Natural Language-Based Correction Method for Autonomous Underwater Vehicle Communications

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Abstract—**University of Idaho (UI) researchers have designed and constructed a fleet of autonomous underwater vehicles (AUVs) that are used to investigate a range of collaborative behaviors. The fleet was initially developed to investigate the use of AUVs to detect and inspect sea mines and mine-like objects in mine countermeasure (MCM) missions. Due to the collaborative nature of the mission, communication is critical to success. The nature of underwater acoustic communication is such that bandwidth is severely limited and errors in messages frequently occur (i.e only 80-90% transmission successes). In this paper we describe a method for correcting messages with errors by anticipating the possible messages being sent. This approach to message anticipation views fleet communication as conversational, allowing application of concepts related to natural human language. Because all the AUVs share the same language and the logic associated with that language, they can all anticipate, to some extent, the message being sent by another AUV. We refer to the use of language and its logic to anticipate and evaluate future hypothetical scenarios as language-centered intelligence (LCI). By applying the principals of fuzzy logic and probability, we expand upon previous message anticipation work at UI and demonstrate that such an approach can be used to repair the majority of a specific class of errors.**

Keywords-Message anticipation, error correction, UUV, acoustic communication, natural language, hypothetical reasoning, language-centered intelligence

I. Introduction

The University of Idaho (UI) fleet of autonomous underwater vehicles (AUVs) as seen in Fig. 1 relies heavily on collaboration and communication during missions. Because the AUV fleet communicates acoustically and in an underwater environment, noise and its effects can interfere with message transmission. Specifically, at typical separation distances for the missions being performed by our AUVs, it has been found that communication success lies in the range of 80-90% [1]. The AUVs use Woods Hole Oceanographic Institute (WHOI) modems [2] for acoustic communication. These modems employ error-checking methods during message receipt to find and eliminate the failed messages but cannot correct them. This paper details a method where the language and the logic used by the AUVs along with the principals of natural language communication are used to correctly anticipate inter-vehicle communications and improve fleet performance by correcting errors in messages. The use of language and its associated logic to anticipate and evaluate future hypothetical scenarios is referred to as language-centered intelligence (LCI) [3,7,8].

In some fundamental manner, human intelligence and language are closely related. Clearly, we are the most intelligent animal on this planet and also the one having the most developed language. Try formulating a thought without using words. Certainly, visualization can be used in some

Fig. 1. UI AUVs in preparation for field testing.

thinking processes but even these processes usually make use of words in helping define or explain any pictures formed in the brain. What role, then, did language play in developing our intelligence? Is language required for our intelligence or simply an artifact or outcome of our intelligence? Because our robotic research deals with acoustic communication, cooperative behavior, and language, a number of similarities between human and robotic behavior can be recognized. Understanding the way humans behave and process information may be very helpful, in a bio-mimetic manner, for robotic development. Alternatively, robotic development may provide some information on how humans developed.

Humans are remarkably adept at correcting messages and use the internal logics that determine message structure (i.e., the syntactic language logic), message content (i.e., the semantic language logic), and implications that can be drawn from messages taken together with facts about human behavior and the operating environment for this purpose. In fact, some of

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the first "thinking" that humans may have done with language was probably thinking about what was said, both the sounds and context. Improving the message transmission rate or being able to correct the corrupted messages in actual practice would be very welcomed and perhaps, in some sense, the AUVs are evolving in a manner similar to humans.

In particular, mine countermeasure missions (MCM) require the use of position estimates, command structure, formation flying and vehicle task data – all of which rely heavily on active inter-fleet communication. During MCM missions, the AUVs attempt to locate and identify mine-like objects (MLOs) in a pre-defined search field. To accomplish this task the subs have a dynamic mission goal and a robust set of allowed (and necessary) cooperative and individual behaviors within the mission framework; as such, this type of mission provides a great opportunity for analysis of communication structures and logical processes. AUV operation within this mission context provides a language and logic that is rich enough to start using correction methods associated with natural language.

II. Natural Language and Anticipation

The key to the goal of anticipating an expected message lies in the understanding of that message (and related communications) in terms of natural language. In human interaction – in conversation as well as reading – predictions of future words are made continuously [3]. Further, it has been found that the predictions are made on a probabilistic basis (i.e. several possibilities for an upcoming word may exist, each with a different probability) and that these probabilities vary as more information becomes available [4].

It seems reasonable, then, that the foundation for the project of message anticipation should be rooted in the means by which humans engage in the same activity. In [5], it is noted that contextual clues not only color a listener's anticipation of what is to come, but can have an effect even on the recognition of the contents of a message. It appears, then, that anticipation of a message is critical to understanding in natural language communication, and that such anticipation is rooted in the context of the conversation. This is further corroborated in [6] and [7], in which researchers draw upon evidence based in event-related brain potential to conclude that anticipation is rooted in the context of the message.

A. *Message Anticipation*

The evidence suggests that message anticipation in human communication is strongly rooted in the content and availability of contextual information. Given the strong support for this conclusion, it is reasonable to attempt to view the AUV communications as having at least some of the properties of natural human language. As such, it is helpful to understand the communication (in particular, communication during a MCM mission) as a conversation occurring between the active subs in the fleet. Each sub waits for its turn to "speak," then communicates some information relevant to the mission. The particular aspects of this conversation will be discussed in section III.

Due to the heavy influence of context on the ability to anticipate and the content of that anticipation, it is worth mentioning at this point that the UI fleet of AUVs has a previously-designed structure in place that provides a great deal of contextual data to the fleet despite the relative isolation of the subs from one another during missions. This can be seen primarily in the construction of the map [8]during and after the mission; greater detail will be provided in section III.

B. *Meaning in Conversation*

Towards the goal of anticipating future pieces of a conversation, it is important to understand the meaning of what has transpired previously. Each word or phrase carries with it a meaning to both the sender and receiver upon which future actions might be based and which is contingent upon past actions and inputs. The task of interpreting the conversation falls to the studies of semantics and pragmatics, in which the meaning of a word or sentence can be determined in a variety of ways.

In the context of an AUV conversation, we will take semantics as pertaining to the meaning of a word insofar as it might be considered as an input for a sub hearing that word or an output from a sub saying it. In this sense, a set of definitions can be applied to the various words in the language used by the AUVs and sets of words can be strung together to form meaningful phrases.

The pragmatic meaning of a word then applies to the things which might have influenced or which might be influenced by its utterance. These comprise the sets of contextual factors and implications which go along with any given word or phrase in an AUV conversation.

1) *Definitional Meaning*

Definitional meaning pertains to the specific, assigned meaning to each word in a sentence. For example, the word "clock" corresponds to "a mechanism for tracking the passage of time." Likewise, each word in an AUV communication has a basic, assigned meaning that lets both AUVs and researchers understand what is being said.

The definitional meaning of a word also relates to the basic syntax of the bit string upon which the word is based. It can be viewed as a tool for getting back and forth between the basic computer language of the subs and the conversational level of the communications.

2) *Implicational Meaning*

In addition to definitional meaning, words and phrases also carry additional meaning in the form of logical implication. If a person says that he is rowing a boat, there is an implication that he is on a lake. If a sub communicates that it is a trailer, there is an implication that it is not the leader. Although not necessarily connected to the definitional meaning of a word, the implicational meaning gives us a basis for generating knowledge about the mission which is not communicated directly. There is also a level of predictive implication which can be applied to AUV communications. For example, it is often the case that certain aspects of a message will be repeated in consecutive communications from a single AUV; thus, a given message carries with it an implication that the next message from that AUV will be the same. Although this is not always the case, it occurs frequently enough to require that a repeated message be at least considered in any anticipation scheme.

It is important to note that implicational meaning in this sense is not always a direct, one-to-one correlation between word and implication. In the above example, there is obviously a possibility that the next message could be different from the last. Many implications, then, do not take a hard *modus ponens* format; rather than "if A then B," implicational meaning in AUV conversation often takes the form of "if A then probably B." As such, it can be useful to consider anticipation from a probabilistic point of view.

3) Contextual Meaning

A word can carry additional levels of meaning (either implicational or definitional) that are dependent upon the context in which it is uttered. An example in English is the word "mouse," which can be taken to mean either a species of small, furry rodent or a tactile input device for a computer. Although the specific intent of the speaker is almost never explicitly stated in conversation, it will nearly always be readily clear to the listener based on contextual clues both within and outside of the conversation.

In AUV communication, an example of this contextual ambiguity can be seen primarily in the reporting of tasks which are being carried out during the mission. Because there are a limited number of words used to describe these tasks, it is often the case that interpretation relies on previous communications and other contextual factors. For example, a single word is used to describe every condition in which a sub is out of formation; this can cover situations ranging from normal mission operation (i.e. the sub is returning to formation after performing a task) to navigation failure and a lost sub.

As with the implicational meaning, the contextual meaning is frequently not a direct correlation between word and meaning.

III. MCM MISSIONS AND AUV STATUS

The primary goal for an MCM mission is to search a specified area for mines and to discover and report the exact location of all mines in the area for possible elimination. Because the AUVs must thoroughly cover the search area and remain close to each other in order to collaborate, a simple lawnmower-sweep pattern was used where the AUVs move in a formation [8]. In order to maximize fleet effectiveness, the subs swim in a formation with swimmers side-by-side leading the sweep and trailers following and inspecting mines as commanded by the leader (the leader is one of the swimmers). This formation, illustrated in Fig. 2, uses a leader-follower control strategy where the leader broadcasts its position and the other AUVs adjust their position based on the location of the leader. This approach provides broad sensor coverage to reduce the number of passes made in a given mission area and has sufficient flexibility to locate and inspect each mine-like object, MLO, for mapping purposes.

A. Map Development

The combination of a known sweep pattern and a known formation allows the AUVs to make estimations of fleet positions despite the bandwidth restrictions and limited position communications. Because each AUV has a designated position within the formation, a single position broadcast from the leader allows any AUV to estimate its position relative to the leader and whether or not it is in formation. Also, any AUV can estimate the position of all the other subs, assuming they are in formation. Of course if an AUV is not in formation, there is insufficient information available for any other sub to estimate its position.

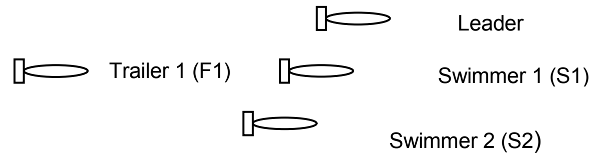

Fig. 2. Leader-follower formation in a four-sub mission. A full fleet consists of five AUVs and will have an additional AUV in the trailer position.

The mapping strategy adopted at the UI [8] for MCM missions accommodates AUVs operating in a low-bandwidth acoustic communication environment. This strategy uses mapping logics to facilitate the creation of a decentralized map of the search area by multiple AUVs working collaboratively. The UI logics rely on acoustic communication among the AUVs. The communication scheme and logics allow each AUV to create a multi-layered map with both low-resolution and high-resolution components. The low-resolution layers are based upon smaller, more frequent communications among AUVs, and include position estimates for other vehicles, search area coverage, estimated MLO locations, and potentially dangerous areas. The low-resolution information is available as a function of each AUV's position estimate for the rest of the fleet, and is based on formation knowledge and status reports. The high-resolution map utilizes larger, less frequent messages, as well as the information gathered by the individual AUV (and therefore unrestricted by communication) to record data about MLO locations and classifications.

Fig. 3 demonstrates the difference between the information contained in the low-resolution map (left) and high-resolution map (right). The low-resolution map, developed in-flight individually by each AUV, relies on fleet position estimates and the information available through communication. The high-resolution map is generated in post-processing by combining the data collected by each sub. Although the low-resolution map contains inaccuracies, the approximate fleet status estimate by each AUV in real time is closely representative of what the vehicles are finding and how they are moving. The multi-layered approach also provides the benefit of data redundancy. Because of the potential for dropped messages and irrecoverable vehicles, it is possible for important information to be lost during the course of an MCM mission. Maintaining a redundant store of data increases the likelihood that all significant information will be available to operators after a completed mission.

B. AUV Language and Communication

Communication between the UI AUVs relies on low-bandwidth acoustic messages that are transmitted and received by a Woods Hole Oceanographic Institute (WHOI) modem [2]. Among the modem's capabilities is a synchronous communication cycle, in which broadcasts by each member in a fleet occur in a designated order and at the top of the second. This scheme is used during MCM missions to provide the AUV fleet with a sufficient number of communications for

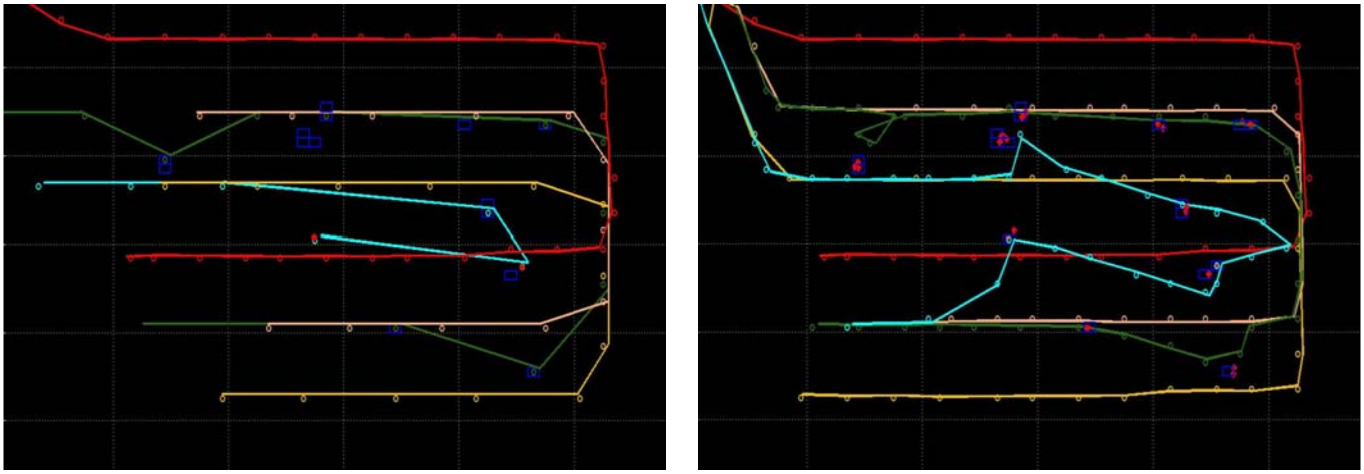

Fig. 3. Comparison of low-resolution (left) and high-resolution (right) maps. The low-resolution map is generated by each AUV in real-time and provides a useful state estimate of the fleet.

navigation and mission completion, and the regularly-timed structure is useful in post-processing.

Due to the low-bandwidth requirements imposed by the nature of acoustic communication and the WHOI modem, a dialect of AUVish designated AUVish-BBM [9] [10] has been developed that distributes the subs' communications between 13-bit and 32-byte messages. The 13-bit, low-informational messages are relayed frequently to help maintain formation stability and provide the fleet with regular updates about any new information or discoveries (such as a newly-detected MLO). This information is used by the leader to determine the contents, if any, of command messages it broadcasts. Other subs use this information to generate a low-resolution map (based on position estimates) of the fleet's course during the mission and any MLOs found.

The 32-byte, high-informational messages are less frequent but contain more detailed information. While the 13-bit messages are used primarily as a method of fleet maintenance and formation stability, the 32-byte messages are primarily used to direct and report objectives related to the mission goal including an accurate location for a mine. The leader uses these messages as a platform for fleet organization and command, as well as to record and catalog fleet operations and MLO locations.

It is worth noting that AUV communication shares important features with human vocal communication. Relevant among these are the facts that both can be considered to be low-bandwidth and both are prone to error. Compared with modern electromagnetically-based communications that transmit messages with rates measured in megahertz or gigahertz, the ability to transmit a single 13-bit message in a two-second window (see Fig. 4) is a very low amount of data; the same can be said about human vocalizations, in which only a few words can be transmitted in that time period.

As discussed in [1] and in Section V of this paper, AUV acoustic communication is frequently hindered by dropped or error-laden messages. It is easy to compare this to human vocal communication: we often stumble over our words, finding ourselves unable to find the appropriate word or mixing the first part of one word with the last of another. As discussed previously, humans have a great faculty for understanding these garbled sentences despite their poor form, gaps in communication and misplaced or meaningless words. This largely has to do with our ability to anticipate what is going to be said next or what word should go in place of a missing or otherwise broken word. It stands to reason, then, that AUV communication can benefit from a similar process of anticipating and replacing lost or garbled messages.

1) Communication Cycle

Communication within the fleet of AUVs during a MCM mission consists of a repetitive cycle during which each sub relays 13-bit and 32-byte messages as designated by the communication protocol or the fleet leader. While each 13-bit message takes only 200 milliseconds to send and each 32-byte message takes only 3.2 seconds, extra time is allotted to allow for timing errors and to prevent message overlap and subsequent loss of data. Each AUV also has an additional one-second window used for independent location of the fleet by a long baseline (LBL) array of tracking transponders (this data can be used in postprocessing to more accurately determine fleet position throughout the mission).

The resulting communication cycle is seen in Fig. 4. It consists of a 3-second window for each sub to ping the LBL tracking system and relay a 13-bit message to the fleet; an empty window reserved for fleet or mission expansion; a 6-second window in which the formation leader broadcasts a command message; and a 6-second window in which another sub has an opportunity to relay additional information requested by the leader.

2) 13-Bit Messages

During MCM missions, 13-bit messages are the primary mode of communication between subs. They relay low-payload updates amongst the fleet about each sub's status and provide information which is used in formation maintenance and assignment of mission-related tasks. To this end, the 13-bit message structure has been divided into four distinct fields seen in Fig. 5 below.

The first of these fields is the sub's role. Consisting of three bits, it describes the vehicle's current position in the formation. The role field itself is divided into two parts: the first bit is the sub's formation role while the following two are its index within that role. Specific to MCM missions, the formation role consists of either swimmer or trailer, while the index extends to three swimmers and two trailers. The function of each role

30-second communication cycle

Sub 1		Sub 2		Sub 3		Sub 4		Sub 5		empty	Command	Assigned
LBL	13b	LBL	13b	LBL	13b	LBL	13b	LBL	13b	---	32x	32x
1s	2s	1s	2s	1s	2s	1s	2s	1s	2s	3s	6s	6s
Cycle Start		→				time		→				Cycle End

Fig. 4. Standard MCM mission communication cycle with 5 AUVs.

within the formation and mission context is discussed later in this paper.

The second field is a single bit that indicates whether or not the broadcasting vehicle is the current formation leader. The specifics of this position are discussed later; for now, it is sufficient to describe the field's function.

The third field in each 13-bit message is the connection vector (CV). Each of the four bits in this field is representative of one of the four vehicles in the formation (with the fifth being the transmitting vehicle). The CV bits serve as indicators of the success of communication from each vehicle during the last message cycle. If the transmitting vehicle received a message from a sub in the previous communication cycle, its corresponding CV bit will be a 1; if not, a 0.

The last field and the remaining five bits comprise the task field, describing the current action being carried out by the broadcasting sub. Although it encompasses thirty-two possible tasks, only six of these are used in MCM missions. Among these are: inactive, in formation, out of formation, mine found in formation, mine found out of formation, and inspecting. The remaining twenty-six available tasks either are not used in MCM missions, or are classified as "invalid" and reserved to allow for future expansion.

Formation Position	Leader Flag	Connection Vector	Current Task
3 bits	1 bit	4 bits	5 bits
13-bit Message			

Fig. 5. AUVish-BBM 13-bit message structure.

3) 32-Byte Messages

For the purposes of this paper, the contents of the 32-byte message can be divided into two types: information and commands. Messages containing information consist of: progress reports (such as the leader's progress between waypoints); mission-specific data (such as the location of a mine-like object (MLO) that has been found); or general sub status and environmental data (such as a sub's remaining battery power).

Command messages are issued by the fleet leader and designate specific changes to formation or sub behavior in order to complete mission objectives. In general these contain mission start and abort commands, formation changes and specific action commands. Significant to this paper are: role replacement commands in which one sub assumes the role of a missing or lost vehicle or two subs are otherwise directed to change roles; inspection commands in which a sub is directed to investigate an MLO that has been found and reported previously; and MLO report commands in which a sub is instructed to relay a 32-byte message containing information about an MLO it has located.

Both 13-bit and 32-byte messages are required to implement the behaviors for doing MCM missions. For example, upon locating a MLO during formation flying, a sub will report a "mine found in formation" in the Task field of its next 13-bit message. This allows the fleet to estimate the MLO's position based on the position of the reporting sub at low accuracy. In order to complete the mission goal of generating a high-resolution map of the MLOs within the search field, the leader will respond by issuing a 32-byte command for the next available trailer sub to inspect the area around the estimated position of the MLO. During inspection, the trailer will report "inspecting" as its Task in the 13-bit message; upon completion it will report the results in a 32-byte message and return (reporting "out of formation") by estimating the fleet's position based on latest progress update from the leader.

IV. LCI AND MESSAGE ANTICIPATION MODULE

In previous work at UI, the use of language and its logic to anticipate and evaluate future hypothetical scenarios has been used to improve the collaborative efforts of the AUV fleet when inspecting MLOs in an MCM mission. We refer to this paradigm as language-centered intelligence (LCI) [11] which is a type of artificial intelligence. As has previously been discussed, the communications between cooperating AUVs can be used to estimate the status of each AUV in order to create a map of the area of interest. With this estimate of the AUV status, LCI can be used to also anticipate the message or possible messages that will be sent by the next communicating AUV.

A. LCI Architecture

Fig. 6 shows the AUV control architecture with the LCI module separate from the standard control module. These modules and their logics are separated to reflect the fact that the standard module will still function if the LCI module does not exist. Note that the memory and language logic appears in both the LCI and standard modules. The memory includes both a message history and the layered map generated from all the AUV messages.

The LCI modules use all available real data as well as hypothetical and anticipated information generated by the LCI modules themselves to evaluate future scenarios. The relevant conclusions based on these future scenarios are passed to the behavioral logic module, which uses the information to make decisions about the AUV's upcoming actions [12]. The relevant conclusions based on these future scenarios are passed to the behavioral logic module, which uses the information to make decisions about the AUV's upcoming actions [12]. The hypothetical information is only included in the LCI system so that it is not confused with the real information being used in the Standard Control System. This is also the reason for having two separate memories and language logics. The control actions generated by the Standard Control System should be

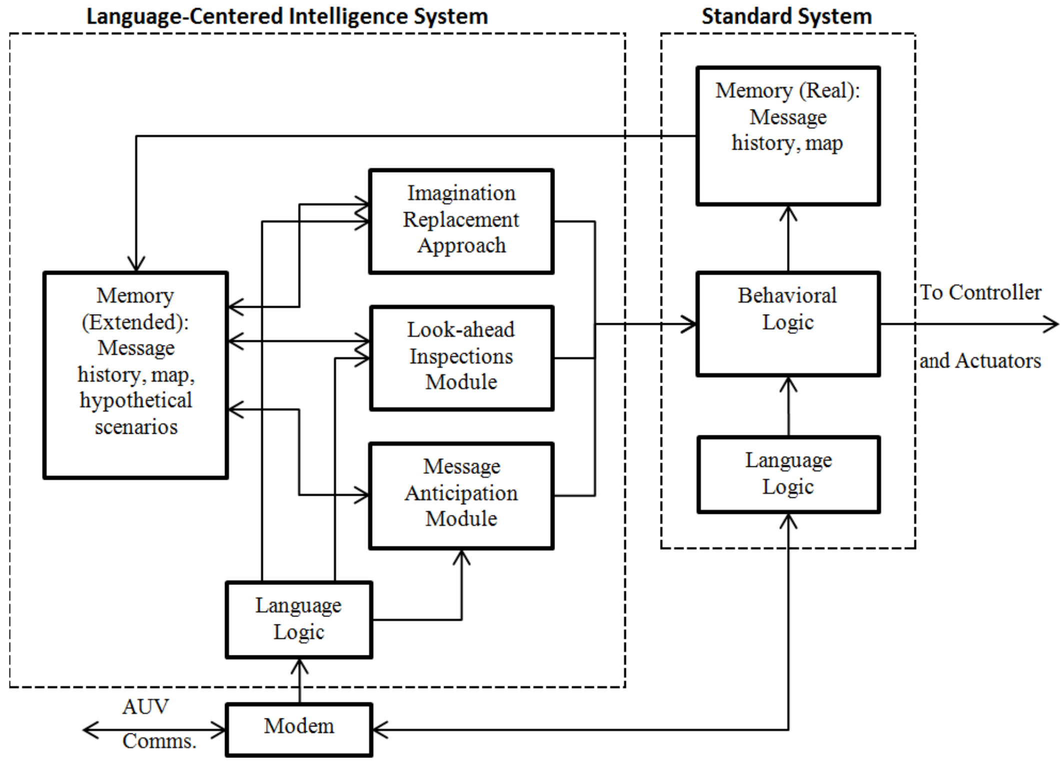

Fig. 6. LCI architecture and interaction with standard AUV controls. Hypothetical data is considered in the IRA, LIM and MAM. The results are considered in conjunction with real data when making control decisions.

based on the real messages and data and only modified by the anticipated or imagined scenarios generated in the LCI module.

B. Message Anticipation Module Development

The Message Anticipation Module (MAM), shown as one of the LCI modules in Fig. 6, is used to correct corrupted messages received by an AUV. The process for correcting the errors begins with the MAM module generating a list of anticipated messages. These anticipated messages are dependent on the status of the AUV. The list is generated by first estimating the most likely status of the transmitting AUV and then including other potential sensor information or communications that would affect that status.

C. Message Anticipation

From the map and previous communications, all the listening AUVs have a very good idea of the status of the transmitting AUV. In general, this status will probably be what the AUV transmitted on the last cycle but not always. If the AUV was reassigned by the leader (for example a trailer was used to replace a swimmer), then the new transmitted message would be different from the previous one and would reflect this change in status. By listening to the previous communications between the leader and the AUV, however, all the other AUVs would be aware of the change in status. This information would be processed by each AUV and their map updated. The most likely anticipated message for this status can then be generated by sending that perceived status into the "language/logic" module and generating the message associated with that status.

When the transmitting AUV has information not available to the other AUVs, then the transmitting AUV status would not be known to the other AUVs. However, these new status states can be estimated because the type of information an AUV receives is known. This information could be from its sensors (i.e. MLO found), the navigation system (i.e. out of formation), or communications (i.e. did not hear from an AUV). The possible status states associated with this new information are then used to generate the other anticipated messages. Again, the anticipated messages for these situations would be produced by sending the estimated status of the AUV as the input to the "language and logic" module.

Fig. 7 shows a schematic diagram of how the list of anticipated messages is generated. One input to the module in the diagram is the present status of the transmitting AUV as defined by the memory that includes both a history of the messages and the map. The other inputs to the module include the possible information available to the transmitting AUV but not the other AUVs. These inputs are used to help define the possible status of the transmitting AUV. All these possible states are then fed into the language/logic module to generate the list of anticipated messages. This list of anticipated messages (see Fig. 8) constitutes the Anticipated Message Array (AMA) which is used in determining what, if any, corrections need to be made when a message is received. Each of the possible methods for arriving at a possible anticipated message can be viewed as a single rule; these can be used (discussed in section V) to determine the weighting applied to each anticipated message in the AMA.

The MAM for each AUV compares every received message with all the anticipated messages in the AMA for that transmission. If no error occurred in the message transmission, then the comparison is used to compile statistics on the likelihood that a particular anticipated message is sent (see last column in Fig. 8). If an error did occur, then the number of bits needed to be flipped in the corrupted message to duplicate each message in the AMA is determined.

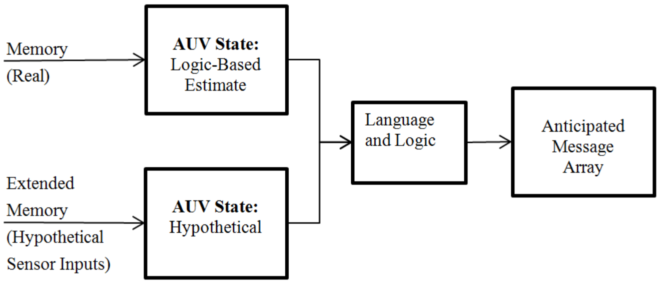

Fig. 7. The Message Anticipated Module (MAM) utilizes existing logical structures along with real and hypothetical memory of the AUV fleet to provide state estimates of the sub that will broadcast next. The state estimates are leveraged to anticipate the contents of the coming broadcast, and the resulting possible messages are combined into the Anticipated Memory Array (AMA) for later comparison with the actual received message.

These two pieces of information, the likelihood that an anticipated message will be transmitted and the number of flipped bits required to duplicate each anticipated message, are calculated and used to correct the errant message. Two methods are used to select the anticipated message that will be substituted for the corrupted message. One is based on probability and the other employs a trained fuzzy logic system.

Fig. 8 illustrates the process for correcting a corrupted message. The MAM first generates a list of anticipated messages. From the previous history of correct messages, the probability is estmated for each anticipated message being sent. The anticipated messages are then ordered according to highest possibility of being sent. This information, the likeliness of the message being sent, along with the number of flip bits needed to correct the corrupted message is used to find the original message.

Further shown in Fig. 8, a trained fuzzy logic system is used to select the correct, anticipated message. The system is trained using previously-recorded mission data and a comparison between each message in the AMA and the actual received message (including messages with and without errors).

D. Machine Learning

The previously-described method of message anticipation and correction has an important feature that contributes to its robustness: it takes into account the reasoning and logical structures that give meaning to the communication cycle rather than simply utilizing the raw communications data. As a secondary method of message anticipation, it is possible to reduce the complexity of the system and train a message anticipator on nothing more than the information available to the subs.

Using this method, we ignore the significance of the data and allow the anticipation algorithm to train and predict results based on communications data alone. As a simple example, we might consider the case of direct probability estimation for a simulation in which no vehicles are lost and no communications are dropped. By counting the total number of each type of entry in each message field over several runs, we can determine the probability that each entry will occur in any given message (again, disregarding context). Figure 9 contains statistical data for a typical run on this scenario; the leader, one swimmer and one trailer were sampled. As expected, both the leader and swimmer have a majority report of “In Formation” for their Task field. The trailer’s Task report varies widely

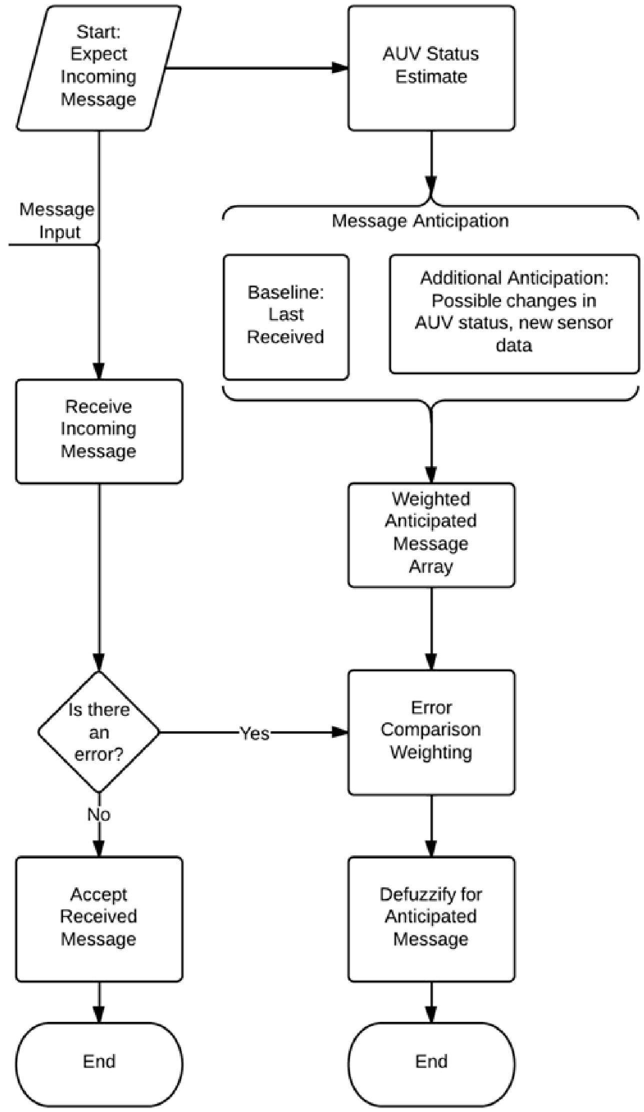

Fig. 8. The internal architecture of the Message Anticipation Module. An AMA is generated for each incoming message and used to correct the message if the WHOI modem determines that it contains an error.

from run to run, depending largely on the distribution of MLOs in the sweep area. In this case, the trailer reported “Inspecting” more often than anything else as its Task. The Connection Vector field (AUV Comms) is trivial in this scenario. A simple probability-based anticipator would use this data, and data from additional simulated runs, to anticipate the next message for an AUV by selecting the most likely Task field based on the expected Role (in this case, Role could be anticipated by the current location in the communications cycle).

More complex machine learning methods are also available. For comparison, we developed an anticipation strategy featuring a feed-forward artificial neural network capable of anticipating incoming messages.

The network was trained to generate the next, anticipated, 13-bit message, based on the previous five, 13-bit, error-free messages (one full communication cycle). Each input and output to the neural network is one message; the network has 65 neurons in its input layer (13 bits times 5 messages) and 13 neurons in its output layer. The network was created using Matlab’s neural network library. The network has one hidden layer with 10 neurons. The activation function for all of the neurons was a sigmoid function. Backpropagation, using Matlab's default settings, was used for training.

V. Message Anticipation Simulation and Results

To simulate and test the application of the message anticipation logic we used a previously-developed software package called the Autonomous Littoral Warfare Simulation Environment – Monte Carlo (ALWSE-MC). This is the same software used by the researchers in [13] to generate strings of messages to test error correction algorithms. Based on the past success of this method, a similar approach was adopted to test the new anticipation logic.

A. Mission Simulation

The ALWSE-MC software suite includes the ability to model internal vehicle logic, inter-vehicle communications, and vehicle dynamic capabilities. Using previously-developed vehicle dynamics, communications and vehicle logics [13], we generated a series of message histories. Each history consisted of the entire record of 13-bit and 32-byte communications for a single MCM run with a pre-designated sweep pattern and randomly-distributed mines. The runs were performed without communications errors or losses.

Because the AUV fleet communicates acoustically and in an underwater environment, noise and its effects must be taken into account. Specifically, there is a chance for any given communication to become distorted during transmission; at typical separation distances during a MCM mission it has been found that 13-bit communication success lies in the range of 80-90% [1]. The error-checking methods employed by the WHOI modem during message receipt find and eliminate the failed messages.

Operating under the assumptions that the errors in any given message occur randomly and with equal probability on each bit and that they consist of one or more bits being flipped from the correct value, this error rate can be extrapolated to find the rate at which different numbers of bits are flipped. Under these assumptions, errors in a 13-bit message string can be modeled using a standard binomial distribution

$$P(error) = \sum_{e=1}^{13} \binom{b}{e} BF^{e}(1-BF)^{b-e}$$

where b is the number of bits (13), e is the number of errors and BF is the probability of an individual bit being flipped. Setting the value of the overall probability to the above error rate in 13-bit communications (0.2 to 0.1) allows a solution for the probability BF; this ranges from approximately 0.008 to 0.017, corresponding to P = 0.1 and 0.2 respectively.

B. Weighting and Error Generation

Because the mission histories were generated without communication errors, it was possible to use them in determining the weights for each rule that would be applied in the message anticipation algorithm. Ignoring the first and last two message cycles (during which the mission is initializing or concluding and the standard message cycle is inapplicable), a selected rule could be analyzed by searching for instances in which it would be fired. For example, it is a simple matter to search the "same as last message" rule and weight it according to how often it occurs in a large sample of communications. Comparing the total possible number of applications for that rule against the number of successful applications yields a simple percentage-based weighting for the rule.

It is important to note that calibrating the message weights in this manner links the resulting logic to a particular set of circumstances within the mission; of primary importance here are the designated sweep pattern and the presence (or absence) of failure-inducing obstacles or conditions, such as counter-countermeasures designed to destroy or disable an AUV. Changing this set of conditions can significantly affect the frequency of various behaviors, leading to reduced effectiveness of a weighting based on different conditions.

Once the anticipation weights were determined, a MATLAB script was developed to randomly seed errors in a selected mission history. The errors were generated on a bit-by-bit basis using the previously-described binomial distribution model. Selected bits were flipped from their actual value, and the message was given an error flag.

C. AMA Generation and Defuzzification

Using this script, it is possible to rapidly seed errors in a message history and subsequently attempt to repair them. Operating on a message-by-message basis simulates the conditions of the (simulated) live run from which the message history was generated. At each step (each message) in the simulation, an AMA is generated by each sub against the possibility that the expected incoming message will arrive with errors or will fail entirely. In this simulation, the available mission context was limited to communication data only, including the previous five 13-bit messages and the last 32-byte message (one full communication cycle).

The simulated communication process, including message anticipation and error correction, follows the earlier-described process shown in Fig. 9. The AMA is generated while the message is being "sent" (accessed in the history in this simulation) and randomly seeded with errors. If the message is found to contain an error, the AMA is accessed and the previously-described method of error-based defuzzification is applied. The resulting message is substituted for the error-laden or missing message, and the mission continues. If the message arrives without errors, it is accepted and the AMA discarded.

D. Results

Statistical data collected indicate that the great majority of errors introduced using this method can be repaired. In this context, a message can be considered to have been "repaired" if the defuzzified anticipated message matches the original, uncorrupted message.

Vehicle	LF	ROLE	TASK	AUV Comms	Probability
Leader	Leader	Swim 1	In Form.	All AUVs	83.9%
			Out Form.	All AUVs	1.2%
			Mine Found	All AUVs	14.9%
Swimmer	not Lead	Swim 2	In Form.	All AUVs	89.2%
			Out Form.	All AUVs	1.7%
			Mine Found	All AUVs	9.1%
			M.F. Out Form.	All AUVs	0.0%
			Inspecting	All AUVs	0.0%
Trailer	not lead	Trailer 2	In Form.	All AUVs	29.9%
			Out Form.	All AUVs	25.3%
			Mine Found	All AUVs	0.0%
			M.F. Out Form.	All AUVs	1.1%
			Inspecting	All AUVs	43.9%

Fig. 9. Message field rates for specific entries across a simplified ALWSE simulation in which no vehicles fail or are lost and all communications are successful.

Table 1 shows the results of a 2000-run simulation using a random selection from 10 different message histories, each of which contains approximately 400 13-bit messages. The rate at which errors were introduced at each level corresponds approximately with the binomial distribution described previously, indicating a successful error-generation algorithm. The results demonstrate a 98.8% success rate in repairing messages with errors. By comparison, the machine-learning approach using the feed-forward artificial neural network was able to successfully anticipate 87% of all messages. With these error correction schemes, the overall success rate for transmitting a message is improved from 90% to 99.88% for the LCI method and 98.7% for the machine learning method.

Bits Flipped in Error Message	Successful Repair Attempts	Failed Repair Attempts	Success Rate (%)
1	80047	976	98.80
2	3233	596	84.43
3	73	25	74.49
4	4	1	80.00
Overall	83357	1598	98.12

Table 1. Data from 2000 simulations of error generation and correction over 10 individual message histories using the AMA bit-comparison approach.

In making a comparison between the results of the various anticipation and correction methods detailed, the method of error generation is significant. In this case, errors were seeded throughout the mission using a pseudorandom number stream in MATLAB, so it is reasonable to conclude that the set of messages with errors is a random subset of the set of all messages. For this reason, the neural network anticipation results can be extended to the set of messages with errors; that is, the reported 87% anticipation rate among all messages is the same rate that would be expected when anticipating against only messages with errors. Thus the neural network method can be said to show an 87% success rate when correcting messages with any type of error – an overall message transmission success rate of 98.7%.

While this is a lower rate than the MAM-based approach, it is significant in that the message itself is not an input to the error correction algorithm. This method of correction completely ignores the incoming message (except to check if an error exists) and is therefore generalizable to any class of error possible within this type of message. The MAM approach, having been developed under the assumption that the number of bits will remain constant in both correct and error messages, is limited to errors in which one or more bits are "flipped" from their correct value. It is possible that future work could expand the MAM and eliminate this assumption, but at this time the neural network method provides a high-accuracy correction method for communications models which are not limited to a particular type of error.

It is important also to consider the implementation cost of each approach. The MAM approach requires a complex logical structure for evaluating hypothetical scenarios and the capability to track contextual information in order for one AUV to closely estimate the status of the other members of the fleet. By contrast, the neural network method requires a processor powerful enough to run the network, and the ability (prior to a mission) to train the network – something which can often be accomplished using previously-acquired real or simulated data. Without the previously-existing architecture on which the MAM was constructed, it is likely that the neural network (or other similar method) would have been the primary consideration for error correction in this system.

Although the purpose of this paper was not to speculate about how the human brain functions, drawing analogies between how our AUVs function and the human brain can perhaps provide insight into both. Miller argues that a linguistic interchange between individual systems is a prerequisite to system-level learning in compound system such as a social group or, in this case, a fleet of cooperating AUVs [14]. In the development of this AUV learning system it was difficult to find a clean break between the processing and logical structures, and the language and the communications themselves. As shown in Figure 6, the language block in our system is referred to as the Language Logic block for this reason; the AUV software both decodes and processes the message.

VI. Conclusion

The data indicates a very high success rate for errors of the type in which one or more bits in a message are flipped.

Currently, the WHOI modem rejects outright any message with an error, leaving a gap in the receiving AUV's awareness of the current mission status; considering that roughly anywhere between 10 and 20% of messages become corrupted, a 98% recovery amounts to one to two additional messages received every two communication cycles. This arguably represents an increase in the effectiveness and autonomy of the AUVs. The leader sub is more likely to have all the information necessary to send out the appropriate command message and, more importantly, is less likely to miss a Task report of "mine found." Given a search pattern designed to maximize coverage and efficiency, a missed report of a located mine is likely to mean a mine that is overlooked.

It is also important to note that the anticipation and correction method is successful for errors in which more than a single bit is flipped, where previous message anticipation work [13] has focused only on a single flip. Using computer simulations and randomly flipping bits, we have found that the MAM presently being used can improve the success rate of transmitting a message from about 90% to 99.8%. In contrast, the NN anticipation module correctly anticipated only 87% of incoming messages. However, the NN is performing "pure" anticipation with no error correction. The generated message is an anticipation of the expected message based on the previous five messages, but doesn't use the current, erroneous, message as part of its input.

This paper describes and demonstrates an application of the LCI paradigm developed at UI. We present evidence that a natural language-based understanding of AUV communications can be applied in conjunction with the principals of fuzzy logic and probability to correctly anticipate incoming messages and correct errors when they appear. Due to the high occurrence of errors in acoustic communication, this increase in communicative capability is likely to correspond to increases in an AUV fleet's ability to collaborate and operate autonomously. It is possible that to some degree, the apparently separate functions of language and logic are in fact inseparable at a fundamental level in both human and cooperative robotic systems.

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