Self Localization Using A Modulated Acoustic Chirp

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ABSTRACT

This paper describes a robust self localization algorithm implemented on a network of acoustic sensors. The sensors are severely constrained in both power and computational performance. An acoustic ranging technique employing a linear frequency modulated chirp is first used to estimate the range between a pair of nodes. The modulated acoustic chirp provides significant benefits in increased range and the ability to separate direct path and multi-path reflections. Localization was performed in the network using a simple trilateration technique based on the estimated ranges to four known beacons. The resulting algorithm is highly accurate under very difficult conditions including significant multi-path and high levels of background noise. The algorithm was implemented and deployed on prototype hardware and operated in real time under realistic operational conditions.

Keywords: Localization, Acoustics, Netted Sensing

1. INTRODUCTION

Node location information is a critical need in many applications for sensor networks. Unfortunately, the nature of emerging small sensor platforms (low power, low cost, severe resource constraints) and the environments where it is most desirable to deploy them (dense cities, inside buildings, highly rugged terrain) preclude the use of most localization solutions. Global Positioning System (GPS) receivers are simply too expensive to include on every sensor node and don't work in many locations in any case.

Most techniques for solving this problem first make some measurement relevant to a node's physical location. This can include radio signal strength (RSSI),[1–3] range between a pair of nodes,[2,4–7] angle of arrival to another node,[4] range to an unknown target,[8] etc. These estimates are then converted into a map of the relative positions of all the nodes again using a large variety of methods.[1–3,5,9,10] The primary reason for the preponderance of localization techniques is to attempt to correct for the large errors in the measurement step of the process. For example, it is not uncommon to see ranging errors equal to 50% or more of the distance between a pair of nodes.[1] We believe that the reason for the large measurement errors is due primarily to multi-path reflections and to a lesser extent low signal to noise ratios (SNR) corrupting the measurement.

In this paper we describe first a ranging algorithm that can separate direct path and multi-path reflections and provides significant integration gain for improved SNR. The resulting improvement in ranging performance allows us to use a very simple localization technique. The overall algorithm provides robust performance under difficult conditions including high levels of background noise and significant multi-path reflections. The remainder of this paper is organized as follows: Section 2 describes the acoustic ranging algorithm. Section 3 describes the trilateration algorithm for converting a set of range estimates into a relative position. Section 4 describes the experiment used to evaluate the algorithm and shows its performance in an operation scenario. Section 5 concludes the paper and discusses future development plans.

2. RANGE ESTIMATION

A common method for estimating the range between a pair of sensor nodes uses an acoustic pulse.[5] In this technique a node first sends a radio message to a second node. At the same time the first node activates an attached speaker and outputs a short acoustic tone. The second node receives the radio message and immediately begins listening via an attached microphone. When the second node hears the acoustic tone it measures the time difference between the receipt of the radio message and the start of the acoustic tone. Multiplying the time difference by the speed of sound provides an estimate of the range. A temperature sensor is sometimes also employed to increase accuracy by correcting for variations in the speed of sound with different ambient temperatures.

This technique relies on accurate identification of the start of an acoustic pulse which can be difficult in noisy environments. Filters can be applied to reduce background noise,[5] but the potential for confusion is still high. Futhermore, there is no way to distinguish between the direct path transmission of the pulse and any echoes off of surrounding objects.

One way around this, commonly used in the radar and sonar communities,[11] is to use a modulated signal instead of a single acoustic tone. The particular modulation we used was a linear frequency modulated (FM) chirp since it has some useful properties that we discuss below.

A linear FM chirp is a constant amplitude pulse with a continuously varying frequency starting at $f_c - B/2$ and ending at $f_c + B/2$ where B is the bandwidth of the chirp.

$$a_0 \sin(2\pi f(t)) \tag{1}$$

Where,

$$f(t) = f_c - B/2 + Bt/T \tag{2}$$

Where T is the time duration of the chirp.

If we correlate a chirp with a time delayed version of itself, we get the following.

$$\begin{aligned} x = a_0 \sin(2\pi f(t)) * a_0 \sin(2\pi f(t+\tau)) = \\ \frac{a_0^2}{2}(\cos(2\pi(f(t) - f(t+\tau))) - \\ \cos(2\pi(f(t) + f(t+\tau))) \end{aligned} \tag{3}$$

Looking at the first term in (3) we see that this is a sinusoid with a constant frequency of

$$f(t) - f(t+\tau) = B\tau/T \tag{4}$$

If we take the fourier transform of (3) therefore, we will see delta functions at frequencies corresponding to the time delay of the transmitted signal. Moreover, we will see additional delta functions for any time delayed echoes of the original signal. The correlation process also provides significant SNR gain by integrating over the entire duration of the chirp. Background noise will not correlate with the reference signal significantly reducing the likelihood of false detections.

We implemented the chirp on a modified Crossbow mica2 mote. The modifications were the same as described in.[5] The standard speaker on the Crossbow mote can only generate a single tone at 4.3KHz. The modification allowed us to generate a crude chirp spanning 3-4.5KHz. Time and frequency domain plots of the generated chirp are shown in Figures 1 and 2.

A typical fourier spectrum after correlating a reference copy of the chirp with a received chirp is shown in Figure 3. The peaks in the spectrum correspond to arrival times of the original signal and echoes off of other objects in the area. In this case the strongest signal is

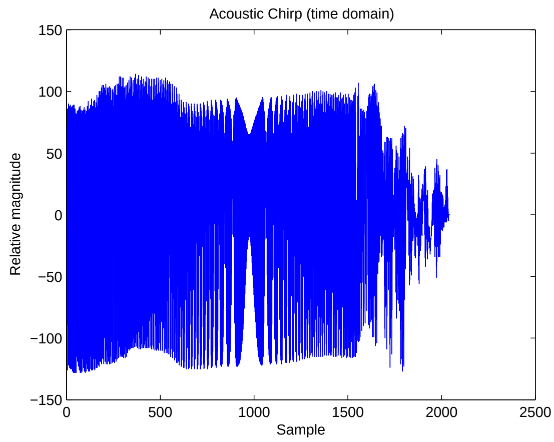

Figure 1. Linear FM Acoustic Chirp (time domain)

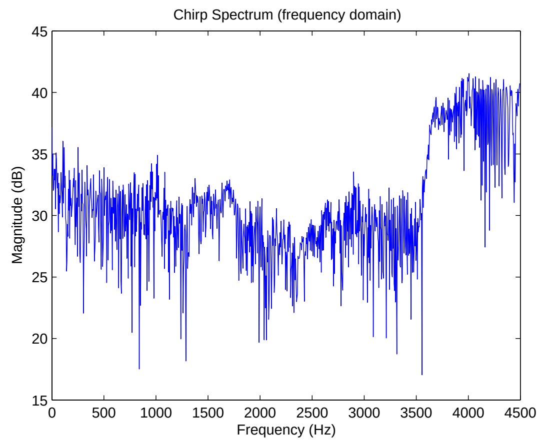

Figure 2. Linear FM Acoustic Chirp (frequency domain)

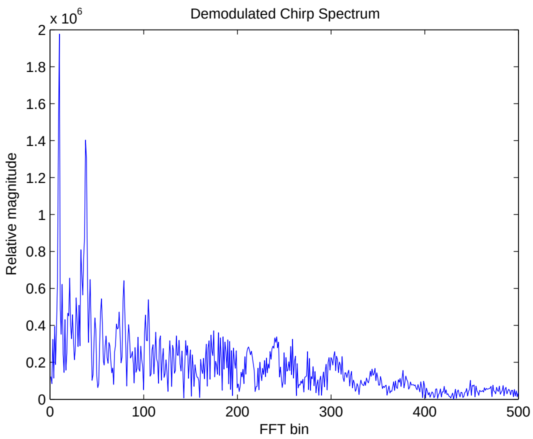

Figure 3. Fourier transform of received chirp correlated with reference signal. Peaks indicate presence of delayed chirp. Multiple peaks are due to reflections from surrounding objects.

the direct path, but this is not always the case. Occasionally the strongest signal will be an echo, but this technique still allows us to determine the arrival time of the direct path signal.

To summarize the steps in the range estimation technique are:

1. Broadcast a radio message indicating that a range estimation process is starting. At the same time begin transmitting the acoustic chirp.

2. Nodes that receive the radio message immediately begin collecting acoustic data for a predetermined duration of time (approximately 1/3 longer than the expected chirp duration).

3. Receiving nodes correlate the collected acoustic data with a reference copy of the chirp stored in memory.

4. Calculate fast fourier transform (FFT) of the correlated signal.

5. Locate peaks in the spectrum.

6. Convert peaks to range

$$r = B/Tf_p \tag{5}$$

   Where f_p is the frequency of a spectral peak.

3. LOCALIZATION

To demonstrate the utility of the new range estimation algorithm we elected to employ a fairly simple localization technique. We assume that we have four anchor nodes located on the periphery of the network. These anchor nodes have been told their locations. After initialization, the anchor nodes perform the range estimation procedure in sequence and include their position information in the radio message broadcast in step 1 of the procedure.

After estimating the range to three or more anchors, the rest of the nodes in the network can calculate their positions via trilateration[12]:

$$position = (A^T A)^{-1} A^T v \tag{6}$$

Where

$$A = \begin{bmatrix} 2(x_2 - x_1) & 2(y_2 - y_1) \\ 2(x_3 - x_1) & 2(y_3 - y_1) \\ 2(x_4 - x_1) & 2(y_4 - y_1) \end{bmatrix} \tag{7}$$

And

$$v = \begin{bmatrix} x_1^2 + y_1^2 - (x_2^2 + y_2^2) - (r_2^2 - r_1^2) \\ x_1^2 + y_1^2 - (x_3^2 + y_3^2) - (r_3^2 - r_1^2) \\ x_1^2 + y_1^2 - (x_4^2 + y_4^2) - (r_4^2 - r_1^2) \end{bmatrix} \tag{8}$$

Where (x_i, y_i) is the location of anchor i and r_i is the range to anchor i.

In the cases where the range estimation algorithm reports more than one possible range to a given anchor (due the presence of multi-path echoes), we simply take the shortest reported range as the most likely direct path transmission.

4. EXPERIMENTAL RESULTS

To test the algorithm we first deployed two Crossbow Mica2 motes in an outdoor parking lot and estimated the range between them at several distances up to 35 meters. The results are shown in Figure 4. The ranging algorithm was 100% successful at every distance with an average error of less than 0.15 meters. We believe the algorithm would be effective at significantly longer ranges, but we did not have the opportunity to test this.

Next we tested the overall localization error by deploying four anchor nodes at the corners of a 7m x 7m area indoors. A single node was then placed in the interior of the area. The anchor nodes were told their locations and the center node used this information and

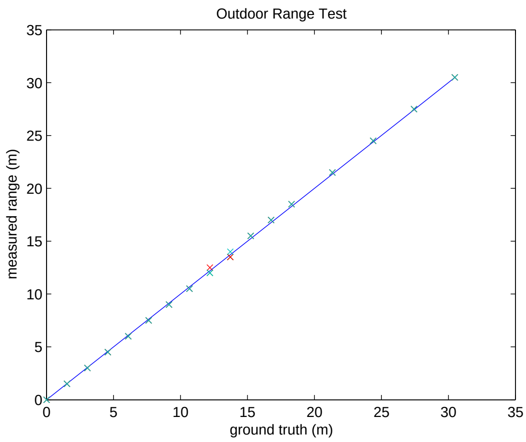

Figure 4. Ground truth range versus estimated range. Test was performed outdoors in an open parking lot.

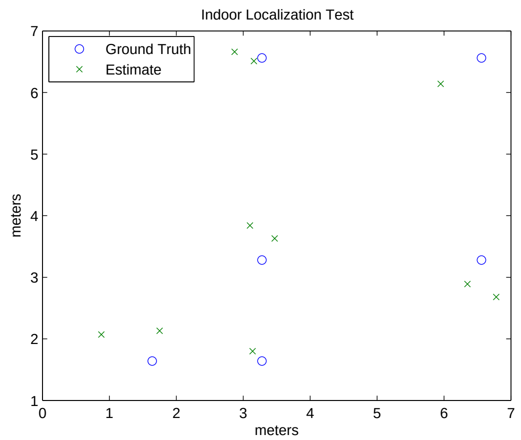

Figure 5. Estimate localization versus ground truth in noisy indoor environment with significant reverberation.

the estimated range to each of the anchor nodes to calculate its relative position. The room where the test occurred was only slightly larger than the deployment area and was known to have significant reverberation effects. This area was deliberately chosen to represent a difficult environment with considerable multi-path reflections. The localization results are shown in Figure 5.

The average localization error is less than 0.5 meters. This compares well with some of the best outdoor localization schemes published to date[5] and to our knowledge is the first time that results of this quality have been demonstrated indoors or under conditions with significant multi-path reflections.

5. CONCLUSIONS

We have demonstrated a robust self localization algorithm operating under realistic conditions. The resulting algorithm is very effective at long range and in the presence of significant multi-path reflections. This was achieved by modifying traditional acoustic time of arrival techniques to use a modulated signal instead of a pure tone. Correlating the received signal with a stored reference provides both integration gain (resulting in increased range) and separation of direct path and delayed echoes. Future research will include modification of the acoustic hardware to operate at ultrasonic frequencies and/or modification of the acoustic chirp to be more similar to background noise allowing for more covert operation.

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