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Formation Maneuvering using Passive Acoustic Communications

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***Abstract*— Interest in the use of unmanned underwater vehicles (UUVs) for both commercial and military uses is growing. Control of UUVs poses a difficult problem because traditional methods of communication and navigation, i.e. radio and GPS, are not effective due to the properties of seawater. Control and communication algorithms were developed to carry out multiple UUV formation maneuvering using acoustic communications and first tested in computer simulation and then on mobile robots. Three control schemes, classic logic, behavior, and neural network were tested in line formations in both simulator and lab environments. Results and issues are discussed along with future directions.**

Keywords-component;

I. Introduction

This paper focuses on the development of control algorithms and communication schemes required for Unmanned Underwater Vehicles (UUVs) to accomplish formation maneuvering using vessel relative navigation. Because seawater dissipates electromagnetic energy (radio, light, etc.) so effectively, traditional positioning systems such as GPS and radio communications are ineffective. Inertial based vessel positioning systems typically yield position error growth on the order of 1% of the distance traveled [5] and thus are not adequate for formation maneuvering. Consequently, acoustics must be used for both vessel positioning and communications underwater, but these systems yield fairly short ranges and very low bandwidths [6]. Acoustic transponder systems can provide accurate vessel position but only in small areas. Vessel relative positioning and navigation using combined communication/position acoustic systems offers a promising alternative for UUV formation maneuvering.

In this work classic logic, behavior based, and neural network controllers have been developed to control multiple vehicle formations. They are fashioned after biologically inspired formations observed in nature, most notably lines of ducks and caterpillars. The classic logic control systems used were modeled after Braitenburg machines and served as a baseline capability for comparison. Neural network controllers, which hold the promise of real-time adaptability, were 'grown' using a genetic algorithm and in-situ sensor data.

Both computer simulations and tests using mobile land robots equipped with frequency multiplexed acoustic communication systems have demonstrated the feasibility of these approaches. Several real world problems have been tackled, including acoustic sensor directivity and reverberation.

This paper gives an overview of a typical UUV mission in order to show how formation maneuvering would be used in the execution of a multi-vessel mission. It then discusses four main categories of formation maneuvering described in the literature. Next, the acoustic based relative navigation approach developed is described from concept to lab testing. Finally, results, conclusions, and future directions are detailed.

II. Background

A typical mission involving multiple UUVs will have many distinct phases. Initially, the UUVs will be onboard their host vessel(s). Depending on the size of the UUVs involved in the mission and the mission goals, there may be more that one host vessel deploying UUVs. Once sea prepped the UUVs will be launched and they will then maneuver into a transit formation and travel to the area of interest. The current assumption is that there will be at least one vehicle that has an accurate positioning system on board and that the others will rely on vessel-relative positioning. Upon getting to the area of interest, the UUVs will change into mission specific formations and execute their respective mission related goals. When the mission is complete they will move back into a transit formation and return to their host vessel(s) and download their data.

Coordinating multiple autonomous vehicles moving in formation has become an active area of investigation in robotics, multi-agent systems, and control. It is important from a robotic/UUV standpoint in that it can be a key part of getting a team of robots to work together. As referred to earlier, one use may be to create a formation of UUVs and travel to a destination of interest in order to collect measurements of depth, physical water properties or to look for hazards. Using a formation helps the team members track other team members, helping to make sure that none of the UUVs gets lost along the way. It also augments communication by reducing the distance that a team member will have to transmit a message. Formation maneuvering based on inter-vessel positioning and navigation has distinct advantages in that it can reduce or eliminate the requirement for pre-deployed positioning systems. Another use of a formation is to increase the sensor footprint in searching and surveying tasks.

Compared with existing works about formation control, this work has some distinctive features: it makes use of a machine learning technique to learn the control laws to move into (acquire) formation, and to keep (follow) formation. In one of the most relevant works, a genetic algorithm is used to evolve neural network controllers for simulated "prey" creatures to learn a herding behavior protecting against predators. However, that work does not address the issue of forming a particular geometric shape (line, tree, etc.). For a more thorough summarization of the background see McDowell et al [1]. Another key difference is the inter-vehicle communication scheme. In our scheme we navigate relative to an assigned leader using a frequency multiplexed chirping scheme and acoustic sensors. The group at the University of Reading [3] has concentrated on both non-adaptive and adaptive flocking behavior with mobile robots using logic based on that of Reynold's boids. Their robots are using ultrasonic sonars for obstacle avoidance and frequency multiplexed infrared light for inter-robot communications.

Other more common methods include the use of camera based, laser based or GPS positioning systems coupled with high-bandwidth communication networks which informs each vehicle in the formation of its position and the position of its leader or leaders. While these approaches have merit and in general work well they are not suited to the ocean environment.

III. APPROACH

This work is based on the leader/follower approach in which all of the robots in the formation position themselves relative to each other or the lead robot. The lead robot is typically controlled by an operator or programmed to do waypoint following. To illustrate the concept, consider one of the simplest formations, a line formation. In a line formation each robot follows the robot in front of it and in turn, leads the one behind it. Figure 1 below shows a conceptual view of a line formation. In this figure the green robot, whose id is 0, is the lead robot. It is followed by the robot whose id is 1, which is in turn followed by the robot whose id is 2, and so on. In this illustration, the follower robots are controlled by neural networks while an operator maneuvers the lead robot.

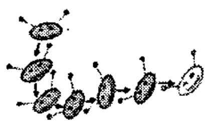

Figure 1. This figure shows a robot line. The green robot is controlled manually. Using their sensors and controllers, the other robots follow.

The system operates in a passive manner meaning that the robots do not exchange position or bearing and range information. Instead, each robot, except the leader, steers itself towards the chirp of the robot in front of it. For example, the leader chirps at frequency range A, the robot directly behind it steers in the direction that it perceives is the source of the chirp in frequency range A, and at the same time chirps in frequency range B. The robot behind it steers towards the source of frequency range B and so on.

Two methods were used to determine source direction. In both methods, microphones are placed on each side of the robot, like ears, and the ear with the strongest signal was used to determine the source direction. The first method uses power summing and the second method uses matched filtering. In ideal acoustic conditions, which were seldom found in the laboratory, the source is louder on whichever side of the robot that it is closest to.

A. Robots and Sensors

Figure 2 below shows a picture of one of the three robots used in this work. The robot is an ActiveMedia Pioneer 2DX. From the factory it comes with bumpers, compass, and sonars, but they were not used for these experiments. Instead, the acoustic communication system was set up using a sound card receiving signals through two voice type karaoke microphones and transmitting information using a small battery powered speaker. To help in calibration and signal amplification, battery powered guitar amplifiers were used to boost the signal coming from the microphones.

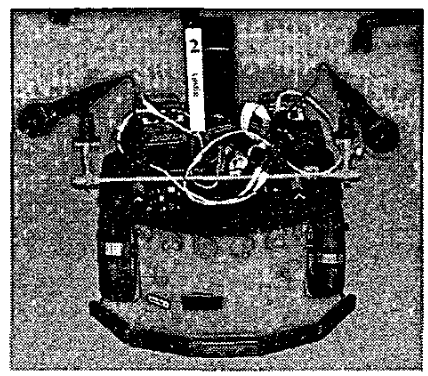

Figure 2. Pioneer 2DX robot with microphones and amplifiers mounted. Notice how the microphones are mounted on each side of robot, like ears.

B. Communications

The system uses chirps in order to minimize problems associated with constant wave (CW) tones or pulses. Because the lab walls and floor are good sound reflectors, its acoustic characteristics are far from ideal. CW tones tend to saturate the air volume and create standing waves to the point that it is almost impossible for a person to audibly discern the location of the speaker. Constructive and destructive interference of the CW tone helps to create several regions of the room in which the sound is very intense, or barely audible. These local minima and maxima make tracking the sound an impossible proposition. Using a chirp alleviates these problems in two ways. First, because there is typically one chirp per second, there is time for the sound to attenuate. Second, because the chirp sweeps from a starting frequency to an ending frequency, there is less time for the energy at any particular frequency to saturate the room and set up a standing wave, so the creation of regions of low and high intensity sound are reduced.

C. *Processing Algorithms*

There are two methods that have been tested for determining signal strength at the robot's microphones. While they both calculate a running average of the signal strength in order to smooth out fluctuations caused by the chirp and environmental effects, they differ in concept, implementation, and efficiency.

The first and much more widely used in this research, quantifies the amount of energy in a particular frequency range at each microphone. This method works by continuously taking the fast fourier transform (FFT) of the incoming time series data collected by the sound card from the robot's two microphones. Briefly, the FFT converts the time series data from the time/intensity domain to the frequency/intensity domain. Once in this form, the energy in the frequency range of the chirp is summed. Sound that bounces off walls, ceilings, etc. is lumped in with the sound that takes a direct path.

The FFT method effectively measures the intensity of the chirp in the requested frequency range. In testing, it responds logically and predictably. Closer, louder chirps produce larger intensity values, and weaker, further chirps produce smaller intensity values. Because of the effective band-pass filtering in this process, it is robust to noise, including other chirps in other frequency ranges, 60hz noise, robots self-noise, etc. For maximum computational efficiency it requires that the data set size be a power of two.

The second method relies on matching the chirp waveform that the follower robot receives to the chirp waveform that the lead robot transmitted. The microphone with the closest match is assumed to be closest to the sound source. This method, called matched filter processing, relies on doing a cross correlation of the incoming signal to a template of the transmitted signal. It is of order N^2 and since the data set is large, it requires much more CPU time than the O(NlogN) FFT based method. Efficiency concerns aside, the matched filter alone is susceptible to noise corruption. It is difficult to detect the chirp without using a band-pass filter before the matched filter. With the band-pass filter, noise from other frequency ranges, such as 60Hz, voices, etc, has a minimal effect. The downside is that the filter requires additional CPU time.

In testing, the matched filter works well with a low to medium volume source and in low noise environments. Unfortunately, this greatly limits the effective range of the power differencing approach. With the equipment used, when the volume is turned up, the speaker distorts the signal degrading the correlation between the transmitted and received signal. Additionally the high multi-path environment of the lab may be further degrading performance of the matched filter. Consequently, most of the work described uses the FFT based listening system.

IV. CONTROL METHODS

Three methods of control have been tested. They are a classic logic approach, a behavioral approach, and a neural network approach. The following sections provide more detail.

A. *Classic Logic Approach*

As a baseline method to be used for testing, the robots were first programmed using simple logic that closely modeled that of Braitenberg vehicles [4]. Instead of heading towards a light source using two photo-eyes controlling right and left motors as Braitenberg vehicles do, microphones and sound were used. The basics of the classic logic method is as follows:

If (either of microphones reads a very loud intensity) **then**
    Velocity = Stop;
Else
    Velocity = Go;
If (microphones read intensities that are *close* to equal) **then**
    Direction = straight;
Else
    If (right microphone value is greater than left) **then**
        Direction = right;
    Else
        Direction = left.

The first if statement keeps a robot from colliding with its leader. The second statement creates an "on center zone" so that the robot will go straight. This statement is not as important in the simulator because reflections, bounces and noise are not accurately modeled, but without it in the lab the robots will always turn left or right, creating a serpentine path. The final if statement selects the direction to turn, given that the microphone intensity was sufficiently different enough to not fall in the on center zone.

B. *Behavior*

Three behaviors are used to find and follow the sound source. They are follow, seek, and search. The follow mode is for maintaining a desired distance behind a lead robot, the seek mode is used when the robot knows the direction to the lead robot but is too far away, and the search mode is needed to determine the direction of the lead robot. The selection of the behavior is based on the gradient history of microphone intensities. Much like subsumption, only one behavior is active at a time, with the added enhancement that some behaviors require a waiting period before they becomes active again. When directly behind its leader, a robot is normally in follow mode, which uses the same basic logic as the classic logic module. If the distance between the two robots is too large or grows the seek behavior becomes active. Seek allows the robot to respond quickly to directional changes by varying the "*close*" parameter as a function of sound intensity, while follow tends to keep the robot moving straighter. If the robot looses track of the source by detecting a negative sensor gradient, search acts to reorient it towards the peak level of the sound source. Once oriented, the robot returns to seek mode, and is prevented from entering search for a specified period of time.

C. *Neural Network*

The neural network controller is based on a feed forward neural network with one hidden layer trained by a genetic algorithm (GA). It was shown [1] that this concept has merit when applied to formation maneuvering.

Although similar, this work has some distinctive differences. In the work mentioned above, the neural network was trained by repeatedly letting a simulated robot controlled by the network follow a computer controlled simulated robot that made random course changes. The fitness function in the GA optimized the distance between the leader and follower. After several generations, a controller was "grown" that could keep a follower robot consistently close to a leader robot. While this approach is ideal for a simulator, physically executing the generations of runs to develop a good controller on the lab robots was not an option.

The solution was to first train the robot to guess where a sound source was in relation to the direction it was currently facing. The robot had three choices; the sound could be either to the left of the robot, in front of it, or to the right. Once the robot could guess where the sound was, that information was used to guide the robot towards the source.

Using this technique, a custom feed forward neural network controller is "grown" or each robot using a simple series of physical measurements. Moreover, this approach allows straightforward compensation for variations in robot characteristics such as voltage levels, leader frequency, microphone response, and amplifier characteristics. Without this simple approach of growing a custom network great care would have to be taken to calibrate each system.

V. RESULTS

The classic logic and neural network control methods both worked well enough to enable line formations of the three lab robots to make several laps around the lab, while the behavior module was lacking. Figure 3 below shows a following test with two robots.

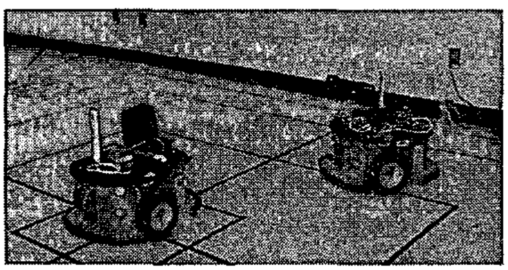

Figure 3. This figure shows a two robot following test. Notice the lead robot is not equipped with listening equipment because it is controlled with the in-house simulator.

Lab and simulator results for the classic logic module were very similar. "Crabbing" and serpentine paths were observed in both environments. Crabbing occurs when the robot is very close to the source, so its velocity is set to "stop", but the reading from the microphones are different enough that the direction returned is not "straight".

The behavior routine works very well in simulation on a fixed sound source. It also works well on moving sources in simulation, but the poor acoustic environment in the lab makes the gradient-based approach ineffective. At best it stayed in seek mode, which led to much crabbing and serpentine paths.

Initially the neural network based method worked, but only after the robots were carefully put into a starting formation. Testing revealed that when microphone intensities moved outside of the range of the training set, the neural network's responses became unpredictable. This behavior was observed in both the simulator and in the lab. Because of this problem, seeking to a fixed source was difficult because the network has to deal with a large range of microphone values, which were not reflected in the training data. Following worked well because once a follower robot has acquired its leader, the range of the microphone values becomes narrower and more constant.

To help alleviate these problems the network was presented with relative sensor values, rather than scaled absolute values. By dividing both sensor values by the larger of the two, their intensities relative to each other is preserved and they always stay in the range of the training set. This simple modification resulted in a significant performance gain. In subjective tests the neural network was able to match the classic logic controller and in some cases reduce some of the serpentine motion.

Note that at this point in time, all the performance comparisons between algorithms are subjective because the lab's robot tracking system is still under development. It is easy to tell if an algorithm works, or does not work, or if one works much better or much worse (as in the case of the behavior based controller) than the others, but making fine comparisons between algorithms by analyzing trajectories is not feasible at the present.

VI. ISSUES

A. Acoustic

The audio equipment gives an effective frequency range from 300Hz to about 4000Hz. Typically the lead robot chirps from 300 to 500Hz for 400 milliseconds. Because a strong 2^{nd} harmonic is generated, the second robot is set to chirp from 1200 to 1400Hz for 400 milliseconds. With both robots chirping asynchronously, the listening programs onboard the 2^{nd} and 3^{rd} robots have no trouble sorting out the two chirps. However, the 700Hz difference between the chirps is sufficient to make the acoustic properties of the two chirps different. In house measurements have shown that the lower frequency chirp radiates in almost a 180 degree pattern from the speaker, while the higher frequency chirps radiate sound in a pattern that is strong at 0, 90 and 180 degrees, but weak everywhere else. The empirical solution to these problems has been to get the chirps as close in frequency to each other as possible, so that both robots are dealing with similar acoustic conditions.

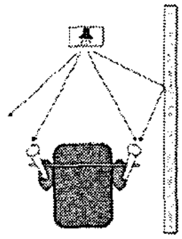

Figure 4. The wall is reflecting sound back to the robot that would normally be radiated elsewhere. In this case the robot will read a higher intensity value on its right side, causing it to errantly turn towards the wall.

Reflections from walls can be especially troublesome because they tend to increase the acoustic energy that arrives at the microphone nearest to the wall. So if a leader/follower pair are traveling parallel to the wall the follower will tend to head to the wall because the wall reflects the sound energy that would normally be radiate into the air. Figure 4 above illustrates this phenomenon.

Sound propagates similarly in water and air. Characteristics such as higher frequencies being more directional but attenuating quicker as compared to lower frequencies hold true. The implication is that some of the same problems that arise in the air will be present in water, especially near ships, or in harbors with rocky bottoms.

A major area of concern is how close the in air analogy is to the underwater environment. To help answer this question, some basic equations [7] showing energy loss due to spreading were used to model the effect. These equations are not medium dependent, so they apply to both air and water.

The situation of a sound source in deep water was modeled using spherical spreading. The situation in which the sound energy is reflected off the sea surface and sea floor are modeled using cylindrical spreading. The equations are shown below.

TLS[R]	Transmission loss at range R due to spherical spreading
TLC[R]	Transmission loss at range R due to cylindrical spreading
R	Range of receiver from sound source
R0	Reference range (usually 1 meter)
S	Intensity of sound at reference range
I[R]	Sound intensity at range R

For spherical spreading:

$$TLS[R] = 20*\log(R/R0)$$

$$I[R] = S - TLS[R]$$

For cylindrical spreading:

$$TLC[R] = 10*\log(R/R0)$$

$$I[R] = S - TLC[R]$$

The results are shown in figure 5. These results were compared to measurements taken using a sound source and a sound meter. While the calculated results are smoother than the measured data, see figure 6, the curves do follow a similar trend, suggesting that the analogy is valid.

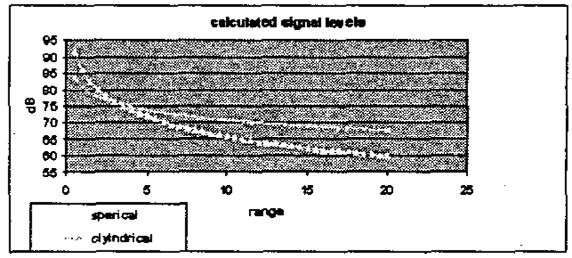

Figure 5. This figure shows the calculated signal loss due to the spreading of acoustic energy. Note that these calculations are medium independent, that is they are applicable to both water and air. The reference intensity was taken from the field experiments illustrated in figure 6.

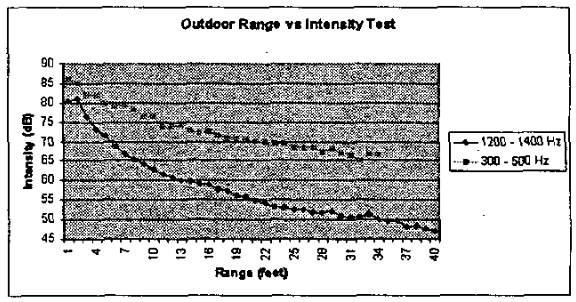

Figure 6. . This figure shows an intensity/distance plot of measurements taken in a quiet non-reflective outdoor environment. Notice how the intensity of the sound in the 1200 to 1400 Hz range drops fairly predictably in the 2 - 27 feet range.

B. Control

Because the classic logic module is reactionary, the robots tend to oscillate between right and left causing crabbing or serpentine paths. Letting the robot turn only when one microphone reads significantly higher than the other can alleviate the serpentine motion. A more serious problem is the ambiguity associated with heading directly towards or directly away from the source. Because it only considers present sound readings in the robot's logic, there is no difference between heading directly towards the sound source and heading directly away from the sound source.

The behavior-based module was created to address the inadequacies of the classic logic module. The source location ambiguity problem is addressed by looking at sensor values over time. If a negative gradient in the microphone intensity values is detected, a search mode is entered, which reorients the robot towards the source. It reduces crabbing and serpentine motion by having an adjustable on center parameter, which makes the on center zone larger or smaller depending on how often a negative gradient is detected. While the behavior based approach works well in simulation, the measurement of gradient proved difficult in an adverse acoustic environment with the signals used.

The neural network technique functionally works the same as the classic logic module, but has the advantage that it can be readily adapted to specific hardware. Changing to recurrent networks that consider more than the current sensor readings, coupled with a data monitoring system that detects when the sensor data is becoming out of the range of the training data should help alleviate the observed problems.

VII. SUMMARY

This work has shown, in concept, that formation maneuvering using acoustic sensors is possible in both a simulated environment and in the physical world of the lab. It has also shown that the structure of the formation can remain viable without using a centralized controller, or using infrastructure based communications. Since the communications between the robots uses very low bandwidth acoustic methods, this work is relevant to the overall goal of searching and surveying using teams of UUVs.

This research has many facets, so the opportunities for improvement are abundant. Aside from equipment related improvements such as better microphones, speakers, and amplifiers efforts need to focus on improved signaling schemes, behavior arbitration, on the fly learning, and inter-robot communications.

On the fly learning needs to be integrated into the control system to allow continuous real-time adaptation in an unstructured environment. To date, the goal has been to show that if a network were tuned correctly it could be used to control the vehicles in a formation-maneuvering situation using acoustic systems. The next step is to automate the learning process.

Because acoustic reverberation and multi-path cause problems with amplitude based following systems, one alternative method that has been considered is low bandwidth acoustic communications between robots that will provide a following robot with the intentions of the leader. This additional information can then be used to assist the following robot in determining the proper actions in the presence of misleading sensor data.

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