Heterogeneous Sensor Networks:  
A Bio-Inspired Overlay Architecture

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ABSTRACT

A team consisting of Teledyne Scientific Company, the University of California at Santa Barbara (UCSB) and the Army Research Laboratory (ARL) is developing technologies in support of automated data exfiltration from heterogeneous battlefield sensor networks as part of a US Army contract with the Institute for Collaborative Biotehnologies (ICB) at UCSB. The objective of the program is to design, develop and test data gathering strategies, feature and information fusion concepts from unattended ground sensor networks in support of situation awareness for dismounts. Networks of heterogeneous sensors are typically deployed in sparse configurations over wide areas (one sensor per square kilometer) in order to detect infiltration and adversarial events of interest to coalition forces. The sensors within a network cannot communicate with each other and consequently require overhead assets to automatically extract and process data in a timely fashion. Unmanned air vehicles (UAV) provide an effective means to autonomously collect data from a sparse network of unattended ground sensors (UGSs) that cannot communicate with each other due to their sparse distribution. In addition to providing a communication infrastructure and a mechanism for implicit synchronization of sensors, UAVs can also be used to reduce the system reaction time by generating autonomous collection routes that are data-driven. Bio-inspired techniques for search provide a novel strategy to detect, capture and fuse data across heterogeneous sensor networks. A fast and accurate method has been developed to localize an event on the ground by fusing data from a sparse number of UGSs involving the use of a bio-inspired algorithm based on chemotaxis or the motion of bacteria seeking nutrients in their environment. A unique acoustic event classification algorithm was also developed based on using swarm optimization to classify events. Very high classification accuracies were achieved against ARL field data using the swarm optimization method. The system was initially implemented and successfully tested using a high level simulation environment with a flight simulator to emulate a UAV collector. The high level simulation was extended by replacing the flight simulator with a real UAV and moving the architecture to the field.
A field test was conducted in November of 2009 at Camp Roberts, CA in conjunction with AeroMech Engineering who provided the UAV to test bio-inspired technologies for source localization, data fusion and classification of acoustic events from a heterogeneous sensor network. The field test results showed that the system can detect and locate the source of an acoustic event with very high accuracy using the bio-inspired algorithms. In nine independent test runs of the UAV using controlled acoustic events, the system located the position of an explosion nine times with an average source location accuracy of 3 meters. The time required to detect an acoustic event and to perform source localization using the UAV was on the order of a few minutes demonstrating rapid response for situation awareness. The field test incorporated an experimental Army Research Lab ground sensor that provided angle of arrival data and demonstrated how heterogeneous sensor network data can be fused and effectively exploited in the field. Future plans include the use of UAV swarms that will act autonomously to support DoD operations and to extend the algorithms to identify the location of gunfire on the ground from a helicopter equipped with multiple microphones.

**Keywords:** Unattended Ground Sensor, Unmanned Air Vehicle, Data Exfiltration, Autonomous Operations, Bio-Inspired Algorithms, Chemotaxis, Likelihood Function, Data Fusion, Route Planning, Source Localization, Acoustic Event Classification, Particle Swarm Optimization, Quadratically Constrained Least Squares Minimization.
1.0 Introduction

Teledyne Scientific & Imaging (TS&I) in cooperation with the US Army Research Laboratory (ARL) and the University of California at Santa Barbara (UCSB) have formed a team and have identified specific problem areas associated with automated data exfiltration and the generation of intelligence from heterogeneous networks from ground based sensors using a sparse network of collectors (e.g., Unmanned Air Vehicles or UAVs).

The key objectives of the ICB program are to aid the Army Research Laboratory to develop capabilities to assist in monitoring broad border areas for infiltration and to provide techniques for detecting anomalous events, locating the source, fusing data and classifying the signatures obtained from heterogeneous sensor networks using aerial assets as a communication relay or as a base station for data processing in support of situation awareness.

This paper will provide an overview and preliminary technical results from research being conducted on the project with emphasis on bio-inspired strategies. The research was performed in coordination with the Institute of Collaborative Biotechnologies funded through the Army Research Laboratory and coordinated through the prime contractor UCSB. Teledyne Scientific Company serves as the program manager for the project and also supports technical research.

2.0 METHODOLOGY

2.1. Bio-Inspired Data Driven Methods for UAV Route Planning

2.1.1 Technical Approach

The primary driver for the research under the ICB program is to exploit bio-inspired techniques to help handle exponential complexity that can arise with large distributed networks of sensors (100 Km²) and their capability to provide timely intelligence to dismounts and upper echelons. Several bio-inspired technologies developed through the ICB in collaboration with ARL and Teledyne Scientific Company highlight the aforementioned capabilities. A bio-inspired algorithm is used to route the sequence in which an aerial collector (UAV) visits unattended ground sensors (UGSs); this is performed in an optimal fashion by minimizing a Cramer-Rao cost function. This sequence is critical for rapid localization of the source as the nonlinearity and complexity (NP hard) of the source localization problem means that some sensors have much more information about the location of the source than others and points to a data dependent solution. However, a route which prioritizes based on the quality of the information will generally perform poorly because the travel time to the sensor must also be considered.

The quality of the information captured by a sensor depends on its location relative to the source, which is unknown. Instead, we compute the expected value of the information held by each sensor using the probability density of the source location given prior information and data from sensors that have already been visited. This probability comes as the product of the prior and the likelihood. After visiting two of the sensors, the likelihood has a hyperbolic shape (see Figure 2.1.1-1), and takes on an ellipsoidal characteristic after the aerial platform visits additional sensors. Computing the expected value of the information held by each unvisited sensor with respect to the underlying probability densities cannot be performed in closed form. Consequently, a more robust
strategy using a bio-inspired algorithm is used to compute the expectations and for handling the exponential complexity associated with scaling the network size.

Figure 2.1.1-1: A typical source likelihood function given the measurement from two sensors. A bio-inspired algorithm is used in computing the expected value of the information held by the unvisited sensors with respect to the source location probability.

The expected value of the information captured at a sensor should be computed as an integral in which the probability of finding the source at a given location is multiplied by the quality of the sensor information given the source location. This integral is well approximated by averaging the information quality at a finite number of points drawn from the probability function in a process known as Monte Carlo integration. Obtaining samples from the source location probability distribution can be challenging, but we employ a chemotaxis model of bacteria seeking nutrients in their environment to obtain these samples from these distributions (see Figure 2.1.1-2).

An important feature of the likelihood-based UAV route optimization is the ability to use any sensor for which a likelihood model can be generated. Our simulation and experimental results are based on time-of-arrival and angle-of-arrival sensors, but the method naturally extends to other types of sensors such as imaging and seismic.
Figure 2.1.1-2a: Swimming behavior in Escherichia Coli. Fairly straight motion arises when the flagella rotate counter clockwise. When the flagella rotate clockwise, the motion of the bacteria exhibits a random change in direction. Below is the stochastic hybrid system (SHS) model for the tumble-and-run motion used by E. Coli and the associated partial integro-differential equation describing the time evolution of the probability density function for the position of the bacteria p. Figure 2.1.1-2b: The bacteria distribute themselves according to the underlying nutrient concentration. By replacing the nutrient density with the source likelihood, the bacteria positions evolve to ideal samples from the source probability density, used to compute the optimal route.

2.1.2 Source Localization and Event Classification

The concept of operations consists of a sparse sensor network laid out over a 100 Km$^2$ area where only a small local number of UGSs will be able to detect an event of interest (e.g. an explosion). The sensors cannot communicate with each other because they are on the ground and widely separated. Source localization refers to a system capability to fuse data from multiple UGSs for the purpose of estimating the location of an acoustic event. In addition, event tracking over time is also needed along with capabilities to handle both the near and far field problems. Event classification refers to deciding what the event is (e.g., tank engine, explosion, etc.), typically from among a database of known events of interest.

2.1.2.1 Approach to Source Localization

Estimating the location of an acoustic event can be solved by a number of known methods [1,2,3,4,6]. The likelihood method described in Section 2.2.1 is primarily designed for route planning; however, it can be used to provide coarse level source
localization. The likelihood method also offers a capability to fuse data from heterogeneous sensors such as time-difference-of-arrival (TDoA) and angle-of-arrival (AoA) data.

In order to compare the performance of the likelihood method with bio-inspired sampling outlined in Section 2.1.1, field data collected during a flight test was analyzed and a comparison of the accuracy of several source localization methods was completed (Section 3.1). The methods include techniques from Smith/Abel [1], Chan/Ho [6], Beck/Stoica [4] and Zhou/Lamont [2]. The method of Zhou/Lamont appeared to provide the best individual algorithm performance relative to a small data set collected during a field test. The Zhou/Lamont is based on solving a quadratically constrained least squares optimization problem to estimate the minimum of a cost function. Specifically, the method of Zhou/Lamont [2] solves the following constrained non-convex quadratic programming problem:

\[
\text{Min} \| Ax - b \| \quad \text{subject to} \quad x^T C x = 0 \quad \Rightarrow \quad x = \left( A^T A + \lambda C \right)^{-1} A^T b
\]

\[\phi(\lambda) = \sum_i \beta_i^2 \sigma_i / (1 + \lambda \sigma_i)^2 = 0\]

The parameter \( \lambda \) corresponds to the Lagrange multiplier used to compose an unconstrained least squares problem. The solution to the quadratically constrained least squares problem is of the same form shown in Equation 2.2.1-2 where \( \lambda \) is obtained by solving Equation 2.2.1-3 over a range that is specified by the eigenvalues of a computed matrix [2]. Matrix \( A \) is derived from the sensor locations and TDoA data as is the vector \( b \). \( C \) is a fixed matrix with diagonal [1, 1, 1, -1].

A modified strategy to source localization can be constructed by employing multiple algorithms and averaging their results. This would lead to a source localization approach with lower average error and reduced variance.

### 2.1.2.1.1 Approach for Helicopter Gunshot Source Localization

RDECOM-ARDEC described a problem concerning the location of gunfire directed at military helicopters. As part of the ICB effort, the team investigated this problem in relation to capabilities (algorithms) developed to locate the source of an acoustic event on the ground. The problem associated with helicopter gunshot source localization is different than detecting acoustic events on the ground since unattended ground sensors are separated by wide distances while the use of sensors (microphones) on-board a helicopter platform are closely spaced (Figure 2.1.2.1.1-1).

Recently, the team was able to exploit a source location algorithm developed for a network of sparsely distributed unattended ground sensors. The initial results (assuming that one can detect a gunshot event given the underlying helicopter interference) were very encouraging and are described in Section 3.1.1.
2.1.2.2 Bio-Inspired Acoustic Event Classification

In general, it is difficult to develop a reliable event classifier based on traditional spectral analysis because of the difficulty of determining subtle differences between different types of events due to variations in the geometry, terrain, environment and in estimating the minima of decision surfaces in feature space distorted by various effects. Moreover, the underlying basis functions in spectral analysis (e.g. sinusoidal, wavelet, etc.) may have little to do with the nature of the underlying event. Consequently, a novel approach to event classification was developed in an attempt to overcome the aforementioned algorithm deficiencies.

The idea developed in the ICB program for event classification compares an exemplar from a known event to sensed data using a specialized matching or correlation process. Figure 2.1.2.2-1 illustrates a bio-inspired process that was used for event classification. In this approach, one needs to estimate the three parameters \((g, \varepsilon, \tau)\) in order to compare or correlate a stored reference signature (exemplar) representative of an event of interest to sensed data. The hypothesis test shown in the lower left hand corner of Figure 2.1.2.2-1 suggests that one needs to model the reference signatures and then to try and optimize the parameter settings \((g, \varepsilon, \tau)\) so that the mean squared distance (cost function) between the modified reference and sensed signature are as close as possible over the extent of the temporal event. Metrics for comparison of reference and sensed signatures include mean squared distance between the two waveforms given an optimal choice of the three parameters \((g, \varepsilon, \tau)\), and the value of the time dilation parameter \((\varepsilon)\) relative to unity. Other metrics for comparison and classification are possible including the correlation coefficient.
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![Functional block diagram for event classification using particle swarm optimization](image)

**Figure 2.1.2.2-1: Functional block diagram for event classification using particle swarm optimization to estimate the best fit parameters \((g, \varepsilon, \tau)\) of the modeled reference signature to compare against sensed data.**

Consequently, the strategy adopted for event classification was to model the reference signature as a function of time and then to adjust the three parameters \((g, \varepsilon, \tau)\) associated with the reference signature to minimize the cost function during the signature comparison or correlation process.

Once the sensed signature is accurately modeled as a function of time, the three parameters \((g, \varepsilon, \tau)\) can be adjusted using a search technique to minimize the cost function.
One technique that has proven to be robust in terms of parameter search is based on a bio-inspired method related to swarm optimization. Particle Swarm Optimization (PSO; [7-8]) has been used to solve such problems and was employed in the event classification system. The dynamics of the swarm are modeled as a coupled system of discrete equations where the coupling is associated with a loose form of communication between agents in the swarm that facilitates convergence to optimal estimates of the parameters.

### 3.0 RESULTS

The methods outlined in Section 2 were evaluated in simulation using Monte Carlo techniques. After completing the simulations in the lab, the software architecture was updated and moved to the field for test with a real UAV and a heterogeneous sensor network.

#### 3.1. Source Localization Performance

Table 3.1-1 shows a comparison of the results (radial error) of different source localization methods applied to data collected from four sensors in a field test conducted in November 2009 at Camp Roberts, CA. The following observations were noted for each method that was investigated: 1) the Smith/Abel algorithm required a minimum of 4 sensors, 2) the Chan/Ho method works with a minimum of 3 sensors; however, the solution involves a quadratic equation that sometimes results in imaginary results, 3) the Bio-Inspired Likelihood technique fuses both TDoA and AoA data; the initial two runs of the method used degraded AoA data, 4) the Beck/Stoica algorithm studied in Year I of the ICB program yielded poor results since it required an initial estimate of the distance to the source from at least one sensor, 4) the Zhou/Lamont method solves a quadratically constrained non-convex least squares equation and requires a minimum of 4 sensors. One can combine the results of Smith/Abel, Chan/Ho, Likelihood, Zhou/Lamont and omit outliers to achieve a fused or averaging algorithm that provides lower mean error and reduced variance. The average of methods showed that one can achieve about a 3 meter radial error for this field data (an exceptional result). Additional logic is required to detect degraded AoA data and would result in improved performance from the Likelihood method.

<table>
<thead>
<tr>
<th>Algorithm (4 Sensors)</th>
<th>Run #1</th>
<th>Run #2</th>
<th>Run #3</th>
<th>Run #4</th>
<th>Run #5</th>
<th>Run #6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smith/Abel</td>
<td>2.7</td>
<td>1.3</td>
<td>2.1</td>
<td>4.9</td>
<td>5.9</td>
<td>4.1</td>
</tr>
<tr>
<td>Chan/Ho</td>
<td>2.7</td>
<td>1.3</td>
<td>1.9</td>
<td>4.2</td>
<td>6.6</td>
<td>3.7</td>
</tr>
<tr>
<td>Likelihood (TDoA + AoA)</td>
<td>10.4*</td>
<td>19.6*</td>
<td>2.6</td>
<td>1.8</td>
<td>2</td>
<td>5.6</td>
</tr>
<tr>
<td>Beck</td>
<td>2.9</td>
<td>5.3</td>
<td>2.9</td>
<td>10.4</td>
<td>9.4</td>
<td>4.6</td>
</tr>
<tr>
<td>Zhou/Lamont</td>
<td>2.3</td>
<td>1.9</td>
<td>0.3</td>
<td>4.7</td>
<td>4.8</td>
<td>4.3</td>
</tr>
<tr>
<td>Average of Methods</td>
<td>2.5</td>
<td>1.5</td>
<td>1.7</td>
<td>3.9</td>
<td>4.8</td>
<td>4.4</td>
</tr>
</tbody>
</table>

* = Degraded AoA Data  

Table 3.1-1: Comparison of field test analysis from data collected at Camp Roberts, CA in November 2009; five different algorithms for source localization were compared including the likelihood method with bio-inspired sampling and fused TDoA and AoA data as outlined in Section 2.2.1; the results indicate that the method of Zhou/Lamont provided the best
individual algorithm results given four sensors; an improved source location algorithm is obtained by averaging the results of multiple algorithms; the averaging technique results in an mean error of about 3 m and has lower variance than the individual methods.

3.1.1 Helicopter Gunshot Source Localization

The performance of a source location algorithm assessed in the ICB program was analyzed using Monte Carlo simulation techniques to determine its capability to provide accurate data to an operator on-board a helicopter. The results of a Monte Carlo simulation study are shown in Figure 3.1.1-1.

![Figure 3.1.1-1: Monte Carlo simulation results for applying a source location algorithm to closely spaced sensors on the bottom of a helicopter; source location radial accuracy (m) is shown as a function of the signal to noise ratio (SNR in dB) of a gunshot at the helicopter; the simulations were performed using different sampling rates at the sensors and the best performance is achieved for a sample rate of 16K/sec with an SNR of 13 dB or better where the radial error is about 10m.](image)

3.1.1.1 Helicopter Gunshot Detection

Since the ICB team did not have access to helicopter data with gunfire, a brief assessment of the gunshot detection problem was conducted by superimposing a gunshot signature over a helicopter waveform. The results of this analysis are shown in Figure 3.1.1.1-1.

Referring to Figure 3.1.1.1-1, when a gunshot signature is superimposed on the waveform generated by a flying helicopter, it appears to be comparable to the helicopter interference in frequency extent. In fact, the spectrum of the composite signatures (helicopter interference and gunshot) is shown in the right hand figure. The spectrum shows that the gunshot is inter-mixed with the helicopter interference spectrum. The use of matched filters is probably required to effectively detect a gunshot event under these conditions.
Figure 3.1.1-1: Insert figure right shows a gunshot signature superimposed on interference generated from a flying helicopter; the base figure shows the estimated joint spectrum; the results show that the gunshot signature lies mixed within the spectrum generated by the helicopter interference making it difficult to detect; matched filters are probably required to detect the occurrence of a gunshot event during helicopter flight.

3.2. Acoustic Event Classification Performance

The process shown in Figure 2.1.2.2-1 was applied to a small database of signatures obtained from ARL (real field data using actual explosions). A single exemplar of raw data was selected at random from each class to form the reference database and a test was conducted to classify the remaining events. The results of the event classification study are shown in Table 3.2-1. The results show that 100% correct classification performance was achieved for this small database of signatures.

<table>
<thead>
<tr>
<th>Event Type Type (# Events)</th>
<th>Explosion Type 1</th>
<th>Rifle</th>
<th>Detonation</th>
<th>Explosion Type 2</th>
<th>Unknown</th>
</tr>
</thead>
<tbody>
<tr>
<td>Explosion Type 1</td>
<td>9</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Rifle</td>
<td>0</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Detonation</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Explosion Type 2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>0</td>
</tr>
</tbody>
</table>
Table 3.2-1: Event classification results from real field data obtained from ARL; results show excellent classification performance over a limited database; the unknown event was correctly classified.

Examples of additional RDECOM-ARDEC acoustic signatures are shown in Figures 3.2-1. There are a number of very subtle details associated with the signature patterns that make classification a difficult problem. The details show subtle nonlinearities possibly due to background interference, reflections, range differences and or atmospheric variation (channel conditions) that contribute to differences between the similar types of mortar launches and impacts. The RDECOM-ARDEC data primarily consists of two classes (large and small projectiles) of mortar launches and impacts events.

Figure 3.2-1: Examples of small sized mortar impacts obtained from RDECOM-ARDEC data; the data illustrates the complexity of the same type of event and possible sub-features that could be exploited to identify the similarity of the events.

A preliminary feature analysis effort was conducted to identify sub-features of the acoustic signatures that could be used to discriminate subtle differences between types of mortar launches and impacts. A modified strategy to detect and classify these acoustic features is being developed using a flexible matched filter method. A matched filter algorithm developed during the Camp Roberts field tests showed exceptional performance in detecting acoustic events even in non-line-of-sight scenarios. The selected features will be evaluated using the swarm optimization method.

3.3. CAMP ROBERTS FIELD TEST

3.3.1 Flight Test Operations

The original purpose of the flight test at Camp Roberts was to check out the basic system architecture and verify the team’s capability to communicate through a UAV (relay) and detect acoustic events in the field. The plan was extended to include path planning using the bio-inspired chemotaxis algorithm with interface to the UAV control software from AeroMech Engineering (SharkFin). In addition, the team asked AeroMech to upgrade the UAV payload to include a downward looking (nadir) camera to image the estimated event location. The flight test experiment involved data exfiltration from a network of acoustic sensors and a UAV to locate/image acoustic events generated using a propane cannon. In addition, the test was designed to calibrate the sensors and capture ground truth data for post flight analysis and study. Figure 3.3.1-1 shows an overview of the planned flight test architecture and the concept of operation. The flight test also involved the use of a sensor system provided by ARL called the Acoustic Transient Detection System (ATDS; shown in the lower right portion of the first figure below); the addition
of the ATDS sensor created a heterogeneous sensor network that provided angle-of-arrival (AoA) data.

The test layout at Camp Roberts involved the distribution of UGSs along with the ATDS sensor (ARL) over the range; a propane cannon (Figure 3.3.1-4) was used to create controlled explosions. Since the sensors cannot communicate with each other or the base station, the UAV was used to monitor the sensor network and relay detected acoustic events (ToA and AoA) to the ICB base station located at the airfield (right hand portion of Figure 3.3.1-1). When an event was detected by the sensors, the information was relayed to the ICB base station from the UAV and was processed and used to create a route (SharkFin) for the UAV to exfiltrate data from the sensors in a prescribed manner (via a bio-inspired algorithm). The automated route instructs the UAV to fly towards individual sensors and collect event data in an optimal fashion to minimize the number of sensors visited and the time needed to fly the route. Data is extracted from individual sensors when the UAV over flies a sensor line-of-sight zone around each sensor (determined from SharkFin analysis prior to the sensor placement). The zones around sensors simulated limited communication ranges between the sensor and the UAV. When three or more times-of-arrival (ToAs) are collected from the sensors, a source location estimate and confidence were computed (propane cannon location). When sufficient accuracy was determined based on the estimated source location and confidence, the UAV was instructed to fly a loiter pattern (figure eight) over that location. The center of the figure eight (Figure 3.3.2-1) represents the estimated source location and the nadir or downward looking camera on the UAV images that area as it passes over the estimated lat/lon of the source.

Figure 3.3.1-4 shows the base station setup (AeroMech SharkFin and ICB) at the McMillan Airfield at Camp Roberts. Figure 3.3.1-4 also shows a picture of the propane cannon (goose gun) mounted on the back of a pickup truck.
3.3.2 Flight Test Results

During the week of November 2nd, 2009, the ICB team conducted a flight test at the McMillan Airfield at Camp Roberts, CA. On Monday, November 2nd, the UCSB and Teledyne Scientific Company team members conducted preliminary tests and calibration of the UGSs and the ATDS (ARL) sensors using the propane cannon. On Tuesday, November 3rd, AeroMech Engineering flew their Fury UAV in coordination with the ICB team. A number of software issues were resolved and towards the end of the day, three successful tests of the system were performed using the propane cannon to generate a timed explosive event. During the three test runs of the system, the UAV detected events from the sensors, flew routes over the sensor network as directed by the ICB algorithms to extract data from the individual sensors, relayed the ToA and AoA data to the ICB base station; once the source location was estimated by the ICB base station. The source location was then communicated to the SharkFin software and AeroMech generated a figure eight route for the UAV which flew the pattern over the estimated position of the propane cannon and successfully imaged its location (i.e., the propane cannon was visible in the camera field of view). The field of view (FOV) for the nadir camera was about 100 m square. Examples of a successful test runs (locating the propane cannon in the field given the sensor measurements) are shown in Figure 3.3.2-1.
(SharkFin); the results showed that the ICB algorithm correctly estimated the source location from the acoustic event; additional examples of the UAV nadir camera imaging the correct location of the propane cannon at different locations on the test range are shown on the right.

### 3.3.3 Heterogeneous Sensor Network

In order to conduct a field test of the ICB technologies, the team needed to design and integrate a number of makeshift unattended ground sensors. ARL provided one sensor (ATDS) that the team integrated with the makeshift sensors as part of the sensor network to simulate a heterogeneous configuration. The ARL sensor was ruggedized and is designed to provide AoA data. UCSB, with aid from Teledyne Scientific Company, worked together to build six new makeshift sensors (not ruggedized). The makeshift sensors consisted of a Dell laptop computer running Java and MatLab under the UBUNTU OS, an industrial grade microphone with wind protector, a Microhard long range radio, a GPS system, a power inverter and a deep cycle marine battery. The makeshift sensor was mounted on a wood platform to provide some protection from the soil and sun. Figure 3.3.3-1 shows one of the makeshift sensors (left hand image) along with the ARL sensor (right hand image).

#### Figure 3.3.3-1: Pictures of the makeshift unattended ground sensor (left) and the ARL ATDS sensor (right); a heterogeneous sensor network was constructed using six of the makeshift UGSs and the ARL sensor for testing at Camp Roberts.

### 3.3.3.1 Sensor Calibration, Event Detection and AoA Estimation

When the ICB team arrived at the Camp Roberts airfield on Monday, November 2nd, the team set up a linear sensor network by placing sensors in a line at various ranges (about 100-200 m apart) from the propane cannon which was located at the start of the McMillan runway. The propane cannon was test fired multiple times and the sensors were calibrated so that they could reliably detect acoustic events generated by the propane cannon. These tests continued into the evening and in one test of the system, a makeshift UGS was placed about 1.5-2.0 Km from the propane cannon in a remote area with no line of sight to the airfield or propane cannon. During the calibration tests, it was determined that the makeshift UGSs could reliably detect non-line-of-sight acoustic events at extended ranges (1.5 - 2.0 Km).

The calibration tests showed that there was a need for an improved event detection algorithm and the team designed (on-the-fly) and integrated a new algorithm based on the use of a matched filter to detect acoustic events from the propane cannon. The use of MatLab as part of the software implementation for each sensor facilitated the rapid development and integration of a new event detection algorithm in the field. Figure 3.3.3.1-1 (left) shows an event signature recorded by an UGS and the corresponding
template used in the matched filter event detection algorithm. Very reliable results were obtained using this technique even in the presence of interfering noise such as the motor noise from the UAV, passing vehicles and the wind. The right hand part of Figure 3.3.3.1-1 shows how the ARL sensor was used to estimate the angle-of-arrival (AoA) using 4 orthogonal microphones.

On the first day of field test, the ARL ATDS sensor provided reasonable estimates of the angle-of-arrival (AoA). On the second day of flight tests, the wind picked up and the AoA estimates degraded. The process of correcting for wind degradation on AoA data is involved and was beyond the scope of the field experiment.

![Figure 3.3.3.1-1: Examples of the acoustic signature generated by the propane cannon and the corresponding matched filter template used for event detection at Camp Roberts; this algorithm was implemented as an improvement to the original event detection process and demonstrated excellent performance in the field; the right hand image shows the how data from the four ARL microphones was processed to estimate the angle-of-arrival (AoA); c is the speed of sound and the AoA ($\theta$) is estimated by searching for a minima of a quadratic cost function.](image)

### 3.3.4 Flight Test Simulation and UAV Plug & Play Architecture

A sophisticated plug and play software system architecture was designed for simulation and leveraged for the field test. A flight simulator (FlightGear) was used for simulation testing and replaced with a UAV interface for field test. Simulation results for source location time and the number of sensors visited for different algorithms is shown on the right in Figure 3.3.4-1. The field test software architecture with UAV is shown on the left in Figure 3.3.4-1. A Java middleware client was used to communicate between the ICB base station and the AeroMech base station that runs the SharkFin ground control software (see Figure 3.3.4-1 left). The Java middleware client was also used as the interface between the ICB base station, the UAV and the ground sensor radios to transmit data and sensor status.

Each ICB computer (base station and sensors) employed the open source UBUNTU operating system (OS). The OS ran the Java middleware client on Dell Latitude laptops to facilitate communications among all network components and MatLab for algorithm processing, data storage and sensor control.
3.3.5 ICB Base Station Display

The ICB base station captured data from all sensors including status, location, ToA and AoA information. The ICB base station also obtained data from SharkFin (AeroMech) on the location and route of the UAV in flight. The data obtained from SharkFin was converted from lat/lon to an x-y representation and displayed on the ICB base station as shown in Figure 3.3.5-1. This display served to highlight those sensors that detected an event generated by the propane cannon, monitored the route of the UAV and displayed the likelihood function and source location estimate (diamond symbol) in near real time.

Figure 3.3.5-1: ICB base station display showing the sensor locations, status, UAV position over time (dynamic display) and ICB algorithm likelihood function with source location estimate in near real time.

3.3.6 Communication and Networks

A network of eight Microhard radios was used to manage the communications for the flight tests. Each of the six ground sensors employed a Microhard Nano radio as well as the Fury UAV and ICB base station. The Microhard network access was TDMA operating at ISM band (900 MHz) and the communication network controller was the ICB base station. The Fury UAV served as a relay node. AeroMech used a 400 MHz military band radio to communicate with the Fury UAV and to download imagery from the cameras on-board the platform. The Fury UAV had two cameras, one mounted as a forward looking system and the nadir or downward looking camera for imaging the location of the propane cannon as designated by the ICB source localization algorithm.
The AeroMech SharkFin software could select either camera for video transmission to the AeroMech base station and was manually designated over time based on the sequence of events associated with a test run (i.e., after a source location estimate was generated by the ICB base station, the nadir camera was selected on the UAV as the source of the video display at the SharkFin base station).

3.3.7 Summary of Flight Test Results

The Fury UAV flew three successful runs on the first day of test flights. A successful test run consists of having at least three sensors detect a propane cannon explosion, routing the UAV over the sensor network area to capture or exfiltrate ToA and AoA data, processing the data at the ICB base station and correctly estimating the location of the source. During the second day of flight tests, the propane cannon was moved to different locations on the range and six additional experiments were conducted to test the accuracy of the system in terms of locating the source of the acoustic event. Table 3.3.7-1 summarizes the source location errors for the two days of test using the likelihood method.

<table>
<thead>
<tr>
<th>Test Run</th>
<th>11/2/09 #1</th>
<th>11/2/09 #2</th>
<th>11/2/09 #3</th>
<th>11/6/09 #1</th>
<th>11/6/09 #2</th>
<th>11/6/09 #3</th>
<th>11/6/09 #4</th>
<th>11/6/09 #5</th>
<th>11/6/09 #6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source Location Error (m)</td>
<td>4.5</td>
<td>4.3</td>
<td>20*</td>
<td>10.4*</td>
<td>19.6*</td>
<td>2.6</td>
<td>1.8</td>
<td>2.0</td>
<td>5.6</td>
</tr>
<tr>
<td>Number of Sensors Visited</td>
<td>4</td>
<td>6</td>
<td>5</td>
<td>4</td>
<td>5</td>
<td>4</td>
<td>5</td>
<td>5</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 3.3.7-1: Summary of flight test results; source location error and number of sensors visited; * indicates that degraded AoA measurements were used in the calculation; these results need to be revisited with the algorithm to correct for the poor data.

4.0 SUMMARY AND FUTURE PLANS

UAVs provide an effective means to autonomously facilitate data collection from a sparse network of heterogeneous sensor systems monitoring large areas where the sensors cannot communicate with each other or the base station. This observation was validated in simulation and proven in real world tests of the ICB architecture. In addition to providing a communication infrastructure and a mechanism for implicit synchronization of sensors, UAVs can also be used to reduce the system reaction time by using information exfiltration routes that are data-driven. Bio-inspired techniques for search provide a novel strategy to detect, route aerial assets, source locate, capture, fuse and classify data across heterogeneous sensor networks.

Real world test of the ICB system demonstrated excellent performance where 9 out of 9 successful test runs of the system using live acoustic events were demonstrated over several days of field tests. The average circular error as measured relative to the location of the source was about 3 meters. Improved source location error performance can be achieved by averaging the results from multiple algorithms and excluding outlier data.
A novel bio-inspired solution to acoustic event classification was also developed and tested against real data obtained from ARL. The classification algorithm is based on using swarm dynamics to estimate the parameters between a reference and model of a sensed signature. The performance of the classification algorithm has shown excellent accuracy when tested on real ARL data.

During the third and final year of the ICB program, the flight test architecture will be integrated with the ARL sensor network fabric. The sensor network fabric being developed under a separate ITA program is a distributed network (middleware) that integrates all test resources including sensors, UAVs, manned platforms and other resources. Additional field tests will be conducted using upgraded ICB algorithms in the final year of the program. In addition, DoD customers will be sought to help transition the technology to a 6.3 program.

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6.0 REFERENCES


