Automated wildlife monitoring using self-configuring sensor networks deployed in natural habitats

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Abstract

To understand the complex interactions among animals within an ecosystem, biologists need to be able to track their location and social interactions. There are a variety of factors that make this difficult. We propose using adaptive, embedded networked sensing technologies to develop an efficient means for wildlife monitoring. This paper surveys our research; we demonstrate how a self-organizing system can efficiently conduct real-time acoustic source detection and localization using distributed embedded devices.

1 Introduction

It is now well-recognized that artificial life systems can make useful contributions to a wide variety of problems in biology [8]. Typically, these contributions have come from the study of complex adaptive systems, simpler versions of natural life. Such abstractions permit isolation and control of features of interest [3]. In this paper we describe a novel application of adaptive systems for biology: looking at natural systems with the purpose of describing their structure and behavior.

The presence of human observers in the field is both time consuming and disruptive to the habitat under observation. An automated system would be desired. However, deployment of unattended recording stations is also fraught with difficulty. Among the current limitations are limited recording capacity and energy, and limited ability to able to adapt to rapidly changing environments.

We illustrate that sensor network technology can be used as an efficient and powerful data collection system that can be easily used by biologists with little programming experience. Beyond simply recording of raw data, these tools have the potential to perform autonomous wildlife monitoring by being programmed to detect and react in a proper way to pre-specified conditions, with almost no human intervention. In addition, they form a network that enables remote management of the system, system health assessment, re-tasking, real-time triggering of additional sensing modalities, and visualization of real-time data from the field.

The distributed structure of these systems allows us to deploy them to cover wide territories and to capture data from different modalities in response to events in real time, e.g., capturing image data only animals are active. Distributed signal processing algorithms are also a promising approach to data reduction. Spatial filtering techniques based on beam-forming using a distributed collection of small arrays, can often identify target species in situations where many species and individuals are present. Also, we will illustrate how self-organizing and adaptive methods can be used to develop robust and efficient methods to detect and localize acoustic sources.

2 Tools and methods

This section describes the embedded platform we used for our experiments, and then we will briefly describe different contexts where adaptive methods have been employed.

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2.1 CENS nodes

For our experiments we have developed a network of Acoustic Embedded Networked Sensing Boxes (Acoustic ENSBox) as a prototype for wildlife monitoring system [5, 6, 7]. Each system is a small embedded computer running Linux, self-contained in a waterproof case, with an external four microphone array and 802.11b wireless communication (Figure 1).

Figure 1: *Left:* Acoustic ENSBOX, the embedded device we used for our experiments. *Right:* close-up of the microphone array.

In comparison to other wireless sensor systems such as the Crossbow Mote, the Acoustic ENSBox has the computational, storage, and network resources to process audio data in real time and to implement distributed algorithms, including high precision 3D location and orientation self-calibration.

This combination of high processing power and communication with a small form factor makes the ENSBox platform particularly well-suited to explore novel solutions for animal vocalization analysis and accurate acoustic source localization through collaboration of multiple arrays.

2.2 Self-configuration

Collections of arrays enable localization by combining bearing estimates and time-difference of arrivals. However, none of this potential can be realized without the ability to rapidly deploy the sensor arrays and to determine their precise location *and* orientation. There are many positioning techniques, including those based on GPS, magnetic compass, sensor correlation, and time-of-flight measurements of radio and acoustic signals, however many of these alternatives are not a good fit for these applications. For example, GPS reception is often poor in locations of interest such as forests and canyons, and even with good reception GPS requires differential corrections to meet the stringent precision requirements for these applications.

The Acoustic ENSBox self-localization is based on measuring time-of-flight and direction of arrival of acoustic signals. This solution has many advantages, including high precision and high resilience to noise. Initially, each node emits a chirp in turn, while all other nodes estimate the range R based on time of flight and bearing θ using local time differences of arrival. Then, a centralized algorithm combines the (R, θ) estimates for every node, and a non-linear least squares algorithm is used to compute the relative map (X, Y, Z, Θ) of the network. Finally, the relative map is fit to surveyed locations to obtain a map in absolute coordinates. This capability eliminates the need to survey the array locations, a process that often takes hours to complete and that is generally extremely challenging to accomplish accurately.

2.3 Adaptive detection

We have developed a detection module that can detect animal vocalizations from background noise, by continuous adaptation to the current noise level. A generic statistically optimum approach to solve this problem is based on the *constant false alarm rate (CFAR)* method that allows to identify high energy segments in continuous streams of audio data.

The algorithm first estimates the statistical distribution of the amount of energy in specific frequency bands contained in the ambient noise on n consecutive samples (we assume that noise follows a normal distribution $N(\mu, \sigma^2)$). Afterwards, the energy present in the same bands is monitored, and a threshold function detects when the energy changes significantly from a statistical point of view, that is when the energy of the current segment exceeds the threshold defined $\mu + \beta \cdot \sigma$, where β is a parameter (usually $\beta = 3$). However, noise in real environments usually varies significantly over time, in which case it is needed to update the noise distribution as it varies. For this purpose, *exponentially weighted moving average (EWMA)* can be used to update iteratively the mean μ and variance σ of the noise power as follows:

$$\mu_{t+1} = \alpha \mu_{new} + (1 - \alpha) \mu_t$$

$$\sigma_{t+1} = \alpha \sigma_{new} + (1 - \alpha) \sigma_t$$

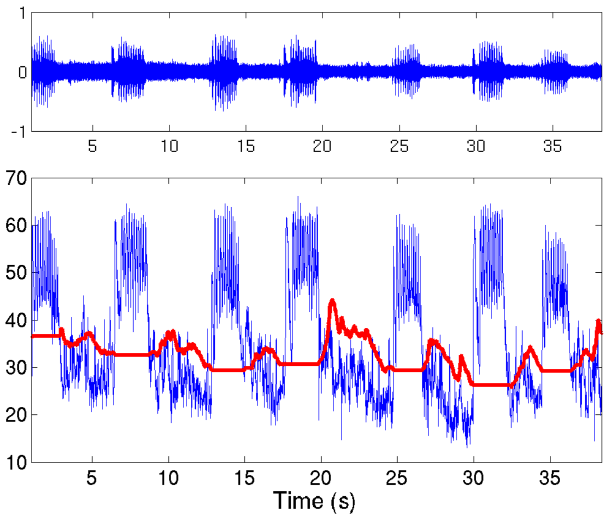

Figure 2: Adaptive detection algorithm. *Top:* Amplitude of the signal of a field recording. *Bottom:* Evolution of the energy in the signal is represented as the thin line. The thick line represents the detection threshold. When a song is detected, one can see that the threshold is not changed to avoid influencing the statistical estimation of background noise.

Where $\alpha \in [0, 1]$ is the changing rate. A low value for α should be used, as we want to avoid to consider spurious and short sounds as part of the background noise and use this insignificant events to update the noise distribution. Figure 2 illustrates the detection process of seven bird songs recorded in the rain-forest at Monte Azules Biosphere Natural Reservation in Mexico.

Using a modified and streamlined version of this algorithm, described in [4], we have also detected yellow bellied marmot (*Marmota flaviventril*) alarm calls in real-time on a network of fielded ENSBoxes. The marmot detector computes a 32-point FFT over each window of samples and computes the magnitude of the complex sum of the frequency bins corresponding to the band used by marmot calls (3-6 KHz). This energy value is then passed into a CFAR detector, with a hysteresis detection to ensure that the complete call is acquired. We found that we could improve efficiency without losing detections by applying the FFT only to 1 out of every 4 32-point windows.

2.4 Collaborative localization

Kung Yao and students have developed a localization algorithm that can track multiple sources in real-time [1]. They developed an approximate maximum-likelihood (AML) method for the localization of wide-band acoustic sources. The ML estimation method is known to be an optimum estimation procedure. The term approximate refers to the condition that the data length is finite and consequent edge effects yield a slight sub-optimality from the ML method. The AML algorithm has been used to perform localization of single and multiple acoustic source(s), even when they overlap in time and frequency, in the near/far-fields as well as in open-field and in reverberant scenarios. For each possible angle of arrival, the signals recorded by each microphone are recombined using a model of the array and the coherence of the resulting signal is obtained for each angle.

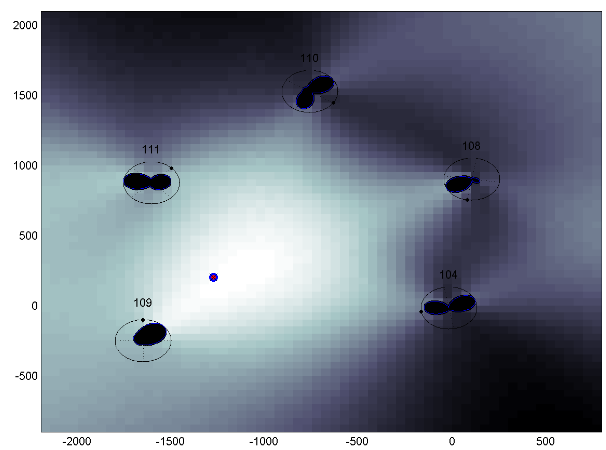

Figure 3: Results of the collaborative localization algorithm, presented as a 2D pseudo-likelihood map. Black lobes represent the likelihood for source AOA. Individual estimates of the angle of arrival (AOA) for each node are combined using their location as estimated by the self-calibration process.

In our implementation, every node that detects a vocalization will also compute a likelihood describing the likely bearing to the source. These likelihoods are collected at a central point and combined together into a 2D pseudo-likelihood map, according to the positions and orientations computed in the self-calibration step. This map is formed by projecting each likelihood metric outwards from each node to form the joint approximate likelihood of a source at every point in the 2D space. Beyond source localization, this information can also enable further signal enhancement through beam-forming, in which signals captured from different sensors are combined together to amplify the target signal and attenuate noise.

3 Results and discussion

Self-configuration The automated self-localization system illustrates many of the same requirements as our target applications, by being a distributed sensing application itself. This feature of the Acoustic ENSBox solves the problem of fastidious deployment by automatically determining array orientations to within 1 degree, and array positions to within 9cm in a 40x70m wooded area. This process can be run periodically, so that calibration of the system is maintained even when the location of the sensors is changed.

Adaptive vocalization detection We originally implemented an offline version of the detection algorithm to automatically isolate tropical bird songs from hours of recordings on a standard desktop computer. Using the streamlined implementation, we have been able to reduce half an hour of raw recording to only 13 seconds of audio, capturing all of the marmot calls as well as a few false positives from other sources. The CFAR method is known to be statistically optimum in the sense of for a fixed CFAR, the probability of event detection is maximized, with the assumption that the nominal background noise is a quasi-stationary stochastic process.

Collaborative localization The collaborative localization algorithm has been used to localize marmot alarm calls in a field test at the Rocky Mountain Biological Laboratory (RMBL), in Colorado. The results of one of the localization tests are shown in Figure 3. The RMBL tests demonstrated that these algorithms could reliably locate marmots by their calls to within 1.5 meters, when compared with ground truth based on human observations, given that collaboration reduces the ambiguity of the local estimations computed by each node.

4 Conclusion

This paper described how adaptive methods can be used to develop robust and self-organized monitoring systems. We have been able to detect animal vocalizations in very noisy environments by using an adaptive threshold mechanism. This approach can be useful in several contexts where detection of acoustic activity is required, as for example, human-robot interaction with humanoid robots [2]. Also, we explained how several acoustic sources can be localized using an efficient direction of arrival estimation method, and how collaboration between sensors can improve the results.

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