Learned Anticipation Strategy for Speed Control in an AUV Fleet

Juan Marulanda
Department of Computer Science
University of Idaho
Moscow, Idaho 83844
Email: maru2593@vandals.uidaho.edu

Dean Edwards
Department of Chemical & Materials Engineering
University of Idaho
Moscow, Idaho 83844
Email: dedwards@uidaho.edu

Robert Heckendorn and Terence Soule
Department of Computer Science
University of Idaho
Moscow, Idaho 83844
Email: {tsoule, heckendo}@uidaho.edu

***Abstract*—Researchers at the Laboratory of Artificial Intelligence and Robotics (LAIR) and the Center for Intelligent Systems Research (CISR) from the University of Idaho (UI) have developed a message anticipation module for use by members of a fleet of autonomous underwater vehicles (AUV). The test scenario is a magnetic signature assessment (MSA) task, in which a fleet of five AUVs must simultaneously pass under a moving Target Ship (TS) at a predetermined location. During the task the TS informs the AUVs regarding its progress, allowing the AUVs to meet the TS at that measurement point despite variations in the TS's velocity. However, the underwater acoustic modems used by the actual AUVs are both low bandwidth and noisy. Thus, messages from the TS may be infrequent or erroneous. The goal of the anticipation module is to anticipate the TS's messages and, when necessary, use the anticipated message to fill in gaps left by dropped or erroneous messages. Successful anticipation depends on an agent having a good knowledge of its environment and mission. Research has shown that anticipation of words and sentences is central to human communication and language understanding. An agent that utilizes similar anticipation methods and is capable of using artificial intelligence techniques to generate, utilize, and adapt its message anticipation module with a more accurate one, would represent a significant advance in autonomous agents. Five different anticipation models were created, 4 of them are based on a neural network model and one of them is based on a fuzzy logic controller model. In order to test effectiveness, robustness, and adaptability of the models used in the anticipation module, multiple tests were conducted in which the behavior of the target ship and the gap between messages were varied. All of the tested anticipation models were able to significantly reduce the error in the meeting point when there was a gap between messages.**

Keywords - Intelligent control, neural networks, fuzzy logic, anticipation

I. Introduction

Currently, autonomous agents are severely hampered by their inability to effectively and efficiently address novel, changing, or noisy environments, conditions, and missions. Agents are capable of operating autonomously with considerable success, which demonstrates the potential of autonomous agents, but the successes are within limited and accurately predefined, and relatively noise-free, environments and missions. More widespread, effective use of autonomous agents will remain out of reach until they are capable of autonomously adapting to noisy and changing conditions.

A common difficulty for autonomous vehicles acting in concert is lost or erroneous messages, either due to communication errors or to human error. Such communication difficulties lead to unexpected changes in the environment (e.g. if the agent receives incorrect information about the environment or fails to receive important information) and create a noisy operating environment. Thus, the goal of this research is to develop a method by which agents can learn to address the particular problem of noisy and/or low bandwidth communications. Our approach is to include an *anticipation* module that allows autonomous agents to anticipate future messages based on previous messages and current mission conditions. When messages are lost or erroneous, the anticipated messages can be used to either fill in for the missing message or help correct erroneous messages.

This article is divided as follows: Section II presents a brief overview of previous work and research which the ideas in this paper are based on. Section III presents a description of the simulated environment used to recreate a magnetic signature mission using 5 AUVs. Section IV presents two different artificial intelligence methods (artificial neural networks and fuzzy logic) that solve the communication problem recreated between the group of submarines and the ship. Section V presents the 3 behaviors and 3 communication situations used to test the accuracy and robustness of the system. Finally, section VI presents some relevant conclusions of the project and the results.

II. Background

This project is part of an on-going project on using Autonomous Underwater Vehicles for multiple tasks including mine-countermeasure (MCM) and magnetic signatures assessment (MSA) missions which are being developed at University of Idaho (UI) ([1], [2], [3], [4], [5], [6], [7]). Because these tasks require coordination between multiple (2-5) AUVs, accurate communications are critical. Thus, a major concern is the low bandwidth and potentially unreliable nature of underwater communications. In this paper, we test the use of anticipated messages as a mean to overcome the limitations of the communication system. Anticipation is a strategy that has been tried before for other types of problems including trying to imitate the natural language of humans in order to correct acoustic messages between Unmanned Underwater Vehicles (UUV) [8] and helping a simulated robot used inside a video game anticipate player movement [9]. Both approaches use previous, but not necessarily full, knowledge about the desired behavior of the model to increase prediction accuracy during the tests. However, the anticipation strategies are not the same as are used in this paper. The anticipation used in [8] is based on a linguistic logic which analyses the structure of a binary string using syntactic, semantic, pragmatical and behavioral logic. In [9], the anticipation strategy is based on a set of general rules which allows the robot to generate a plan in order to ambush the other player in specific situations effectively. Both strategies are based on static rules and use several variables to get the information from the environment to make a decision. In this research, we present two additional strategies for anticipation, which use flexible rules, limited information from the environment, and one of the models is capable of learning.

In [10] and [11], anticipation is used to predict a stock price behavior. Each article describes a different strategy to solve this problem: [10] solves this problem by using a neural network and [11] uses fuzzy logic model. Both articles used real stock prices values as input data in order to predict future behaviors. The results showed that these models are capable of solving this type of anticipation problem. Other similar approaches to solve this problem also use a neuro-fuzzy model [12] and a model based on support vector machines (SVM) [13]. This work supports the idea that anticipation is a promising approach although in that research it was not applied to robotic agents.

Following these ideas the Center for Intelligent Systems Research (CISR) at UI has developed a computational architecture called Language-Centered Intelligence (LCI) which allows autonomous agents to reason hypothetically about their environment and mission via ”anticipated” observations [1]. These anticipated observations guide the agent in its mission and serve, when compared to actual, future observations, to measure the accuracy of the current model, thus, mitigating the risk of identifying a failure in current model.

The test problem in this research is a Magnetic Signature Assessment (MSA) mission which uses a fleet of AUVs to record the magnetic signature of a target ship (TS). The AUVs must pass under the TS in a pre-defined measurement zone, allowing them to measure the TS’s magnetic signature. In a full mission the TS makes two to four passes through a measurement zone; if two passes, then one East/West pass and one North/South, and if four, then one pass in each of the cardinal directions. During each pass through the measurement zone, the fleet of AUVs passes underneath the ship. The system assumes that there is a sufficient number of AUVs to capture all of the necessary data for each direction with a single pass and that the AUV fleet approaches the ship from the opposite heading (i.e., bow to bow). The simulation used in this research to test the anticipation models is based on one pass in the MSM.

III. Environment

The simulation environment was developed using C# and the AForge library for the AI resources. The environment simulates one pass of the MSA mission with a focus on the control of the group of AUVs using the communication link

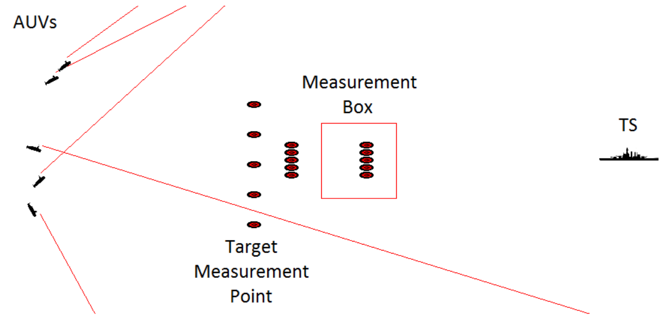


Fig. 1. Simulation environment for the anticipation tests showing a typical starting configuration. The five AUVs are on the left, their initial positions are semi-randomized and their headings are random. The target ship (TS) is on the right, it always begins with the same position and heading. Ovals are the AUVs’ waypoints.

with the TS. In the simulation, the TS regularly broadcasts its current progress toward the measurement box to the AUVs. Using this information, the AUVs are able to adjust their current speed in order to maintain formation and reach the meeting point at the same time as the TS. The metric of success is how close the AUVs are to the center of the measurement box when they pass under the TS. A fuzzy logic controller on each AUV is in charge of this function, it uses the current progress of the AUV and the message that it receives from the TA to determine speed. The heading of the AUVs is determined by 3 sets of waypoints, which are used to calculate the current progress of the AUVs (the sets of ovals in Figure 1). To increase the complexity and realism of the problem, the AUVs are assigned random starting positions and headings in each run. Figure 1 shows a group of AUVs and the ship at the start of a mission run. Figure 1 also shows the waypoints along the path of the AUVs (ovals).

The TS can be configured with any of 3 different behaviors that, in general, make the TS change its speed and/or its acceleration in different sections of a mission. This behavior forces the AUVs to vary their speed accordingly, in order to reach the measurement point at the same time as the TS. The TS behaviors are described in detail later in Section V. The AUVs initially have no information about which behavior was chosen for TS, thus they must rely on the messages from the TS to reach the measurement point at the same time as the TS.

IV. Methods

The simulation determines how the TS behaves and how often the AUVs receive messages from the TS regarding its progress. The TS uses a fuzzy logic controller to control its speed. The controller calculates fuzzy membership in five variables that measure progress. These five fuzzy values are sent as the message from the TS to the AUVs. The five fuzzy variables are: way behind, behind, on schedule, ahead, or way ahead, and are calculated based on the initial, scheduled meeting time (Figure 2). Each variable can have a value between 0 and 1, but, because the message is informing about a specific state of the TS, there can be only at most 2 variables whose value is greater than 0.

The ship sends messages at specific, adjustable intervals. Longer intervals represent limited bandwidth or a noisy en-

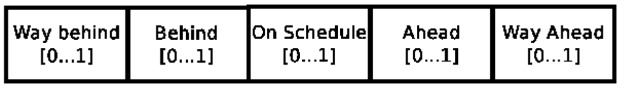


Fig. 2. Messages from the target ship (TS) consist of five fuzzy values.

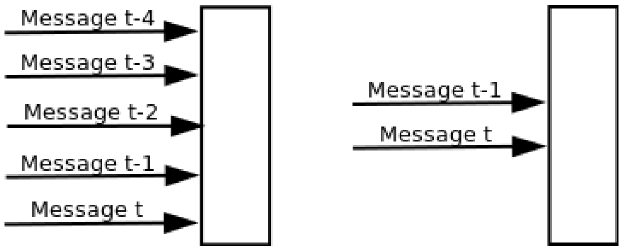


Fig. 3. Message-list structure: the anticipation module uses a history of previous to generate the possible next message. The Neural Network models were trained using both structures; the fuzzy logic model use only the structure with 2-messages input

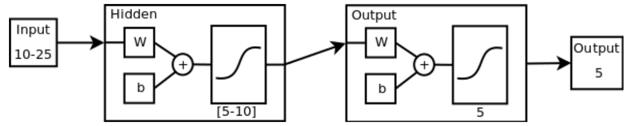


Fig. 4. General Neural Network structure. The network has 10 or 25 inputs, depending on the size of the message history, a single hidden layer, and 5 outputs, one for each value in the anticipated message. A sigmoid function is used for the activation function.

TABLE I. GENERAL FUZZY RULES

Message / **Error**	*MZ*	*TL*	*L*	*M*	*H*	*TH*	*MO*
VN	MZ	MZ	TL	TL	L	M	MO
N	MZ	TL	L	L	M	H	MO
EZ	MZ	TL	L	M	H	TH	MO
P	MZ	L	M	H	H	MO	MO
VP	MZ	M	H	TH	TH	MO	MO

vironment where messages often do not arrive. In a situation like this, the AUVs do not receive updated values for the TS's position at each time step. Their default solution is to assume that the ship is returning to the initial schedule, and the AUVs' fuzzy controllers attempt to return to the schedule as well.

Our alternative approach is based on anticipation. An anticipation module in each AUV attempts to generate an anticipated message when a message from the TS is missing. The anticipation module is configured to create a new anticipated message from the TS based on a set of the previous messages received from the ship. When a message is missing, the anticipated message is used by the AUV as the regular message allowing the AUV to update its current velocity by anticipating the TSnext message.

A. Anticipation

Anticipation is performed by using a list of prior messages as inputs to predict a missing message. This list includes a fixed number of recent messages, thus the anticipation module works with recent information and not the overall record (Figure 3). Every time the list is updated with a new message from the ship, the oldest message is removed from it, thus the list of previous messages used to anticipate future messages is a FIFO list.

Several models for the anticipation module based on artificial neural networks and fuzzy logic were tested to determine which is able to anticipate future messages most accurately. Either 2 or 5 previous messages are used, to test whether a model can produce better results if it uses a longer message history to anticipate future messages.

B. Neural Networks

To test the robustness of the neural network approach and learning algorithms 4 models were compared. The number of messages used as inputs and the numbers of neurons in the single hidden layer were modified to measure the resulting behavioral changes (Figure 4). The following combinations were tested:

- 2 messages (10 inputs) and 5 neurons in the hidden layer.
- 2 messages (10 inputs) and 10 neurons in the hidden layer.
- 5 messages (25 inputs) and 5 neurons in the hidden layer.
- 5 messages (25 inputs) and 10 neurons in the hidden layer.

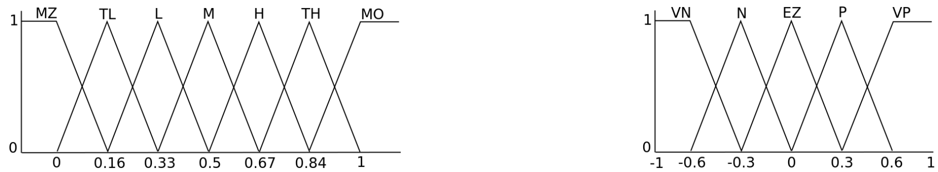
The neural networks were trained using back-propagation ([14] and [15]). 10000 epochs were used in the training phase of each neural network. Training data consisted of messages from the 3 TS scenarios described below. Note that a single neural network was trained on and tested on all 3 cases, so it had to learn to generalized across the 3 test behaviors of the TS.

C. Fuzzy Logic

One fuzzy logic model was tested. 2 previous messages are used as the inputs for this model [14]. The two previous values of each of the 5 fuzzy values is used to calculate the next, anticipated, value. E.g. the two previous values of the first fuzzy variable are used to anticipate the future value, by evaluating the last received value and the difference between its the last received value and the value before that. Using the two previous values allows the anticipation module to determine how fast each fuzzy value is increasing or decreasing as part of the anticipation process.

The value of each variable in a message is assigned a membership in 7 fuzzy sets: Zero (MZ), Too Low (TL), Low (L), Medium (M), High (H), Too High (TH) and One (MO) (Figure 5(a)). The change in value of each variable (the difference between the previous two values in a message) is assigned a membership in 5 fuzzy sets: Very Negative (VN), Negative (N), Zero (EZ), Positive (P), Very Positive (VP) (Figure 5(b)). Based on these sets, a group of basic rules were created, defined in as a fuzzy associative matrix: Table I.

Basically, the fuzzy logic module takes each of the 5 values inside the most recent message (Figure 2) and compare it with



(a) Variable Input

(b) Fuzzy Difference Input

Fig. 5. Fuzzy Sets that describes the current current value of one variable inside the message and the difference that it has with it previous value

the value from message before that by applying the rules in Table I. These rules are used to anticipate the next value for each of the five variables in a TS message.

An additional small set of rules was added to the fuzzy logic module to allow it to create a crossed relationship between the values in a message. The additional fuzzy rules associate the anticipated value of a message value m_i with its neighboring message values. These fuzzy rules are used to check if a value in a message has a current value of 0 and if one of its neighbors (message values m_{i-1} or m_{i+1}) are close to their medium value and decreasing. If so, it can be anticipated that the message value m_i will be about to change. The actual fuzzy rules are:
$TL_{m_i} = MZ_{m_i} \&\& M_{m_{i+1}} \&\& (N_{Ei+1} || VN_{Ei+1})$
$TL_{m_i} = MZ_{m_i} \&\& M_{m_{i-1}} \&\& (N_{Ei-1} || VN_{Ei-1})$

These rules anticipated that if a message value's is currently zero (MZ), it's anticipated membership in the TL (two low) set depends on the neighboring messages values.

Note that the TS message describes the condition of the TS at most using 1 or 2 of the 5 variables in the message; the other 4 or 3 variables remains at 0. For example, if the TS is getting behind schedule, the values for the sets behind schedule and way behind schedule get progressively larger (Figure 2) while the other values remain at zero.

V. RESULTS

To evaluate the anticipation module and its robustness, 3 different behaviors for the TS were created:

- *On schedule (OnS):* the TS maintains a constant velocity using its correct speed and reaches the measurement point on schedule.
- *0.8 speed (0.8S):* the TS maintains a constant velocity of 0.8 of its correct speed. Thus, the TS reaches the measurements point significantly behind schedule and the actual measurement, which take place when the AUVs and the TS pass each other, may occur significantly before (to the right of the measurement box in Figure 1) the measurement point.
- *1.2 speed (1.2S):* the TS maintains a constant velocity of 1.2 of its correct speed, and reaches the measurement point significantly ahead of schedule and the actual measurement, which take place when the AUVs and the TS pass each other, may occur significantly after (to the left of the measurement box in Figure 1) the measurement point.

The anticipation module was tested using 6 different strategies. No anticipation, 4 different neural networks, and a fuzzy logic model:

- *NA:* No Anticipation
- *NN1:* 10 inputs (2 messages) and 5 neurons in the hidden layer.
- *NN2:* 10 inputs (2 messages) and 10 neurons in the hidden layer.
- *NN3:* 25 inputs (5 messages) and 5 neurons in the hidden layer.
- *NN4:* 25 inputs (5 messages) and 10 neurons in the hidden layer.
- *FL:* Fuzzy Logic, using 2 input messages.

The anticipation modules were tested using 2 different strategies:

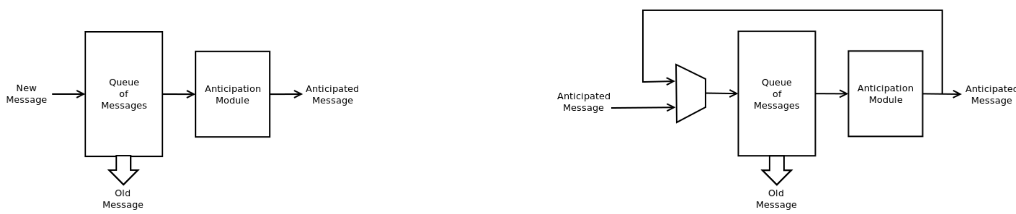
- *Without feedback:* the module uses only the actual messages received from the TS (Figure 6(a)). When a message from the TS does not arrive, the anticipation module uses the last N (2 or 5) received messages to anticipate the next message. A list is used to store these messages and it is updated only when a new message from the TS is received.
- *With feedback:* the anticipation module treats anticipated messages as received messages (Figure 6(b)). The message list is updated every time a new message is received from the TS. But when a message does not arrive, the anticipated message is included in the message list that will be used the next time a message is anticipated.

For training, AUVs received messages every time step, the optimal condition for all the TS behaviors. For testing the number of time-steps that the TS waits to send a message was varied. The three test cases were, 1 message per time step, one message every 2 time steps, and 1 message every 6 time steps.

Performance is judged by measuring the distance between the target measurement point and the actual meeting point between the TS and the AUVs. Each test consists of evaluating one anticipation model for each value of each experimental variable (steps/message, TS behavior). 10 trials were performed for each test, which gives a total of 3600 trials for the entire experiment, 720 trials for each anticipation model. Table II shows the average values for the meeting points between the group of AUVs and the ship. Lower values are better. The highlighted values represent the best results between the 5 anticipation models for each test.

TABLE II. ABSOLUTE VALUE OF GROUP MEETING POINT ERROR AND STANDARD DEVIATION. EACH ANTICIPATION MODEL SHOWS THE RESULTS OF RUNNING THE SIMULATION WITHOUT FEEDBACK (TOP VALUE), AND WITH FEEDBACK (BOTTOM VALUE), RESPECTIVELY. FOR EXAMPLE, FOR THE 0.8 BEHAVIOR WITH 6 TIME STEPS PER MESSAGE (6S/M) AND WITHOUT ANTICIPATION, THE TS AND AUVS MET 41.77 M AWAY FROM THE TARGET POINT; WITH ANTICIPATION USING NO FEEDBACK AND NN1, THEY MET ONLY 13.65 M AWAY FROM THE TARGET POINT; AND WITH ANTICIPATION USING FEEDBACK AND NN1, THEY MET 14.95 M AWAY FROM THE TARGET POINT.

Test		NA	*NN1*	*NN2*	*NN3*	*NN4*	*FL*
OnS	1 S/M	1.06(0.27)	1.06(0.28) 1.06(0.28)	1.06(0.28) 1.06(0.28)	1.06(0.27) 1.06(0.27)	1.06(0.28) 1.06(0.27)	1.06(0.28) 1.06(0.28)
	2 S/M	0.70(0.51)	0.89(0.26) 0.87(0.28)	1.01(0.28) 1.02(0.27)	1.02(0.27) 1.02(0.26)	1.00(0.27) 0.97(0.27)	1.16(0.28) 1.00(0.26)
	6 S/M	0.70(0.62)	0.75(0.28) 0.51(0.63)	0.99(0.27) 0.66(0.28)	1.00(0.27) 0.82(0.74)	0.93(0.28) 0.70(0.62)	1.21(0.29) 0.61(0.26)
0.8S	1 S/M	10.98(0.18)	10.98(0.18) 10.98(0.18)	10.98(0.18) 10.98(0.18)	10.98(0.18) 10.98(0.18)	10.98(0.18) 10.98(0.18)	10.98(0.18) 10.18(0.28)
	2 S/M	28.30(0.27)	12.66(0.32) 12.66(0.19)	12.56(0.46) 12.27(0.19)	11.92(0.44) 11.95(0.44)	12.68(0.19) 12.43(0.46)	11.30(0.43) 11.30(0.43)
	6 S/M	41.77(0.26)	13.65(0.29) 14.98(0.28)	10.99(0.18) 14.90(0.31)	12.47(0.36) 13.74(0.06)	13.19(0.26) 15.65(0.42)	11.59(0.31) 14.05(0.25)
1.2S	1 S/M	1.09(0.26)	1.09(0.26) 1.09(0.26)	1.09(0.27) 1.09(0.26)	1.09(0.26) 1.09(0.26)	1.09(0.26) 1.09(0.26)	1.09(0.26) 1.09(0.27)
	2 S/M	16.25(0.08)	2.87(0.27) 2.77(0.29)	3.83(0.28) 3.77(0.27)	3.53(0.27) 3.96(0.27)	3.81(0.27) 4.00(0.28)	1.63(0.25) 2.63(0.51)
	6 S/M	31.67(0.07)	4.46(0.26) 6.09(0.49)	5.07(0.27) 8.60(0.15)	5.02(0.39) 18.87(0.04)	4.93(0.26) 7.60(0.19)	2.47(0.32) 10.57(0.14)



(a) Without Feedback (b) With Feedback

Fig. 6. Anticipation Strategies: the anticipation module can generate a brand new message every time a real message is inserted in the queue of messages or it can use a feedback to insert a new anticipated message in the queue every time a real message is missing which allows the module to generate a brand new message more often.

The results with no anticipation (the column labeled NA in Table II) show that when the TS is on schedule (rows 1, 2, and 3) the TS and AUVs meet close to the designated meeting point - just over 1 simulated meter away - despite the randomized starting positions and angles of the AUVs. This result confirms that the fuzzy controllers responsible for keeping the TS and AUVs on schedule perform correctly.

The results with no anticipation, when the TS is off schedule (rows marked 0.8S and 1.2S) show that when messages are received frequently (rows labeled 1M/S) the AUVs do fairly well even without anticipation, although when the TS is slow (row 0.8S) the are off by roughly 10 meters. However, as messages become increasingly infrequent (2S/M and 6S/M) AUVs with no anticipation fail to meet the TS near the designated meeting point, with larger message gaps leading to worse results.

Table II shows that all anticipation models showed a significant improvement over no anticipation, when the TS was off schedule and there were gaps between the messages. I.e. anticipation does, partially, and in many cases completely, makes up for the large gap between messages. In the worst case, a slow TS (0.8S) and infrequent messages (6S/M), AUVs without anticipation met the TS, on average, almost 42 meters from the designated measurement point. In contrast, AUVs with any of the anticipation models, on average, met the TS within 15 meters of the designated point.

Overall NN1 and the fuzzy logic models had better results on 5 of the test cases each. These two models showed the smallest error between the correct meeting point and the one obtained in the experiment. Model NN4 also had good results on most of the tests, but did not have the best results in any of the 18 configurations used for the experiment.

In general anticipation models using feedback performed slightly worse than models not using feedback.

Figures 7 and 8 show quartile plots for the results obtained from all the anticipation models for 2 TS behaviors: OnS and 0.8S. Each figure shows 3 main groups which represent the three types of simulations that were tested: No Anticipation, Anticipation with Feedback and Anticipation without Feedback. Within each group, there are three additional groups that represent the possible message gaps: 1 step/message, 2 steps/message, and 6 steps/message. Each of those groups has 5 elements which represent the anticipation models that were used for this experiment: NN1, NN2, NN3, NN4, and FL. Figure 7 shows that as the message gap increases there is generally wider variability in the meeting points. This is also true in Figure 8, but the change in scale obscures the dispersion. Figure 8 also shows how increasing the message gap significantly impacts the meeting point when there is no anticipation of the missing messages, but not with anticipation. Figure 7 suggests that the dispersion in the meeting points is generally reduced by using anticipation.

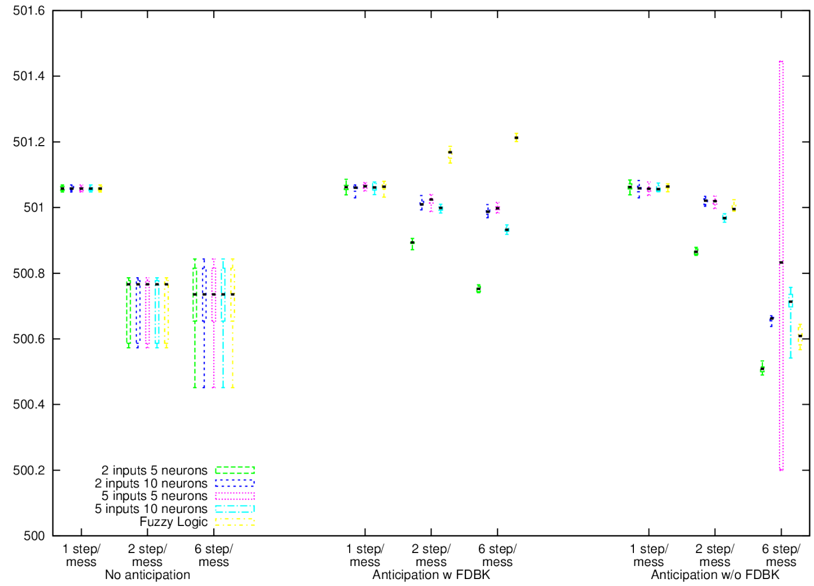


Fig. 7. Average and quartile results with all anticipation models when the TS is on schedule. Overall results are similar, with small errors in the meeting point for all cases, but using anticipation reduces the variability in the meeting point, except for anticipation using the neural network with 5 input messages and 5 neurons in the hidden layer, with feedback, when there one message is received every 6 time steps.

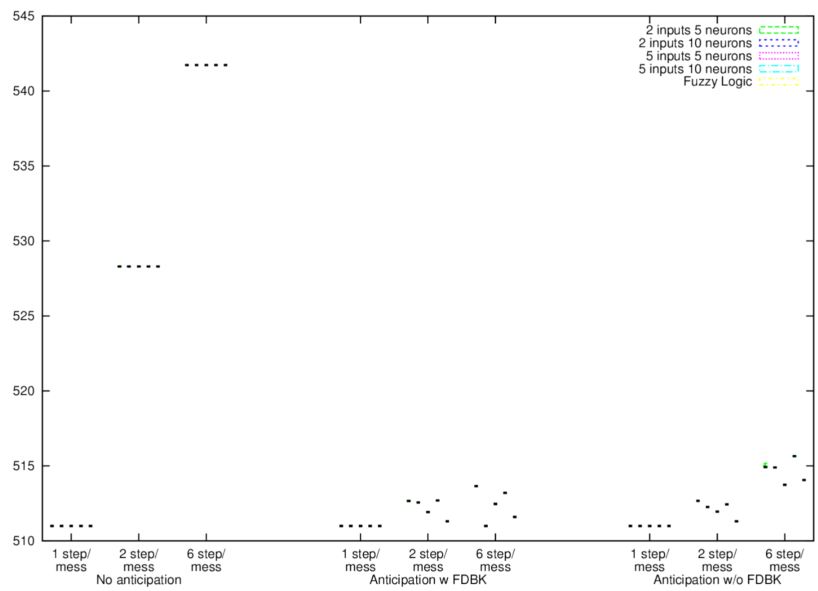


Fig. 8. Global average of the meeting point results for the AUVs obtained with all anticipation models when the TS is traveling at 0.8 of its correct speed.

Figures 9, 10, 11 and 12 show the average position of the the individual AUVs (1-5) with NN1 and FL (which produced the best behaviors during the experiments). Figures 9 and 11 show the results when the TS behavior is OnS, and Figures 10 and 12 show the results for behavior 0.8S. These figures show that both anticipation models reduce the error for every AUV. Equally important these figures show that the errors for the individual AUVs are similar. Thus, in general the anticipation modules not only reduce the meeting point error, but also maintain the formation that the group has in optimal conditions.

Figure 9 shows that anticipation reduces the variation in the meeting point, keeping the AUVs in formation. For example, once the value of the steps/message increases, the variation in AUV position with no anticipation increases considerably, especially in AUV 5. The other 2 models, which use anticipation, sproduce much smaller variation in the AUVs' positions. For example, the variation for AUV 5 decreases considerably with both models compared to no anticipation. Additionally, anticipation helps the AUVs get to the meeting point in formation. Most notably the error with both anticipation models and 2 or 6 steps per message were similar to the results with no anticipation and one message per time step. This show that anticipation is successfully "filling in" the missing messages.

Figures 11 and 12 show the results for the same cases as in Figures 9 and 10 but using the fuzzy logic model. Figure

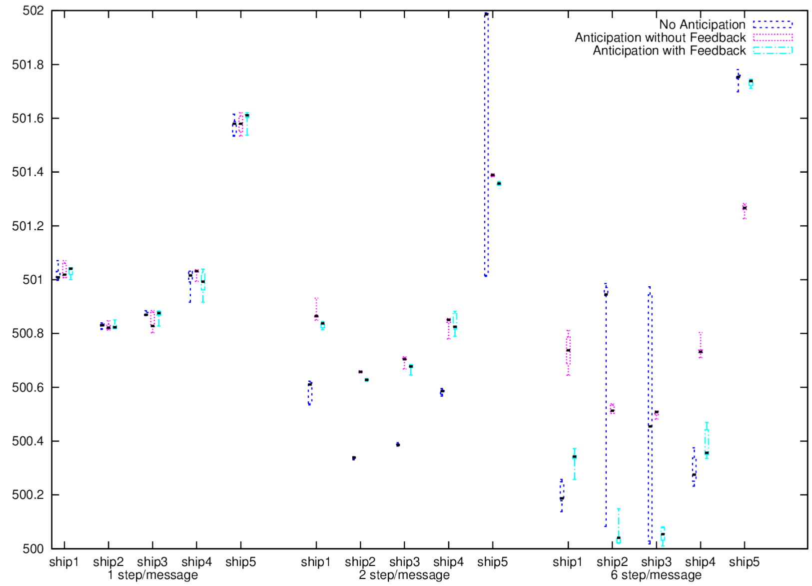


Fig. 9. Average and quartile results for the meeting point by AUV, when using a neural network with 10 inputs and 5 neurons in the hidden layer when the TS is on schedule. AUV 5 tends to be slightly further from the measurement point. Variability in the AUV position, particularly for AUV 5, is highest with no anticipation.

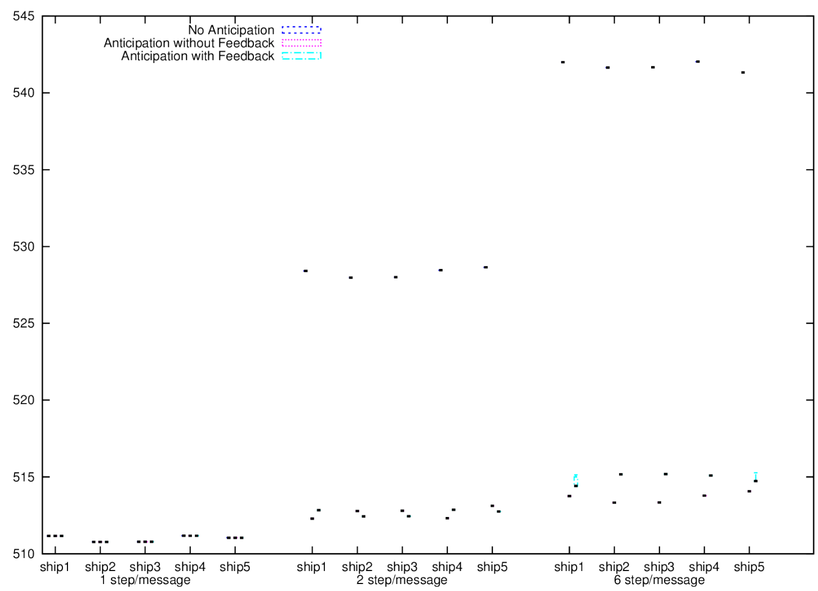


Fig. 10. Average and quartile results for the meeting point by AUV, when using a neural network with 10 inputs and 5 neurons in the hidden layer when the TS is using 0.8 of its correct speed. All AUVs have similar errors, showing that they remain together. Errors are much larger when there is no anticipation and a messages are infrequent.

11 shows that the fuzzy logic model also reduces the variation in the AUVs' position when the anticipation is enabled, but slightly less than the neural network model. On the other hand, Figure 10 shows that the fuzzy logic model does a better job of maintaining the group formation, getting them closer, on average, to the correct meeting point.

VI. Conclusions

The results shows that all of the anticipation models were able to significantly reduce the error in the meeting point when the TS was off schedule and messages were infrequent. This is a very promising result, as it strongly suggests that anticipation can be an effective method to address communication problems cause by noisy or low bandwidth communication channels. In our results NN1 model had, in general, the best performance followed by the fuzzy logic model. The other neural network NN2 and NN3 models had good results with values that were better than the NN1 and fuzzy logic models, but only under a few of the test cases. Both NN1 and the fuzzy logic model only used the two previous models, suggesting that, at least for this problem, a short message history is sufficient to anticipate future messages.

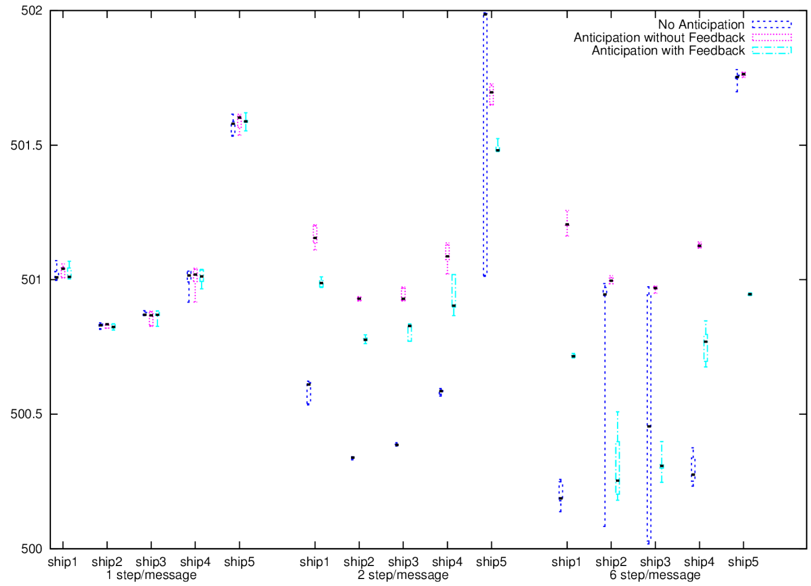


Fig. 11. Individual average of the meeting point results obtained using fuzzy Logic when the TS is on schedule.

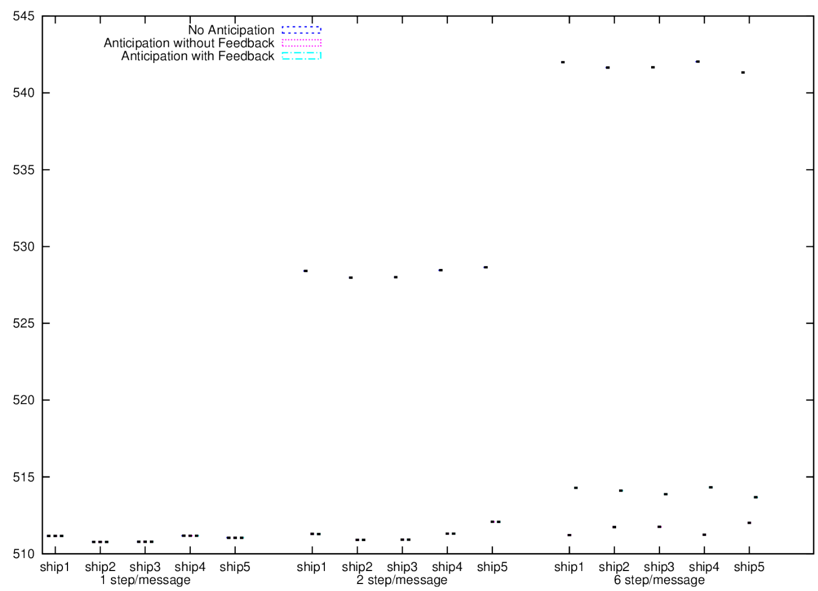


Fig. 12. Individual average of the meeting point results obtained using fuzzy logic when the TS is using 0.8 of its correct speed.

The results (Figures 9, 10, 11 and 12) also show that anticipation models without feedback produced better results than models with feedback, although both models were successful at significantly reducing the error in the meeting point. This suggests that using feedback, i.e. using anticipated messages to predict future messages, may magnify the errors in the anticipated messages.

All of the anticipation models also reduced the variation in the meeting position with the TS, but models with feedback had slightly larger variations than models without feedback. Overall, it is clear that the anticipation models presented here are effective at anticipating messages and that the anticipated messages can be successfully used in the place of lost messages (or messages that are forced to be discarded due to errors). Finally, it is worth noting that the test problem used in these experiments required a fleet of five autonomous to reach a specific location, as a group, at a time determined by the behavior of another vehicle. This type of coordinated, group behavior with a dynamic goal represents a very general and useful behavior, thus the results of this research has potential benefits for a wide range of applications.

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