Improving the Coordination Efficiency of Limited Communication Multi-AUV Operations using a Multi-Agent Architecture

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Abstract

This research addresses the problem of coordinating multiple autonomous underwater vehicle (AUV) operations. An intelligent mission executive has been created that uses multi-agent technology to control and coordinate multiple AUVs in communication deficient environments. By incorporating real time vehicle prediction, blackboard-based hierarchical mission plans, mission optimization and a distributed multi-agent based paradigm in conjunction with a simple broadcast communication system this research aims to handle the limitations inherent in underwater operations, namely poor communication, and intelligently control multiple vehicles. In this research efficiency is evaluated and then compared to the current state of the art in multiple AUV control. The research is then validated in real AUV coordination trials. Results will show that compared to the state of the art the control system developed and implemented in this research coordinates multiple vehicles more efficiently and is able to function in a range of poor communication environments. These findings are supported by in water validation trials with heterogeneous AUVs.

1 Introduction

As autonomous underwater vehicle (AUV) technology matures there is a growing need for multiple vehicles to work together. The potential benefits of multi-vehicle operations are many and include force-multiplier effects (simultaneous data gathering, asset redundancy, etc.), spatial and temporal simultaneity, and the utilization of heterogeneous vehicle configurations.

Current architectures for such operations are often simple extensions of single vehicle designs

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that in order to coordinate actions depend upon reliable communication. This dependency upon communication reliability however is unrealistic in the marine environment where inter-vehicle message passing is accomplished via acoustic transmissions. These messages are often corrupted in transit or lost all together. In order to successfully coordinate multiple AUVs in these environments a solution is needed that will take into account the inherent unreliability of underwater acoustic communication.

A robust multi-agent architecture should allow for a significant increase in mission efficiency without requiring a proportional increase in communication. This study utilizes a standard hybrid, tri-level architecture (Figure 1) and creates an intelligent mission executive (the DELPHÍS system) that aims to minimize the need for mission re-planning by maximizing coordination on the executive level. In architectures such as these missions are planned in the deliberative layer using an adaptive mission planning module. These plans are then passed to the executive layer where they are completed by the mission executive. When faced with problems or new information the mission executive traditionally requires the mission planner to perform a mission re-plan. This process is time consuming and often not practical in real world situations.

Aimed to work in conjunction with a mission planner such as the one described in (Patrón et al., 2008), this work presents an intelligent mission executive that can coordinate vehicles in poor communication environments while keeping the need for a mission re-plan to a minimum. This executive repair functionality aims to keep conflicts local (solvable by the mission executive) and not global (only solvable by the mission planner). To handle the likely event of communication blackouts this work includes prediction functionality so that agents can make accurate predictions of other agents intent. In addition the use of a single mission plan for all vehicles simplifies operations and allows for the additional vehicles to be added at runtime.
2 Background and related work

2.1 Multi-agent systems

A multi-agent system is a computational system where two or more software modules known as agents work together to solve a problem. An agent is considered to be a locus of problem solving activity that tries to fulfill a set of goals in a complex, dynamic environment (Lesser, 1999). Depending on the type of environment, an agent can take many different forms. Robots can be considered agents that can sense and actuate in the physical world. The ability of such systems to exchange information, decisions and plans at distance and on heterogeneous platforms make them a powerful tool.

2.2 Cooperative robotics

One application of multi-agent system technology is multi-robot cooperation. In these systems agents are used to control individual autonomous mobile robots (AMRs) and there are many examples ranging from the CEBOT system (Fukada and Nakagawa, 1988) in the 1980’s to more current applications like the control architecture presented in (Ogras et al., 2004). Multi-robot systems have many uses and many benefits over single robot applications both because of the force multiplication aspect as well as their ability to accomplish tasks that a single robot system could not.

Many of the real-world applications being undertaken and proposed for AMRs are highly task and plan oriented. Examples of applications include exploration/mapping (Sotzing et al., 2005), area patrol (Girard et al., 2004) and formation control (Edwards et al., 2004). Existing architectures draw strongly on conventional computer structures and symbolic algorithms (for example, script-based task execution, and expert knowledge systems).

2.3 AUV control architectures

The current state of the art in AUV control consists of three different types of architectures: deliberative, reactive and hybrid (Ridao et al., 1999). Deliberative architectures are based around planning and do so via a world model that consists of a set of goals (Albus et al., 1994). A plan is generated based on these goals and then executed by a control system. One of the setbacks of this is that all actions have to be planned by the high level planner modules. This becomes a computationally expensive problem when a plan has to be modified during execution.

Reactive architectures are event based systems where certain situations result in certain corresponding behaviors (Lane and Knightbridge, 1995) (Russell and Lane, 1986). The real world acts as a model to which the robot reacts. Though reactive architectures solve the quick reaction time problem present in deliberative architectures, they lack their global planning ability and consequently aren’t as able to solve complex problems without large populations of robots.
Hybrid architectures combine the benefits of both deliberative and reactive architectures. As shown in Figure 1 normally these systems are divided into three distinct layers: the deliberative high level layer for planning, the executive layer for vehicle instruction and sensor processing, and the functional reactive layer for data input and motor control (Gat, 1998). Because hybrid architectures implement characteristics from both deliberative and reactive architectures, they are currently the most common choice for AUV control (Evans et al., 2006).

2.4 Multi-AUV coordination

Multi-AUV systems allow for missions that would be otherwise infeasible using only one vehicle and can benefit particularly when heterogeneous vehicles are utilized. These systems are still relatively new but there is research being conducted in both the scientific and military communities.

Representing the scientific community, the National Oceanic and Atmospheric Administration (NOAA) uses multi-AUV technology in a number of its departments including the National Marine Fisheries Service, the Office of Coast Survey and the National Undersea Research Program (Manley, 2004). The goal is to use multi-AUV technology to obtain oceanographic data from a wide area in one mission; i.e. the more AUVs working together, the more data that can be collected. Another multi-AUV project was conducted in the field of adaptive ocean sampling in Monterey Bay, California (Fiorelli et al., 2004). By using a group of AUV gliders spread across the bay, the system hopes to use their data to help analyze and predict ocean processes and create a dynamic model based on this data. A single AUV would not be suited for this task because it requires data to be recorded simultaneously in variable locations, which also eliminates the possibility of using buoys for data collection. Other research in multi-AUV coordination can be found in (Shao and Wang, 2007) and (Zhang et al., 2005) where multiple robotic fish are coordinated in a box pushing task and water polo respectively. Though they both illustrate the benefit of multiple vehicles, these systems rely on surface wireless communication and are therefore limited to solely laboratory experiments.

The military is also looking into multi-AUV technology. One of the main applications of these systems is in mine countermeasures (MCM). In the US Navy UUV Master Plan (United States Navy, 2004) this type of mission is referred to as the most problematic of the missions facing the UUV community and the Navy at large and is therefore an extremely important issue. A major setback to missions of this type is the communication issue, an issue fundamental to the problem of cooperation (Stilwell and Bishop, 2000). In order for an MCM mission to function the AUVs need to be able to work together and because communication underwater is difficult there are major hurdles that need to be addressed. Because of this the MCM mission vignette has been chosen as one of the test scenarios for this research.

2.4.1 Architectures

Currently there are two main approaches towards getting AUVs to cooperate: the adaptation of single vehicle architectures, and the application of current cooperative robotics
The state of the art in AUV mission control is script-based sequential mission execution systems. In these systems task order is predefined by the user though event-based script-switching is possible. The benefit of such systems is that because all vehicle actions are predefined, behavior is very predictable. Conversely, though predictable, scripted plans don’t allow for dynamic task allocation and consequently often do not optimally execute the mission given unforeseen events.

The most common way to coordinate multiple AUVs is what is known as a stoplight or synchronous rendezvous system. In these systems current single-AUV script execution systems are modified to include stoplight points where vehicles can synchronize with each other. The benefit of such systems is that current AUV control architectures can be utilized with few modifications. However, autonomy is sacrificed because the user has to plan the static sequence of the mission in advance including all synchronization points (synchronization points negotiated on the fly requires good inter-vehicle communication, a limited commodity in marine operations).

Another approach to multi-AUV cooperation is the modification of existing cooperative robotics approaches to the underwater domain. In (Jouvencel et al., 2001) a reactive architecture is proposed to control a flotilla of underwater vehicles using both centralized and distributed decision making. Sariel et al. (Sariel et al., 2006) proposes a bidding system used to coordinate simulated AUVs in a mine-countermeasures operation. In this system any vehicle can act as auctioneer to generate bids on a task, and assuming good communication, allows for dynamic goal selection and a high level of cooperation. This dependency on consistent communication however is a major limitation in the sub-sea environment.

3 System design

This research aims to embrace the limitations of the underwater environment and create a multi-AUV control architecture that can maintain coordination efficiency in the presence of unreliable acoustic communication.

Incorporating multi-agent and collaborative robotics technologies this research has created the DELPHÍS system (Sotzing et al., 2007), an architecture that allows for efficient multi-AUV coordination in environments where communication cannot be guaranteed. Because it doesn’t rely on centralized task allocation the system remains completely distributed and it avoids unnecessary complexity by requiring only one plan for all vehicles in the collective. A custom hierarchical, blackboard-based mission representation allows missions to be executed in a dynamic manner by choosing the most suitable goals from a common plan while also considering the intent of other vehicles. To handle the intermittent communication rates of the marine environment the DELPHÍS system employs real time agent prediction in conjunction with a broadcast (as opposed to unicast) communication protocol.

The system acts as the mission executive in a standard hybrid three-layer architecture (Figure 1) and is run on every vehicle acting in the collective. The sub-architecture for the DELPHÍS
system is shown in Figure 2. Within the DELPHÍS system there are three major modules: the Mission Model, AUV Database and Mission Controller.

### 3.1 Mission model

The Mission Model module contains the mission file and controls interaction with it, including status updates, goal retrieval, etc. A custom mission representation system has been created that embraces the limitations of underwater operations in addition to allowing for intelligent multi-agent, multi-vehicle coordination. The system, known as BIIMAPS (Blackboard Integrated Implicit Multi-Agent Planning Strategy) (Sotzing et al., 2008), is based on both blackboard and hierarchical task network technologies and is described in more detail below.

In the BIIMAPS system (Figure 3), mission plans are represented as a tree of goals. The tree structure was chosen because it is a logical way of breaking up tasks into sub-tasks. Goals (represented by large circles in Figure 3) can either be atomic (leaf goal), or divided into sub-goals. Each goal can be in one of three states: complete, ready or locked. Goals are not defined for specific agents and these states help vehicles decide when execution can be attempted.

All leaf goals have operations associated with them (represented by white circles in the diagram). An operation is the behavior associated with the certain goal. For instance, in a waypoint goal the operation would be to navigate to a set of coordinates. In addition non-leaf goals can also have operations associated with them. If a goal’s sub-goals were a set of waypoints the root goal’s operation could be to operate a camera so that it recorded throughout the execution of all sub-goals. This situation is represented in Figure 3.

To determine when a goal has been completed, each has a condition. Conditions can be simply the completion of a goal’s operation or they can be externally dependent, such as a message received from another agent. The conditions for non-leaf goals can be a logical combination (“and”, “or”, etc.) of their sub-goals, as shown in the diagram.
Goals can also have dependencies and constraints applied to them to determine when they are available for execution. Unless these are applied all goals in the BIIMAPS system can be executed concurrently. Dependencies are when a goal relies upon another (represented by the dotted arrow in Figure 3). A constraint is similar, but instead of referring to another goal, it refers to the state of the world. Goals can also be constrained in terms of a priority so as to allow more crucial goals to be given more weight.

The BIIMAPS system can further constrain mission execution through the use of execution and completion locks. An execution lock can be applied to a parent goal indicating that if one of its sub-goals is being executed no other agent acting in the system can attempt another sub-goal. Completion locks function in a similar manner and require that if one sub-goal is executed, the remaining sub-goals must be completed before any other available goals.

Because this system was designed to work with multiple distributed agents it can be passed a list of changes (for instance from another agent) and update itself. In this way it can be distributed across groups of vehicles. In addition the BIIMAPS system was designed as a mission representation system with blackboard functionality. In this case BIIMAPS itself can be considered the blackboard and the AUVs updating the mission act as the knowledge sources. Because of this the system can be rolled back to a previous state should any previous update that other updates depend upon become untrue. A detailed description of the BIIMAPS mission representation system can be found in (Sotzing et al., 2008). An excerpt from an XML BIIMAPS mission plan can be seen in Figure 4.
3.2 AUV database

The AUV Database is a module that contains information about all of the AUVs in the mission, a system similar to that being used in (Sariel et al., 2006). This information includes static data such as vehicle type and dimensions as well as variable data like battery life, average speed, sensors, and sensor status. Variable data is updated periodically to ensure that each AUV has the most recent status of its peers.

The aim of the AUV Database is to allow for intelligent goal selection as well as behavior prediction in the case of dropped communications. In these situations, each vehicle still has to make decisions about the mission, despite not being able to contact the others. By consulting the AUV Database, predictions can be made using the most recent status of each vehicle.

3.3 Mission controller

The Mission Controller is the main decision making unit in the executive. It is made up of a number of sub-modules that fall into three main categories: communication, goal selection and agent prediction. Communication will be described here followed by goal selection and prediction in the next section.

Communication in the mission controller consists of both internal and external message passing. Internal communication utilizes the OceanSHELL broadcast message system (Ocean Systems Laboratory, 2008) to allow simple communication with any other OceanSHELL compliant software module. External communication is accomplished via an acoustic broadcast system whereby vehicles periodically send out status information to all other vehicles in range. A similar system is proposed in (Jouvencel et al., 2001). This information includes AUV data with a unique ID number, AUV type, current position, average speed, battery life as well as mission information, consisting of current goal, a list of previously achieved goals and newly discovered targets (coordinates and unique ID for each). An XML representation
of this broadcast message can be seen in Figure 5. For these experiments the Woods Hole Oceanographic Institution Micromodem was utilized. This was chosen to compliment the WHOI micromodem incorporated in the REMUS AUV and subsequently messages passed between all vehicles had to conform to the REMUS acoustic data rate. This resulted in a 32 byte maximum message size however this small size was still usable since mission and AUV data could be communicated in the form of simple IDs.

Broadcast communication has been chosen over vehicle to vehicle (unicast) transmissions to allow for greater ability to handle intermittent communications, which is common in systems operating in the underwater environment. A dependency upon unicast communication adds unnecessary complication as it requires all vehicles to always be within range of each other. In addition in practice this paradigm usually requires acknowledgment messages to be sent which again is a challenge in intermittent communication environments. Although acoustic collisions are possible due to overlap, especially when large groups of vehicles are working together, the periodic nature of the broadcast system allows messages to be missed without consequence. Because vehicle broadcasts always contain the most recent data there is little chance that data will be outdated upon reception (although the Mission Optimization module can handle this). This will be explained in more detail in the next section.

3.4 System functionality

In the DELPHÍS system each AUV is considered an agent and functions as such. Initially, all AUVs start out with an identical copy of the mission plan. Before beginning execution of the mission, the acoustic broadcast status beacon is started so that vehicles can register with each other, subsequently populating each other’s AUV databases. This allows for external AUV information (including position, current goal, etc.) to be factored in to initial AUV goal selection. Vehicles aren’t explicitly “added to the system” as such but instead make themselves known to each other via acoustic broadcast during runtime. In this way group size is kept dynamic. Initial vehicle position is not encoded in the mission and vehicles can start from any location.
Goal selection works in conjunction with the Mission Model to select the best possible goal for the AUV to achieve. Utilizing the BIIMAPS system, the Mission Model is able to return a list of only the goals in the mission that are available for execution. This list is then passed to the goal selection algorithm where it is pruned down to a single goal representing the best available task for the given AUV. If no goal is available the AUV will wait in a holding pattern until one becomes available. The Mission Controller functions as a simple finite state machine with three goal states: “In Progress”, “Finished” and “Break”. When a goal is selected the state is set to “In Progress” and it is executed. Once the goal is completed the state is set to “Finished”, its status is updated in the mission model and the loop repeats until there are no more goals. The “Break” state is used to break out of the current goal execution and select another. The algorithm is shown in pseudocode in Figure 6.

3.4.2 Multi-vehicle coordination

When AUV broadcasts are received, the information pertaining to the sending AUV is used to update the receiving AUV Databases. In addition, the current goal and list of completed goals from the sending AUV are passed into the receiving Mission Model, synchronizing it. In this way all Mission Models contain the same data across all vehicles. Vehicles all have the same mission plan, and thus goals can be referred to by ID number only, keeping the size of the message relatively small. Newly discovered targets (mines, pipeline anomalies, etc.) are given unique IDs created from the ID of the AUV that discovered them. Targets are then transmitted in the broadcast with both the ID and the coordinates. In the event of a mission re-plan by the mission planner, the current plan can be effectively invalidated (but not removed) and a new one added on to the root goal. In this way goal IDs would always be associated with the correct goal. This situation is not shown in this research however as it is the functionality of the mission executive, not the planner, that is being tested.

Information in the broadcast relating to the mission status is continually built upon throughout runtime. As the vehicles run the mission their list of completed goals (and discovered targets) continually grows. Due to this, every message received contains the recent mission
The history of the sending vehicle (The limitation of 32 byte message size mentioned in 3.3 meant that only the most recent 10 goals and 2 targets could be transmitted although with higher bandwidth communication this could easily accommodate complete mission histories). This is extremely important for two reasons: first it allows for simple reconciliation of mission data in the likely event of dropped communications, and second, it allows for new AUVs to easily enter the mission during mission execution.

3.4.3 Prediction

The ability to handle and synchronize data in intermittent communications is not enough for a multi-AUV coordination system since in many cases vehicles may be out of contact for extended periods of time. In these scenarios it is important to be able to predict the actions of other AUVs to enable more intelligent goal selection.

Currently one of the main research topics in agent prediction is behavior recognition systems. In these systems the behavior of an agent, be it a software agent, robot or even a person, is inferred by its actions (an example system can be found in (Baxter et al., 2009)). Often using machine learning techniques, plan recognition learns to detect certain action states and then predict what behavior will follow. One of the benefits of these systems is that no prior knowledge of the agent decision making process is necessary. The converse of this benefit is that these systems require training a priori and are often computationally expensive.

In this system all agents are homogeneous (even though they can be used to control heterogeneous vehicles) and therefore are controlled by the same architecture. This simplifies the prediction problem greatly and subsequently the Recursive Modeling Method (Durfee, 1995) can be utilized. Using this method the local agent’s decision making algorithm is used to predict a plausible next step of other agents by passing in their information. This prediction system avoids the infinite prediction loop by only predicting what a certain vehicle is going to do next and not factoring in its own prediction algorithm. This allows for simple yet accurate predictions while keeping computation overhead low.

This architecture contains an AUV Monitor module that keeps track of the AUV Database and makes predictions for vehicles when the time since last communication rises above a certain threshold. Utilizing the most recent data from the AUV Database (last known position, average speed, current goal, etc.) the AUV Monitor can estimate the current position of the vehicle. It can then update the Mission Model should the predicted position indicate that the vehicle has achieved its current goal (in this case the updated status is recorded in the mission model with a predicted flag). The AUV Monitor can calculate the most probably next goal of any other vehicle by passing the AUV information into its own goal selection algorithm (Section 3.4.1) and updating the Mission Model with the output, flagged predicted. When communication returns, the Mission Model is re-synchronized and the predicted values replaced with actual data.
3.4.4 Mission optimization

As multiple vehicles are working together and constantly updating a common plan, in certain cases the current goal for a certain AUV may become less suitable than another during execution. Rather than force complete execution on any goal attempted, this architecture has a Mission Monitor module that keeps track of the Mission Model and constantly checks to see if the current goal is the best possible choice by re-running the algorithm shown in Figure 6. Should it be determined that this is not the case, the current goal execution is stopped and goal selection is run again. In this way the system ensures that each vehicle is always performing the best possible action.

In the cases of intermittent communications, it sometimes occurs that two AUVs are found to be executing the same goal. The Mission Monitor is able to detect this and calculate which AUV is most suited for execution. Because this module is running on both vehicles and each one has information about the other in their AUV database, they will in theory come to the same decision (The exception to the rule is when vehicles have the same capabilities and are exactly equidistant from the goal, however due to the amount of precision in the position this is unlikely and has so far yet to be observed.).

4 Experiments

To evaluate the ability of the DELPHÍS system it was tested to see how its coordination efficiency compared to the current state of the art in multi-AUV control architectures. The tests aimed to show that in addition to being faster and more efficient than the leading system it is also far more robust and able to handle the loss of communication common in multi-AUV missions.

This work was first evaluated in simulation by testing it against the leading multi-AUV coordination system (Script-based stoplight control). As mentioned in Section 2.4.1 these architectures are the most common ones used for the multi-AUV coordination systems currently in use. In addition two alternate versions of the DELPHÍS system were also tested, each with specific optimization modules turned off to show their effect. These systems were tested in a range of communication success rates for two different mission vignettes, representing two common applications of multi-AUV systems today: mine countermeasures and pipeline tracking. Experiments were evaluated for efficiency and the systems’ performance was compared.

Following the simulated experiments real vehicle trials were conducted. The goal of these trials was twofold. Firstly it was important to demonstrate the ability of the DELPHÍS system to successfully coordinate real AUVs in the real world. Secondly the results from the trials acted to validate the results recovered in simulation and support their accuracy. This section will explain both the simulated and real experiments.
4.1 Systems

This work was tested by comparing the performance of the DELPHÍS system with that of the state of the art in multi-AUV control. This section will describe these systems in more detail.

4.1.1 Multiple AUV - Stoplight

Section 2.4 described the current state of the art in multi-AUV operations, namely script-based, stoplight systems. In this study these systems were represented by a heavily restricted BIIMAPS mission plan that functioned like a script. Each mission was essentially broken up into pre-scripted sections (one for each vehicle), the number of which dependent upon the number of expected AUVs operating in the system.

For instance in a typical mine countermeasures mission there are two main objectives: search an area and identify mines (and eventually neutralization, though this part of the mission was left out of this study for simplicity sake). To represent a script-based, stoplight system these objectives were each restricted. In a two vehicle operation the mission was broken up so that one vehicle performed the search while the other investigated the targets. As more vehicles were added to the operation, the search was broken up as evenly as possible by the user before the mission, with one vehicle assigned to target identification.

In addition to the limitation of the BIIMAPS plan, all the mission optimization functionality of the DELPHÍS system was turned off. In this way the current state of the art in multi-AUV operations could be easily tested.

4.1.2 Multiple AUV - DELPHÍS

The second system being tested is the architecture created in this study, the DELPHÍS system (section 3). Unlike the previous control system this system executes the mission dynamically and aims to remain efficient in the presence of less than optimal communication environments.

4.1.3 Multiple AUV - DELPHÍS (Un-Optimized)

To help demonstrate the usefulness of the mission optimization functionality the DELPHÍS system was also tested with these modules disabled. These modules include prediction and dynamic goal optimization described in sections 3.4.3 and 3.4.4 respectively. This system was compared to the optimised DELPHÍS system to show the benefit of such modules.

4.1.4 Multiple AUV - DELPHÍS (Prediction Failure)

In addition to testing the DELPHÍS system with its mission optimization tools disabled it was also tested with one of its mission optimization tools functioning incorrectly. In this case the prediction module was set to predict events twice as fast as they were actually
happening. The aim was to show that even with incorrect prediction the DELPHÍS system would be able to successfully control multiple vehicles better than the stoplight system.

4.2 Efficiency Metrics

In order to accurately compare these different approaches to multi-AUV coordination, there needed to be a value or metric that could be tested in a controlled experiment. In this work, efficiency was determined to be the most suitable value. Before this could be used as a comparison value however it had to be formally defined. To do this a number of characteristics were selected that have the most effect on efficiency in multi-AUV operations: mission speed, mission accuracy and target acquisition.

Speed is important in AUV missions because the faster an area can be cleared and/or data recovered the faster the results can be exploited. Mission accuracy is also necessary as any missed goals create gaps in the data and redundant goals waste system resources unnecessarily. Finally related to mission accuracy is the acquisition of targets where failure to do so completely can be very dangerous.

4.2.1 Mission Speed

Mission speed is defined as the time required to complete the mission. In this study it is given a value by determining how closely it relates to the expected mission time as recorded by the DELPHÍS system time when run with 100% communication. Thus the mission speed metric \( t \) is:

\[
t = \frac{\text{time}_{\text{expected}}}{\text{time}}
\]

If the mission time returned is longer than the expected time \( t \) can range from 0-1, the higher the number the faster the time. If mission time is less than the expected time \( t \) will be greater than 1. This rewards systems for speed.

4.2.2 Mission Accuracy

In this study mission accuracy is defined by the number of goals that have been missed as well as those that have been accomplished more than once. The missed goals metric \( m \) is calculated by subtracting the number of missed goals from the total number of goals and then dividing by the total. The formula for missed goals is:

\[
m = \frac{\text{goals}_{\text{total}} - \text{goals}_{\text{missed}}}{\text{goals}_{\text{total}}}
\]

Mission redundancy \( r \) is calculated by a similar method except the total number of goals is weighted by 2. This effectively gives goal redundancy half the weight of that of missed
goals. This was done because it was deemed that missed goals should affect efficiency more than redundant ones. In addition this is also because a goal can effectively be redundant more than once. The formula for mission redundancy is:

\[
    r = \frac{2(goals_{total}) - goals_{redundant}}{2(goals_{total})}
\]

For both missed and redundant goals the values range from 0-1, the higher the number of missed and redundant goals the lower the value of m and r respectively. This penalizes systems that return missed and redundant goals (though redundant goals are weighted less as just explained).

### 4.2.3 Target Acquisition

Target acquisition \((x)\) is defined as the percent of targets that were detected and subsequently investigated. This is calculated by dividing the number of investigated targets by the total number of targets expected to be in the world. The formula used is:

\[
    x = \frac{targets_{detected}}{targets_{total}}
\]

Like the mission accuracy values the target acquisition value ranges from 0-1, the higher the value the more targets that were discovered. Again, this penalizes systems for missing targets.

### 4.2.4 Evaluation Formula

Mission efficiency is calculated by taking the previous 4 metrics and combining them into the following formula:

\[
    efficiency = 100(t \times m \times r \times x)
\]

Using this formula efficiency values normally range from 0-100, with 100 being perfect efficiency. An important note is that this value in theory can rise above 100 in the case where the mission time is faster than the expected time. This will be described in more detail in section 5.

### 4.3 Mission Vignettes

This study uses two common applications for multi-AUV systems to compare the different approaches: mine countermeasures and pipeline tracking. These two mission vignettes are currently the most important applications of multi-AUV technology to the military and offshore industries respectively and both are being currently undertaken on a regular basis.
As described in section 3.1 BIIMAPs plans can be generated either by a high level mission planner or by a human user. Because in this study it is the mission executive that is being tested, not the planner, missions were written by the user to avoid unnecessary complexity. Each mission was written using simple waypoint goals and no customization was required for either vignette. The two scenarios used in these experiments will be described here.

### 4.3.1 Mine Countermeasures

The mine countermeasures mission used in this study consists of an area search with targets to be identified. The area search is done via a lawnmower search pattern that can be broken up into individual legs so vehicles can break up the task. There are 5 simulated targets in the world for the vehicles to discover. A diagram of the mission can be seen in Figure 7a.

In practice targets are discovered by an onboard CADCAC (Computer Aided Detection, Computer Aided Classification) system, however to simplify this experiment a simulated target acquisition system was developed and utilized. As targets are discovered they are added as new goals in the mission plan. The lawnmower legs are 40m long and spaced 10m apart. Compared to most MCM missions this is a rather compact search however due to the number of trials run in this experiment a smaller mission is proportionally faster while remaining long enough to prove the concept.

### 4.3.2 Pipeline Tracking

The pipeline tracking mission used for this study contains many of the same traits of the MCM mission previously described. As shown in Figure 7b it consists of three tracks: one low altitude track over the pipe for camera inspection and two higher altitude offset tracks for sidescan sonar.

Each leg has been broken up into sections so that like in the MCM mission vehicles can break up the task. Each sub-leg is 30m long and mission legs are spaced 10m apart. Again, like the MCM mission, this mission is smaller than most pipeline tracking missions to allow
for many experiments.

4.4 Methodology

It is often necessary to run experiments in simulation before they are demonstrated on real platforms. In this study this was not only a good idea but also very necessary for a number of reasons. First of all because of the large number of variables that were to be tested large numbers of experiments were required to obtain sound data. To run over 1000 experiments with real AUVs isn’t a viable option especially since the differing environmental conditions could add an unwanted skew to the data. Simulation provides a consistent environment between trials to maintain data comparability.

In this research a highly accurate dynamic model of an intervention AUV was utilised. This model was created in the Ocean Systems Laboratory and reproduces with a high level of precision the way that these types of AUV handle in the water. Using this in conjunction with the real embedded auto-positioning system allows for extremely accurate control of the vehicle in simulation. Because it responds to the same messages that real OceanSHELL enabled vehicle do, when simulation is complete, the dynamic model can be simply unplugged and replaced with the AUV with very minor if any code modification. In these tests the environment was not simulated however noise was included in the simulated inputs to the navigation module so as to mimic the real environment. This allowed tests to focus specifically on the decision making abilities of the system.

In simulating acoustic communication it was decided that the lack of information being passed between vehicles was most important, rather than the acoustic communication itself. A special message was created using the OceanSHELL system that contained the information that was to be sent acoustically. This message was then sent on a separate port reserved for and representing a simulated acoustic channel. To simulate acoustic message loss a module was created that simulated the worst-case scenario where all vehicles were unable to communicate. Messages were prevented from being received by blocking the acoustic message port. This was done in a controlled manner so that the user could enter the percentage of messages that should be let through and the maximum length of time that communication could be down. A random duration in seconds was selected between zero and the entered maximum. Communication would be allowed for the percentage entered by the user and then prevented for the remaining seconds.

For each experimental vignette each of the four control systems were tested in simulation using 1, 2, 3 and 4 vehicle operations (This work is designed to handle many more than 4 vehicles however because of the computational load caused by simulation on one computer 4 was the largest size tested in these experiments.). For each number of vehicles, a range of communication loss was tested. For each communication rate (100-10% in 10% intervals) each system was run 10 times. Data was then analyzed and the efficiency value calculated using the formulas described in section 4.2.

Despite this requirement to run experiments in simulation when working with systems designed for real vehicles it is important to validate the simulated results on real platforms.
The inconsistent environment of the real world that could impede testing is in itself one of the main challenges that can trip up simulation-only systems. By testing this work on real vehicles the aim is to both show that it can handle the hostile environment of, as well as prove that the tests conducted in simulation were valid representations of, the real world. By showing that real world trials return comparable results to the simulated trials the simulations themselves are validated.

Therefore in addition to the aforementioned simulated experiments tests were carried out using real vehicles to validate the simulated results. Using REMUS and Nessie a number of MCM missions were carried out to prove the ability of the system in the uncertain environment of the real world. These two platforms will be described in more detail in the next section.

4.4.1 Vehicles

Nessie (Figure 8a) is an intervention AUV built in the Ocean Systems Laboratory to compete in the Student Autonomous Underwater Challenge Europe (SAUC-E) competition (DSTL, 2008; Cartwright et al., 2008), of which it was the 2008 and 2009 champion. Nessie can move in 4 degrees of freedom and has the ability to maintain position with a high amount of accuracy. Sensors on board include binocular forward and down facing cameras, DVL and acoustic modem. On board navigation is calculated via dead reckoning from a known GPS origin. Its relative small size and weight results in an extremely powerful platform that is extremely easy to work with.

The Remote Environmental Monitoring UnitS (REMUS) AUV (Figure 8b) is an industry standard AUV. Unlike Nessie this is a transit AUV which means it flies through the water much like a plane through the air. Though it lacks the hovering capabilities of an intervention AUV, it is significantly faster and can cover a lot of sea in a relatively small amount of time. Sensors include sidescan sonar, DVL (both downward and upward facing) and acoustic modem in addition to a host of environmental sensors (water temperature, salinity, etc.). The REMUS AUV can navigate using a GPS however in these trials it uses a pre-deployed LBL system. In addition to its sensors the Ocean System Laboratory REMUS AUV also
includes a PC104 computer which was used to run the DELPHÍS System. This computer is able to request control from the REMUS control system allowing the DELPHÍS System to command the vehicle in the form of waypoints.

The REMUS vehicle was chosen for its speed, sidescan sonar and proven ability in the field. Nessie was selected as the second vehicle due to its relatively small size and manoeuvrability. These different capabilities serve to highlight the functionality of multi-AUV missions while demonstrating the ability of this research to coordinate heterogeneous platforms.

5 Results

This section will present the results of the aforementioned experiments. First the simulation trials will be presented followed by the in-water validation trials.

5.1 Simulation Results

Using the data collected about redundancy, missed goals, target acquisition and mission time, the efficiency of each mission run was calculated for each system type. In the MCM vignette for all three vehicle group sizes the un-optimized DELPHÍS system showed a clear decreasing trend in efficiency as communications worsened (Figure 9). The efficiency of the DELPHÍS system with prediction failure performed well in most situations only showing a decreased efficiency in the very low communication rates. The optimized DELPHÍS system recorded even higher efficiencies, remaining close to 100% in all three group sizes. It too was affected by only very low communication rates and in these scenarios only very slightly.

The stoplight system efficiency varied depending on the group size. In the 2 vehicle scenario (Figure 9a) the system was initially notably less efficient than the DELPHÍS systems. This was because of the extra long time it took to accomplish the mission. In fact in the 2 vehicle scenario the mission time was the only negatively contributing factor to efficiency as there were no redundant or missed goals and all the targets were acquired.

As more vehicles were added to the system however the data changed. Where it recorded the least efficiency before, now in the 3 vehicle scenario (Figure 9b) the stoplight system improves and surpasses that of the un-optimized DELPHÍS system. This is mainly due to a decrease in mission time as compared to the un-optimized DELPHÍS system though the increase in redundant goals had a slightly negative affect as well towards the lower range of the communication rate. In the 4 vehicle scenario (Figure 9c) the efficiency is virtually the same as with 3 AUVs. This is because though the mission time improved, the goal redundancy increased as well, consequently negating any time benefit in the efficiency equation.

An interesting note is that initially the stoplight system starts off with an efficiency value above 100%. This is because in full communications the stoplight system was able to accomplish the mission faster than the optimized system, which at 100% communication is the benchmark for comparison.
Figure 9: Simulated MCM vignette results.
Figure 10: Simulated Pipeline Tracking vignette results.
The pipeline tracking mission efficiency data showed many of the same trends as the MCM data. In the 2 and 3 vehicle scenarios (Figures 10a and 10b) the un-optimized DELPHÍS system again showed a clear decrease in efficiency as communications lessened. The prediction failure and optimized DELPHÍS systems also repeated the trends seen in the MCM mission vignette with the optimized system staying close to 100% efficiency and the prediction failure system either reflecting the same result, as in the 2 vehicle scenario, or falling just below it. Like with the stoplight system in the 4 vehicle MCM scenario the optimized DELPHÍS system’s efficiency rises above 100% in both the 2 and 3 vehicle scenario (so does the prediction failure system). This is for the same reason mentioned before where in these cases the system was accomplishing the mission faster than it did in 100% communications.

The stoplight system’s efficiency was again dictated mostly by time. In the 2 and 3 vehicle scenarios efficiency starts off significantly lower than that of the other 3 systems. This is due to the longer time required to accomplish the pipeline tracking mission with the stoplight system. As expected, efficiency dropped with the communication rate though not as steeply as the un-optimized DELPHÍS system.

The 4 vehicle pipeline tracking scenario (Figure 10c) showed somewhat different results than the previous two scenarios. Here the 3 DELPHÍS systems showed the same relationship to each other with the un-optimized system recording the worst efficiency, the optimized system recording the best and the prediction failure system falling just below the optimized. In all 3 systems however efficiency decline was greater than in previous scenarios. In addition, the stoplight system showed an entirely different trend compared to its past performance. Rather than starting off significantly below the others in terms of efficiency and slowly decline it started off better and only barely dropped below the 100% efficiency mark.

There are two main explanations for this change in relationship between the 4 multi-AUV systems. First of all as in the MCM vignette the more vehicles added to the system the harder it is to coordinate behaviors, especially in the lower communication rate environments. This in combination with the fact that the pipeline tracking mission vignette is more complicated than the MCM (9 legs as opposed to 5 results in more goals and consequently more decisions that need to be made and predicted by other vehicles) is the most likely cause for the steeper efficiency decline in the 3 DELPHÍS systems. The cause of the stoplight system’s efficiency improvement is much simpler. As it turns out the stoplight approach to coordinating 4 vehicles in this mission is most likely the best solution. In fact, as shown in Figure 10c, the efficiency of the stoplight system is initially far above 100% due to the initial high mission speed described in the previous section. The stoplight system is still affected by the complexity of the mission which accounts for the dip in efficiency as communication makes coordination more and more difficult however it still remains very efficient.

Though mostly clear there are few trends in the results that without explanation stand out, namely why efficiency doesn’t show a consistent decrease with communication. This can be explained by the relatively small sample size (10 repetitions) for each communication rate and the random nature of the acoustic communication simulation. A good example can be seen in the data for the un-optimized system in the 4 AUV MCM mission. As shown in Figure 9c the efficiency spikes towards the lower end of the communication spectrum. This was because simulated acoustic broadcasts were by chance received at crucial times thereby
minimizing the need for prediction. Because for each communication rate there were only 10 trials these anomalies didn’t get averaged out. Interesting future work would be to increase these sample sizes to confirm this hypothesis.

5.1.1 Key Performance Indicator

When looking at this data it is important to look back upon the original metrics used to calculate multi-vehicle efficiency and determine which had the greatest effect on the results. In this research the most influential metric, or key performance indicator (KPI), was mission time. Although there were only minor benefits over the stoplight system in terms of goal redundancy, missed goals and target acquisition the DELPHÍS system was far better at keeping mission times down due to its ability to optimize on the fly. Conversely the stoplight system was unable to resolve mission conflicts and wasted a lot of time, often resulting in an inability to complete the mission (due to a simulated battery life constant in all systems). This had a major effect on efficiency and shows a clear benefit of the mission optimization techniques of this research including agent prediction and dynamic goal re-selection. It also illustrates the need for a more robust control architecture that can handle the kind of coordination errors that are likely in practice.

5.2 In-Water Results

As mentioned in section 4.4, in addition to the simulated trials the DELPHÍS system was also demonstrated in the real world by coordinating a mine countermeasures mission with the AUVs REMUS and Nessie. Trials were conducted to both validate the simulated results as well as demonstrate the ability of the DELPHÍS system (fully optimized) in the presence of real world environmental factors, mainly communication unreliability. Initial trials to demonstrate coordination between a real and simulated AUV were run at Threipmuir
5.3 AUV/Simulated AUV Trials

Once the DELPHÍS system had been validated on the vehicles and the acoustic communication functionality tested the next step was to begin the coordination trials. Before putting two vehicles in the water together however, tests were conducted between a real AUV and a simulated one. The goal was to have a real AUV in the water coordinating acoustically with a simulated vehicle operating on a computer on shore. This would prove the system able to handle the difficulties of in water acoustic communication without the complexity of two mobile robots. Trials were carried out at Threipmuir Reservoir on September 18th, 2008 and aimed to show coordination between Nessie and a simulated vehicle. The mission demonstrated was a small MCM consisting of 4 30 metre legs and 2 simulated mines. A diagram of Threipmuir Reservoir and the mission can be seen in Figure 12a. It is a small, shallow body of water with the mission executed in between 3 and 5 meters of water.

Three separate experiments were run to test the coordination ability of the DELPHÍS system. In the first experiment the lawnmower leg super-goals (made up of two completion and execution locked waypoints) were encompassed in a “Search” super-goal and restricted by both execution and completion locks. This resulted in only one vehicle being allowed to execute the search. In this test Nessie started the mission first and completed the lawnmower while a simulated vehicle investigated discovered targets as they were added to the plan. The second experiment removed the “Search” super-goal so that both Nessie and the simulated
AUV could attempt the lawnmower concurrently. This resulted in the search being split up between the two vehicles dynamically. To simplify this test the mine detection ability was deactivated on both vehicles. The third experiment however reactivated the mine detection ability resulting in vehicles splitting up the search task and the investigate tasks.

Data from these experiments showing the behavior of both Nessie and the simulated vehicle can be found in Figures 12b, 12c and 12d. Nessie’s path is represented in blue with the simulated vehicle path shown in dotted gray. Note that in these figures paths are used to illustrate task order and do not show the actual track of the vehicle which was slightly less smooth due to navigational sensor noise.

5.3.1 Trial 1

In the first trial the mission was limited such that only one vehicle could attempt the search. Because Nessie started first this goal was selected resulting in the simulated vehicle having to wait in a holding pattern until goals (discovered targets) became available. Once the first target was discovered the simulated vehicle began the investigation process. The second target however was investigated by Nessie. This was the result of the second target being discovered during a period of no communication between the vehicles. It was shown that Nessie predicted that the simulated vehicle would attempt the recently discovered target. In the time between this prediction and the completion of the “Search” super-goal (waypoint 8) Nessie received an update from the simulated vehicle that showed that in fact the target was not being executed and was therefore reset to available in the mission model. Before the information of the original target discovery could be broadcast Nessie began investigating the second target. This trial also illustrates accurate prediction of vehicle intention, specifically the simulated AUV prediction of Nessie actions as shown by the accurate predictions of waypoints 3, 4, 5 and 6.

5.3.2 Trial 2

Trial 2 removed the target discovery aspect of the mission (by turning off the simulated CADCAC system) but also removed the limitation on the search so that multiple vehicles could concurrently achieve the goal. This resulted in the lawnmower being broken up into its component legs. The mission was completed as expected with Nessie executing a majority of the legs due to its higher speed as compared to the simulated vehicle. The simulated vehicle attempted execution of waypoint 7 but stopped, as can be seen in the aborted path in Figure 12c. This behavior was due to a period of no communication and a delayed and therefore incorrect prediction. Nessie predicted that the simulated vehicle would next attempt waypoint 3 when in fact it was seconds away from executing waypoint 7. Due to this incorrect prediction Nessie proceeded to finish its current goal and start waypoint 8, a goal in an execution lock with waypoint 7. During this execution Nessie sent a broadcast alerting the simulated AUV to the problem which resulted in it’s aborting the goal. Goal redundancy was avoided and the mission was completed without a problem.
5.3.3 Trial 3

In trial 3 the simulated CADCAC system was re-enabled while the search remained unconstrained resulting in both AUVs being able to detect targets. As can be seen in Figure 12d the search was broken up between the vehicles and targets were investigated as they were discovered. Due to their high priority targets took precedence over search legs and therefore were investigated as soon as they were available. However due to a minor mine classification bug on this trial targets were incorrectly duplicated resulting in vehicles seemingly investigating targets more than once. In addition it can be seen that Nessie attempted waypoint 7 while the simulated AUV was already executing that locked leg. As in trial 2, the DELPHÍS system was able to recognize this conflict and resolve it, avoiding any mission redundancy.

5.4 Multi-AUV Trials

Having demonstrated the ability of the DELPHÍS system to coordinate a real AUV with a simulated one the final test was to replace the simulated vehicle with a real platform. Held from September 30th to October 2nd trials were conducted at Loch Earn to demonstrate coordination between the REMUS and Nessie AUVs. Like the Threipmuir tests the mission was a lawnmower consisting of 4 legs (200 meter) and 2 simulated mines. A diagram of the mission and Loch Earn can be found in Figure 13a. Unlike Threipmuir Reservoir, Loch Earn is a large, deep body of water with depths surpassing 70 meters. This mission occurred in 40-50 meters of water.

Due to the speed difference between REMUS and Nessie (2.0 and 0.4 meters per second respectively) the lawnmower legs were again encompassed in an execution and completion locked “Search” super-goal so that only one vehicle (in these trials REMUS) could attempt it. A number of trials were run with REMUS conducting the search and Nessie investigating discovered targets. The data from these experiments can be found in Figures 13b and 13c. Again, as mentioned in Section 5.3 tracks shown aren’t exact but are used to illustrate goal order.
5.4.1 Trial 1

In trial 1 the mission was executed exactly as expected however due to the last target’s location being so close to the end of REMUS’s last leg it was taken on by REMUS before being broadcast to Nessie. This resulted in the targets being split between the vehicles, as can be seen in Figure 13b. An interesting behavior was discovered in this trial and then witnessed in all the following multi-AUV trials done during this trip. When the vehicle executing the last available goal in the mission (in this trial this was REMUS executing the second target) finishes the goal it recognizes the mission is complete and exits just after a final message is broadcast to notify other AUVs of its status. However in the real world experiments where communication was unreliable this broadcast is often not received. Despite this, Nessie was able to predict that REMUS had finished the goal thereby rendering the mission complete.

5.4.2 Trials 2 & 3

For the remainder of the trials (2 & 3) the second simulated target was moved north by about 40 meters so that the Nessie vehicle would have a better chance of selecting it before REMUS. Although the data returned after the first trial was good, it was thought that by moving the target Nessie would be more active and this would act as a more difficult scenario for the DELPHÍS system to coordinate. This proved successful and in both trials 2 and 3 Nessie executed both targets while REMUS waited in a holding pattern following the completion of the lawnmower search (Figure 13c). In both trials the prediction of the mission completion behavior mentioned in the previous section was evident. In addition trial 3 showed more examples of prediction where Nessie was able to correctly predict the actions of REMUS within reasonable degrees of time error. In both trials 2 and 3 the mission completed successfully with no redundancy or missed goals.

Having proved the DELPHÍS system able to coordinate two real AUVs the same mission was performed in simulation using the same communication rates observed during the in water trials. Results showed that the mission was executed in exactly the same manner and thereby validated the results obtained in simulation.

5.4.3 Simulation Validation

To validate the simulated findings of this study the multi-AUV mission run at Loch Earn with the real AUVs REMUS and Nessie was also run in simulation. Using simulated versions of both vehicles the exact same mission used in the real tests was run. The Nessie vehicle was programmed to broadcast information every 29 seconds to mimic the average 28.23 seconds seen in the trials and REMUS was limited to broadcast every 159 seconds to represent the average time between unique broadcasts. Aside from these modifications all the code used was the exact same as in the aforementioned real world experiments.

As was expected the results from this simulated experiment was virtually identical to the data returned from the in water trials (particularly trials 2 and 3 as this experiment used the updated target position). As REMUS executed the lawnmower search, Nessie waited in a holding pattern until targets were available. Once these targets were discovered and
broadcast (both were broadcast at the same time due to communication lag) they were executed in turn. This simulation also mimicked the prediction behavior explained in section 5.4.1 when Nessie finished the second target.

6 Conclusion

This research has investigated the use of a multi-agent based control architecture to coordinate multiple autonomous underwater vehicles and to increase efficiency over the state of the art. Through the use of real time vehicle prediction, blackboard-based hierarchical mission plans, mission optimization and a distributed multi-agent based paradigm the DELPHIS system was successfully able to increase the efficiency of multi-AUV operations in realistic communication environments. Results were presented in the form of simulation trials and validated via in-water trials with the REMUS and Nessie AUVs.

The work presented here has a number of immediate benefits for multi-AUV operations both in the military and offshore sectors. First of all mission definition is far simpler. Users only have to define one mission and don’t have to worry about what each vehicle will do to accomplish said mission or even how large the group will be since this is all handled by the system at runtime. Another benefit of the DELPHIS system is its ability to optimize on the fly. This optimization takes many forms from vehicle intent prediction to the ability to add more vehicles as required while the mission is being accomplished. These benefits have been shown to minimize mission errors and consequently maximize coordination efficiency in realistic environments. This functionality is unavailable to current multi-AUV coordination systems thereby proving the worth of this research.

With these benefits in mind there are a number of research areas that can be studied further. The prediction functionality of the DELPHIS system is one of the main aspects that allows it to return such favorable coordination results in poor communication environments. This functionality could be improved by exchanging predictions across vehicles so that a local prediction could be used and possibly confirmed by other vehicles in the collective. In addition although predicting the next move for AUVs in the system proved to work well, extending the prediction module to make decisions more than one step ahead could improve performance. Other research directions could include the use of a mission planner to plan and re-plan missions on the fly. Currently missions are written by the user however the inclusion of a planner such as that found in (Patrón et al., 2008) would allow the system to recover from situations where the current mission is found to be unachievable.

In the end the choice of the DELPHIS system over the current state of the art simplifies to flexibility. Though stoplight systems can successfully coordinate multiple vehicles in good conditions this research has shown that when these conditions deteriorate so too does mission coordination efficiency. The DELPHIS system can maintain efficiency in a much wider range of conditions and this makes it a good choice for multi-AUV operations.
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References


