, distances between pursuer and evader pairs were calculated at each iteration of the Intercept Behavior. The distance was published along with other data to a variable in the MOOS database on the pursuer vehicle. After each simulation run, log files were used to determine the time and distance at which the defender intercepted the attacker.

The engagement metrics application tracks intercept parameters, namely distance between vehicles and time at which this distance occurs. It uses a threshold distance to consider whether a vehicle has successfully intercepted another. While running the comparative trials this threshold distance was set to 1 meter to require approximately point-blank intercept rather than an area-of-effect intercept that would be seen in the example of an exploding interceptor missile. The application tracked the minimum intercept distances between attacker and defender and between attacker and HVU as well as the times at which these intercepts occurred. The application checked for the earliest intercept time between vehicles, with the rationale that multiple successful intercepts would be redundant provided that the earliest intercept was below the threshold distance.

The application also calculated a performance metric, called optimality index in the source code, on vehicles running the Intercept Behavior. When a vehicle maneuvered due to the behavior, the index was calculated by first looping through all available courses in one-degree increments and determining the closest point of approach for each course. The index was then calculated as a cumulative ratio providing the percentage of decisions in which the optimal or nearly optimal course was chosen. The metric was not fed back into the Intercept Behavior or Tactical Decision Manager to influence behavior decisions, but rather used to judge to what extent the intercepting vehicle was choosing course consistent with the optimal solution. It had been considered that calculating the metric by looping through all possible courses would significantly delay the decision calculations, so the metric provided a means to evaluate to what extent other weight parameters should be adjusted.

3.6 Results and Comparisons to MATLAB Solution

The three-party defense scenario was simulated in MOOS-IvP for each of the trial scenarios listed in chapter 2. The Intercept and Evasion Behaviors were both observed to determine the helm decision variables through their respective objective functions. In each trial, the attacker commenced attack on the HVU, prompting the defender to initiate intercept against the attacker while the HVU sought to evade away from the incoming attacker. Similar to the MATLAB trials, in each case the defender engaged the attacker at a stand-off distance from the HVU. It was observed that the attacker performed evasive maneuvers by trying to steer around the defender. Because of its determination factor, it sought to still continue attacking the HVU rather than simply fleeing from the defender outright . The defender was able however to still close with the attacker to a sufficiently small distance to be considered a successful engagement. As noted in the assumptions, this was not set as a termination criteria in order to observe dynamics later in the simulation. The attacker therefore continued past the engagement with the defender in pursuit. The superior speed of the attacker compared to the HVU enabled the attacker, assuming it survived the initial engagement with the defender, to overtake and intercept the HVU. This caused the HVU's Evasion Behavior to drive the vehicle in a series of oscillatory swerves with the attacker repeatedly maneuvering to follow and the defender maneuvering to follow the attacker.

For each trial the time and distance of intercept was recorded between the attacker and defender and then between the attacker and HVU. These values were compared against those determined by the MATLAB trial solutions and are presented in Table 3.1 for intercept times and Table 3.2 for intercept distances. Multiple successive runs of a given trial scenario did not result in varying outcomes. Of particular note is that in each trial scenario, the distances between vehicles was sufficiently small as to represent successful intercept. As such, the most significant variation between results of the MATLAB model and the MOOS-IvP implementation were the times at which intercepts occurred. Because the intercept times were observed to still be appreciably close in all scenarios, this agreement was accepted as adequately demonstrating that the distributed decentralized optimization via MOOS-IvP approaches the optimal solution. If closer agreement were desired, it could be accomplished through iteratively changing behavior priority weights and some of the various scaling factors used in the algorithms.

Trial Scenario	*MATLAB* $T_{intercept}$ $Def-Att$	*MOOS−IvP* $T_{intercept}$ $Def-Att$	*Percent Difference*	*MATLAB* $T_{intercept}$ $Att-HVU$	*MOOS−IvP* $T_{intercept}$ $Att-HVU$	*Percent Difference*
1	13.82	14.65	6%	43.94	45.26	3%
2	19.59	20.76	6%	61.64	64.12	4%
3	13.89	14.24	2%	44.16	47.01	6%
4	13.75	14.31	4%	43.94	45.92	5%
5	19.39	20.66	7%	61.64	65.05	6%
6	13.75	14.72	7%	44.16	46.14	4%
7	13.89	14.37	3%	43.72	46.61	7%
8	19.39	20.27	5%	62.26	64.43	3%
9	13.82	14.79	7%	43.94	46.57	6%
10	13.75	14.31	4%	43.94	45.48	4%
11	19.39	20.80	7%	62.26	65.98	6%
12	13.82	14.72	7%	43.72	46.81	7%

Table 3.1: Comparison of Intercept Times for Trials in MATLAB and MOOS-IvP

Trial Scenario	*MATLAB* $D_{intercept}$ $Def-Att$	*MOOS* $D_{intercept}$ $Def-Att$	*MATLAB* $D_{intercept}$ $Att-HVU$	*MOOS* $D_{intercept}$ $Att-HVU$
1	<0.01	<0.01	<0.001	<0.001
2	<0.01	<0.01	<0.001	<0.001
3	<0.01	<0.01	<0.001	<0.001
4	<0.01	<0.01	<0.001	<0.001
5	<0.01	<0.01	<0.001	<0.001
6	<0.01	<0.01	<0.001	<0.001
7	<0.01	<0.01	<0.001	<0.001
8	<0.01	<0.01	<0.001	<0.001
9	<0.01	<0.01	<0.001	<0.001
10	<0.01	<0.01	<0.001	<0.001
11	<0.01	<0.01	<0.001	<0.001
12	<0.01	<0.01	<0.001	<0.001

Table 3.2: Comparison of Intercept Distances (meters) for Trials in MATLAB and MOOS-IvP
Note: All trial scenarios resulted in point-blank intercept between vehicles for both MATLAB and MOOS-IvP. Given the close values of intercept times shown in Table 3.1 this indicates close agreement between the two formulations

Chapter 4

Extrapolation Toward the Swarm Defense Scenario

Having demonstrated that distributed decentralized multi-objective optimization in MOOS-IvP approaches optimal solutions in the three vehicle case for scenarios comparable to published defense games, this research turned to the consideration of defense scenarios with additional layers of complexity in decision-making and response. The implementation of such layers were desired in order to demonstrate the suitability of MOOS-IvP for providing realistic and effective defense in a simulated tactical environment. Time constraints motivated that the additional focus on more MOOS-IvP implementations proceed without first formulating additional game theoretic scenarios for comparison.

4.1 Seven Vehicle Baseline Scenario

A seven vehicle baseline scenario was created as the next step to achieving realistic modeling and response for a defensive swarm engagement. Although for the three-party scenario this thesis followed a sequence of first establishing a theoretical formulation with MATLAB and then MOOS-IvP implementation, the same approach was not taken for extending beyond the three-party scenario. The three-party equations have been expressed as being able to expand for additional parties [18], though some key decisions with regard to targeting determinations were not described. Specifically, whether for a multi-target environment if the formulation of the performance indexes would require deterministic assignments of defender to attacker or if the indexes would reflect every possible combination of pairings. In preliminary attempts during this thesis, efforts to formulate a seven vehicle scenario in game theoretic context were unsuccessful. Additionally, attempts to find published documentation of continuous differential games for more than three parties were unsuccessful. In the absence of a comparable game theoretic formulation, this research instead focused on demonstrating the capability of MOOS-IvP to extend to realistic swarm defense rather than performing comparative analytics for optimality of scenarios that are still farther from tactically realistic.

In this baseline, there is the HVU, three defenders, and three attackers. The number of defenders had been chosen based on operations analysis performed in the study of a concept design for a new class of surface combatant, as described in Appendix C. Specifically, the number was solved for in order to maintain a specified classification, identification, and engagement area to a desired probability of success. The number of attackers were then chosen to ensure that at a minimum the defenders did not possess inherent superiority under the assumption that this HVU possessed minimal or no defensive capabilities. The sequence of events for the scenario will first be detailed in Section 4.1.1 and modifications to the Tactical Decision Manager required to enable extrapolation to seven vehicles will be detailed in Section 4.1.2.

4.1.1 Sequence of Seven Vehicle Baseline Scenario

The primary objective in the simulations of the seven vehicle baseline was to verify that modifications to the Tactical Decision Manager application could enable the extension of the fundamentals implemented in the three-party MOOS-IvP formulation to a larger number of vehicles. As such, the allied formation and OPFOR formation were positioned separately in loiter patterns to allow the tactical decision manager on each vehicle to observe opposing vessels, make decisions, and activate the appropriate behaviors. This resulted in the scenarios progressing in fairly distinct phases which could then be evaluated in post-simulation analysis to ensure proper calculation of decision variables and triggering of behaviors.

Using existing IvP behaviors, attackers began the scenario using the Trail Behavior to maintain a column formation while using the Loiter Behavior to allow the Tactical Decision Manager application to make determinations based on the allied formation. Defenders began in a screen formation around the HVU with one vehicle astern and the other two at the port and starboard beams as shown in Figure 4-1. Defenders maintained formation using Trail Behavior during the HVU's transit with the Waypoint Behavior.

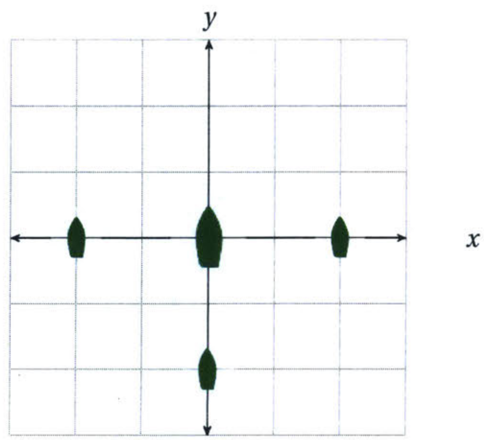


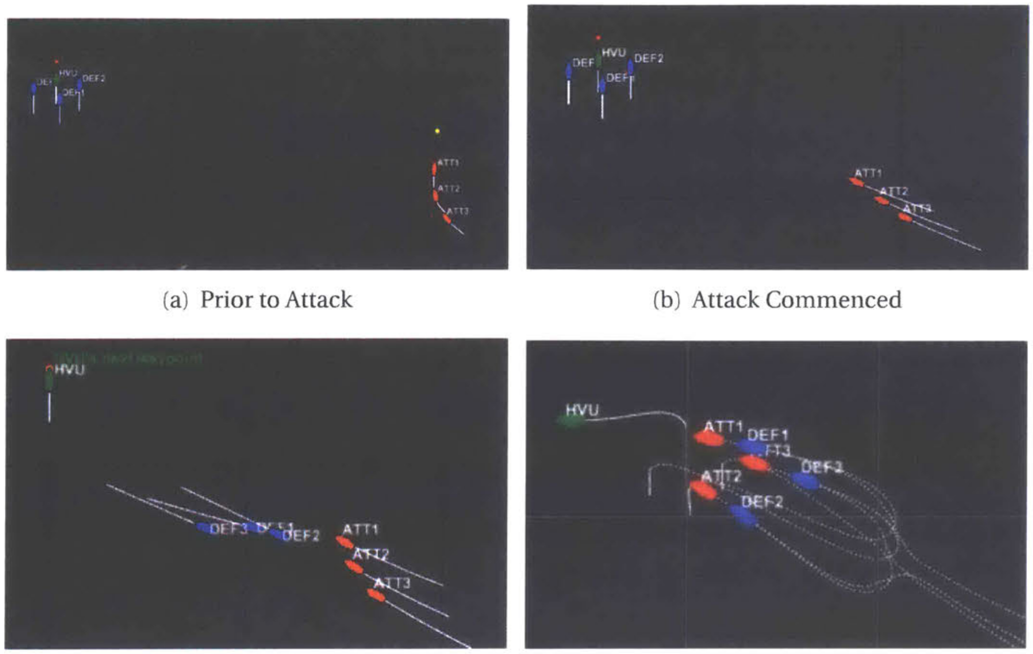
Figure 4-1: Representation of Initial Screen Formation

The first observed phase, shown in Figure 4-2(a), consists of both formations monitoring and storing data about the respective opposing parties. The defenders are determining a defensive response at each time iteration, while the attackers are localizing and identifying the HVU.

Having determined the HVU from among the allied formation, the OPFOR vessels commence attack as shown in Figure 4-2(b). The defenders meanwhile, continue calculating their response at each time interval while observing the attackers until criteria are met to confirm hostile intent.

Once the defenders have confirmed the hostile intent of the inbound OPFOR vessels, they move to intercept as shown in Figure 4-2(c). Each defender chose its target based on which was best situated to engage each attacker.

As with the three-party scenario, the attacking vehicles maneuver to attempt evasion of defenders and, when assumed to survive initial intercept by defenders, maneuver to



(a) Prior to Attack

(b) Attack Commenced

(c) Defenders Intercepting Attackers

(d) Attackers Closing HVU Post-Intercept

Figure 4-2: Demonstration of Seven Vehicle Baseline

close with the HVU. This initiates the HVU's evasion behavior as seen in Figure 4-2(d) while defenders pursue the attacking vessels at close range. In further developments presented in following sections, this would provide additional opportunities for the defenders to engage attacking vessels with weapons in order to provide more opportunity to remove the threat than provided by only considering the initial intercept event.

4.1.2 Modifications to the Tactical Decision Manager

The Tactical Decision Manager initially served the purpose of managing behavior run criteria for the three-party engagement and feeding data to Intercept and Evasion Behaviors. Modifications to algorithms were required though in order to transition to scenarios with more vehicles in efforts to approach more realistic defense engagements. With the inclusion of additional vehicles for both allies and OPFOR, the attacking and defending vehicles required mechanisms by which to determine targets. The modified application is presented in Algorithm 3 and modifications are described throughout the remainder of this section.

Algorithm 3 Tactical Decision Manager - Seven Vehicle Scenario

```
Require: Allies know Allies' identities; OPFOR know OPFOR identities
   {HVU and Defenders have "Allies" or "Allied" or "Allied Forces" affiliation}
   {Attackers have "OPFOR" affiliation}
while Vehicle is in OPREGION do
   Check for updated data
   if Ownship is HVU then
      Algorithm 2: Threat to Ownship
   else if Ownship is Defender then
      if Threat to HVU exists then
         for i = 1 to Number of OPFOR do
            Calculate distance from HVU to OPFOR_i
            Prioritize threats using distance
         end for
         for i = 1 to Number of Defenders do
            for j = 1 to Number of Threats do
               Determine intercept time from Defender_i to threat OPFOR_j
               Assign own target based on minimum intercept time
            end for
         end for
         Post to Intercept Behavior report variable
         Set Intercept Behavior run condition to true
      else
         Reset Intercept Behavior run condition to false
      end if
   else
      {Ownship must be Attacker}
      Determine centroid of Allied formation
      for i = 1 to Number of Allied Forces do
         Check proximity to centroid
         Check simulated size factor {represents either visual size or radar return}
         Compare vehicle position and size factor to find HVU
      end for
      if HVU located then
         Post to Intercept Behavior report variable
         Set Intercept Behavior run condition to true
      else
         Reset Intercept Behavior run condition to false
      end if
      Algorithm 2: Threat to Ownship
   end if
end while
```

Tactical Decision Manager on Attacking Vessels

For attackers, the additional vehicles necessitated including means to determine which vehicle in the allied formation was in fact the HVU. This was accomplished by considering two primary factors: orientation of the defensive formation and relative size of vehicles. The attacking vehicles used the position data obtained for each of the allied vehicles to determine which vehicle was nearest to the forward center position of the formation. Although this was developed primarily in response to the defenders being placed in a screen formation, the algorithm was supplemented by having the attackers observe which vehicle initiated turns in transit to determine the guide-ship of the formation. This would enable attackers to determine the HVU for a range of standard formations. Though this work did not directly simulate visual or radar sensing by the vehicles, a relative size parameter was applied for each of the allied units to simulate the attackers differentiating the largest vessel in the allied formation either through visual observation or radar return. By combining this size determination with observations of the formation, the attackers determined the contact representing the HVU. Once the HVU was identified, the tactical decision manager deactivated the pre-existing IvP behaviors and activated the Intercept Behavior to commence attack.

Tactical Decision Manager on Defending Vessels

For defending vehicles, the most significant additions were related to threat prioritization. Although the Tactical Decision Manager had initially included calculations to prioritize threats, it was unnecessary until the implementation of the seven-vehicle scenario. For the seven-vehicle scenario however, the defenders used these calculations in order to assign their targets. Each defender would calculate the intercept time that itself and each other defender would have against each threat vehicle, starting with the highest priority threat. Each defender would then assign itself a target threat vehicle and pass reports with the target's data to the Intercept Behavior, but would not activate the Intercept Behavior until making a determination of hostile intent. Once the attackers were verified to have reached a threshold range, defenders checked if the attackers were maintaining course to intercept the HVU based on the closest-point-of-approach with the HVU being below a specified threshold value. The Tactical Decision Manager used these observations as determination of hostile intent to deactivate the screen behavior and activate the Intercept Behavior to engage the attackers. Although in seven-vehicle scenarios each attacker could be matched by a defending vessel, the Tactical Decision Manager's handling of threat priority would ensure that defenders each focused on the attackers that posed greatest threat to the HVU. Once weapons engagement and disabling of attackers was implemented, this would enable defenders to cycle through attacking vehicles in order of threat priority to allow defense against greater numbers of attackers.

4.1.3 Operational Region Containment

In publicly available releases of MOOS-IvP, the IvP Helm already possesses an OpRegion behavior to monitor vehicles and warn if a vehicle leaves an operating environment [24]. This behavior was adapted in the seven-vehicle baseline in order to ensure that the Evasion Behavior did not simply drive evaders continuously out of the operational area, thereby preventing some interactions from being observed. This enabled the development of scenarios of interest such as an HVU being escorted through a strategic chokepoint border by potentially belligerent territory. Additionally, it was considered to allow additional realistic considerations in future scenarios such as restriction to safely navigable waters or demarcation of territorial waters.

4.2 Seven Vehicle Enhanced Scenario

The final culmination of this research was to demonstrate the viability of the distributed, decentralized optimization approach and show that the combination of algorithms in the Tactical Decision Manager application, the behaviors which were created in this research, and the other behaviors and applications that were leveraged from the MOOS-IvP release could enable autonomous defense response in a tactically relevant situation. This was accomplished by simulating a realistic engagement in the seven vehicle enhanced scenario. The simulation was enabled through further modifications to the Tactical Decision Manager to include both improvements to existing decision-making processes and the incorporation of additional decision factors. The scenario, shown in Figure 4-3, will be described in detail in the next section followed by treatment of the algorithmic modifications that enabled it in the following sections.

4.2.1 Sequence of the Seven Vehicle Enhanced Scenario

The HVU and defenders began transit through a strategic choke-point using a screen formation shown in Figure 4-1. They detected vessels with unknown intentions entering the waterway from a possibly belligerent port of origin as shown in Figure 4-3(a). The allied forces monitored the OPFOR vessels while the OPFOR vessels shadowed the formation at stand-off range and began locating the HVU from among the contacts.

The OPFOR formation gradually decreased stand-off range and closed with the HVU, causing the autonomous formation adaptation of the defenders to be initiated. The defenders took stations as seen in Figure 4-3(b) without requiring inter-vehicle coordination, and the OPFOR vessels determined the HVU's identity.

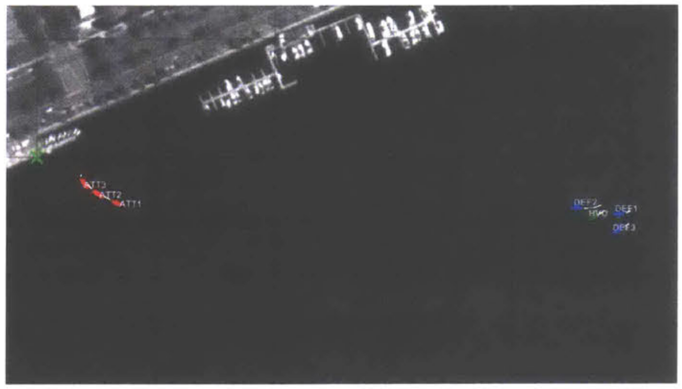
The OPFOR vessels moved to intercept the HVU at maximum speed as shown in Figure 4-3(c). The defending vessels continuously adapted their formation and continued to track the inbound vessels to determine hostility.

Figure 4-3(d) demonstrates that once defenders confirmed the hostility of the inbound vessels, they began weapons engagements to prevent the attackers from reaching weapons engagement range with the HVU.

Once the defenders successfully eliminated all attackers, they resumed formation as shown in Figure 4-3(e) to continue transit and escort the HVU through the remainder of the constrained waterway.

4.2.2 Distinct Variants of the Tactical Decision Manager

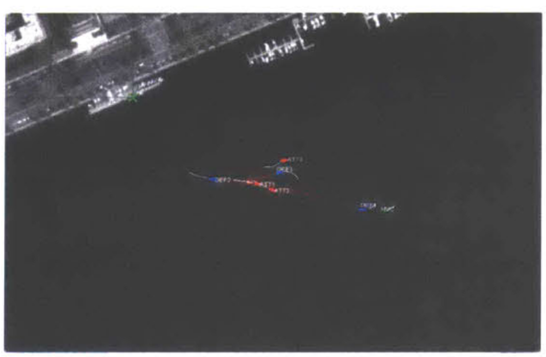
The first step in implementing the enhancements to the seven vehicle scenario was splitting the tactical decision manager into three variants: general (pTacDecisionMgr),



(a) Allies and OPFOR Begin Observing

(b) Defenders Take Stations, OPFOR Determine HVU

(c) Attackers Begin Attack, Defenders Adjust and Monitor



(d) Hostility Confirmed, Defenders Begin Firing

(e) Attackers Disabled, Defenders Resume Initial Screen for Transit

Figure 4-3: Demonstration of Seven Vehicle Enhanced Scenario

OPFOR (pTacDecisionMgrO), and allies (pTacDecisionMgrA). The general variant was maintained as the same application developed for the baseline scenario and was run on the HVU since it was not as significant for the objectives of this research for the HVU to possess as complex decision-making as the defenders and attackers.

OPFOR Tactical Decision Manager

The OPFOR application was modified primarily in two notable aspects and is presented in Algorithm 4. The first modification was to control more behaviors prior to beginning attack. The intent was that the OPFOR vessels would act more similar to manned fast attack craft prior to the attack phase of the scenario. The modified behavior mode hierarchy model is presented in Figure 4-4.

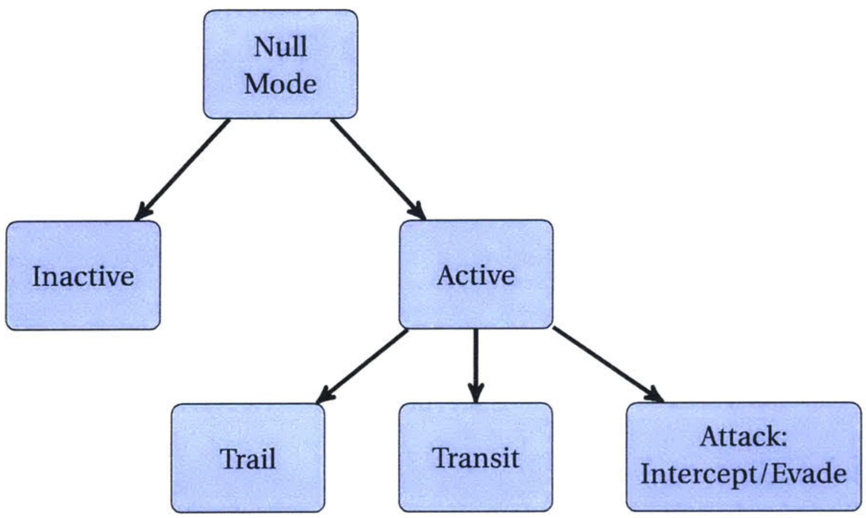


Figure 4-4: Behavior Hierarchy Model for Attacker - Seven Vehicle Enhanced Scenario

Whereas in the seven vehicle baseline the OPFOR formation loitered at a stand-off distance from the HVU, in the enhanced baseline the vehicles were made to behave less overtly. They used waypoint behaviors to transit along the waterway while gathering their initial data of the allied formation. They then used the trail behavior at a stand-off distance to match the HVU's approximate speed while slowly altering course to decrease separation from the HVU. As the attackers gradually reach a close enough distance that the defender's respond, the second notable modification to the OPFOR decision manager is executed. The OPFOR vessels observe the reaction of the defensive formation, and since the new formation is more disbursed the vessels prioritized tracking the formation guide-ship rather than the formation centroid in order to better correlate the HVU's identity. This additional determination step was then the trigger for initiating attack.

Algorithm 4 Tactical Decision Manager - OPFOR

```
Require: OPFOR know OPFOR identities
while Vehicle is in OPREGION do
    Check for updated data
    Vehicles follow Waypoint Behavior until within given standoff range of Allied formation
    Initiate Trail Behavior at standoff range to help monitor formation
    Determine centroid of Allied formation
    for i = 1 to Number of Allied Forces do
        Check proximity to centroid
        Check simulated size factor {represents either visual size or radar return}
    end for
    if Allied formation maneuvers in transit then
        Verify which vessel initiated maneuver first
        Use cumulative observations to estimate the ship about which the formation is oriented(guide ship)
    end if
    if Allied formation disperses/expands then
        Determine which vessel maneuvered least to estimate guide ship
    end if
    Weight determination based on centroid, based on size factor, and based on guide ship estimate to locate HVU
    if HVU located then
        Set Intercept Behavior run condition to true
    else
        Gradually decrease standoff range in Trail Behavior to gauge Defender's response
    end if
    Algorithm 2: Threat to Ownship
end while
```

Allies Tactical Decision Manager

The modifications to the allied Tactical Decision Manager included more detailed monitoring of suspect and adversarial contacts, improvements to threat determination, and

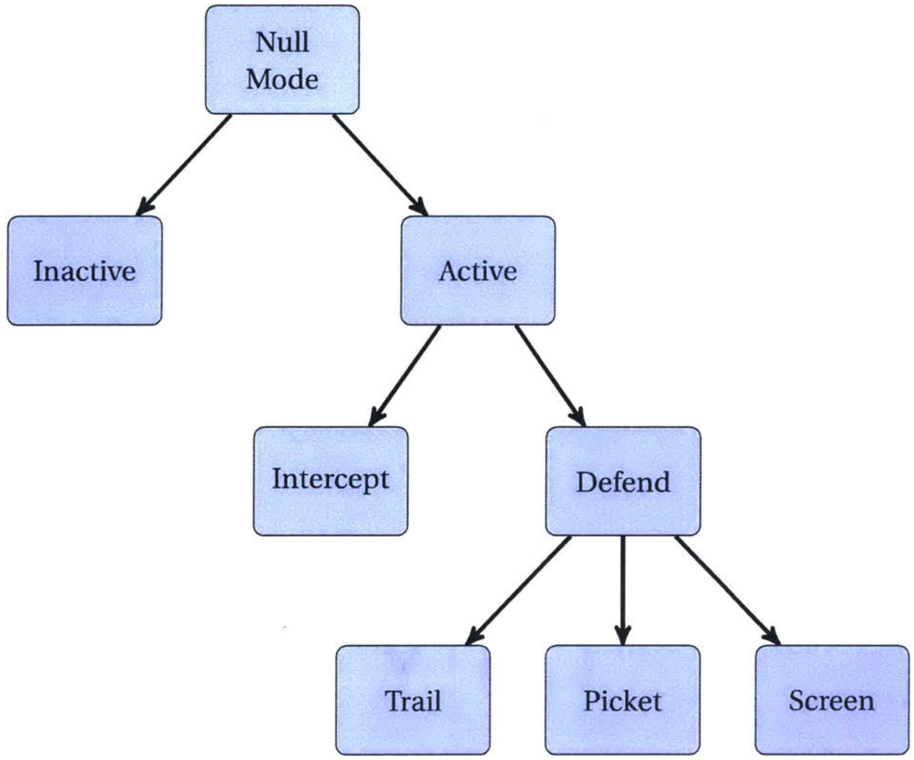


Figure 4-5: Behavior Hierarchy Model for Defender - Seven Vehicle Enhanced Scenario

improvements to the disposition of defending forces. These modifications are presented in Algorithm 5 and are described in detail in this section.

Due to the increased number and complexity of decisions made by the allied decision manager and the additional data required for such decisions, the decision manager application was restructured with regard to its handling of contact data. Every vessel reported to the decision manager was stored as a surface track, where this nomenclature was chosen in order to be readily comparable to contact management terminology aboard naval surface combatants. In the context of this research, the decision manager generates a track for each vessel in order to store and manage information to include position, speed, heading, friend or foe status, and health status. Uses for position, speed, and heading were previously described with regard to the Intercept and Evasion behaviors, but the parameters would be required for additional considerations described in later sections. Although the friend or foe status implies a binary status between "friend" and "foe", it was also used for an "unknown" status that preceded either the confirma-

Algorithm 5 Tactical Decision Manager - Allies

```
Require: Allies know Allies' identities
  {HVU and Defenders have "Allies" or "Allied" or "Allied Forces" affiliation, but this
  version runs on Defenders only}
while Vehicle is in OPREGION do
  Check for updated data
  [threat_exists, imminent_danger] ← Algorithm 6:Threat to HVU
  if threat_exists then
    Determine range and bearing to centroid of OPFOR formation
    Calculate position for picket station: Equation 4.1
    Calculate position for screen station: Equation 4.3
    Determine closest OPFOR to HVU for trail station
    for i = 1 to Number of Defenders do
      Calculate distance to each station
      Determine which defender should take each station based on distance
    end for
    if Assigned Picket then
      Move to picket station and run StationKeep Behavior
    end if
    if Assigned Trail then
      Move to trail station and run Trail Behavior
    end if
    if Assigned Screen then
      Move to screen station and run Trail Behavior
    end if
    if imminent_danger then
      Post to Intercept Behavior report variable
      Set Intercept Behavior run condition to true
      Engage OPFOR inside danger range with weapons
      Assess damage to OPFOR to determine when no longer a threat to danger
    end if
  else
    Ensure Trail Behavior run condition for initial defensive screen set to true
    Ensure Intercept Behavior run condition set to false
    Ensure StationKeep Behavior run condition for picket station set to false
    Ensure Trail Behavior run condition for initial defensive screen set to true
  end if
end while
```

tion of allied status or the determination of hostile intent. The health status parameter was used for inclusion of vehicle battle damage as described in a later section. Each defender running the allied decision manager stored the data for each vessel in a track database designed to loosely mimic the way in which combat systems provide information to tactical watch-standers in managing the surface warfare common operational picture. Each defender maintained its own track database, but could be allowed to share track data if required.

The application checks each non-friendly track to determine if it represents a threat to the HVU or if it poses immediate danger to the HVU. In this context a threat to the HVU is considered to have deliberately closed within a specified threat range, but is outside of the range at which it would be considered to intend to attack the HVU. The vessel is then considered a danger if it is inside the specified danger range which would indicate that it intends to attack the HVU and the track is designated as a foe. Both ranges are set in such a way as to allow modification based on simulated rules of engagement or based on different types and ranges of weapons used by opposing forces. As the application makes these determinations, the disposition of enemy forces is checked to verify whether the vessels are distributed approximately in a single formation or if there exist multiple formations and therefore multiple threat axes. The tracks for threats and dangers were grouped based on priority and, if applicable, according to geometrically separated formations for use by the application in later decisions.

Once a threat was determined, the defenders calculated a number of distinct stations for which to adjust the defensive formation. The station positions included a trail station, a picket station, and a screen station. In the context of this work, the trail station is located behind the non-friendly formation. The picket station is located between the HVU and the non-friendly formation, slightly closer to the formation than to the HVU. The screen position is also located between the opposing formation and the HVU but close to the HVU. These positions can be seen in Figure 4-6, where vehicle "DEF3" is taking the trail station, "DEF2" is assuming duties in the picket position, and "DEF1" is maneuvering into the screen position.

If the opposing vessels had been determined to be distributed into distinctly sep-

Algorithm 6 Threat to HVU

```
threat_exists ← false
imminent_danger ← false
for i = 1 to Number of OPFOR tracks do
    if Range to OPFOR < observation threshold range then
        Calculate closest-point-of-approach between OPFOR and HVU
        if Closest-point-of-approach < threat threshold range then
            Add OPFOR track to threat list
            threat_exists ← true
        end if
        if Range from HVU to OPFOR < enemy weapons range + buffer then
            Add OPFOR track to danger list
            imminent_danger ← true
        end if
    end if
end for
return [threat_exists, imminent_danger]
```

arate formations, for instance on the HVU's port and starboard sides, the screen position would instead be replaced by a second picket station on the side opposite the first picket. In such a case the first picket position as well as the trail station would be oriented based on the opposing formation which is closest to the HVU. The trail position was determined by projecting a point astern of the opposing formation at a distance of 35m. The picket station was situated along the axis between the HVU and the centroid of the opposing formation. The range from the HVU to the picket station was calculated as a fraction of the range between the HVU and the centroid of the OPFOR formation based on the ratio of defender and attacker vessels' available speed(s) as well as the ratio of the defender's effective weapons range to the difference between threat range and danger range.

$$r_{HVU-picket} = r_{HVU-OPFOR}\frac{s_{max_{attacker}}}{s_{max_{defender}}}\frac{r_{effectiveweapons}}{r_{threat}-r_{danger}} \tag{4.1}$$

subject to the constraint

$$r_{HVU-picket_{max}} = 0.9 \cdot r_{HVU-OPFOR} \tag{4.2}$$

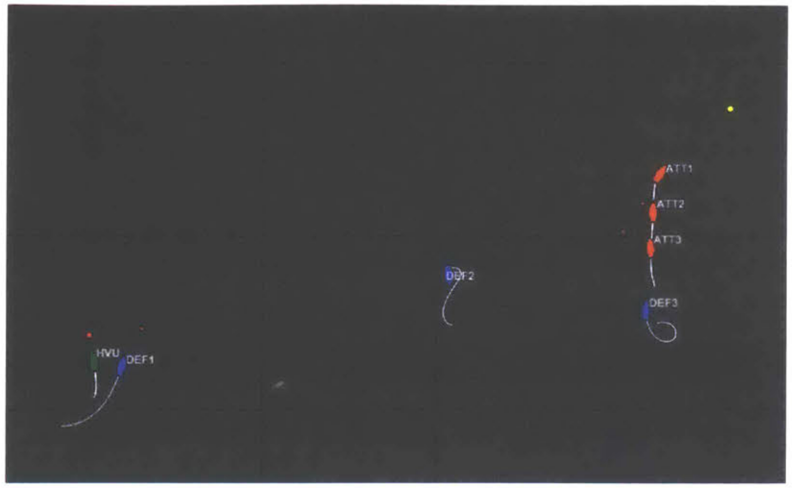


Figure 4-6: Defensive Formation Adapts Autonomously to Threat. Vehicles orient based on opposing formation and take station in a trail position, a picket position, and a screening position. Determining and moving to positions requires no inter-vehicle agreements.

The screen position was similarly located along the axis between HVU and OPFOR formation at a distance:

$$r_{HVU-screen} = 0.1 \cdot r_{HVU-OPFOR} \frac{s_{max_{attacker}}}{s_{max_{defender}}} \tag{4.3}$$

subject to the constraint

$$5m \leq r_{HVU-screen} \leq 0.2 \cdot r_{HVU-OPFOR} \tag{4.4}$$

In the case of OPFOR formations on separated on either side of the HVU, the screen position is instead not used and a second picket station is calculated using Equation 4.1 with respect to the second OPFOR formation. If there are more than two distinct formations, the first picket is calculated based on closest formation to the HVU, the second picket based on the second closest, and then the trail position shifts to a picket station with respect to the third closest once the closest formation is no longer a threat due to retreating or neutralization by defenders. Once the defender's have calculated the stations, they each calculate which of the defenders is most suitable to take each station. Because each vehicle has awareness of the other vehicle's positions, course, and speed, there is no inter-vehicle coordination or agreement required to make these determinations. This approach was chosen in order to make the autonomous adaptation of the defensive formation more robust in its execution by being possible in situations with failure of communications systems or in communications-denied environments. The primary determination of which vehicle takes which station is based on distance between the vehicle and the station. Although it is unlikely that there would be an exact tie in the distance calculations, additional checks were applied as tie-breakers. For instance, if two vehicles are equally close to the trail position the vehicle that has a more aft bearing from the HVU (i.e. closer to 180 relative) takes the station. Similarly if there is a tie for vehicle closest to the primary picket station, the vehicle with the more forward bearing from the HVU (closer to 000 relative) takes the station. Maneuver to the stations was performed using the Intercept Behavior by providing the behavior an intercept report for the station point vice a vehicle. Once at the trailing station, the decision manager switched the vehicle to a trail behavior included in the MOOS-IvP release in order to maintain station. Similarly, the picket vessel began using a station-keeping behavior from the MOOS-IvP behavior library while the screen vessel used a trail behavior to maintain station.

While transiting to station and upon achieving stations, the defenders continually monitored OPFOR for indications of hostile intent while also autonomously adjusting formation based on OPFOR disposition of forces. Once opposing vessels maneuvered around the picket boat to intercept the HVU and approach the danger range, defending vessels considered such actions as confirmation of hostile intent. With hostile intent confirmed, defenders initiated the Intercept Behavior to close each vessel's closest respective attacker and commenced weapons engagement.

4.2.3 Weapons Engagement Modeling

The weapons engagement modeling that was implemented in this research was created within the Tactical Decision Manager to facilitate more rapid integration into the simulated scenarios than if it had been created as a separate application. Future work beyond this thesis could separate the weapons engagement functionality into a stand-alone application in order to provide additional modeling considerations and further improvements to realism.

When attacking vehicles were deemed to not only pose a threat to the HVU, but also to have reached a specified danger range they became eligible for the defenders to engage with simulated weapons fire. The defenders were constrained with a minimum time interval between initiating weapons fire, set at 5 seconds to simulate a reasonable time to execute a controlled burst of weapons fire and assess the effect. The probability of hitting the target when firing was modeled as being dependent on both range to target and fire bearing. It was approximated using piecewise linear functions fit to notional curves as estimates of effective range and fire bearing.

$$P_{hit} = P_1(r)P_2(\theta) \tag{4.5}$$

where

$$P_1(r) = \begin{cases} 1 - 0.0029r & r < 35m \\ 1.833 - 0.0267r & 35m \leq r < 50m \\ 3 - 0.05r & 50m \leq r < 60m \\ 0 & r \geq 60m \end{cases} \tag{4.6}$$

$$P_2(\theta) = \begin{cases} 1 - 0.0067\theta & 0^\circ \leq \theta < 30^\circ \\ 1.25 - 0.015\theta & 30\deg \leq \theta < 50^\circ \\ 3 - 0.05\theta & 50^\circ \leq \theta < 60^\circ \\ 0 & \theta \geq 60^\circ \end{cases} \tag{4.7}$$

The firing was then simulated by publishing a firing report and creating a visual artifact to display during simulations as shown in Figure 4-7.

4.2.4 Battle Damage Assessment

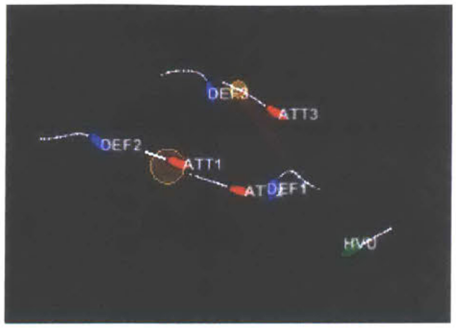
After beginning weapons engagement, the defenders begin monitoring for indications of battle damage on the attacking vehicles. Battle damage is simulated through progressive degradation of the vehicle's health status parameter. Although some consideration

Figure 4-7: Defenders Fire on Dangers to HVU

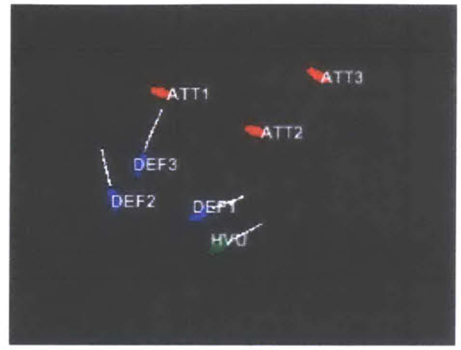
had been given to causing a vehicle's max speed and turning ability to be degraded based on progressive degradation of the health status, these limitations were instead applied in a binary manner. While the vehicle's health status was any value above fully degraded, speed and maneuvering were not restricted. Once the health status became fully degrade, an all-stop condition was initiated for the vehicle to force it to slow until reaching dead-in-the-water (DIW) condition. Visual artifacts were created to provide indications when the vehicle was fully disabled in simulations and to provide a variable to simulate the defenders' observation of this damage. Defenders, when firing on attackers, shared firing reports to provide other vehicles with information about successful hits. The defending vehicles then combined firing reports, postings to the observed damage variable, and vehicle speed reaching DIW status in order to determine that a vehicle was successfully disabled. Figure 4-8 shows indications of battle damage successfully disabling attacking vehicles.

4.2.5 Results of Seven Vehicle Enhanced Scenario

After each of the aforementioned improvements to algorithms in the Tactical Decision Manager, the individual components were tested in brief scenarios designed to verify their function. The demonstrations presented in Figure 4-3 represented the culmination



(a) Defenders Observe Indications of Damage



(b) Defenders Observe Targets Disabled

Figure 4-8: Defenders Perform Battle Damage Assessment of Hostile Targets

of testing all enhancements together in a realistic tactical scenario.

The successful execution by defending forces in this scenario demonstrated that autonomy solutions implemented in MOOS-IvP can be practically extended to realistic defensive engagements. Moreover the algorithms presented in this research enable USVs to approach the level of autonomy required to be considered operationally effective in surface warfare defense engagements.

Chapter 5

Conclusions

This research determined an optimal theoretical basis to consider the HVU defense scenario for three parties in terms of differential game theory. The theoretical basis then supported comparative analysis to demonstrate that the distributed decentralized multi-objective optimization approach implemented in the MOOS-IvP formulation presented in this work approached the optimal solution for HVU defense. This research additionally demonstrated that the MOOS-IvP implementation could readily extend to support autonomous tactical response in swarm defense scenarios.

5.1 Recommended Areas for Further Study

During the course of this research, a number of subjects were identified which could represent useful extensions of this work. Such topics are presented here, though the author does not have immediate intention to continue in these areas.

5.1.1 Game Theoretic Formulation of Seven Vehicle Scenarios

This research did not perform comparative analytics for optimality between a game theoretic seven-party engagement and the seven vehicle scenarios presented. Further studies could develop a game theoretic formulation of the seven vehicle cases in order to evaluate whether MOOS-IvP implementations for increasing number of vehicles would approach or diverge from an optimal solution. Such studies could analyze whether the theoretical model could predict the simulated results for either deterministic target assignments (i.e. each defender is assigned a known attacker to pursue) or for cases where defending vessels are allowed to solve for their targets.

5.1.2 Rules of Engagement

This research intentionally avoided the explicit consideration of rules of engagement, but rather used reasonable criteria for defensive action such the consideration of threat and danger ranges as some measures for determination of hostile intent. Additional details for rules of engagement are beyond the scope of this work and are to be determined by appropriate military and legal authorities. Should rules of engagement be developed for unmanned surface vehicles in a potential combat situation, behavior-based algorithms and control applications could be applied as an additional layer onto the work presented. Such algorithms could enforce criteria that would be met before a vehicle acts to defend the HVU or could provide additional evaluation required prior to allowing the autonomously adaptive formation to close with aggressors in such a way that might escalate a situation.

5.1.3 Determining the Impact of Environmental Effects on Defense Response

Throughout the chapters of this research, the models and simulations formulated did not address environment factors such as wind and current. Additional studies could determine to what extent perturbations from environmental effects might influence the decision-making processes for defending units. It is foreseeable that relatively small perturbations (i.e. currents or winds appreciably smaller than a vehicle's available speed) could likely be easily corrected for. In more significant sea states though, such as 5 or above on the Douglas Sea Scale, small craft like the defenders and attackers would be heavily impacted by wave and wind forces. As such, the decision-making algorithms could benefit from analyses to determine the extent of such impact and develop mechanisms to adjust for this manner of environment.

5.1.4 Human Machine Interface

A human machine interface could be adapted in such a way as to simulate a relevant tactical watch-stander's interactions with the vehicles. Specifically, the interface could be developed to allow a human onboard a Navy vessel, notionally in the vessel's command information center, to supervise a swarm of defenders, task specific actions, authorize or deny requested actions by the swarm or individual vessels, or order engagements against hostile craft. This interface could provide a human-in-the-loop that would likely be required as a result of the development of rules of engagement for USVs in a combat environment.

5.1.5 Enhanced Kinematics to Compare Classes of Vessels

More in depth kinematics modeling could be included for more accurate simulation of characteristics to include turn radius, advance and transfer, acceleration and deceleration. These characteristics could be made to emulate to specific classes of craft in order to provide comparative analytics of one type of craft versus another. Such studies could provide insight into force compositions based on known adversary capabilities in order for deployed USV-capable vessels to adapt mission load-outs to specific operational areas.

5.2 Planned Areas for Future Work

Among the possible topics for continuation of this work, a number were identified as desirable next steps. These will motivate follow-on testing or help determine the scope of additional research.

5.2.1 Machine Learning for Tactical Adaptation

This research could readily be extended to include the application of machine learning in responding to enemy tactics. Defending vessels could be trained to develop even more effective responses than those demonstrated in the seven vehicle enhanced scenario. Additionally, the inclusion of adversarial neural networks on both the attackers and defenders could provide a means to adapt to even more advanced tactics than might be apparent to developers of swarm defense algorithms.

5.2.2 Improved Determination of Hostility

There is significant room for further detailed study to enable USVs to autonomously determine whether a vessel should be considered hostile. One aspect of this is the incorporation of machine vision technology for identification of vessel type and possibly markings indicating nationality if applicable. Similarly, various sensors to include imaging devices could determine whether suspect vessels are equipped with weapons or equipment such as fire control radars which could support determination of hostility. Additionally, more sophisticated analytics than used in the algorithms presented could continuously monitor suspect vessels and use a cumulative measure of aggressive actions to consider the intent of the vessel.

5.2.3 Saturation Studies

Additional research is planned to evaluate the extent to which the algorithms can still achieve success before becoming overwhelmed. The intent is to determine a defense saturation limit beyond which the defenders are no longer able to stop all attackers. The study would include analyses with regard to whether numerical superiority of attackers or increased number of threat axes are the primary drivers in order to determine the most effective means to scale a defensive response. Such a study would also evaluate the nature of scaling the number of defenders and the number of attackers capable of being engaged (i.e. does increasing defenders have a linear or other response to the number of attackers engaged).

5.3 Final Conclusions

This research successfully framed the defense of a high value unit for the three vehicle case in terms of differential game theory by applying published theory for three-party differential games [18] in order to provide optimal solutions to this surface warfare scenario. This scenario was additionally implemented in MOOS-IvP, and the results of this formulation demonstrated that distributed, decentralized multi-objective optimization approached the optimal solution provided by differential game theory. Behaviors and applications were presented that were created in order to facilitate this comparative formulation of the three-party game and to allow extension to more realistic defense scenarios. The ability of MOOS-IvP, with the addition of the algorithms presented in this work, to provide a realistic defense solution was demonstrated first for a seven vehicle scenario to extend beyond published differential game theory solutions. Finally, the validity of using such algorithms was demonstrated to provide an effective defensive response to a swarm attack in order to demonstrate tactical autonomy for allied unmanned surface vehicles.

Appendix A

Frequently Used Abbreviations

Abbreviation	*Meaning*
A	Attacker, in context of equation notations
ASV	Autonomous Surface Vehicle
D	Defender, in context of equation notations
FAC	Fast Attack Craft
FIAC	Fast Inshore Attack Craft
H	HVU, in context of equation notations
HVU	High Value Unit
IFF	Identification Friend or Foe
IvP	Interval Programming
MOOS	Mission Oriented Operating Suite
OPFOR	Opposing Forces
OPREGION	Operational Region
UAV	Unmanned Aerial Vehicle
USV	Unmanned Surface Vehicle
UUV	Unmanned Underwater Vehicle
UxV	Unmanned Vehicle in general; plural often indicates of a mix of UAVs, USVs, and UUVs

Appendix B

Behavior Appcasting Application

The Behavior Appcaster was created to facilitate rapid trouble-shooting and verification of intended performance by custom behaviors. The term "appcasting" describes a method of output information readily available when running simulations with MOOS applications configured for such output [25]. The IvP Helm, as a MOOS application, provides a certain amount of information via it's own appcasting as shown in Figure B-1. Additional details about the helm can be obtained by using a scope application [25]. The Behavior Appcaster was created to provide further information than would otherwise be available.

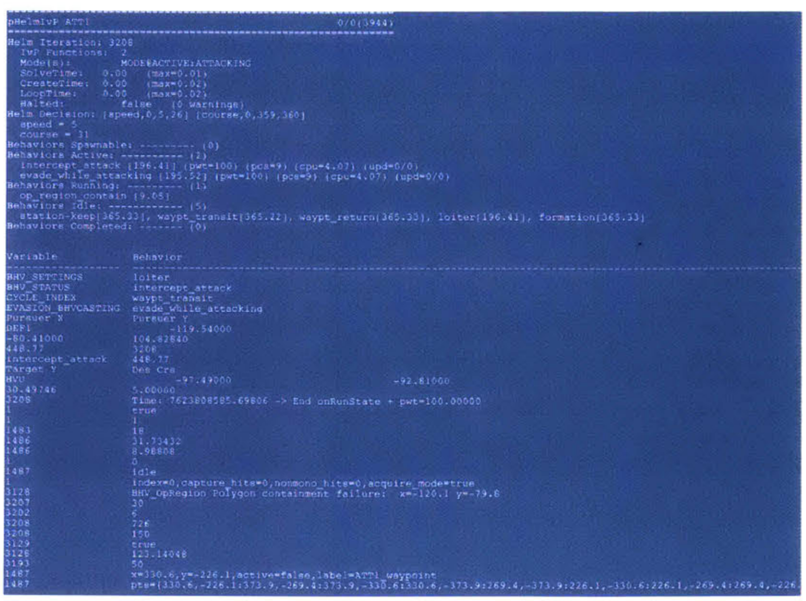


Figure B-1: Example of Helm Information Readily Available During Simulation

The design of the Helm includes a solver which applies multi-objective optimization to determine helm decision variables based on IvP objective functions from each running behavior. As such, the helm does not inherently output variables internal to the workings of the running behaviors. Since these variables include parameters and calculated values used by behaviors for deciding the characteristics of the output objective functions, it can be useful to monitor such parameters mid-simulation in order to diagnose the causes of anomalous vehicle actions not consistent with the expected outcome of a running behavior. The behavior appcaster provides the interface for such decision variables to be continuously observed during a simulation. It requires the custom- written, or modified, behaviors to write decision variables or calculated parameters of interest to a variable which is then published to the MOOS database on the vehicle. The behavior appcaster then uses a configuration parameter to register for a list of behaviors of interest and will provide the data for each registered behavior during simulations. An example of a vehicle running two behaviors written for this output is shown in Figure B-2.

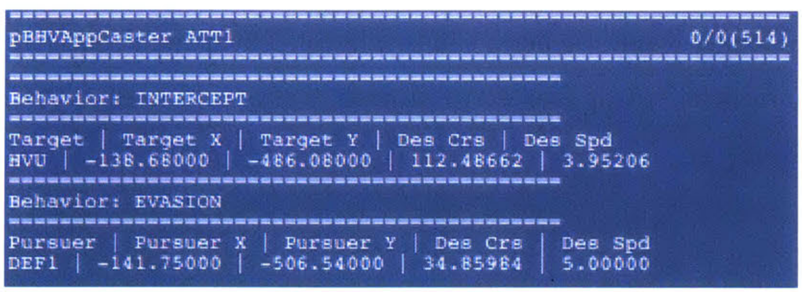


Figure B-2: Output of Behavior Appcaster for Intercept and Evasion

Appendix C

Determination of Defending Units

In other work by this author[26], a study was performed in support of a capstone design project. The project focused on the concept design of a Large Surface Combatant (LSC) to replace the Navy's cruisers and possible destroyers. One requirement, emphasized by project sponsors, was the inclusion of onboard UxV capability. As such some aspects of the study proved informative toward this thesis research.

C.1 Concept of Operations

The Large Surface Combatant would serve as the primary warfare commander for anti-air warfare, surface warfare, and anti-submarine warfare, whether deploying with a carrier strike group or on independent operations. As an extension of its role as surface warfare commander, it would act as the commander of surface action groups formed to prosecute enemy surface vessels. It would additionally be responsible for maintaining the surface warfare operational picture in its area of operations and ensuring defense of allied assets in the area. It would be capable of deploying its onboard UxVs in support of its mission responsibilities. As such, unmanned surface vehicles could be utilized to maintain the classification, identification, and engagement area (CIEA) to which the LSC is assigned.

C.2 Operations Analysis Model

Since the fundamental requirement of maintaining the CIEA is the detection of suspect vessels, probabilistic detection models were used as the foundation for determining the number of USVs required to maintain a CIEA of a given size. The detection model uses lateral range curves with exponential distributions to quantify sensor performance [27]. The probability of detection is then given by:

$$P_d = 1 - e^{\frac{-2wvt}{A}} \tag{C.1}$$

where w denotes the effective sweep width of the sensor, v is the patrol speed of the vessel, and A is the area of search region.

C.3 Relevant Results of Study

The number of defending units was chosen for the LSC design based on the assumption that one vehicle would take station near the host vessel while others patrolled the outer CIEA. Analysis showed that if the vehicles were equipped only with line-of-sight communications, vice satellite communication circuits, careful planning of patrols would be required to minimize intermittent dropping of communications for 50NM or larger CIEAs. As such, the 30NM CIEA was chosen for the baseline. The minimum number of units to maintain greater than 90% detection was therefore determined to be three USVs.

$Number\ of\ USVs$	$CIEA\ Radius$	P_D
1	30NM	0.803
3	30NM	0.992
4	30NM	0.998
1	50NM	0.362
3	50NM	0.740
4	50NM	0.834

Table C.1: Sample of Detection Probabilities Based on Size of CIEA and Numbers of USVs Patrolling

Appendix D

Unmanned Systems Levels of Autonomy

Level	Name	Description
1	Human Operated	A human operator makes all decisions. The system has no autonomous control of its environment although it may have information-only responses to sensed data.
2	Human Delegated	The vehicle can perform many functions independently of human control when delegated to do so. This level encompasses automatic controls, engine controls, and other low-level automation that must be activated or deactivated by human input and must act in mutual exclusion of human operation.
3	Human Supervised	The system can perform a wide variety of activities when given top-level permissions or direction by a human. Both the human and the system can initiate behaviors based on sensed data, but the system can do so only if within the scope of its currently directed tasks.
4	Fully Autonomous	The system receives goals from humans and translates them into tasks to be performed without human interaction. A human could still enter the loop in an emergency or change the goals, although in practice there may be significant time delays before human intervention occurs.

Figure D-1: Defined Autonomy Levels for Department of Defense Unmanned Systems [1]

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