Incorporating Contact Management and Marine Dynamics in Decentralized Autonomous Surface Vehicles

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This thesis studies techniques that can be applied to practical multi-task multi-vessel marine applications to manage mission planning for autonomous surface vehicles (ASVs). This thesis investigates the use of a decentralized Consensus Based Auction Algorithm (CBAA) for marine autonomous vehicles while incorporating contact management and marine vehicular dynamics. The Mission Oriented Operating Suite with Interval Programming (MOOS-IvP) was utilized to demonstrate this capability and perform an analysis of simulated data runs.
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Incorporating Contact Management and Marine Dynamics in Decentralized Auction Bidding for Autonomous Surface Vehicles

by

Brian Stanfield

Submitted to the Department of Mechanical Engineering in partial fulfillment of the requirements for the degree of Masters in Mechanical Engineering and Naval Engineer

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

May 2020

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Abstract

This research studies techniques that can be applied to practical multi-task multi-vessel marine applications to manage mission planning for autonomous surface vehicles (ASVs). This thesis investigated the use of a decentralized Consensus Based Auction Algorithm (CBAA) for marine autonomous vehicles while incorporating contact management and marine vehicular dynamics [1]. CBAA is a task allocation system that does not require a central agency. The task investigated in this thesis is to transit to a waypoint in a dynamic environment, including other moving vessels to avoid.

To reach the goal of this thesis, this methodology is implemented to assign a value to an auction bid given the contact environment and vehicle dynamics. The Mission Oriented Operating Suite with Interval Programming (MOOS-IvP) was utilized to demonstrate this capability and finally, this work provides an analysis of MOOS-IvP simulated data runs utilizing contact management and vehicular dynamics.

Thesis Supervisor: Michael Benjamin
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Abbreviations

ASV  Autonomous Surface Vehicle

CBAA  Consensus Based Auction Algorithm

CBBA  Consensus Based Bundle Algorithm

CPA  Closest Point of Approach

HVU  High Value Unit

IvP  Interval Programming

MDUSV  Medium Displacement Unmanned Surface Vehicle

MOOS  Mission Oriented Operating Suite

SA  Situational Awareness

UAV  Unmanned Aerial Vehicle

USV  Unmanned Surface Vehicle

UUUV  Unmanned Underwater Vehicle
Nomenclature

c  Vector of Task Bids

$G(\tau)$  Adjacency Matrix

$h$  Vector of Valid Tasks

$i$  Agent

$j$  Task

$l$  Straight Line Length

$p$  Vector of Decision Variables for each Task

$q$  Vector of Winning Bids

$t$  Iteration Step

$u$  Turning Rate
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Chapter 1

Introduction

Advances in the development of unmanned systems has seen an increased attention for potential military and commercial applications. This focus has already seen a massive development and production of unmanned aerial (UAV) and unmanned underwater vehicles (UUV). Additionally, military experts have identified missions for unmanned surface vehicles (USVs). This has led to the development of technologies to safely develop these unmanned vehicles as well as autonomous surface vehicles (ASV). The US Navy has already developed their first Medium Displacement Unmanned Surface Vehicle (MDUSV), called the Sea Hunter [2]. Recently, an internal Office of the Secretary of Defense assessment has recommended the reduction of Air Craft Carries as well as an addition of dozens of unmanned vehicles to be added to the fleet [3].

Implementing autonomy on a marine vessel provides the ability to allow the vehicle to perform human-like decisions and applications and greatly increases the potential operations applicable to a USV. This allows for accomplishments of missions that would be risky for a manned vessel, such as minesweeping. Mutli-ship multi-task allocation is a current problem that is studied in the autonomy field [4].
1.1 Objective

The objective of this thesis is to develop a process for multiple task management for multiple vehicles while considering both ownship vehicle turn characteristics, and collision avoidance with other contacts. This thesis will analyze this approach through simulated data runs and statistical analysis.

1.2 Motivation

There are many desirable missions or tasks that would be appropriate for a USV. Modern day applications could include mineweeping, cable laying, surveying, and underway ship replenishment. Utilizing USVs allows the ability to place vehicles in areas where it would be undesirable for humans to enter. Having a large group of USVs allows for the accomplishments of tasks that could not be completed by a single agent in the same period of time.

A hypothetical mission or task that would be undertaken by an autonomous vehicle could be thought of as a mission to drive to a specific waypoint. The process of task delineation is commonly referred to as the assignment problem. The assignment problem has been approached many different ways including the Hungarian method [5] and auction algorithm [6]. Both of these methods have been applied in autonomy for multi-task multi-robot missions to delineate task assignment typically based on range to a waypoint. In 2015, an auction algorithm for assigning the task of transiting to a waypoint in dynamic environments using A* path determination was demonstrated [4].

USVs provide the advantage of being able to transit to places impractical for a manned vessel. A group of USVs could operate quickly and could complete many more tasks than a single vessel could on its own. However, navigational safety is paramount in the continued development and use of these vessels. Having a collision at sea needs to be avoided and autonomous vessels need to be capable of not just avoiding collisions with each other but also with manned vessels that they may encounter during their
missions. Steps need to be done that both allow vessels to accomplish these types of tasks while maintaining themselves to be COLREGS compliant [7]. Rolls-Royce and Finferries have already demonstrated an autonomous surface vessel with the ability to navigate autonomously utilizing COLREGS algorithms [8].

1.3 Literature Review

1.3.1 Auction Algorithm

Many approaches have been taken to task assignment to a multi-agent problem. Various solutions rely on a central agent that uses an optimization technique to determine the agent that is assigned to a given task. A central agent can be a shore side component or a single vessel in the group of USVs. Each agent provides its own situational awareness (SA) to this central command and that central command makes a determination of which agent is assigned the task. The vulnerability of communications to the central command can make this method of tasks undesirable. Additionally, the central command also becomes a single point of failure in the system in the algorithm process.

![Central Command Formation Control](image)

**Figure 1-1: Central Command Formation Control**

Each vessel is controlled by a central command to maintain it in formation.

Further research has been made in developing decentralized task assignment meth-
ods, where the prospective agents act as individual central commands in collaboratively determining the agent assigned to a task. Each agent determines its own SA and shares this with the other agents. However, this relies on perfect communications and can lead to inconsistencies if there is a discrepancy in the current SA that the agents have made. This can lead to multiple agents being assigned the same tasks, or no agent being assigned to that task. Therefore, modern decentralized algorithms have been developed that typically converge on a consensus SA prior to issuing a task to an agent to prevent miscommunication between agents.

One such method is by utilizing an auction algorithm. The auction algorithm was first introduced in 1979 by Dimitri Bertsekas as a method for solving the assignment problem [6]. In its original form, the auction algorithm uses an iterative method to maximize the net benefit in a bipartite graph. This algorithm was further utilized as a solution to the shortest path problem where at each iteration a node is added or subtracted from the task list based on its eligibility. It has been shown that the auction algorithm is inferior to other algorithms in solving the shortest path problem [9]. The Hungarian algorithm has been shown to be more optimal in solving the assignment problem than the auction algorithm however, it requires a complete SA to execute.

The auction algorithm was developed into a consensus decentralized algorithm to produce a conflict-free feasible solution called a Consensus Based Auction Algorithm (CBAA) [1]. This is performed in a two phase process. The first phase of CBAA is to complete an auction phase where each agent places a bid on a task asynchronously with the rest of the group. The goal of the second phase is to come to a consensus. These phases are demonstrated in Algorithms 1 and 2.
Algorithm 1 CBAA Phase 1 for agent $i$ at iteration $t$ [1]

1: procedure SELECT TASKS($c_i, p_i(t - 1), q_i(t - 1)$)
2:    $p(t) = p_i(t - 1)$
3:    $q_i(t) = q_i(t - 1)$
4:    if $\sum_j p_{ij} = 0$ then
5:        $h_{ij} = 1(c_{ij} > q_{ij}(t)), \forall j \in J$
6:            if $h_i \neq 0$ then
7:                $J_i = \arg\max_j h_{ij} \cdot c_{ij}$
8:                $p_{i,J_i}(t) = 1$
9:                $q_{i,J_i}(t) = c_{i,J_i}$
10:        end if
11:    end if
12: end procedure

Algorithm 1 represents the task selection portion of CBAA. At each iteration, a given vessel, $i$, will perform Algorithm 1. Vessel $i$ will have three vectors: $c_i, p_i(t - 1)$ and $q_i(t - 1)$. $c_i$ represents the bid of each task for vessel $i$. The term $p_i(t - 1)$ represents a vector of decision variables for each task at iteration $t - 1$; $p_{ij} = 1$ if agent $i$ is assigned task $j$ and 0, otherwise. The term $q_i(t - 1)$ represents a vector of the winning task bids that agent $i$ recognizes at iteration $t - 1$. Vectors $p$ and $q$ are null vectors at iteration 0. Since $p_{ij}$ is a null vector, no task has been assigned and a winning task needs to be determined. A list of valid tasks, $h_i$ is thus generated using Equation 1.1.

$$h_{ij} = 1(c_{ij} > q_{ij}(t)), \forall j \in J$$  \hspace{1cm} (1.1)

The term $1(\cdot)$ is the indicator function that is unity if the argument is true and zero otherwise. Once the list of valid tasks is generated, agent $i$ assigns itself the highest bid of valid tasks. If a winning task is already determined, then Algorithm 1 would be complete. If no valid task is determined, then agent $i$ does not assign itself a task.
Algorithm 2 CBAA Phase 2 for agent $i$ at iteration $t$ [1]

1: SEND $q_i$ to $k$ with $g_{ik}(\tau) = 1$
2: RECEIVE $q_k$ from $k$ with $g_{ik}(\tau) = 1$
3: **procedure** UPDATE TASKS($g_i(\tau), q_{k_{\tau(kg_{ik}(\tau) = 1)}}, J_i$)
4: $q_{ij}(t) = \max_k g_{ik}(\tau) \cdot q_{kj}(t), \forall j \in J$
5: $z_{i,j_i} = \max_k g_{ik}(\tau) \cdot q_{ki}(t)$
6: **if** $z_{i,j_i} \neq i$ **then**
7: $p_{i,j_i}(t) = 0$
8: **end if**
9: **end procedure**

Algorithm 2 represents the consensus phase of CBAA. At the end of iteration $t$ of Algorithm 1, agent $i$ will transmit its winning bid vector, $y_i$, to agent $k$, where a line of communication exists between agent $i$ and agent $k$. A communication network is represented with symmetric adjacency matrix $G(\tau)$, where as line of communication exists if $g_{ik}(\tau) = 1$ and doesn’t exist if zero. Agent $i$ will then compare any discrepancies between its winning bid vector as well as the winning bid vector from agent $k$. If a higher bid exists from agent $k$ for task $j$, agent $i$ will replace its own value for that task, with that from agent $k$ and ensure that $p_{ij} = 0$. Each agent will repeat Algorithms 1 and 2 until a consensus has been achieved.

Efforts have been made to extend the capability of the auction algorithm to incorporate a multi-task assignment case. Various research has been done proving this to be accomplished by running a sequential auction algorithm and awarding a single task at a time until there are none left to assign [10] [11]. Bundle approaches have been developed that group common tasks into groups and then assigning these bundles to an agent. These algorithms converge faster than a sequential algorithm but have shown its own difficulties due to the computational cost of determining all possible bundle combinations and computing the winning bid among those bundles. A consensus based bundle algorithm (CBBA) has been developed that builds the bundle based on the improvement that a task adds to that bundle [1].
1.3.2 COLREGS and Contact Management Autonomy

The study and development of COLREGS compliant autonomous marine vessels is ongoing [12]. Integrating these autonomous vessels with existing manned vessels has its challenges. There have been many difficulties with applying these regulations to a autonomous vessel from a liability and legal standpoint [13]. COLREGS were written for humans, however they are a sufficiently written rule set that can be captured and interpreted from a robotic system.

Various research has been done in the development of COLREGS-compliant navigation for autonomous vehicles as well as improved collision avoidance [14] [15]. Various research has been done to develop these tools. MOOS-IvP software has been developed to utilize velocity functions for USVs to make COLREGS compliant decisions [16]. Additionally, there are numerous MOOS-IvP algorithms for determining various contact SA. There is a clear desire for a USV to maintain a safe distance from other naval vehicles.

1.3.3 Dubins Path

The basis for turning a surface vessel is dependent on the advance and transfer of the ship. The advance of the ship through a turn is the forward progress made between the time that the rudder is put over and the time steady on course. The transfer is the horizontal displacement of the ship through this maneuver. This is displayed in Figure 1-2. The maneuver is dependent on the physical nature of the ship and rudder, and the choice of rudder position through the turn. In MOOS-IvP, the physics is simulated in an app called uSimMarine. The control settings are set in a separate app called pMarinePID. The pMarinePID App is used in both in simulation and vessels in-water.

In 1957, Lester Eli Dubins proved that the shortest path for two points was constrained by the maximum curvature and straight line path between the tangents of the curvature [17]. This theory has been commonly applied in path planning for wheeled robots, aircraft as well as underwater vehicles for various applications [18].
The Dubins path applies an assumption of constant speed and turning radius. The Dubins path can be applied to surface ships when verifying a surface ship’s kinematics. This leads to a difficult analysis as the maximum turning radius of a boat is based on the ship’s non-linear equation of motions. They can also be estimated utilizing a ship’s Advance and Transfer table. An example of a ship following a Dubins path is shown in Figure 1-3.

To calculate a Dubins turn, it’s assumed that the vessel will move at a constant
forward speed as well as a maximum turning radius. The task is to minimize the amount of distance traveled between any two points. The Dubins path is a solution to minimize the cost function [19]:

$$L = \int_0^{t_F} \sqrt{\dot{x}(t)^2 + \dot{y}(t)^2} dt$$  \hspace{1cm} (1.2)

where $t_F$ represents the time at which the destination is reached and $L$ is the distance traveled to reach the destination.

The Dubins path can be simplified to Equation 1.3, where $u$ is the vessel speed.

$$\dot{x} = \cos \theta$$

$$\dot{y} = \sin \theta$$

$$\dot{\theta} = u,$$  \hspace{1cm} (1.3)

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Steering: $u$</th>
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<tbody>
<tr>
<td>S</td>
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<td>L</td>
<td>1</td>
</tr>
<tr>
<td>R</td>
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Table 1.1: Dubins Path Motion Primitives

Using the set of equation in 1.3, the shortest path can always be expressed as a combination of no more than three motion primitives. The only actions that are needed to transit the shortest path are $u \in \{-1, 0, 1\}$ described in Table 1.1.

After accounting the kinematics of a surface vehicle’s advance and transfer, the predicted Dubins path can be utilized for path planning for an autonomous vehicle. A bid based on the distance traveled to a waypoint will be more accurate when considering the Dubins path rather than a straight line path, because it would be more realistic of the actual path that the vehicle would take.
Consider a situation similar to what is displayed in Figure 1-4. In this example, the straight line path for the blue vessel to reach the waypoint, designated by a star, is shown in brown. Its actual path would be similar to that of its Dubins path displayed in black. If shortest distance was used for tasking the waypoint to a vessel, using the straight line distance would result in the blue vessel transiting to the waypoint instead of the orange vessel. If the Dubins path is taken into consideration, then the orange vessel would be allocated this waypoint.

1.4 Thesis Overview

A task assignment for a marine vessel could be thought of as a mission to transit to specific waypoints. This could be useful for assigning a vessel to scout a location for minesweeping, surveying, or for other purposes. With multiple USVs and multiple possible tasks, this situation could be thought as a simple bipartite graph as shown in Figure 1-5.
Figure 1-5: Marine Vessel Bipartite Graph
Each vessel is red and each waypoint is a black star. The lines between represents the potential bids each vessel would have for each waypoint.

A value assessment has to be done to determine which vessel is assigned to which task. Simple intuition would base this on the distance to the task. Another appropriate analysis would be to predict the amount of time it would take to transit to the waypoint. Predicting the time to transit would require having understanding of the relative distance, orientation as well as maneuverability restraints of the vessel. Not all vessels have the same maneuverability and perhaps this should be taken into consideration when assigning a task. This could be accomplished by using kinematic equations, Advance and Transfer tables or a Dubins path to estimate the distance it takes for a vehicle to reach the waypoint desired or the vehicle's range to that waypoint. A simple setup for a mission could be seen in Figure 1-6.
Figure 1-6: Vessel Layout for Auction Algorithm
Four vessels are at different locations and will have a separate bid based on their own distance to a waypoint, shown as a blue dot.

In addition to vehicular maneuverability, contact situational awareness should be taken into consideration. With all else equal, it would be more desirable to have a vehicle that wouldn’t have a small Closest Point of Approach (CPA) to another vessel. Perhaps, it would be best if no USV had to cross the bow too closely of another ship to accomplish a task.

Figure 1-7: Marine Vessel Bid Scenario (Crossing Situation)
Bidding vehicle 1 and 2 are blue. The red vehicle is an existing contact to avoid. Using distance alone, the blue vehicle would win this bid.

Figure 1-7 demonstrates a situation of this type of scenario. A transiting non-autonomous ship is shown in red and is transiting between two USVs. The waypoint task issued is shown as a yellow star. Based upon distance alone, vessel 2 would be able to reach the waypoint first and would therefore be awarded the waypoint in an auction algorithm based on distance alone. However, vessel 2 would also be in a
standon vessel and should not turn left in this situation; vessel 1 should be awarded the bid to transit to the waypoint.

This thesis will investigate the uses of a CBAA system to determine the assignment of multiple tasks of transiting to a waypoint while taking into consideration contact management and vehicular dynamics. This thesis will develop a bidding system that assigns a bid based on the relative merits of (a) minimizing the distance traveled, and (2) avoiding close CPAs.

1.5 Approach

Task allocation is initiated by a task request to all potential agents. For the purposes of this research, the task will be a waypoint that a vessel must transit to and enter within a designated capture radius to consider this task complete.

The bid calculation of a vehicle is determined by the predicted distance of travel of the agent as well as consideration for the contact situation awareness. The predicted distance of travel will utilize the predicted advance and transfer of the vessel to determine the Dubins path of the vessel. The distance that a vessel actually transits will be measured for each scenario.

Marine environments typically offer fewer obstacles but more difficult vehicle maneuverability. Therefore, adequate prediction of a vehicle's turn capabilities are important when both calculating their potential CPAs as well as in determining the shortest path to that object. The Dubins path will also be used for predicting CPAs with other marine vessels for bid scenarios.

Upon calculating the CPAs for other vessels, each vessel will calculate its bid for a waypoint based on the closest anticipated CPA and expected distance traveled in performing a Dubins path. Various equations for incorporating CPA in the bid calculation will be utilized and evaluated in the performance of this thesis.
1.6 Analysis

This thesis also involved performing data-analysis of simulated autonomous multi-vessel task management. This thesis will first analyze the result of including a Dubins path for bid determination compared strictly to the straight line distance path that will be taken.

A second set of simulated data will be completed to analyze the difference of incorporating auction bids while incorporating anticipated CPA in the bid calculation. These studies will be discussed in further detail in Chapters 2 and 3.
Chapter 2

Process

2.1 MOOS-IvP

For the experimental setup, the MOOS-IvP software will be utilized. MOOS is a C++ cross platform middleware software platform that is based on a publish-subscribe architecture used for robotics research. Core MOOS is composed of communications layer that allows applications that are built to communicate with each other. An Essential MOOS layer is a network of functional applications that use Core MOOS. MOOS-IvP is a set of open source C++ modules for providing autonomy on robotic platforms, in particular autonomous marine vehicles. Various autonomous behaviors have been previously designed and integrated into a helm application for marine vehicles. Through this application, autonomous behaviors have been designed including COLREGS compliance, collision avoidance and waypoint following. Through this software, and extensions developed in this work, simulations of multiple vehicles in a marine traffic situation were able to be performed.

2.1.1 Simulated USVs Dubins path

To simulate vehicle dynamics, MOOS-IvP uses the app uSimMarine. A separate app, pMarinePID, converts a desired heading and speed to a desired rudder and desired thrust. The PID controller applies a standard PID equation to calculate the
desired rudder and desired thrust that is then sent to the simulator engine. The simulator engine propagates the vehicle’s position 20 times a second based on rudder, thrust and hydrodynamic properties of the vessel. The calculated rudder and speed directly effect how the vehicle position and pose are affected by uSimMarine. To adequately predict the exact vehicle behavior at the end of a turn, thousands of iterations of equations would be required. The time required to make this calculation would greatly interfere with determining an actual bid. Therefore, a quick calculation of an estimated turn radius is necessary.

For the purposes of this thesis, multiple turn analyses were performed to determine the average turn radius of a given vessel for changes in vehicle speed and heading. This was used to determine an average turn radius for a given simulation. This simulation could be expanded by developing Advance and Transfer tables for the vehicles under different situations.

2.1.2 Simulated Traffic Lane

To simulate a traffic lane, a single vehicle was tasked to transit to a set of waypoints that simulated a simple north-south transit lane. This vehicle’s path was followed by a single vessel which was trying to establish a specified trailing range utilizing the convoy behavior already developed in the MOOS-IvP behavior library. Each subsequent vehicle introduced in the traffic separation scheme was given the convoy behavior to follow its predecessor. This allowed for a group of vessels to simulate a north-south transit lane equal distant from each other.

2.2 Task Behavior

2.2.1 pCBAAManager

The primary MOOS app developed in this work is called pCBAAManager. pCBAAManager is an app that runs on each individual vessel that is performing the CBAA bidding. This app contains a list of potential waypoints, calculates bids for each
waypoint based on its own position. Through the use of the CBAA Algorithm, the vessels converge on a winning solution and the winning vessels transit to their waypoint destination.

CBAA_POINTS

To assign a point as a task bid, CBAA must subscribe for the variable CBAA_POINTS. A typical message is a comma-separated list of key-value pairs. The order of the pairs is insignificant. The following is an example message:

```
CBAA_POINTS="x=20,y=30,id=task1,exempt=deb"
```

In the above example, the point is assigned at x=20, y=30, the x and y location of an individual waypoint. The id is used for indexing purposes. The term exempt=deb refers to any vehicles that are running pCBAAManager but are excluded from being assigned a specific waypoint. The exempt key-value pair is not required in a CBAA_POINTS message and all vehicles are included when this value-pair is omitted. These tasks are stored in a class CBAATask, which tracks a list of all assigned waypoints, their ids and exempted vehicles. These values are utilized in the calculation of bids \( c_i \) that each vehicle will use in the CBAA process.

CBAA_ASSIGN_TASKS

The app, pCBAAManager, subscribes to a variable CBAA_ASSIGN_TASKS. The list of tasks in CBAATasks are assigned when this message is assigned with the value of \texttt{true}. Once this message is received, each vehicle will iterate through the list of tasks in CBAATask and calculate and assign its bid value of \( c \) for each task, \( j \).

Once all tasks have a bid value, Algorithm 1 is used to update a winning task list. Each vehicle will determine its own bid based on its own position and pose relative to the waypoint. Upon determining what bids are assigned, each agent will send a message to all other agents with a message called TASK_BID. This thesis assumes that no messages are dropped. An example of a TASK_BID is as follows:

```
TASK_BID="iter=4,p=2,q=2,3,5,6"
```

31
Each vessel now performs Algorithm 2 with these values obtained from the other bidding vessels. The term $\text{iter}$ refers to the iteration or $t$ in the algorithm. The term $q=2, 3, 5, 6$ refers to an array of winning bids that are assigned for all known tasks. In this example, task 1 is assigned a winning bid of 2, task 2 is assigned a winning bid of 3, task 3 a winning bid of 5 and task 4 a winning bid of 6. $p=2$ refers to which task the vehicle sending the message has assigned to itself. If the vehicle does not assign itself a winning bid, it omits the $p$ in this message. Each vehicle sends this message at each iteration until consensus has been reached.

Upon receiving a TASK_BID from another vehicle, the receiving vehicle will compare the $y$ winning bid lists. If there is a discrepancy in winning bids, a new bid for that vehicle will be determined using Algorithm 1 and a new iteration of winning bids will be distributed to all other vehicles as a TASK_BID as previously explained. Vessels will continue to re perform Algorithms 1 and 2 until all $q$ winning bid lists are the same, and thus convergence has occurred. After convergence has occurred the winning vessels will transition to a waypoint behavior assigned with the x and y locations of the bid that it has won.

2.3 Bid calculation

2.3.1 Nominal Bid Calculation

The Nominal Bid for a given waypoint is based purely on the range to that point. The Nominal bid calculation is shown in Equation 2.1 and Figure 2-1.

$$c_{t,0} = \frac{1000}{(\sqrt{x_0 - x_{wpt}})^2 + (y_0 - y_{wpt})^2}$$ (2.1)

The distance is placed in the denominator of Equation 2.1 such that the smaller the distance, the larger the bid. This equation results in a double data type. MOOS messages only are able to transmit 5 decimals. Placing 1000 in the numerator was a simple method to increase the number of digits that are passed from one vessel to another to increase the fidelity of the value of the bid that is transmitted between
vessels.

Using Equation 2.1, the nominal bid is based on the straight line distance between a vessel (orange), and a waypoint (yellow).

The denominator in Equation 2.1 is a simple straight line distance from a vessel to the waypoint. The closer a vessel is to the waypoint, the higher its bid for that waypoint.

2.3.2 Dubins Path Bid Calculation

The Dubins path for each vessel is calculated based on an assumed turning radius that was determined for the simulated vessels prior to running the experiment. This path is used in lieu of the straight line distance utilized in Equation 2.1.

\[ c_{i,D} = \frac{1000}{L} \]  \hspace{1cm} (2.2)

where \( L \) is the length of the Dubins path calculated by Equations 1.2 and 1.3. The Dubins bid calculated by the \( i \)th vessel is represented by \( c_{i,D} \) and will be adjusted for CPA management in the subsequent section. Again, the 1000 in the numerator is utilized to improve the fidelity of the bid value that is transmitted between vessels. The shorter the Dubins path, the higher the bid for a waypoint utilizing Equation 2.2.
2.3.3 Contact Management Bid Calculation

The given contact situation is important when determining which vehicle will win a bid and thus maneuver for a given waypoint. That said, the given contact, ownership maneuverability as well as the situational awareness of other vehicles are all complex factors that go into the determination of which vehicle should be assigned a waypoint.

To manage the situational awareness, a Dubins path was utilized to predict the CPA for each vehicle. Only the minimum CPA that each vessel predicted was utilized in determining the bid for any specific task. To calculate the CPA, the heading and speed of each transiting vessel was considered.

The summary of CPA assumptions for this thesis are as follows:

1. Ownship path is based on a Dubins Path and transiting speed.

2. The path of each contact is based on its current position, course and speed and the assumption that it will maintain that heading and speed.

3. It was assumed that CPA would not occur until the vehicle completed its turn and was on a straight line path to the waypoint.

Various consideration needs to be given to determining the effect that CPA has for bid calculation. To begin to investigate how to properly apply a contact management system, this study will first understand the scoring metrics that will be applied based on CPAs. The following arbitrary CPAs will be noted during experimentation:

1. CPAs > 30 m will be considered benign

2. CPAs ≤ 30 m will be considered close encounters

3. CPAs ≤ 10 m will be considered near collisions

Multiple experimental runs were performed investigating various techniques for calculating CPAs. This experiment will utilize the following methods for having CPA contribute to a bid for CBAA.
CPA Management 1 Calculation

The first trial will place an extreme penalty for CPAs that are less than 40 m, by applying a scoring factor of 1/100 for any predicted CPAs less than 40 m. Predicted CPA is based on a perfect Dubins path in which the vehicle of concern doesn’t alter speed or course. No CPA is calculated during the circular part of the Dubins path. Changes in both speed and course as well as differences between the Dubins path and actual path are expected. The 40 m distance is chosen as a 10 m buffer to the threshold for close encounters.

The equation for bid calculation is shown below.

\[
c_{i,\text{cpa}} = \begin{cases} 
  c_{i,D} & CPA_{\text{min}} > 40m \\
  \frac{1}{100} \times c_{i,0} & CPA_{\text{min}} \leq 40m 
\end{cases} \tag{2.3}
\]

As seen in Equation 2.3, CPA only adjusts the CBAA bid when the anticipated minimum CPA is less than 40 m. Any CPA that is greater than 40 m would have no effect in the calculation of the CBAA bid.

CPA Management 2 Calculation

A second equation was developed to adjust the bid based on CPA. In this equation, the bid is multiplied by a factor that includes the expected minimum CPA, if less than 40 m. In the event that the minimum CPA is anticipated to be within 40 m, the bid is multiplied by the factor \((\frac{CPA_{\text{min}}}{40m})^n\).

\[
c_{i,\text{cpa}} = \begin{cases} 
  c_{i,D} & CPA_{\text{min}} > 40m \\
  \left(\frac{CPA_{\text{min}}}{40m}\right)^n \times c_{i,0} & CPA_{\text{min}} \leq 40m 
\end{cases} \tag{2.4}
\]

The closer the CPA, the larger the effect would be on the resultant bid. The weight at which CPA affects the bid calculation is affected by \(n\). The higher the value of this exponential, the larger the effect would be in the bid calculation. This thesis will further evaluate the effect that different values of \(n\) has in CBAA bidding with regards to distance traveled as well avoiding Near Collisions and Close Encounters.
Chapter 3

Implementation

3.1 First Simulation Environment

This thesis first implemented CBAA to delineate a list of waypoints to a group of vehicles. In the initial implementation of CBAA in this thesis, the straight line distance between a vehicle’s position and waypoint at the start of the auction is used to determine the winning bid as described in Section 2.3.1. This would only be true if the vessel adhered to a holonomic assumption. In actuality, marine vessels have non-holonomic constraints. Following simulations of using only straight line bidding, simulations factoring in a Dubins path are used to calculate the bid for each waypoint as discussed in Section 2.3.2. The vehicle that is issued the winning bid transited to the waypoint and the highest bid is based upon the shortest distance to the waypoint.

3.1.1 Initial Setup

The initial conditions for the initial CBAA simulation in MOOS-IvP were as follows:

1. number of vehicles: eight
2. speed of vehicles: three m/s
3. vehicles equal distant apart
4. vehicles following each other in a 50 m radius circle pattern, traveling counterclockwise.

The vehicles with the initial conditions established are shown in Figure 3-1. All USVs have the same communication systems as well as the same simulated PID controls for rudder and thrust as well as the same simulated hydrodynamics. There are eight regions that surround the initial position which are equal in area and approximately 25-50 m away from the vehicle’s encircled position. Each quadrant is color coded.

![Figure 3-1: Initial Setup Simulation 1](image)

Eight vessels (yellow) are shown encircled and transiting at a constant speed. The different colored polygons around them represent the different areas where a random waypoint could be generated.

Upon the vehicles establishing the initial conditions, a waypoint is chosen randomly from its respective quadrant boxes and assigned to the collective group. These
four waypoints are shown as yellow points in Figure 3-2. This simulation could mimic ASVs protecting a High Value Unit (HVU) in an encircle pattern and distributing waypoint tasks to investigate.

Figure 3-2: Simulation 1 - Waypoints Issued
Four randomly generated waypoints (yellow) have been issued to the eight vehicles. One waypoint is located in each colored region.

These waypoints are then assigned using CBAA where the bid is determine by distance to the waypoint alone. Once all vehicles have converged on a solution, the waypoints are assigned to each winning vehicle to transit. The winning vessels transit to the waypoint as shown in Figure 3-3. Each winning vehicle records the distance traveled between being assigned a winning task and transiting within five meters of its assigned waypoint through the use of an odometry app.
Figure 3-3: Winning Vessels Determined and Transit to Waypoints
Each vessel transmits its bid to every other vessel (shown as white lines). The winning bids are calculated using CBAA and the vessels that have won are seen transiting to the waypoints.

The same analysis is performed using a Dubins path instead of straight line distance in bid determination.

3.1.2 Analysis

The first simulated environment was focused on the improvement of utilizing Dubins path in placing a bid for a waypoint utilizing CBAA. This simulation was performed without accounting for turn dynamics nor consideration for turn dynamics to investigate the statistical improvement. Over 1000 data runs were made with and without utilizing turn radius in the calculation of the bid used in a CBAA auction for waypoints. The total distance that each vessel transits from the completion of
the bid to the waypoint was measured in both cases. The distance traveled in the
two data runs were compared utilizing a two sample t-test. This t-test was used to
determine if there was a statistically significant improvement in this simulation for
utilizing a Dubins path bid vice a nominal bid.

3.2 Second Simulation Environment

The second simulation environment was focused on factoring CPAs in calculation
of the bid for a vehicle. In particular, transit lanes were simulated in between regions
where waypoints may be assigned. The purpose of this simulation was to determine
the effectiveness of applying a weighted bid on a task due to concerns for other
transiting vehicles.

3.2.1 Initial Setup

The initial conditions for the second CBAA simulation in MOOS-IvP are as fol-
lows:

1. number of bidding vehicles: two

2. number of transiting merchant vehicles: 12

3. speed of transiting merchant vehicles: five m/s

4. range between transiting merchant vehicles: 85 m

5. no collision avoidance behaviors were applied to either the transiting vehicles
   or the bidding vehicles.

6. both bidding vehicles approximated distance traveled using a Dubins path in
   their bids.

The second simulation environment was set up with two bidding boxes which are
located on either side of a simulated transit lane. The transit lane had 12 vehicles
transiting on north-south legs at four m/s. A waypoint was randomly generated in each box for the two vehicles to bid on. Simulations were made with and without factoring CPA for calculation of bids. Figure 3-4 illustrates the initial setup of this simulation.

![Initial Setup - Simulation 2.](image)

Two bidding vessels participate in Simulation 2, one in the upper left portion of the map and one in the lower right portion of the map. The two bidding vessels are transiting at a constant speed in a circular pattern. 12 vessels are transiting between the bidding vessels in north-south legs, representing a transit lane. The bidding areas are shown in blue and are on either side of the transit lane. Two randomly generate waypoints (yellow) have been generated.

Upon establishing the merchant transit lane, the two randomly generated waypoints were put up for auction to the two loitering bidding vessels. Each vessel that
won a waypoint in the bid transited at five m/s to that waypoint. The closest CPA that the assigned vehicle had with any of the transiting vehicles, was recorded. Figure 3-5 shows each vessel transiting to their respective waypoints.

![Figure 3-5: Transiting to Waypoint Simulation 2](image)

The two transiting vessels have completed their CBAA bids for the waypoints. Each vessel is transiting to the waypoint that it won in the CBAA process.

### 3.2.2 Analysis

Data runs were conducted in this simulation with and without factoring CPA into the determination of assigning waypoints. Again, each vessel recorded its total
distance traveled from being assigned a winning bid until it has reached within five meters of its winning waypoint. Additionally, each bidding vessel recorded the closest CPA that vehicle encountered with any of the transiting vessels during its transit to its winning waypoint. A two sample t-test was again used to determine if factoring in CPA for CBAA bidding resulted in a statistically significant longer transit path. A vehicle encounter is comprised of two vehicles closing range, reaching CPA, followed by an opening of range. For each transit of the bidding vehicle to the waypoint, the only encounter recorded during the transit was the encounter that had the smallest observed CPA. The CPA value for each recorded encounter was classified into three categories as described below:

1. Near Collision - Any CPA that occurs within 10 meters between two vessels.

2. Close Encounter - Any CPA that occurs within 30 meters between two vessels but greater than 10 meters.

3. Benign - Recorded encounters with CPA value at or above 30 meters.

Upon performing the second data simulation, a proportional test was performed between the two samples analyzing both Near Collisions and Close Encounters. Additional runs of Simulation 2 were performed with adjusting the value of $n = 2$ in Equation 2.4.
Chapter 4

Results and Conclusions

4.1 First Simulation Results

Simulation 1 produced two data sets; Run 1 in which a Dubins turn was used to incorporate bidding for CBAA and Run 2 in which a holonomic assumption was used to calculate bidding for CBAA. Over 1000 runs were performed under each condition. A boxplot of the two datasets are shown in Figure 4.1.

![Boxplot](image.png)

Figure 4-1: Simulation 1 Boxplot

Observing the boxplot in Figure 4.1, it can be noticed that the mean distance
transited when using a holonomic assumption was larger than assuming a Dubins 
turn for placing a bid. To further understand this data, a f-test on the two data 
sets is performed to analyze the variances. This f-test was performed with the Null 
Hypothesis that the variances are equal and the Alternative Hypothesis that the 
variances are not equal, shown below in Equations 4.1 and 4.2.

\[ H_0 : \sigma_1^2 = \sigma_2^2 \quad (4.1) \]

\[ H_A : \sigma_1^2 \neq \sigma_2^2 \quad (4.2) \]

The results of the f-test can be seen in Table 4.1.

<table>
<thead>
<tr>
<th>CBAA bid</th>
<th>Run 1</th>
<th>Run 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Distance Traveled</td>
<td>47.1</td>
<td>51.9</td>
</tr>
<tr>
<td>Variance</td>
<td>54.5</td>
<td>65.7</td>
</tr>
<tr>
<td>Observations</td>
<td>1230</td>
<td>1040</td>
</tr>
<tr>
<td>Hypothesized Mean Difference</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>df</td>
<td>1039</td>
<td>1039</td>
</tr>
<tr>
<td>F</td>
<td>1.2</td>
<td></td>
</tr>
<tr>
<td>P(F&lt;=f) one-tail</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>F Critical one-tail</td>
<td>1.1</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.1: f-test Simulation 1

From Table 4.1, it can be seen that the value of F is 1.2 which is greater than the 
value of F Critical one-tail, 1.1. Thus, the Null Hypothesis, that the variances of the 
two sample distributions are equal, is rejected. The Alternative Hypothesis, that the 
variances of the two sample distributions are not equal, is accepted. A 2-sample one-
tailed Welch’s t-test is then performed to statistically analyze the difference in the 
means of the two samples. The Null Hypothesis of the t-test is that the Dubins turn 
(Run 1) would result in an equal distance traveled as the straight line distance (Run 
2), with the alternative being that the Dubins turn(L) results in a shorter distance 
traveled than the straight line distance (l). These are listed in Equations 4.3 and 4.4.

\[ H_0 : L = l \quad (4.3) \]
The results of the t-test are shown in Table 4.2.

<table>
<thead>
<tr>
<th></th>
<th>Run 1</th>
<th>Run 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Distance Traveled</td>
<td>47.1</td>
<td>51.9</td>
</tr>
<tr>
<td>Variance</td>
<td>54.5</td>
<td>65.7</td>
</tr>
<tr>
<td>Observations</td>
<td>1230</td>
<td>1040</td>
</tr>
<tr>
<td>Hypothesized Mean Difference</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>df</td>
<td>2124</td>
<td></td>
</tr>
<tr>
<td>t Stat</td>
<td>-14.7</td>
<td></td>
</tr>
<tr>
<td>P(T&lt;=t) one-tail</td>
<td>1.07E-46</td>
<td></td>
</tr>
<tr>
<td>t Critical one-tail</td>
<td>1.65</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.2: t-test Simulation 1

From Table 4.2, it can be seen that t Stat of -14.7 is < t Critical one-tail -1.65. Therefore, the Null Hypothesis, that the two sample means are equal is rejected. The Alternative Hypothesis, that the average distance traveled utilizing Dubins turn in CBAA bidding is statistically shorter than that utilizing just a straight line is accepted.

### 4.2 Second Simulation Results

Simulation 2 was utilized to determine the effect of applying a CPA prediction to the calculation to the overall bid for each waypoint. It is important to state that this is not a dynamic model and that transiting vessels that change direction or speeds will have different actual CPAs than that which was calculated in the bidding process. The differences in actual CPA’s are due to inaccuracies in ownership’s maneuver and speed as well as changes in speed and heading of the contact in question.

Run 1 in Simulation 2 utilized a Dubins path determination only for the calculation for each waypoint bid. Run 2 utilized a penalty for CPAs that were deemed too close. The box plot of distance traveled between the two simulations is shown in Figure 4.2.

As observed in the boxplot in Figure 4.2, the average distance traveled when considering CPA was greater than when not considering CPA. A two sample f-test
was performed to compare the variances of the two data sets. The Null Hypothesis for the f-test was that the variances of the two data sets were equal and the Alternative Hypothesis for the f-test was that the variances of the two data sets were not equal, as shown in Equations 4.5 and 4.6.

\[ H_0 : \sigma_1^2 = \sigma_2^2 \]  \hspace{2cm} (4.5) \\
\[ H_A : \sigma_1^2 \neq \sigma_2^2 \]  \hspace{2cm} (4.6)

The results of the f-test are shown in Table 4.3.

<table>
<thead>
<tr>
<th></th>
<th>Run 1</th>
<th>Run 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Distance Traveled</td>
<td>230.3</td>
<td>218.0</td>
</tr>
<tr>
<td>Variance</td>
<td>9964.4</td>
<td>9720.5</td>
</tr>
<tr>
<td>Observations</td>
<td>1000</td>
<td>1045</td>
</tr>
<tr>
<td>Hypothesized Mean Difference</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>df</td>
<td>999</td>
<td>1044</td>
</tr>
<tr>
<td>F</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>P(F&lt;=f) one-tail</td>
<td>0.35</td>
<td></td>
</tr>
<tr>
<td>F Critical one-tail</td>
<td>1.1</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.3: f-test Simulation 2

Upon performing the f test on Simulation 2, it can be seen that the value of F, 1.0251 is less than the value of F Critical one-tail of 1.10842. Therefore, the
Null Hypothesis, that the variances of the 2 data sets are equal, is accepted. The differences in the mean distance traveled between the two data sets is investigated by performing a two sample t-test with equal variances with the Null Hypothesis that the two sample runs had equal means and the Alternative Hypothesis being that not considering CPA resulted in a lower average mean. This is summarized in Equations 4.7 and 4.8. As can be observed in Figure 4.2, taking consideration for CPA resulted in a slightly higher average distance traveled compared to that of just utilizing a Dubins path.

\[ H_0 : p_1 = p_2 \quad (4.7) \]

\[ H_A : p_1 < p_2 \quad (4.8) \]

The results of the 2 sample t-test are shown in Table 4.4.

<table>
<thead>
<tr>
<th></th>
<th>Run 1</th>
<th>Run 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Distance Traveled</td>
<td>230.3</td>
<td>218.0</td>
</tr>
<tr>
<td>Variance</td>
<td>9964.4</td>
<td>9720.5</td>
</tr>
<tr>
<td>Observations</td>
<td>1000</td>
<td>1045</td>
</tr>
<tr>
<td>Pooled Variance</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Hypothesized Mean Difference</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>df</td>
<td>2043</td>
<td></td>
</tr>
<tr>
<td>t Stat</td>
<td>2.8</td>
<td></td>
</tr>
<tr>
<td>P(T&lt;=t) one-tail</td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td>t Critical one-tail</td>
<td>1.65</td>
<td></td>
</tr>
<tr>
<td>P(T&lt;=t) two-tail</td>
<td>0.005</td>
<td></td>
</tr>
<tr>
<td>t Critical two-tail</td>
<td>1.96</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.4: t-test Simulation 2

As can be seen in Table 4.4, the t Stat of 2.8 is greater than the t Critical one-tail of 1.65 and thus the Null Hypothesis, that the two samples have equal means is rejected. The Alternative Hypothesis, that considering CPA will result in a lower average distance traveled, is accepted.

Finally, the differences in Close Encounters and Near Collisions was investigated. As stated in section 3.2.2, a Close Encounter is defined as being any CPA being less than 30 meters and a Near Collision as being any CPA being less than 10 meters. For
these simulated data runs, the following hypothesis was utilized with a significance level of $\alpha = 0.05$:

\[ H_0 : p_1 = p_2 \]  \hspace{1cm} (4.9)

\[ H_A : p_1 > p_2 \]  \hspace{1cm} (4.10)

These values are shown below in Table 4.5.

<table>
<thead>
<tr>
<th></th>
<th>Run 1</th>
<th>Run 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observation</td>
<td>1000</td>
<td>1045</td>
</tr>
<tr>
<td>Close Encounters</td>
<td>38</td>
<td>231</td>
</tr>
<tr>
<td>$z$ value</td>
<td>-12.2</td>
<td></td>
</tr>
<tr>
<td>$\alpha$</td>
<td>.05</td>
<td></td>
</tr>
<tr>
<td>$p$</td>
<td>&lt;.00001</td>
<td></td>
</tr>
<tr>
<td>Near Collisions</td>
<td>14</td>
<td>163</td>
</tr>
<tr>
<td>$z$ value</td>
<td>-11.4</td>
<td></td>
</tr>
<tr>
<td>$\alpha$</td>
<td>.05</td>
<td></td>
</tr>
<tr>
<td>$p$</td>
<td>&lt;.00001</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.5: $z$-test Simulation 2

As shown in Table 4.5, the $p$ value for Close Encounters and Near Collisions was less than 0.00001, indicating that there are statistically significant fewer Close Encounters and Near Collisions in the population utilizing CPA during CBAA bid calculation.

### 4.2.1 Further CPA Analysis

An additional data set of this experimental setup was performed using a value of $n = 1$ and $n = 2$ in Equation 2.4. A summary of all data sets using Simulation 2 are shown in Table 4.6. A histogram of the data is shown in Figure 4-3.

From Figure 4-3, it can be seen that there is significant effect in the number of Close Encounters and Near Collisions when incorporating CPA in the bid calculation. Additionally, a slight increase in average distance can be seen, as would be expected.
<table>
<thead>
<tr>
<th></th>
<th>Run 1</th>
<th>Run 2</th>
<th>Run 3</th>
<th>Run 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bid Equation</td>
<td>2.3</td>
<td>2.2</td>
<td>2.4, n = 1</td>
<td>2.4, n = 2</td>
</tr>
<tr>
<td>Observations</td>
<td>1000</td>
<td>1045</td>
<td>1012</td>
<td>1020</td>
</tr>
<tr>
<td>Average Distance Traveled</td>
<td>230.32m</td>
<td>218.02m</td>
<td>230.38m</td>
<td>229.47m</td>
</tr>
<tr>
<td>Close Encounters</td>
<td>38</td>
<td>231</td>
<td>66</td>
<td>47</td>
</tr>
<tr>
<td>Near Collisions</td>
<td>14</td>
<td>163</td>
<td>37</td>
<td>20</td>
</tr>
</tbody>
</table>

Table 4.6: Simulation 2 Data Sets

Figure 4-3: Simulation 2 Data Set Comparison.
Data set 1 used no CPA in bid calculation. Data set 2 utilized Equation 2.3 in bid calculation. Data set 3 utilized Equation 2.4 with n = 1. Data set 4 utilized Equation 2.4 with n = 2.

4.3 Future Research

As shown in this thesis, when used in a bid calculation for CBAA, Dubins path provided a statistically significant improvement in results. This path could be estimated by developing Advance and Transfer tables for Autonomous vessels and applying them to a turn analysis behavior to provide a more accurate calculation for a vehicles turn. This, in turn, would provide a better estimate for calculation of potential CPAs for transiting vessels.

Further research could be done to consider other variables besides the anticipated CPA based on another vehicles heading and speed. The contact’s speed, and frequency of changes in speed and course should be considered. Also, whether we would
be crossing in front of a contact or astern should be considered. Consideration could also be given for vehicles that have shown to maneuver more frequently than others. Additionally, the type of vehicles and their predicted maneuvering limitations should be considered.
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