

# A Passive Approach to Sensor Network Localization

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**Abstract**—Sensor networks present the opportunity to accurately localize phenomena of interest. To be able to do so however, sensor nodes, need to themselves be accurately localized. We present an algorithm to do this based on uncontrolled environmental sounds observed by each of the sensor nodes. A probabilistic generative model is presented and it is shown that the sensor node localization problem is equivalent to maximum likelihood estimation in the model. Experimental results are presented for both simulated sensor nodes and Crossbow MICA2 sensor nodes.

## I. INTRODUCTION

Recent developments in manufacturing technology have created a new generation of very small computers equipped with one or more sensors, limited computational capabilities, and wireless radio links. As the cost of manufacturing these so called sensor nodes decreases, the possibility of using large numbers of sensor nodes in aggregate to form a sensor network has become possible. Such networks are essential for monitoring large environments unobtrusively and at a finer scale than was previously possible. Sensor networks can be used in a variety of civilian and military contexts, including factory automation, inventory management, environmental and habitat monitoring, health-care delivery, and battlefield awareness.

Most sensor network algorithms need to know the physical locations of individual sensor nodes. While it is sometimes possible to measure these locations by hand, a rich body of sensor network localization algorithms [1], [2], [3], [9], [10], [11] has emerged to allow the sensor network to do this task autonomously. These techniques

typically however take an active approach to localization. Some approaches place special beacon nodes with known location into the environment while others require the sensor nodes to beep to one another.

We offer a passive solution to the sensor network localization problem. Our algorithm allows sensor nodes to localize themselves from sounds naturally occurring in their environment. These sounds can be anything that has clear onsets, e.g. birds chirping. Our algorithm works despite knowing neither where nor when the external events generating these sounds take place. This passive approach expends less sensor node energy, does not require infrastructure outlay, and makes the sensor network less detectable than when employing active methods. Moreover, it provides results almost on par with beacon-based localization methods [3], [9], [10], [11] and more robust than other passive localization techniques [1], [2].

Our approach structures the relationship between the sensor node locations, the locations and times of the external events generating the sounds heard by the sensor nodes, and the recorded times as a Bayesian network. We show how the localization problem reduces to maximum likelihood estimation in the Bayesian network and explain how we do this via gradient descent in an expression monotonic to the negative likelihood.

We synchronize the clocks of the sensor nodes with respect to one another with the Reference Broadcasts (RBS) protocol [4]. RBS is capable of synchronizing sensor node clocks to within microseconds of one another, which allows us to assume that a time recorded at one sensor node

is directly comparable to a time recorded at another. We also assume that sounds are sufficiently well dispersed so as to prevent data association ambiguities between events.

## II. PROBLEM DEFINITION

### A. Overview

Let the sensor network consist of  $N$  sensor nodes at locations  $S = \{S_1 \dots S_N\}$ . Let  $S_i^x$  refer to the x-coordinate of the location of the sensor node  $i$  and let  $S_i^y$  refer to the y-coordinate. We assume 2-D locations but the same technique will work in 3-D as well. These locations are not known to us.

Second, let there be  $M$  sound-generating events at locations  $E = \{E_1 \dots E_M\}$ . Moreover, let  $E_i^x$  and  $E_i^y$  represent the respective coordinates. These locations are not known to us.

Third, let the times of the sound-generating events be  $T = \{T_1 \dots T_M\}$ . These times are not known to us.

Fourth, let there exist up to  $M \cdot N$  variables  $R_n^m$  that specify the time recorded at sensor node  $S_n$  for sound  $E_m$ . We will revisit these variables in Section III when we structure the relations between them as a Bayesian network.

Given the sensor measurements  $R$ , we seek the sensor node locations  $S$ .

### B. Sensor Model

We assume that  $R_n^m$  is distributed as follows:

$$R_n^m \sim N\left(T_n + \frac{d(S_m, E_n)}{s}, \sigma\right) \quad (1)$$

$$d(S_m, E_n) = \sqrt{(S_m^x - E_n^x)^2 + (S_m^y - E_n^y)^2}$$

where  $s$  is the speed of sound in free space,  $\sigma$  is the standard deviation of the error in recording times, and  $N(\mu, \sigma)$  is a Normal distribution with mean  $\mu$  and standard deviation  $\sigma$ .

## III. OUR APPROACH

In this section, we encapsulate the relations between variables as a Bayesian network and show how the sensor node localization problem reduces to that of maximum likelihood estimation in this Bayesian network. We start with the formal definition of our Bayesian network, give

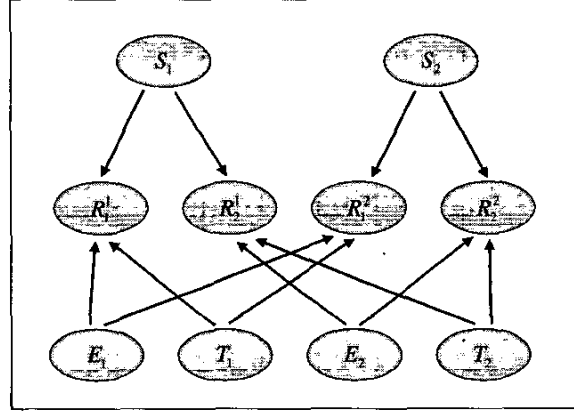


Fig. 1. Bayesian Network with 2 sounds and 2 sensor nodes

conditions for when an unique solution exists, compute the likelihood, and show how gradient descent is used to perform likelihood maximization.

### A. Bayesian Network

A Bayesian network [7] is characterized by its variables and the prior and conditional probabilities relating the variables to one another. We start with the variables and what they represent, then move on to the prior and conditional probabilities. Figure 1 shows a Bayesian network for the case of two sounds and two sensor nodes. Each of these variables are identical to the variables discussed in Section II-A.

In the Bayesian network, there will exist a variable of the form  $R_n^m$  whenever sensor node  $n$  hears sound  $m$ . These recorded times are stochastically determined by sensor node locations, sound locations, and sound times as presented in Section II-B. Thus the conditional probability is:

$$P(R_n^m | S_n, E_m, T_m) = \frac{1}{\sqrt{2\pi}\sigma} \cdot \exp\left(\frac{-(T_j + d(S_i, E_j)/s - R_j^i)^2}{2 \cdot \sigma^2}\right). \quad (2)$$

This equation is simply Equation 1 in an expanded form.

### B. Existence of an Unique Solution

Since there is no global reference frame, we impose the following arbitrary conditions to regularize our solution.  $S_1$  is set to be (0,0).  $S_2$

is set to lie on the positive x-axis.  $S_3$  is set to lie above the x-axis, i.e. have a positive y-coordinate. These conditions serve only to establish a reference frame and does not further constrain the solution space. This canonical form of the solution space is easily adapted if one or more sensor nodes have known location with respect to a global reference frame.

It is possible that  $R$  does not provide enough information to determine  $S$ . Sometimes, this lack of information is predictable given  $M$ ,  $N$ , and  $P$ . Each variable  $S_i$  has components  $S_i^x$  and  $S_i^y$  so introduces two unknown variables. Each variable  $E_j$  does the same and each  $T_j$  variable introduces one unknown variable. Each variable  $R_j^i$  introduces one equation. Moreover, when  $M \geq 2$ , the canonicalization of the solution sets  $S_1$  to  $(0,0)$  and constrains  $LS_2$  to  $(x,0)$ , thereby eliminating three unknown variables.

Thus, it is necessary for:

$$P \geq 2 \cdot M + 3 \cdot N - 3 \quad (3)$$

to hold for there to exist an unique solution. In situations where the inequality is strict, we have an over-constrained set of equations. This information is necessarily not contradictory given the nature of the scenario. Even when the inequality is satisfied, there exist degenerate situations where the information is not sufficient for unique localization. For example, the Bayesian network may not be connected and this will lead to two sets of sensor nodes whose relative positions may remain unknown.

### C. Maximum Likelihood Estimation

Let  $L(R|S, E, T)$  be the likelihood of the data given the model in the Bayesian network. This likelihood is simply the product of each of the conditional probabilities.

Expanding the likelihood, we obtain:

$$L(R|S, E, T) = \prod_{m,n} P(R_n^m | S_m, E_n, T_n) \quad (4)$$

$$\propto \prod_{m,n} \exp\left(-\frac{(T_n + (d(S_m, E_n))/s - R_n^m)^2}{2 \cdot \sigma^2}\right) \quad (5)$$

Since a scalar multiple of the log-likelihood is monotonic in the likelihood, we can take the log of Equation 5 and multiply by  $2 \cdot \sigma^2$  to obtain:

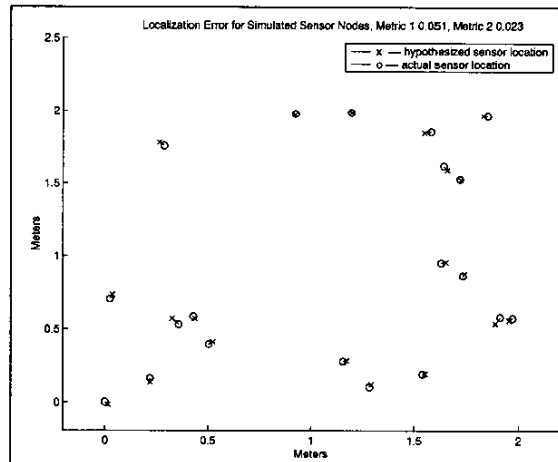


Fig. 2. Twenty Sensor Sensor Nodes in Simulation

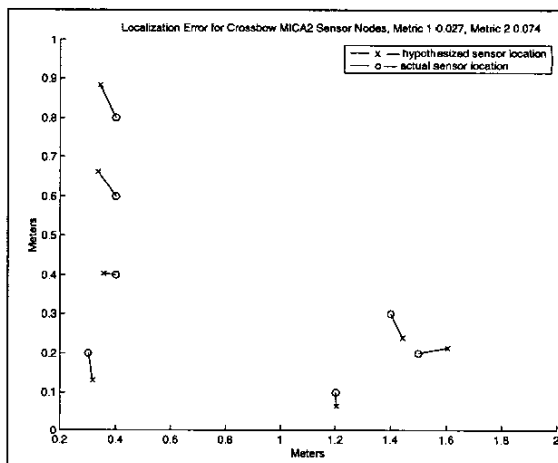


Fig. 3. Seven Crossbow MICA2 Sensor Sensor Nodes

$$l = \sum_{m,n} -\left(T_n + \frac{d(S_m, E_n)}{s} - R_n^m\right)^2 \quad (6)$$

We use gradient descent with both line search and momentum to maximize  $l$ . Due to the monotonicity of  $l$  with the likelihood, this process effectively finds the maximum likelihood estimate of the sensor node locations given the model parameters.

## IV. EXPERIMENTAL RESULTS

We show in this section some examples of the sort of localization results the algorithm produces. First, we define the metrics we will use

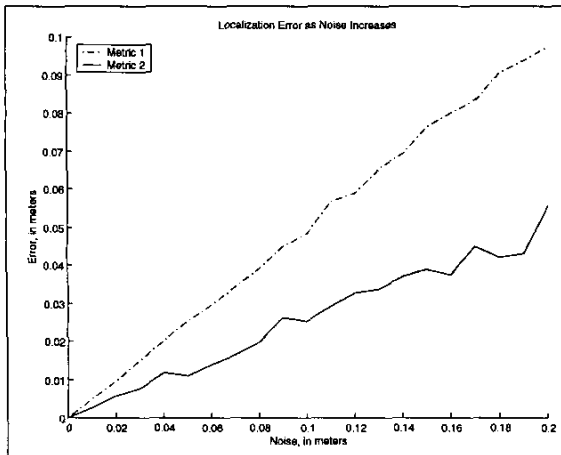


Fig. 4. Effects of Changing Sensor Noise

to evaluate the quality of our results. Second, we present the results of two specific networks. Third, we show how the error varies as we modify different parameters of the localization scenario.

#### A. Crossbow MICA2 Sensor Nodes

The Crossbow MICA2 sensor nodes (see Figure 5) have on-board microprocessors and two-way radios through which they are able to communicate with other MICA2 sensor nodes as well as MICA2-PC conduits. In our experiments, these sensor nodes are typically stationary; capable of both indoor and outdoor operation; and are equipped with a microphone, tone generator, light sensor, and thermometer. The simulator emulates the observed characteristics of these sensor nodes.

#### B. Error Metrics

1) *Metric 1: Scaled Likelihood*: We use  $\sqrt{-\hat{V}}$  as our first metric. Intuitively, this metric measures the standard deviation of the expected distances between sounds and sensor nodes suggested by the data versus the distances stemming from the hypothesized solution.

2) *Metric 2: Actual Error*: For our second metric, we use the actual standard deviation of the predicted sensor node locations from the actual sensor node locations, given optimal alignment between the two coordinate frames.

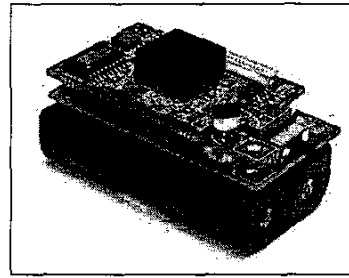


Fig. 5. Crossbow MICA2 Sensor Node

#### C. Specific Networks

1) *Twenty Sensor Nodes in Simulation*: Figure 2 shows localization results for a scenario with twenty sensor nodes, twenty sounds, and a standard deviation in recording error that corresponds to 10 cm. The predicted error, given by Metric 1, is 5.1 cm and the actual error is 2.3 cm. The circles in the figure represent the true sensor node location and the crosses represent the predicted location.

2) *Seven Crossbow MICA2 Sensor Nodes*: Figure 3 shows localization results using seven Crossbow MICA2 sensor nodes and seven sounds. The predicted error is 2.7 cm and the actual error is 7.4 cm.

#### D. Effects of Changing Network Parameters

In this section, we examine the effect of different parameters on the localization algorithm.

1) *Effects of Changing Sensor Noise*: Figure 4 shows the effect of varying the standard deviation of the recording time to the equivalent of 0 cm to 20 cm. Twenty sensor nodes and twenty sounds are used throughout. We find that both errors rise approximately linearly as the noise increases.

2) *Number of Sensor Nodes*: Figure 6 shows the effect of varying the number of sensor nodes being localized from four to twenty. Twenty acoustic events are used and the standard deviation in the recording error is set to correspond to 10 cm. We find that the algorithm is initially overconfident when dealing with less than seven sensor nodes. With more than eight sensor nodes, the error levels off to approximately 3 cm.

3) *Number of Sounds*: Figure 7 shows the effect of varying the number of sounds used for localization from four to twenty. Twenty sensor

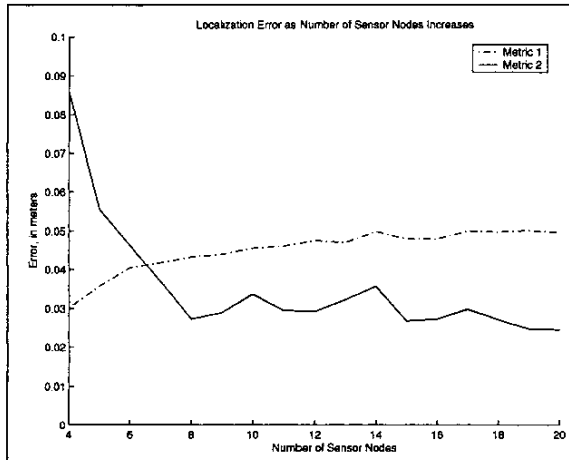


Fig. 6. Effects of Changing Number of Sensor Nodes

nodes are localized and the standard deviation in the recording error is set to correspond to 10 cm. We find that the error initially drops sharply and continues to decrease slowly as the number of sounds increases.

## V. PRIOR WORK

A very popular technique often used outdoors is the Global Positioning System (GPS) [5]. It offers an inexpensive solution for many applications but lacks the relative accuracy generally required for sensor network applications.

Methods based on received signal strength (RSS) of radio signals as well as radio connectivity (e.g. [1], [2]) offer inexpensive passive solutions for both indoor and outdoor environments but are often not robust enough for many sensor network applications.

Another class of localization schemes assume the presence of so called beacon nodes that know their location with respect to a global reference frame [3], [9], [10]. While these methods are both robust and accurate, they require substantial cost and effort to set up beacon nodes and measure their locations by hand.

It is also possible to use ultrasonic ranging [11] or laser-range finders to perform ranging as an input to a localization system. These schemes require precise instrumentation or multiple microphones per sensor node because the sender and the receiver need to be precisely oriented to one

another. The cost of this equipment substantially raises the cost of sensor network deployment.

Ranging in the audible domain [11] offers a solution that is both relatively inexpensive and reliable. It requires the sensors to beep to one another though. This expends both extra energy and may cause unwanted disturbance by or detection of the sensor nodes.

In terms of algorithms, our problem has strong analogues to the statistical problem of multi-dimensional scaling. There, dissimilarities between points are used to compute a planar embedding. Indeed, multi-dimensional scaling offers a direct solution to localization from ranging data but not knowing when the sounds occurred preempts its use in this domain.

The problem also resembles the affine structure from motion problem in computer vision when the sounds and the sensor nodes are sufficiently distant. There, corresponding points between multiple images are used to recover both camera position as well as the 3-D structure of a scene. In both cases, we seek to recover the rotations and translations of sensors observing common phenomena and with this information, complete the locations of points in a higher dimensional space.

## VI. CONCLUSION

We have presented herein a localization algorithm for sensor nodes that uses cheap, commodity hardware and relies only on uncontrolled sounds for localization. A probabilistic generative model is presented and it is shown how the localization problem reduces to maximum likelihood estimation on this model. Experimental results are presented for both simulated sensor nodes and Crossbow MICA2 sensor nodes.

While the algorithm works well when all sensor nodes hear all sounds, the algorithm unfortunately does not fare as well when only a subset of the sensor nodes hears each sound. There are two typical failure modes.

First, the predicted error may be low but the actual error is high. This suggests that the problem is ill-conditioned in a way even when the condition of Equation 3 is met. We plan to explore the conditions under which the predicted error is or is not a reliable estimate of the actual error.

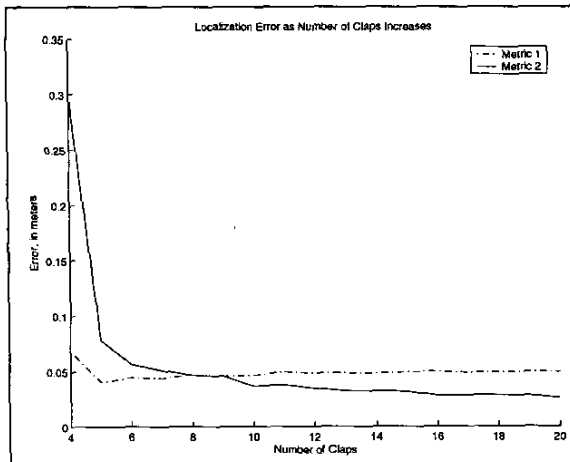


Fig. 7. Effects of Changing Number of Sounds

Second, gradient descent may get stuck in local minima, even with random restarts. We plan to explore more robust probabilistic reasoning algorithms to help deal with this case.

## VII. ACKNOWLEDGMENTS

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