The Design and Evaluation of a Hybrid Sensor Network For Cane-toad Monitoring

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***Abstract*— This paper investigates a wireless, acoustic sensor network application — monitoring amphibian populations in the monsoonal woodlands of northern Australia. Our goal is to use automatic recognition of animal vocalizations to census the populations of native frogs and the invasive introduced species, the Cane Toad (see Fig. 1). This is a challenging application because it requires high frequency acoustic sampling, complex signal processing and wide area sensing coverage.**

We set up two prototypes of wireless sensor networks that recognize vocalizations of up to 9 frog species found in northern Australia. Our first prototype is simple and consists of only *resource-rich* Stargate devices. Our second prototype is more complex and consists of a *hybrid* mixture of Stargates and inexpensive, resource-poor Mica2 devices operating in concert. In the hybrid system, the Mica2s are used to collect acoustic samples, and expand the sensor network coverage. The Stargates are used for resource-intensive tasks such as Fast Fourier Transforms (FFTs) and machine learning.

The hybrid system incorporates three algorithms designed to account for the sampling, processing and communication bottlenecks of the Mica2s (i) *high frequency sampling*, (ii) *compression and noise reduction*, to reduce data transmission by up to 90%, and (iii) *sampling scheduling*, which exploits the sensor network redundancy to increase the effective sample processing rate.

We evaluate the performance of both systems over a range of scenarios, and demonstrate that the feasibility and benefits of a hybrid systems approach justify the additional system complexity.

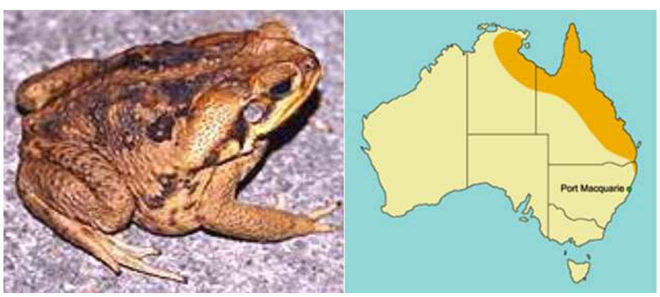

Fig. 1. The Cane Toad and its 2003 Australian distribution.

I. Introduction

This paper explores the use of wireless sensor network technology for monitoring amphibian populations in remote areas of Australia's Northern Territory.

The Cane toad (*Bufo marinus*) was introduced to Australia in the 1930s in the belief it would control pests in Sugar Cane crops [1]. Since their introduction they have progressively spread through north-eastern Australia. Their expanding distribution, density and ecology characteristics have raised grave concerns regarding their impact on Australia's native fauna. Fig. 1 illustrates their 2003 distribution. Of particular concern is Kakadu National Park, a vast World Heritage area, recently colonized by Cane Toads [2].

In previous work, Taylor *et al* have developed software to census frog populations by automatic recognition of their vocalizations based on machine learning algorithms [3]. They have deployed frog monitoring stations in Kakadu National Park and the Roper valley of the Northern Territory. Each of these monitoring stations contains a solar panel, battery, power management electronics, microphone & preamp, temperature sensors, rain gauge, and a *Pleb*. The Pleb is a single board computer built at UNSW based on a 200MHz StrongArm processor. These monitoring stations have no communications capability. Condition monitoring and data collection can only be done by expensive, typically annual, site visits.

Our goal is to deploy a large scale, inexpensive wireless sensor network that can operate unattended and is capable of monitoring, tracking and measuring the impact of cane toads in areas such as Kakadu National Park from acoustical observations. It is challenging to implement such a real world sensor network application which incorporates *in-network reasoning*. Our work builds on lessons in robust, adaptive system design from current sensor deployments for habitat monitoring [4], [5] which focus primarily on simple data collection tasks (e.g. collect temperature and humidity data).

The purpose of this paper is to explicate these systems contributions which enable in-network reasoning:

- We describe a novel real-world sensing application (cane toad monitoring), which consists of many resource-intensive tasks. Accordingly, we set up the first prototype that has purely resource-rich sensors. One of the key disadvantages of the first prototype is the high financial cost of such a system. Therefore, we design a hybrid system that consists of both resource-rich and resource-impoverished sensors, where resource-impoverished sensors extend sensing coverage and are used for simple tasks like collecting acoustic samples, and resource-rich sensors are used for resource-intensive tasks like FFTs and machine learning procedures.
- To enable the hybrid system, we design and incorporate three algorithms to account for the sampling, processing and communication bottlenecks of resource-impoverished sensors — (i) *high frequency sampling*, (ii) *compression and noise reduction*, to reduce data transmission by up to 90%, and (iii) *sampling scheduling*, which exploits the sensor network redundancy to increase effective sample processing rate.
- We implement and evaluate the performance of both systems over a range of scenarios, and demonstrate that the feasibility and benefits of a hybrid systems approach justify the additional systems complexity.

In the rest of the paper, we discuss related work in sensor network deployments and acoustic sensing applications (Section II); provide an overview of our frog *vocalization recognition* algorithm (Section III) which drives our system requirements and design; describe the components, systems architecture and design contributions of our two systems prototypes (Section IV); evaluate our system prototypes and discuss the results in (Section V). Section VI describes future research directions, and our conclusions.

II. Related Work

Sensor networks have invoked heavy research activities in the past few years. Numerous applications and data dissemination protocols have been proposed for sensor networks. In this section, we cover relevant research in sensor network deployments, and acoustic sensor applications.

A. Sensor Network Applications

Numerous sensor network applications have been proposed at the areas like habitat monitoring [4] [5], health [6], education [7], structure monitoring [8] and precision agriculture [9]. Two significant sensor network deployments are:

- Habitat Monitoring on Great Duck Island [4]: In Spring 2002, researchers from College of the Atlantic in Bar Harbor and the University of California at Berkeley began to deploy a wireless sensor network to monitor microclimates on Great Duck Island. More than 100 nodes have been deployed and millions of readings have been transferred to a central database thousands kilometers away via wireless channels since then.
- Scientists and engineers from UCLA and UCR have operated a 10 node, 100 microclimate sensor array at James Reserve over 12 months continuously. Significant climate data has been stored in a database and available for web query. Apart from simple attributes like temperature, humidity, barometric pressure, and mid-range infrared, they are also collecting data from soil and video sources. They are extending the system to consist of more than 100 nodes and thousands of sensors for larger and deeper coverage.

Current sensor network deployments are mostly homogeneous and only perform simple data collection. We are planning to deploy a sensor network that can handle significantly more complicated tasks, which include much higher sampling frequency, complex signal processing, and vocalization recognition.

B. Acoustic Sensor Applications

Rama et al. provide a data fusion framework [10] for vehicle detection and tracking using acoustic and video sensors. To reduce the amount of transmission, task decomposition and collaboration have been investigated in [11]. The authors try to filter data and transmission by preprocessing acoustic data at each sensing node. In contrast to previous acoustic sensing applications, our goal is to investigate which parts of application can be offloaded to inexpensive but resource-impoverished Mica mote.

Taylor et al. implemented a vocalization recognition algorithm in [3] on a stand-alone computing platform based on machine learning techniques. In [12], Saurabh et al shows how wireless sensor network technology might be used for monitoring amphibian populations.

C. Summary

Previous sensor network deployments only perform data collection of simple environmental data like temperature, humidity, barometric pressure, and video. While these deployments can provide unprecedented fine-grained environmental data to users, many applications involving complicated processing tasks have not been investigated. Previous mechanisms for cane-toad monitoring using stand-alone PLEB devices has the disadvantages of insufficient coverage, slow feedback and high cost. Our approach of using a hybrid wireless sensor network, described in next few sections, is tailored to address the above constraints.

III. A Frog Vocalization Recognition Algorithm

In this section, we provide an overview of the frog vocalization recognition algorithm [3] which we use to motivate and build our prototypes. Acoustic features in the time and frequency domains (see Fig. 2) can be used to distinguish the vocalizations of different amphibians. Possibly useful features include call rate, call duration, amplitude-time envelope, waveform periodicity, pulse-repetition rate, frequency modulation, frequency and spectral patterns. Frog vocalizations are much simpler than human speech but they must be recognized in very difficult conditions with multiple competing uncooperative "speakers" which are distant from the microphone and with a variety of noise sources such as wind, rain and insects present. The demands of this difficult acoustic environment do not allow the recognition algorithm to segment or isolate individual vocalizations. The input signal is converted into a spectrogram of time-frequency pixels (see Fig. 3) by a Fast Fourier Transform (FFT) algorithm.

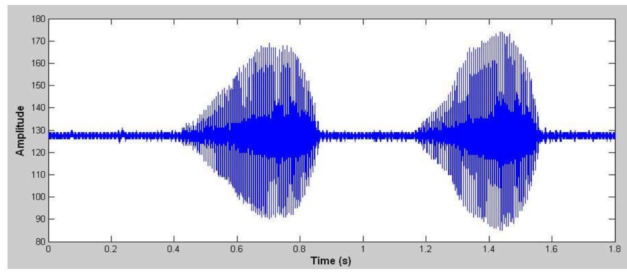

Fig. 2. The waveform graph of *Cyclorana cryptotis.*

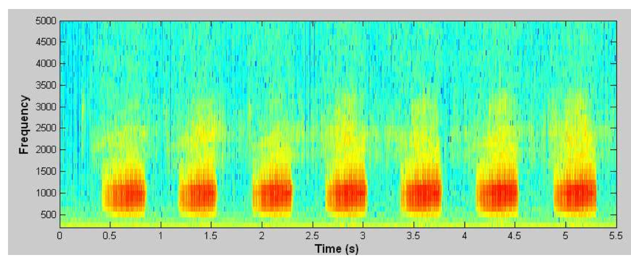

Fig. 3. The spectrogram graph of *Cyclorana cryptotis.*

The algorithm examines each slice (about 1 millisecond each in length) of the spectrogram and tries to estimate the frequencies that have more energy than neighboring frequency bins (local peaks). The slices are passed to the next stage of three levels of classifications if there are also local peaks in nearby time slices. Attributes extracted from these local peaks' occurrences along with attributes extracted from the signal waveform are used to identify individual species of frogs.

Quinlan's machine leaning system, C4.5 [13], is used to build the classifiers. Our system builds one classifier for each frog vocalization and makes a decision about the existence of each frog independently, which is different to Taylor's system that has one classifier for all species.

To increase the reliability of the system, a hierarchical-decision mechanism is used to identify the existence of each frog species. There are three levels of identifications in our system. For a specific species that has a vocalization lasting for 300 milliseconds and wherein each vocalization consists of a number of mini nodes which are 30 milliseconds long, our system will work as follows. The level

0 will be 30 milliseconds long; the identification of one species will be proceeded to the next level (level 1) which is 300 milliseconds in length if the local peaks occurring within 30 milliseconds are more than a threshold. Similarly, the identification process will be proceeded to level 2 which is 3 seconds long if the locals peaks occurred within 300 milliseconds are more than another threshold. If a number of level 2 vocalizations have been identified within 3 seconds, the species is identified reliably.

IV. Cane-toad monitoring using sensor networks

In this section, we describe the framework of our cane-toad monitoring system and the two sensor network prototypes that we have designed for the cane-toad monitoring application.

A. The Framework of Cane-toad Monitoring System

The long term goals of our cane-toad monitoring system are to pinpoint the regions habitated by cane-toads, and to track their macro movement directions. We use the mechanism described in section IV-C.2 to estimate and pinpoint the locations of cane-toads. The system should be deployed to those regions that are about to be inhabitated by the cane-toads, namely, the boundary regions. Therefore, we can estimate the macro movements of cane toads by comparing the cane-toad existence snap-shots at different times. Note that our objective is macro group movement tracking as opposed to individual centimeter scale tracking, it is not necessary to have fine-grained time synchronization at each node. We can instead synchronize a selective number of them (e.g. the Stargates in a hybrid system described in section IV-C.2) only.

B. Wireless Sensor Hardware

We use the following hardware platforms for our sensor network prototypes.

- Mica mote family: Mica2 (see Fig. 4) is the third generation of Berkeley mote manufactured commercially by Crossbow [14]. It has a 7.7 MHz Atmega processor and 512 kilobytes on-board flash memory. It can transmit at a maximum data rate of about 19 kbps and is powered by two AA size batteries. Its recent cousin Micaz has a ZigBee compliant RF transceiver and can support up to 250 kbps transmission rate. We use the Mica2 sensors as our *resource-poor* sensors.
- X-Scale Single Board Computer: Stargate (see Fig. 4), also manufactured by Crossbow [14], is a high performance processing platform that offers much more resources than Mica motes in terms of computation power, memory, energy and transmission capability. It is working on a 400 MHz Intel PXA 255 processor and has 96 megabytes memory in total (64 megabytes SDRAM and 32 megabytes flash memory). It can be powered by a li-Ion battery and can support Wi-Fi (11 mbps when using IEEE 802.11b) transmission. We use Stargates as our *resource-rich* sensors.

Building a wireless sensor network for cane-toad monitoring is challenging because of of the following requirements:

- High Frequency Sampling. To differentiate the calls of cane toad from other 8 native frog species and other environmental noises like sound of rain and/or crickets, the cane toad monitoring system must be able to provide at least 10 KHz. Note that 10 KHz sample rate is an empirical result.
- Complex Signal Processing. In our system, an FFT is used to produce a spectrogram in frequency domain from the sampled inputs of time domain. FFT algorithm needs to be processed by a device that has much heavier computation power and larger memory space than Mica.

Fig. 4. Mica2 and STARGATE.

C. Cane Toad Monitoring Prototypes

1) Pure: Stargates only (see Fig. 5): Since our frog-detection system involves many resource-intensive tasks, it is natural to use resource-rich Stargate to build such a system. A Stargate can achieve up to 44 KHz sampling rate, which is more than enough for our system. However, it could only process about 5 percent of the inputs sampled at 22 KHz in our initial implementation due to its slow floating point calculation emulations. We addressed this problem using integer-only Fast Fourier Transform (FFT) implementation. The system can currently process all inputs at 22 KHz sampling rate, which is about 4 times greater than that of the previous system used in [3]. Note that the required sampling frequency is still 10 KHz. The use of 22 KHz sampling with Stargate is because of its availability.

Moreover, equipped with a wireless transmission channel, our Stargate devices can also communicate and co-ordinate with each other to form an Ad-hoc network. This network can provide real time feedback to the user if connected to the Internet or satellite channel. Furthermore, it can estimate the migration direction of the cane-toad by analyzing the network-wide cane-toad existence snapshots at different time.

2) Hybrid: Stargates and Mica2s (see Fig. 6): The major problem of Stargates prototype introduced in section IV-C.1 is the financial cost of the system. The cost of a Stargate is quite high because of its powerful functionalities. Therefore, we introduce a hybrid mixture of Stargate and Mica2 system to make the system cost-effective. Mica2s can be scattered to collect acoustic samples because of their low cost. However, it is very challenging (if not impossible) to implement resource-intensive tasks like FFT algorithm and machine learning procedures in a tiny device that has a 7.7 MHz Central Processing Unit (CPU) and 8 Kbytes (Random-Access Memory) RAM. Therefore, we use resource-rich device Stargate instead. Mica2 does some preliminary processing to reduce the transmission size and environmental noise before it transfers the samples to the Stargate. Then the Stargate uses these inputs to determine the existence of frogs. It can either save the results to its flash or transfer them to user via the Ad-hoc network that it forms with other Stargates. Anycast communication paradigm [15] can be used for the Micas to locate the nearest Stargate. We design and implement the following algorithms to make the hybrid system effective.

- *In-Network Reasoning.* A naive approach for hybrid system design is to transfer all acoustic samples to an off-line server and then perform all computation on the server. The major disadvantage of this approach is the requirement of transferring a huge amount of data via *long-range* wireless radios. Since our system operates at a high sampling rate, the number of acoustic samples is large and therefore, the size of long-range wireless transmissions is also large. Consequently, the financial cost of wireless transmissions could be high, and the lifetime

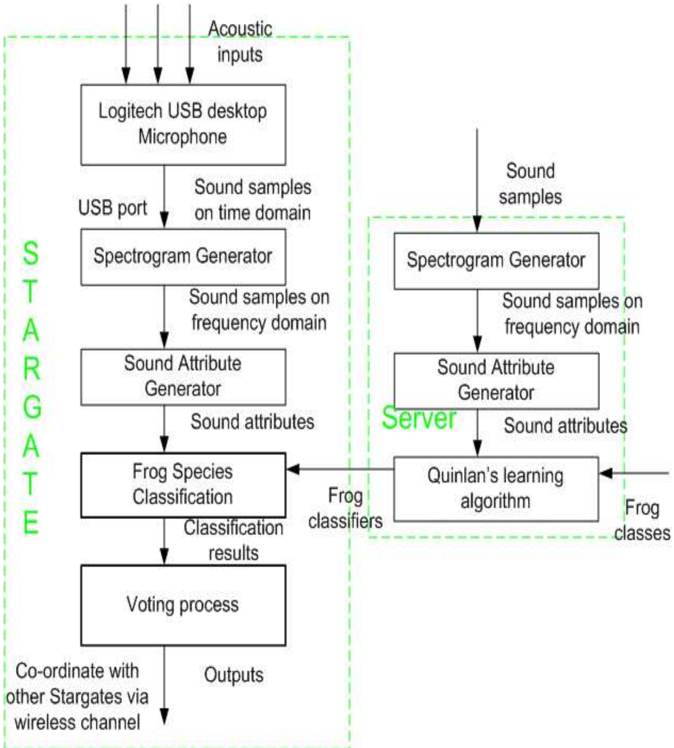

Fig. 5. The architecture of *Stargates Only* system. Stargate samples acoustic data using a desktop microphone via Universal Serial Bus (USB) port. The sound spectrogram is then generated to get signals in frequency domain from input in time domain. The sound attributes, including local peaks and other necessary variables, are extracted from the spectrogram and used as the input of machine learning classifiers, one for each frog species. To increase correctness and reliability of the recognition, a hierarchical recognition structure is employed, termed as voting process in above figure. Note that the training (classifier building) process is done in a server machine at early stage. Then the classifiers can be transferred and stored in Stargates.

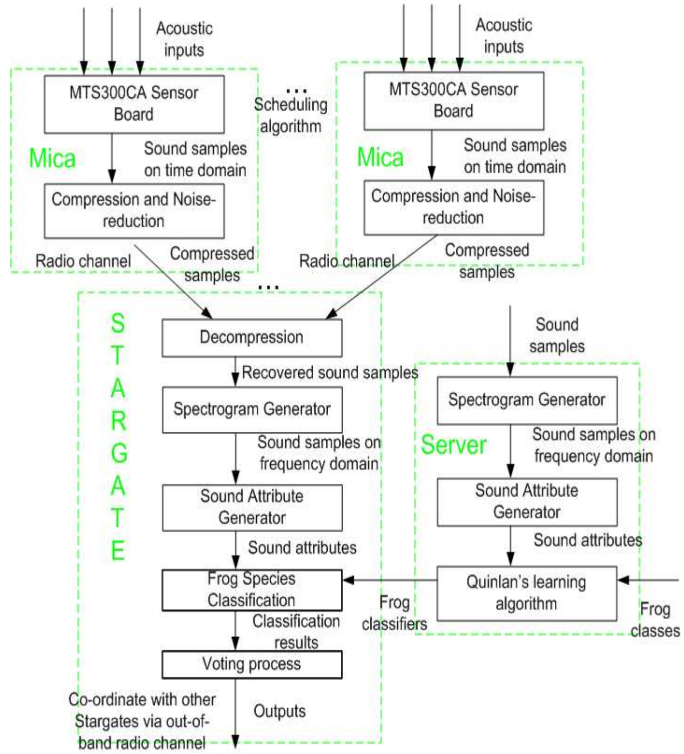

Fig. 6. The architecture of *Hybrid (Stargates and Mica2s)* system. In this system, instead of sampling acoustic data using desktop microphone, we use MICA2s to sample acoustic data, and compress it before sending to the Stargate via radio channel. Upon receiving data from the satellite motes, the Stargate will decompress received data before processing it.

of the system will be very limited because long-range wireless transmissions are costly in terms of energy. Instead, we adopt application-specific in-network reasoning, i.e. analysis of sensor data inside the network (e.g. determine existence of cane-toads); and only the final result (present/absent) will be transferred.

- *High Frequency Sampling.* The Mica can sample at up to 200 Hz normally. With the HighFrequencySampling component recently introduced by [16], it can achieve up to 6.67 KHz sampling rate after turning off the wireless radio of Mica while sampling. Because we need a sampling frequency of at least 10 KHz, we have to further change the clock rate of the Analog-Digital Converter (ADC) on the sensor board so that it can provide such a sampling rate.
- *Compression and noise-reduction.* To reduce environmental noise and transmission size, we design a simple yet effective algorithm as follows. It divides the whole period into a number of time slices which is 1 millisecond in length. Therefore, there are 10 samples in each time slice when sampling at 10 KHz. If the amplitude level of the whole period is under a threshold (for example, from -20 to +20), we call it a *silent/noise-only* period. For a silent/noise-only period, we use one special character which is one byte in length for the whole period which is 10 bytes in length originally. This can reduce the size of transmission by up to 90 percent (see section V for the details). When a Stargate receives the packet, it replaces the special character with ten silent values to recover the original signal. The environmental noise is also reduced (see Fig. 7). Note that some characteristics of the original signal will be lost after the conversion. However, the frequency signature of the frogs' calls will be preserved with carefully chosen silent/noise-only threshold.
- *Cane-toad Localization.* We use the location of the sensor device that detects the existence of a frog species through vocalization as the location of the frog species. The locations of sensors can be calculated by either Global Positioning System (GPS) or other localization algorithms like [17]. If a frog species is detected at more than one adjacent sensor, we calculate their region of overlap coverage as a frog species location. This location information is more than adequate for tracking long-term migration patterns and introducing isolating gene viruses.
- *Sampling Scheduling.* The bottleneck of our hybrid system is the transmission link between a Mica and Stargate. With our compression algorithm, it takes about 30 seconds to transfer a segment of 15 seconds acoustic samples. That is about a 30 percent process rate. To enlarge the process rate, we design and implement a scheduling algorithm which exploits the redundancy of sensor networks as follows. Based on their locations, two Micas are grouped together if they can detect the same acoustic signal. Then, the Stargate controls the sampling and transferring periods of two Micas such that when one Mica is transferring, the other is sampling. Thus, the processing rate can be increased to about 50 percent which is 60 percent more than

TABLE I

TESTS RESULTS OF OUR TWO PROTOTYPES WITH RESPECT TO FROG SPECIES IDENTIFICATION.

		Stargate		Hybrid	
		IND	MIX	IND	MIX
Indoor	Correct	9	4	9	4
	Wrong	0	2	0	2
Outdoor	Correct	9	4	9	3
	Wrong	0	2	0	3

IND — 9 types of individual frog's call
MIX — 6 types of mixtures of frogs' calls

that of using one Mica only.

In the future, we envision a single Stargate device to be used with many smaller motes. Our plan is to move from Mica2's to MicaZ's, which have a significantly higher bandwidth specification (250 Kbps as opposed to 20 Kbps). Moreover, we anticipate the monitoring system to be used most heavily during midnights of the wet season. We further anticipate that most monitored areas will be "quiet". The system transfers another special character if the acoustic samples of the whole sampling period (15 seconds) is "quiet". Therefore, the size of data transmission can be further reduced and thus one Stargate can work with more motes.

Once sounds are detected, even with the MicaZs, we need to coordinate transmissions to avoid collisions using a sampling scheduling algorithm. In such a system, we plan to maximize the effective sensing coverage and sampling rate by using a network flow model to inform our sampling scheduling.

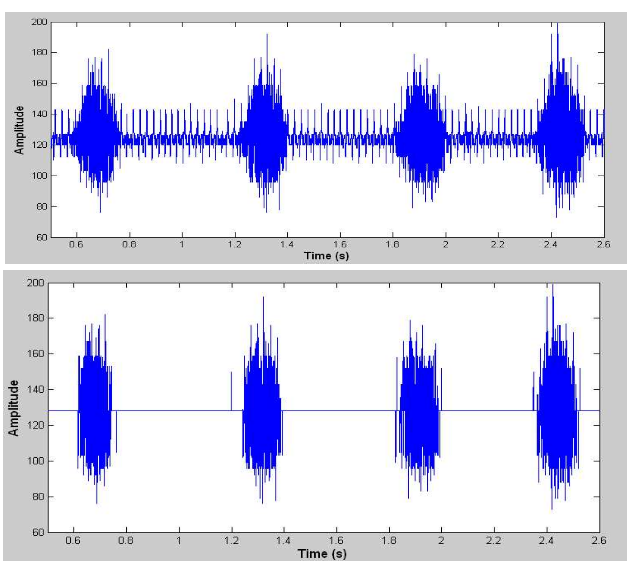

Fig. 7. The waveform graphs of *Cyclorana Cultripes* without (top) and with (bottom) noise reduction. (The samples are collected by Mica on field)

V. EXPERIMENTAL RESULTS

To evaluate the performance of our systems, we test them over a range of scenarios. Our performance metrics include not only baseline systems criteria like transmission sizes and operational latency; but also application-determined criteria, in this case, whether the frog species were correctly identified.

- *Test environments*. In our experiments, the playbacks of 9 individual frog's calls and 6 mixtures of frogs' calls are used as sound sources. Our Stargate system consists of a Stargate with Logitech USB Desktop Microphone that can respond to 100-16 KHz frequencies. In the hybrid system, Mica2 uses the standard microphone on MTS300CA sensor board. We test the systems in both indoor and outdoor environments. The indoor tests are conducted in our lab where external noise is minimal. The outdoor tests are conducted on a lawn with environment noises such as insect and bird calls present.
- *Performance test results*. The test results are summarized in Table I. Both indoor and outdoor tests show that our systems can recognize the individual calls of 9 species of frogs successfully. Not surprisingly, it is more difficult to recognize the mixed calls of different species. The system gives incorrect results between similar species a few times. The pure Stargate system achieves one more correct recognition outdoors than the hybrid system since it is operating at wider frequency ranges. The Hybrid system performs better indoor than outdoor because of outdoor environmental noises. *However, they never give incorrect results for the cane toad species (our principal species) since it has a very different vocalization compared to the other native species.* Fig. 8 shows the result screen shot of one of the experiments. A mixed sound of two frogs' (*Bufo marinus/cane toad* and *Cyclorana cryptotis*) calls were played back in this experiment, and both calls were detected successfully by our hybrid system.

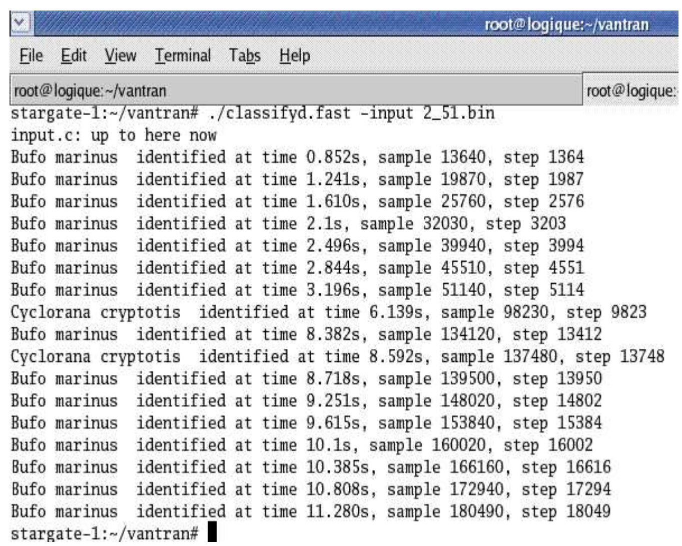

Fig. 8. Screen shot of one of the experiments, where two frogs (*Bufo marinus/cane toad, Cyclorana cryptotis*) are detected successfully by our hybrid system.

- *Transmission sizes*. We collect the calls of frogs on the field using Micas and store them as raw data. Then we use our compression algorithm to compress the raw data before transmission. The results are summarized in Table II. It shows that the algorithm achieves 25 percent to 45 percent compression ratio in different scenarios. The lower bound of the compression ratio is 10 percent that occurs when the whole sampling period is "silent". Since the frogs are active during mid-night only, the system is operating within that period. There will be large periods of "silence" and the compression algorithm should be

TABLE II

COMPRESSION RATIO FOR DIFFERENT SCENARIOS.

Frog(s)	Original Size	Compression Size	Compression ratio
1	99366	26319	26.59%
2	99622	25561	25.66%
3	99622	32699	32.82%
4	99544	36688	36.86%
5	99466	41623	41.85%

1 — *Bufo marinus call*
2 — *Notaden melanoscaphus call*
3 — *Cyclorana cryptotis call*
4 — Mixed sound of 1 and 3
5 — Mixed sound of 1, 2 and 3

more effective.

- *Latency and cost*. As shown in section IV-C.1, the first prototype can provide real time feedback to the users. The second prototype has about 45 seconds latency, which includes 15 seconds' sampling time, and about 30 seconds transmission time. This latency is inconsequential for our purposes. However, the costs between the two prototypes have large differences since the cost of Mica is projected to drop dramatically. Therefore, we believe the hybrid model is more suitable for the cane-toad monitoring application.

VI. CONCLUSIONS AND FUTURE WORK

We presented the design and evaluation of two sensor network architecture prototypes — *pure* and *hybrid* for cane toad monitoring, an application characterized by high frequency sampling, complex signal processing for in-network reasoning, and wide-area sensing coverage. Our prototypes can recognize the call of up to 9 species of frogs in northern Australia. To enable the hybrid architecture, we also design and implement a compression and noise-reduction algorithm, which can reduce the transmission size by up to 90 percent and increase the performance of the system dramatically. Moreover to enlarge the sampling frequency for a given monitoring period, we design a sampling scheduling algorithm which exploits the redundancy of sensor networks and increases the system process rate by up to 60 percent. We compare the performance of the two systems by evaluating them over a range of scenarios, which demonstrates the feasibility of a hybrid systems approach.

To extend system lifetime, it is desirable to further reduce transmission size. We are planning to investigate the methods to implement FFT and some parts of our vocalization recognition algorithm within Mica. We are looking to use the same frame work for other acoustic monitoring applications like monitoring breeding populations of endangered birds. Having validated our systems approach, we are planning to deploy our hybrid sensor network in northern Australia, over the next few months. More details about this research can be found at:
http://www.cse.unsw.edu.au/s̃ensar/research/projects/cane-toads.

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