# Acoustic Self-Localization in a Distributed Sensor Network

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*Abstract*—**The purpose of this paper is to present a technique for determining the coordinate locations of nodes in a distributed sensor network. This technique is based on the time difference of arrival (TDOA) of acoustic signals. In this scheme, several sound sources of known locations transmit while each node in the sensor network records the wave front time-of-arrival. Data from the nodes are transmitted to a central processor and the nonlinear TDOA equations are solved. Computational simulation results are presented in order to quantify the solution behavior and its sensitivity to likely error sources. Results based on experimentally collected data are also presented in order to demonstrate the potential for this approach in solving the self-localization problem.**

*Index Terms*—**Acoustic array, sensor localization, sensor network.**

## I. Introduction

DISTRIBUTED sensor networks have received a great deal of attention recently [1]. These systems consist of numerous "nodes" each possessing a microprocessor, power supply, either wired or wireless network communications with other nodes, sensors appropriate for the application, and the associated signal conditioning circuitry. Possible applications include distributed robotics, environmental monitoring, security surveillance, industrial automation, infrastructure monitoring as well as numerous military applications. Enabled by recent developments in MEMS transducers, as well as computing hardware and software, researchers have focused their efforts on some of the key elements of these systems. Among the areas that have been identified as particularly important include ad hoc networking and message routing, distributed data fusion and signal processing, and security. One further element that is critical in many applications is self-localization.

Self-localization is the processes of determining the $(x, y, z)$ coordinates of all nodes in the network relative to each other and relative to an absolute reference frame. This knowledge is critical to many sensor network applications since the ability of a sensor network to locate whatever is being sensed will only be as good as the networks self-localization. The first technique one might consider for self-localization is to equip each node with GPS. While this would be accurate, it is not in keeping with the over-riding philosophy of many distributed sensor networks: That they are cheap, low power, and semi-disposable.

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The scenario that motivates the current work involves numerous sensor nodes being distributed around an area of interest. These sensors may be distributed by hand, dropped by unmanned air or ground vehicles, or some other means. Then a GPS equipped device equipped with an acoustic source could be moved through the area and emit a sound while simultaneously communicating its location to the sensor network. Data would be collected until an accurate solution could be obtained. Such an approach would remove the power drain of an acoustic source off of the sensor nodes and also prevent revealing node locations.

Although there are many other methods for accomplishing self-localization, the most accurate method is based on either acoustic or RF wave propagation and time-of-flight measurements. The most common method studied so far is based on RF signal propagation [2]–[6].

While-RF based localization is promising, there are several reasons why acoustic techniques may be more desirable. First of all, the relatively low acoustic wave speed results in less expensive hardware as compared to high-bandwidth RF hardware. The lower wave speed also means that the system will be less sensitive to errors in time-of-flight measurements, node clock synchronization and other timing errors. However, acoustic techniques also have two distinct disadvantages over RF techniques. First, acoustic waves are sensitive to environmental factors such as temperature, humidity and pressure resulting in nonuniform wave speeds over the area of interest. Second, acoustic waves suffer far greater attenuations through walls and other physical objects rendering it nearly ineffective when such obstacles exist.

Work has been done for some time using acoustic time-of-arrival (TOA) approaches for locating sensor arrays. Smith and Abel presented a method of locating sensors using a least-squares optimization technique on linearized TOA equations [7]. More recently, Dosso *et al.* solved linearized TOA equations with an iterative regularized inversion technique for locating hydrophone arrays [8]. Dosso's work also dealt with the case where the sensor and source locations where unknown.

The specific application to distributed sensor networks has also received attention most recently. The approach of Girod and Estrin [9] and then Chen *et al.* [10] was that each node would produce and acoustic "chirp" while simultaneously sending a network message containing the time when the chirp was produced. Other nodes would detect the chirp with a matched filter and determine the time of arrival. Knowing the time of arrival and the time of transmission the time of flight was calculated which, with knowledge of the wave speed, permitted direct calculation of the distance between nodes. By progressing through all nodes, the ranges between each node and every other node were calculated and an optimization algorithm was used

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to calculate absolute coordinates. The system was successful in self-localizing nodes to within about 11 cm [11]. In this approach, although the source locations where not known, they were constrained to be the same as the sensor locations.

The approach taken in this work is based on the time-difference-off-arrival (TDOA) method presented by Mahajan and Wallworth [12]. TDOA is a special case of TOA approaches utilized when the source time is known. This method is analytical in nature and uses the TDOA between groups of nodes. The resulting equations are nonlinear but can be linearized in the solution process. The approach is based on acoustic sources emitted at known, but arbitrary, locations in and around the sensor field. Each source is broadcast one at a time and the TOA is recorded by each sensor. These TOAs are gathered at a centralized location (although this algorithm could easily be distributed). The TDOAs are calculated and the equations are solved in a least-squares manner. The locations of the nodes themselves can then be communicated back to the nodes.

There are two distinct advantage of this approach over other acoustic methods. First of all, by using TDOA instead of time of arrival, effects of timing delays associated with the system are minimized. Causes of such delays include microphone phase lag, signal conditioning circuitry delay, ADC delay and delays associated with signal detection. Presumably these types of delays will be nearly identical for each node and will, therefore, be subtracted out in the TDOA calculation. The second advantage of this approach is that the speed of sound can easily be introduced as an unknown in the solution process. Another advantage is that the calculations are very simple and could be carried out is a distributed fashion performing the calculations on the network nodes.

Although the approach taken by Girod and Estrin, in which each node emits an acoustic signal to determine ranging, is very accurate, there will be applications in which this approach would be undesirable. An example would be the case where the user does not want the sensor node locations to be revealed to observers in the area. If the nodes themselves are chirping, then the security of the nodes would be compromised. Furthermore, acoustic emission is a power-hungry process if the signal must propagate very large distances. If the nodes themselves must be responsible for delivering this power, their life expectancy will be significantly limited.

The discussion of self-localization in a distributed sensor network begins with an overview of the TDOA equations and the solution method. This is followed by a computational investigation of the accuracy and sensitivity of the algorithm. Finally, self-localization results based on experimental data will be presented.

## II. TDOA Self-Localization Formualtion

The basis for self-localization within a distributed sensor network is the TDOA approach [12]. If we define the TDOA between a reference node and any other node based on the absolute times when the acoustic sources are detected by each node, then

$$T_{1i} = T_i - T_1 \tag{1}$$

where $T_i$ is the time that the $i$th node detected the source emitted at $T_1$. Note that, in practice, sensors measure the TOA while these equations are based on the calculated TDOA of (1). Then, the equations for the distance between each of $N$ nodes and the source can be written in three-dimensional space as

$$\begin{aligned} d^2 &= \left(x_1^2 - u\right)^2 + \left(y_1^2 - v\right)^2 + \left(z_1^2 - w\right)^2 \\ (d + cT_{12})^2 &= \left(x_2^2 - u\right)^2 + \left(y_2^2 - v\right)^2 + \left(z_2^2 - w\right)^2 \\ (d + cT_{13})^2 &= \left(x_3^2 - u\right)^2 + \left(y_3^2 - v\right)^2 + \left(z_3^2 - w\right)^2 \\ &\vdots \\ (d + cT_{1N})^2 &= \left(x_N^2 - u\right)^2 + \left(y_N^2 - v\right)^2 + \left(z_N^2 - w\right)^2 \end{aligned} \tag{2}$$

where $d$ is the distance from node 1 to the source located at absolute coordinates $(u, v, w)$, $(x_i, y_i, z_i)$ is the absolute coordinate of the $i$th node and c is the speed of sound. Expanding these equations yields

$$\begin{aligned} d^2 &= x_1^2 - 2ux_1 + u^2 + y_1^2 - 2vy_1 + v^2 \\ &\quad + z_1^2 - 2wz_1 + w^2 \\ d^2 + 2cT_{12}d + c^2T_{12}^2 &= x_2^2 - 2ux_2 + u^2 + y_2^2 - 2vy_2 + v^2 \\ &\quad + z_2^2 - 2wz_2 + w^2 \\ d^2 + 2cT_{13}d + c^2T_{13}^2 &= x_3^2 - 2ux_3 + u^2 + y_3^2 - 2vy_3 + v^2 \\ &\quad + z_3^2 - 2wz_3 + w^2 \\ &\vdots \\ d^2 + 2cT_{1N}d + c^2T_{1N}^2 &= x_N^2 - 2ux_N + u^2 + y_N^2 - 2vy_N \\ &\quad + v^2 + z_N^2 - 2wz_N + w^2. \end{aligned} \tag{3}$$

Now, defining the distance from the origin to each node and to the source as

$$\begin{aligned} R_i^2 &= x_i^2 + y_i^2 + z_i^2 \\ R_s^2 &= u^2 + v^2 + w^2 \end{aligned} \tag{4}$$

and using this in the first of (2) yields

$$d^2 - R_s^2 = R_1^2 - 2ux_1 - 2vy_1 - 2wz_1 = B. \tag{5}$$

Now, it is assumed that the location of one sensor node (node 1 located at $(x_1, y1, z1)$ and referred to as the reference node) is known. This assumption is necessary in order to "anchor" the solution in the absolute coordinate frame. If a reference node is not available, the equations can still be solved; however, only relative coordinates can be obtained. Substituting (4) and (5) into all but the first of (3) yields

$$\begin{aligned} B + 2cT_{12}d + c^2T_{12}^2 &= R_2^2 - 2ux_2 - 2vy_2 - 2wz_2 \\ B + 2cT_{13}d + c^2T_{13}^2 &= R_3^2 - 2ux_3 - 2vy_3 - 2wz_3 \\ &\vdots \\ B + 2cT_{N4}d + c^2T_{1N}^2 &= R_N^2 - 2ux_N - 2vy_N - 2wz_N. \end{aligned} \tag{6}$$

The result is $N$-1 nonlinear equations in the 3($N$-1) unknown sensor coordinates. There are many approaches available to solve such equations. Here, we will follow that of Mahajan and Wallworth [12]. In this approach, the nonlinear terms in

(6) $(R_2^2 \cdots R_N^2)$ are assumed to be independent (and unconstrained) unknowns. Now, (6) can be solved as a set of linear equations with 4($N$-1) unknowns. While this increases the number of unknowns, it does result in a solution that can be quite accurate [12]. Note, furthermore, that (6) could easily be rearranged so that the wave speed $c$ is also an unknown, thus introducing two more (nonlinear) unknowns ($c$ and $c^2$).

One will note that (6) for each node (with the exception of the reference node) is independent of all other nodes. Therefore, all subsequent equations will be expressed in terms of the reference node and one other arbitrary node.

Clearly, (6) is underdetermined when only one source is considered. An exactly determined solution requires four sources (at different locations). More than four sources can be introduced resulting in an over-determined set of equations. The expansion of (6) to include $S$ sources (denoted by subscripts $(a, b, c, \ldots)$ for each source) and for a single node (denoted by subscript $i = 2, 3, \ldots, N$) results in equations of the form

$$\begin{aligned} B_a + 2cT_{1ia}d + c^2T_{1ia}^2 &= R_i^2 - 2u_ax_i - 2v_ay_i - 2w_az_i \\ B_b + 2cT_{1ib}d + c^2T_{1ib}^2 &= R_i^2 - 2u_bx_i - 2v_by_i - 2w_bz_i \\ &\vdots \\ B_c + 2cT_{1ic}d + c^2T_{1ic}^2 &= R_i^2 - 2u_cx_i - 2v_cy_i - 2w_cz_i \\ &\vdots \end{aligned} \tag{7}$$

Equation (7) can be interpreted as a set of $S$ linear equations with four unknowns of the form

$$\mathbf{A}_i\mathbf{x}_i = \mathbf{b}_i \tag{8}$$

where

$$\mathbf{A}_i = \begin{bmatrix} 1 & -2u_a & -2v_a & -2w_a \\ 1 & -2u_b & -2v_b & -2w_b \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix} \tag{9}$$

$$\mathbf{b}_i = \begin{bmatrix} B_a + 2cT_{1ia}d + c^2T_{1ia}^2 \\ B_b + 2cT_{1ib}d + c^2T_{1ib}^2 \\ \vdots \end{bmatrix} \tag{10}$$

and the unknown vector of the form

$$\mathbf{x}_i = \left\{R_i^2 \quad x_i \quad y_i \quad z_i\right\}^T. \tag{11}$$

A variety of techniques exist for the solution of (8) including inversion, elimination, reduction techniques and various optimization approaches. A least-squares solution is used here. Therefore, at least four sources are required to locate each node in three dimensions.

## III. Simulation Results

A computational simulation of the solution to (8) was undertaken. The purpose was to quantify the solution accuracy when the source and anchor node locations are not exactly known. Also of interest is the effect of inaccuracies in node clock synchronization, TOA measurements and speed of sound estimates on the self-localization accuracy. However, all three of these errors sources directly introduce errors in the TOA measurements and, therefore, affect the solution in the same manner. Therefore, only source location error and TOA measurement error will be considered.

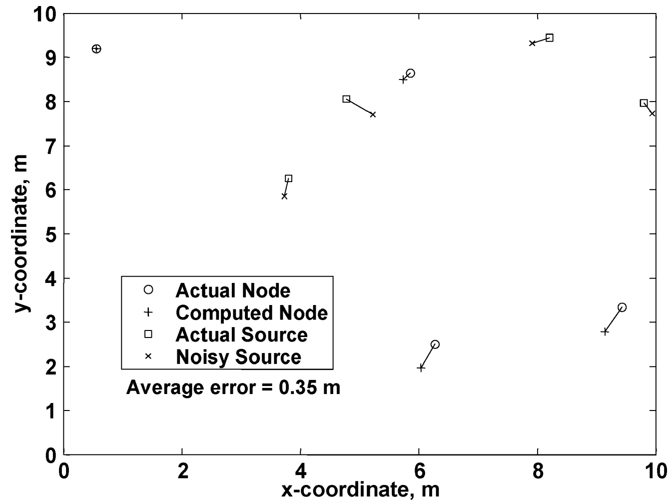


Fig. 1. Plot of sensor/source locations for one self-localization simulation example with $S = 4$, $N = 4$, and a source location error standard deviation of 0.5 m.

To quantify the sensitivity of the solution, a random sensor field was generated within a 10-m per side cube as was an array of acoustic sources. The source TOA at each sensor was calculated based on the exact source locations. Next, each sensor location was perturbed by a random amount. The perturbation consisted of a normally distributed random number with zero mean and some prescribed standard deviation. Furthermore, the TOA measurements were similarly perturbed. Finally, the sensor node locations were calculated according to (8) based on the perturbed node locations and TOA values. Results from one such calculation are shown in Fig. 1, which shows the actual sensor node locations, the calculated sensor node locations, the actual source locations, and the perturbed source locations projected into the $x, y$ plane. In this example, $S = 4$, $N = 4$ and the source location standard deviation is 0.5m. Note that the sensor location errors are roughly the same magnitude as the source location errors.

In order to obtain results of statistical significance, 500 trials were conducted for each combination of $2 \leq N \leq 10$ nodes and $4 \leq S \leq 12$ sources. In all trials, a single randomly selected sensor field was used and held fixed while the $S$ source locations were randomly selected for each trial. The individual sensor location errors for all trials were accumulated and then the average and standard deviations of this error distribution was calculated. The error was defined as the distance between the actual node locations and the predicted node locations. An example of the distribution of errors for 500 trials for the case when $N = 7$, $S = 8$ is shown in the histogram of Fig. 2. Note that the distribution of errors is skewed due to a few "outliers" among the solutions. These outliers correspond to configurations in which the matrix solution is relatively ill-conditioned. The likelihood of such ill-conditioned solutions is high for exactly

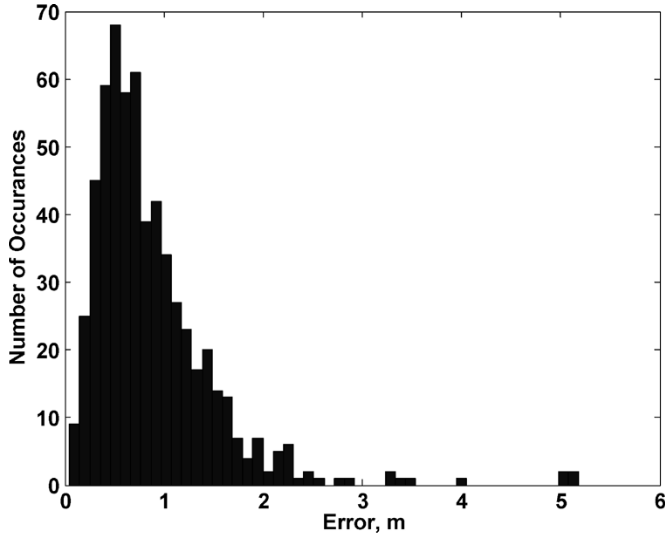


Fig. 2. Histogram of the sensor node position error for 500 simulations when $N = 7$ and $S = 8$ and a source location error standard deviation of 0.5 m. Average error is 0.89 m.

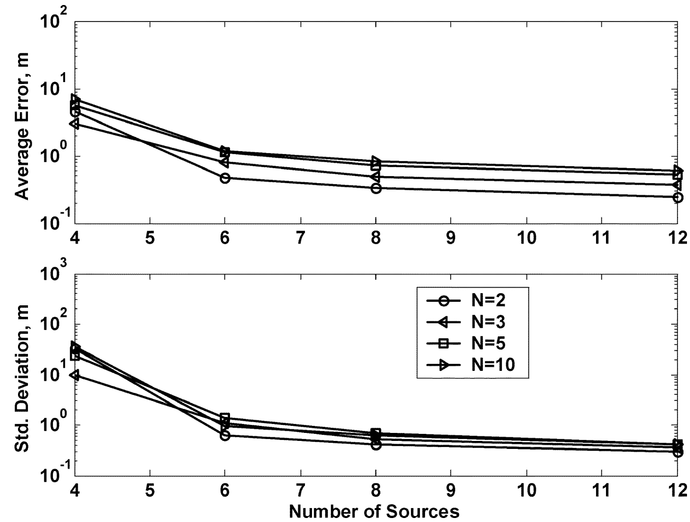


Fig. 4. Average sensor node location error and standard deviation as a function of the number of sources and for various numbers of sensors, based on 500 simulations with a source location error standard deviation of 0.5 m.

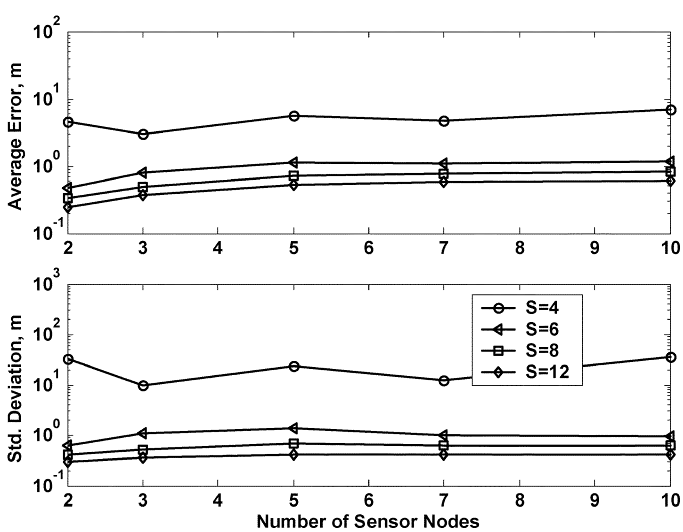


Fig. 3. Average sensor node location error and standard deviation as a function of the number of sensors being located and for various numbers of sources, based on 500 simulations with a source location error standard deviation of 0.5 m.

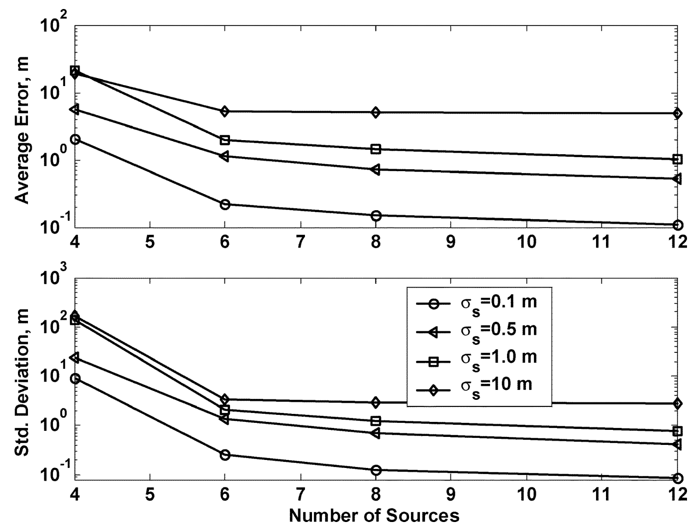


Fig. 5. Average sensor node location error and standard deviation as a function of the number of sources and for various source location estimate errors, based on 500 simulations with seven sensors $(N = 7)$.

determined equations, but decreases dramatically when (8) is over-determined.

This effect is demonstrated in Fig. 3, which shows the sensor node location error average and standard deviation as a function of the number of sensors being located. This data was generated over 500 trials with a source location error standard deviation of 0.4 m. Note that the curve for $S = 4$ represents the exactly determined equations and those for $S > 4$ are over-determined. Clearly, all solutions for the exactly determined equations have unacceptably large average errors on the order of 4 to 5 m. This is due to the ill-conditioned solutions mentioned previously. However, as more sources are added the equations become over-determined and the self-localization error decreases significantly (note that the error and standard deviation scales are logarithmic). In order for the standard deviation on the self-localization error to be approximately equal to that of the source location error, standard deviation from six to eight sources are required.

Also apparent from Fig. 3 is that the error is a rather weak function of the number of sources. This is due to the fact that the equations for different nodes are independent. The error average and standard deviations are more strongly dependent on the number of sources as shown in Fig. 4, which is derived from the same data set as Fig. 3. As can be seen in Fig. 4, the exactly determined set of equations $(S = 4)$ have large average errors and even larger error standard deviations of 10 to 30 m again due to ill-conditioned matrices. Note that the gains in accuracy are small when more than six to eight sources are used to locate the sensors

Also of importance to the quality of the solution is the accuracy with which the sources and anchor node locations are known. This effect is demonstrated in Fig. 5, which shows the sensor localization error average and standard deviation as a function of the number of sources and for various source/anchor location errors $(N = 7)$. Note that the solution accuracy

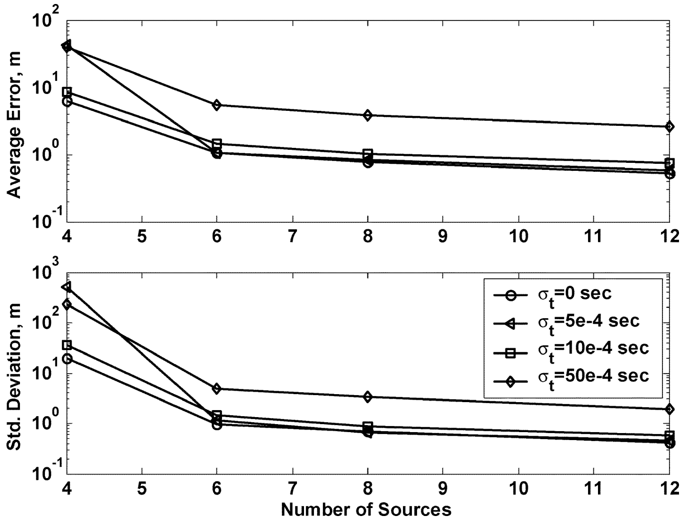


Fig. 6. Average sensor node location error and standard deviation as a function of the number of sources and for various TOA measurement errors, based on 500 simulations with seven sensors $(N = 7)$.

depends strongly on the accuracy with which the sources and anchor are located. Furthermore, in order to achieve a sensor location standard deviation similar to that of the source/anchor locations, more than eight sources are necessary. As one would expect, the solution standard deviations converge to the source/anchor standard deviations for large numbers of sources.

The final influence on self-localization solution to be investigated is the effect of errors in the TOA measurements. Such errors can result from node clock synchronization errors; TOA measurement hardware and software issues and speed of sound estimate errors. Since each of these influences manifests themselves as TOA measurement errors they are considered together here. The effect of TOA measurement error on the solution is shown in Fig. 6. This figure shows the error average and standard deviation as a function of the number of sources for the case where $N = 7$ and the source location estimate standard deviation is 0.5 m. The most important result to note is that the effect of TOA error is very small when the standard deviation on TOA is less than 5 ms.

Recent publications have demonstrated sensor network-based TOA measurements of less than 500 $\mu$s in field trials [13] and even less in laboratory tests [14]. As one can see from Fig. 6, the error predicted for 500-$\mu$s error is nearly indistinguishable from the error predicted for no TOA measurement error. Therefore, in general, TOA measurement error should not be a significant issue in systems of this nature.

## IV. Experimental Results

The effectiveness of the previously described self-localization technique can be further demonstrated by postprocessing a set of experimental data. This data was collected as part of field experiments conducted at the U.S. Army's Dismounted Battle Space Lab Military Operations in Urban Terrain (MOUT) training facility in Fort Benning, GA [13]. This facility, a small village consisting of 15 buildings, was developed in order to recreate urban terrain for training and experimentation. An overhead photograph is shown in Fig. 7. The purpose of these specific field experiments was to demonstrate the feasibility of a distributed sensor network to detect and locate rifle fire in an urban setting. The distributed sensor network consisted of 56 Mica2 Motes manufactured by Crossbow Technology, Inc. [15]. Shots were fired from numerous locations around the facility and the times of arrival at each node were recorded. This data set is used here to demonstrate the feasibility of self-localization with rifle shots as sources and the Mote network as sensors.

These Mica2 sensor nodes consist of an 8-bit microprocessor, a wireless communications chip, 4 kB of RAM and 128 kB of flash memory. A custom sensor expansion board, shown in Fig. 8, was developed for these experiments. This sensor board consisted of a microphone, amplifier, a 1-MHz ADC and an FPGA chip for implementing signal processing algorithms. No effort was made to calibrate these sensor boards either absolutely or relatively. Such a lack of calibration will contribute error to the TOA measurements. This effect was minimized by employing a zero-crossing algorithm for determining the TOA of each event [13]. Microphone signals sampled by the ADC where compressed by the FPGA using zero-crossing coding [13]. These coded signals were compared to parameter ranges developed from a large library of recorded events. If the coded stream was determined to contain a muzzle report the time of arrival was determined. This information was communicated to a base station via a preestablished ad hoc network.

One of the most important tasks performed by the sensor network was node clock synchronization. In order to obtain TOA data that is referenced to some arbitrary reference time, each nodes independent clock had to be reconciled with that of the base station. This was accomplished by using a flooding time synchronization protocol [16]. Using this approach, the nodes were synchronized such that the maximum error between clocks was 20 $\mu$s [13]. Recall that it was demonstrated in Fig. 6 that a TOA measurement error of less than 500 $\mu$s would have negligible affect on the self-localization accuracy. Therefore, node clock synchronization should not cause significant errors in the self-localization results.

The data used in this analysis was the result of blank ammunition being fired from an M4 rifle at nine different locations (indicated by circles in Fig. 7). Data from ten of the 56 sensor nodes were then used in with the self-localization calculations (indicated by triangles in Fig. 6). To demonstrate the accuracy, node locations were measured to within 0.3-m accuracy and the rifle shot locations were measured to about 0.5-m accuracy.

The accuracy of the self-localization algorithm is shown in Figs. 9 and 10, which show the node location error average and standard deviation. Average error is defined here as the average distance between the actual node locations (measured to 0.3-m accuracy) and those predicted by the self-localization algorithm. Note that the average error can be very large (on the order of 100 m) when the equations are exactly determined $(S = 4)$. However, as shown by the simulation results, as the number of sources increases and the equations become over-determined, the error drops significantly. The least error occurs when only two nodes are localized by six or more shots. In this case, the average error is about 0.2 m.

These results compare well with the simulation results shown previously. Overall, the error decreases when the number of

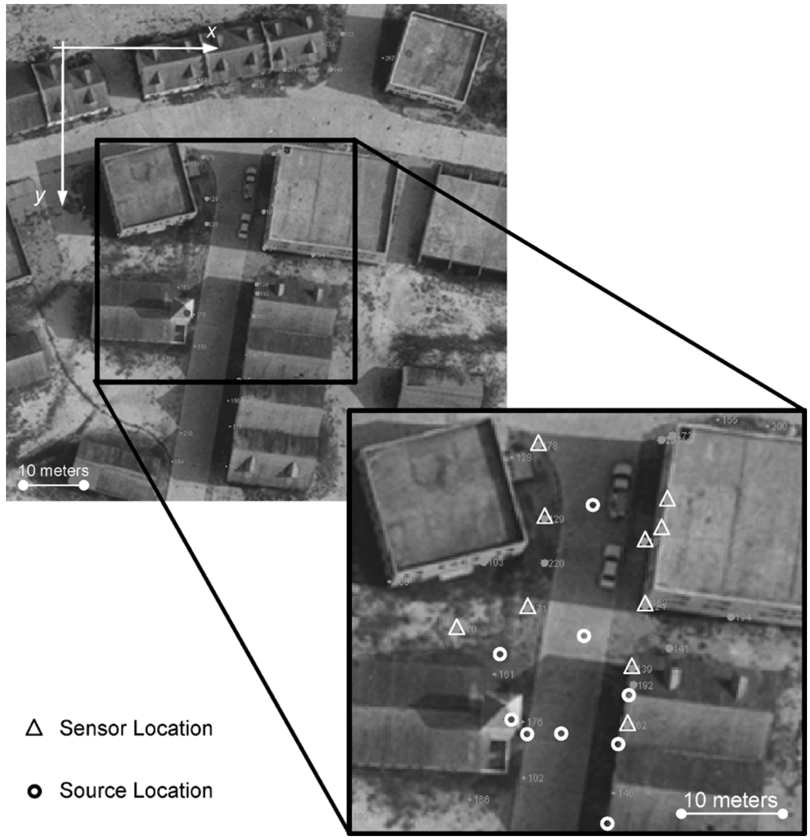


Fig. 7. Overhead photograph of the MOUT training facility in Fort Benning, GA. Locations of the sensor nodes and shots are indicated.

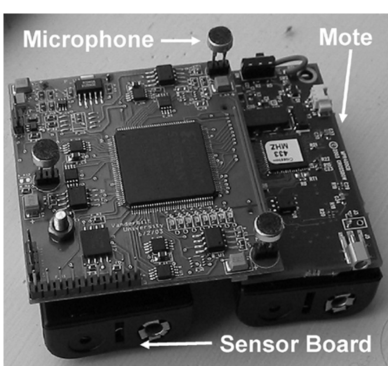


Fig. 8. Photograph of the Mica2 mote and the custom sensor board.

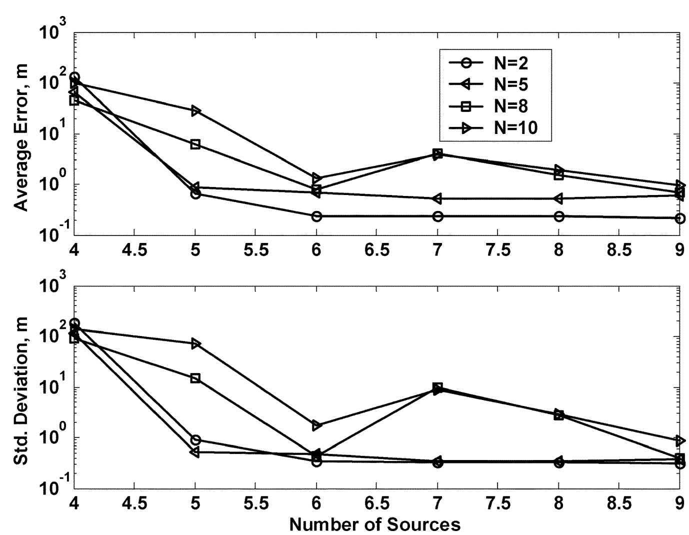


Fig. 9. Average sensor node location error and standard deviation as a function of the number of sources and for various numbers of sensors, based on experimental data with an estimated source location error standard deviation of 0.5 m.

sources increases. The error was also found to increase as the number of nodes localized increases. Just as in the simulation results, the best result obtained yielded an average localization error about 2/3 of the maximum source location error. However, achieving the best results required seven to nine sources as compared to the six to eight sources required in the simulation results.

It is interesting to note that when seven sources were included the error increased significantly over six sources. This is due to the fact that source 7 (which is the source near the bottom of Fig. 7) was not directly in the line of sight of Node 171 (located farthest left in Fig. 7). Therefore, the TOA recorded by node 171 of source 7 was from a reflection off of one of the buildings resulting in a TOA measurement with a particularly large error. All other solutions which included this measurement had also had more error. This situation highlights a particularly challenging situation for self-localization of sensor networks: the rejection of reflected path data in TOA measurements. The solution to this problem will be left for future work.

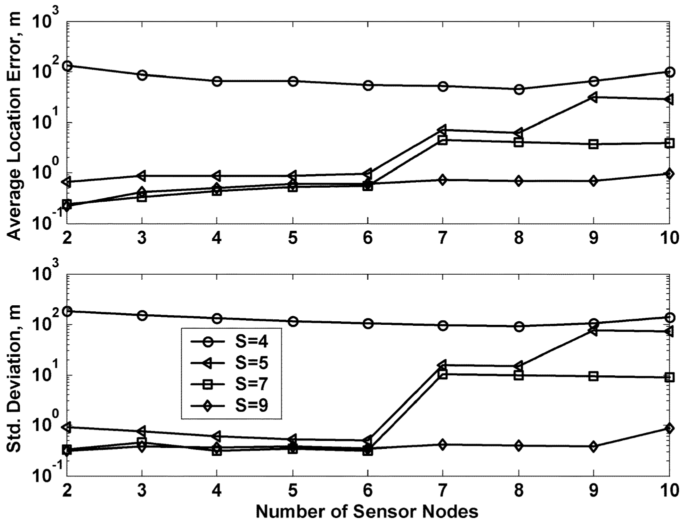


Fig. 10. Average sensor node location error and standard deviation as a function of the number of sensors being located and for various numbers of sources, based on experimental data with an estimated source location error standard deviation of 0.5 m.

## V. Conclusion

An acoustic method for self-localizing a distributed sensor network has been presented. This technique is based on measuring the TOA of acoustic sources at each sensor node. The locations of the sources are known as is the location of one reference sensor. The equations for this technique were presented and simulations were carried out. Of particular interest was the sensitivity of the solution to the number of sources and sensors involved, errors in the known source locations, and errors in the TOA measurements. It was noted that when six to eight acoustic sources are utilized the equations are over-determined and the average location error reduces to less than the source location error. It was also noted that TOA measurement errors of less than about 500 $\mu$s has a negligible effect on accuracy. These conclusions were supported by postprocessing a field measurement data set for self-localization. Results from this data set matched well with the results based on simulations. Overall, the approach allowed self-localization within about 20 cm of average location error when the source locations where known to within 30 cm. It was noted that increasing the number of sources decreased the error while increasing the number of nodes being localized increased the error.

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