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Decentralized acoustic source localization in a distributed sensor network

Stephen M. Williams, Kenneth D. Frampton *, Isaac Amundson, Peter L. Schmidt

Department of Mechanical Engineering, Vanderbilt University, VU Station B 351592, 2301 Vanderbilt Place, Nashville, TN 37235-1592, United States

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Abstract

The purpose of this work is to investigate acoustic source localization algorithms suitable for use with distributed sensor networks. Traditional sensor networks employ a central controller; however centralized data processing in large-scale sensor networks is not always desirable because of the excessive communication and computational complexity it requires. Therefore, fully distributed localization algorithms are considered. The most important aspect of these algorithms is that they be scalable for use in large sensor networks. The scalability is achieved by forming sensor nodes into groups which collaborate to locate sources. Source locations are determined from time of arrival (TOA) information of the acoustic wave front. Two source location solution methods are used: least squares (LS) and Tikhonov regularized inversion (RI). Experimental results validate the accuracy of a distributed localization approach, and the effectiveness of the LS and RI methods are compared. Additionally, important parameters of the distributed localization algorithm are considered.

Keywords: Source localization; Sensor network; Distributed algorithm

1. Introduction

The availability of miniature, low-power sensing devices has inspired the development of distributed sensor networks for a variety of applications [1,2]. Among these are acoustic

* Corresponding author. Tel.: +1 615 322 2778; fax: +1 615 343 6687.
E-mail address: Ken.Frampton@Vanderbilt.edu (K.D. Frampton).

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source localization and tracking, two integral tasks in surveillance, and habitat monitoring. Of interest here are systems that can effectively monitor a large area. This is a task naturally suited to a distributed sensor network made up of numerous “nodes” each possessing a microprocessor, power supply, wired or wireless communication capability, sensors and signal conditioning circuitry.

Distributed sensor networks face a number of technical challenges such as energy and bandwidth constraints, ad hoc networking, collaborative information processing, message routing, and security. The degree of information sharing among network nodes and the manner in which nodes fuse information from other nodes effects performance of the sensor network. Including information from more sensors typically results in better system performance, however; this also increases communication demands on the system, effectively reducing the lifetime of sensor networks with finite energy resources. Therefore, researchers must consider the tradeoff between system performance and energy demands when designing a distributed sensor network.

The scenario that motivates the current work involves numerous (10 s, 100 s, or 1000 s) of inexpensive sensor nodes distributed around an area of interest with the objective of locating acoustical phenomena in that area. While this work envisions a land based scenario, the work presented could also be applied to an underwater setting. These nodes may be placed by hand, dropped by UAV (Unmanned Aerial Vehicle) or UGV (Unmanned Ground Vehicle), or distributed by some other means. It is also assumed here that the positions of every node in the network are determined prior to system use. To effectively monitor the area, the sensor network must sense and identify acoustic sources, determine their position, and make this information available to the user.

Traditional sensor networks employ a centralized controller which directs all network activity and performs all computation. Using a centralized localization algorithm for the large-scale sensor network described above would likely overload the internode communication network and create an excessively large computational burden due to the large amount of measurement data. Decentralized algorithms, also called localized algorithms, may be used in place of centralized algorithms to reduce energy demands, communications demands and computational burden on the system. These decentralized computations are performed by nodes throughout the network, and incorporate information from nodes near those performing the computations. When nodes are added to a centralized system communication requirements increase dramatically as all information must be sent to a central controller. A system utilizing a decentralized algorithm will not see this dramatic increase in communication cost as nodes are added. The result is a scalable system which is more robust than its centralized counterpart. Additionally, decentralized algorithms are attractive because they are robust to network changes and node failures [1–3].

Source localization using sensor arrays has been a studied for many years and currently sees application in radar, sonar, and wireless communication [4]. Recently, a number of distributed source localization systems have been proposed to estimate the position and/or the direction of arrival (DOA) of an acoustic source from phase and time-of-arrival (TOA) information measured by multiple receivers [5–9]. These systems vary in their method of localization (beamforming, DOA, TOA), as well as the nature of the sensor network that they employ (centralized, distributed), and there is generally a tradeoff between accuracy and computational demands. Lendeczi et al. [8] present a centralized system for battlefield surveillance consisting of 56 Mica2 Motes manufactured by Crossbow Technology Inc. [8]. The system performs a grid search to find the location from which a rifle was fired using TOA information of the muzzle blast and shock wave generated by the projectile fired from the rifle. Chen et al. [5] present a distributed sensor network capable of locating continuous near and far-field sources using approximated maximum likelihood and TOA methods in [5]. These systems relay information of the acoustic signal to a base station or laptop where the source location is estimated.

Estimating source position from a set of measured TOA data represents a nonlinear inverse problem in which the accuracy of the solution is dependent upon the solution method. The general least squares (LS) solution to the inverse problem seeks to minimize misfit to the measured data but may result in significant error due to the problem frequently being ill-posed. The ill-posed nature of this problem is caused by having multiple times of arrival very close to the same value. This can be caused by sensor array geometry, measurement uncertainty or a combination of both factors. Node positions are treated as known parameters when solving the inversion process using LS, however, error in node position measurements may introduce significant error to the solution.

Dosso et al. [10] present an iterative solution technique to localize elements of a horizontal line array which avoids the ill-posed nature of the problem [10]. The method is formulated to obtain a solution consistent with estimated uncertainties of the data, while including independent information about the solution, known as *a priori* information, in the inversion. This error may be reduced by treating both node and source positions as unknown parameters, and then including node position estimates as *a priori* information in the iterative solution process.

A distributed sensor network utilizing a decentralized localization algorithm will maintain advantages in scalability, fault tolerance, and communication requirements over a comparable centralized system. Accordingly, the objective of this work is to produce a scalable distributed sensor network from commercial off-the-shelf (COTS) products that can localize a single acoustic source. Solutions of TOA equations by LS and regularized inversion (RI) are presented in Section 2 of this paper. A distributed system based on PC/104 computational modules is then introduced in Section 3. The system is used to localize sources in the near and far-fields by both LS and RI methods, and results of these experiments are presented in Section 4. Conclusions based on these results are provided in Section 5.

2. Time difference of arrival formulation

Estimating the source location from measured times of arrival (TOAs) represents an ill-posed, non-unique, non-linear inverse problem. The non-linearity of the problem is inherent in the equations used in distance calculations. The problem is ill-posed and non-unique if arrival times at individual nodes are very close to the same value, as discussed in the previous section. This paper will consider two methods for solving this inverse problem, and discuss the effectiveness of each method.

The first solution technique that will be considered is that formulated by Mahajan and Walworth in [11], in this work referred to as LS. The formulation is based on differences in time-of-flight from a single source to multiple sensors. If we define the TOA of the acoustic source at the ith node as T_i, the time-difference-of-arrival (TDOA) between a reference node and any other node is

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

where T_1 is the absolute arrival time of the acoustic source at the reference node. We can write the two-dimensional set of non-linear equations representing the distances between the source and N nodes as

$$\begin{aligned} d^2 &= (x_1 - u)^2 + (y_1 - v)^2, \\ (d + cT_{12})^2 &= (x_2 - u)^2 + (y_2 - v)^2, \\ &\vdots \\ (d + cT_{1N})^2 &= (x_N - u)^2 + (y_N - v)^2, \end{aligned} \tag{2}$$

where d represents the distance from node 1 to the source located at coordinates (u, v), (x_i, y_i) is the position of the ith node, and c is the speed of sound. Expanding these equations and substituting the first equation for d^2 into the remaining equations results in the following linearized system of $N - 1$ equations

$$\begin{bmatrix} 2x_1 - 2x_2 & 2y_1 - 2y_2 & -2cT_{12} \\ 2x_1 - 2x_3 & 2y_1 - 2y_3 & -2cT_{13} \\ & \vdots & \\ 2x_1 - 2x_N & 2y_1 - 2y_N & -2cT_{1N} \end{bmatrix} \times \begin{bmatrix} u \\ v \\ d \end{bmatrix} = \begin{bmatrix} c^2T_{12}^2 + x_1^2 + y_1^2 - x_2^2 - y_2^2 \\ c^2T_{13}^2 + x_1^2 + y_1^2 - x_3^2 - y_3^2 \\ \vdots \\ c^2T_{1N}^2 + x_1^2 + y_1^2 - x_N^2 - y_N^2 \end{bmatrix}. \tag{3}$$

This formulation (speed of sound is considered constant) can be solved when four nodes hear the acoustic source, and the system is overdetermined when more than four nodes are present. The above analysis can easily be extended to the three-dimensional case, requiring a fifth receiver to hear the source [11]. The estimate of the source location from Eq. (3) is then found by the method of least squares (LS). The system matrix in (3) may be ill-conditioned when relative time delays are approximately equal, resulting in significant error in the source position estimate. This is more likely to occur when the system is exactly determined, thus it is desirable to include more than four nodes in the problem formulation [6].

The second method used in this work to estimate source position was adapted from a technique formulated by Dosso et al. [10] to localize horizontal line array elements [10]. Using this method, an iterative linearized inversion is developed below which results in a stable solution to the ill-posed inverse problem.

Writing two-dimensional equations for the TOA of a single source at each node results in the following:

$$\begin{aligned} T_1 &= \frac{\sqrt{(x_1 - u)^2 + (y_1 - v)^2}}{c} + \gamma, \\ &\vdots \\ T_N &= \frac{\sqrt{(x_N - u)^2 + (y_N - v)^2}}{c} + \gamma, \end{aligned} \tag{4}$$

where γ is the source instant. Note that this formulation may be extended to three-dimensions by including a third spatial coordinate in (4). Node locations were considered to be known in the previous formulation but will instead be treated as unknown, but well estimated, here. The sensor node locations were included as unknowns even though their locations were assumed to be known *a priori*. This is because it has been previously shown that allowing the sensor location solutions to "float" results in a better solution [10]. The system in (4) is a set of N non-linear equations in M unknowns where M is equal to $2N+3$ (two spatial unknowns per node in addition to the source location and source instant). This set of equations written in general vector form is

$$\boldsymbol{T} = \boldsymbol{F}(\boldsymbol{m}), \tag{5}$$

where $\boldsymbol{T}$ represents the vector of arrival times at each node, the operator $\boldsymbol{F}$ represents the relationships shown in Eq. (4), and $\boldsymbol{m}$ is the vector of model parameters (node locations, source locations and source occurrence times). A local linearization of the system is obtained by performing the Taylor series expansion of $\boldsymbol{T} = \boldsymbol{F}(\boldsymbol{m}_\mathrm{o} + \boldsymbol{\delta m})$ about an arbitrary starting model $\boldsymbol{m}_\mathrm{o}$. Disregarding higher order terms, the linearized system can be written as

$$\boldsymbol{T} = \boldsymbol{F}(\boldsymbol{m}_\mathrm{o}) + \boldsymbol{J\delta m}, \tag{6}$$

where $\boldsymbol{\delta m}$ is the model perturbation, and $\boldsymbol{J}$ is the Jacobian matrix consisting of elements $J_\mathrm{kl} = \partial F_\mathrm{k}(\boldsymbol{m}_\mathrm{o})/\partial m_\mathrm{l}$. Defining the residual $\boldsymbol{\delta T} = \boldsymbol{T} - \boldsymbol{F}(\boldsymbol{m}_\mathrm{o})$ (6) can be written as

$$\boldsymbol{J\delta m} = \boldsymbol{\delta T}, \tag{7}$$

which is a set of linear equations that can be solved for the model perturbation $\boldsymbol{\delta m}$. The model perturbation may be written as $\boldsymbol{\delta m} = \boldsymbol{m} - \boldsymbol{m}_\mathrm{o}$ so that (7) can be rewritten in terms of the actual model, $\boldsymbol{m}$, as

$$\boldsymbol{Jm} = \boldsymbol{\delta T} + \boldsymbol{Jm}_\mathrm{o}. \tag{8}$$

This linearized inverse problem can then be solved for $\boldsymbol{m}$. However, $\boldsymbol{m}$ may not adequately reproduce the measured data because nonlinear terms were neglected. If the model $\boldsymbol{m}$ does not reproduce the measured data, the starting model $\boldsymbol{m}_\mathrm{o}$ is replaced with the current model $\boldsymbol{m}$, and the process repeated iteratively until an acceptable solution is found or the iterations converge.

The LS solution of the overdetermined system of linear equations given in (8) is found by minimizing the χ^2 misfit defined by

$$\chi^2 = |\boldsymbol{G}(\boldsymbol{Jm} - (\boldsymbol{\delta T} + \boldsymbol{Jm}_\mathrm{o}))|^2, \tag{9}$$

where $\boldsymbol{G}$ is a diagonal weighting matrix, $\boldsymbol{G} = \mathrm{diag}[1/\sigma_1, \ldots, \sigma_N]$. Note that Eq. (9) is the misfit of the model to the linearized inverse problem, and σ_i is the standard deviation of the TOA measurements at each node, assuming that the TOA measurement error is Gaussian with zero mean. The objective of this regularization is to formulate a unique, stable inversion by specifically including *a priori* information about the solution. This may be accomplished by minimizing an objective function Φ which combines the χ^2 term representing the data misfit, and a regularizing term that imposes the condition that the solution $\boldsymbol{m}$ resemble a prior estimate $\boldsymbol{m}'$ that includes *a priori* information

$$\Phi = |\boldsymbol{G}(\boldsymbol{Jm} - (\boldsymbol{\delta T} + \boldsymbol{Jm}_\mathrm{o}))|^2 + \mu|\boldsymbol{H}(\boldsymbol{m} - \boldsymbol{m}')|^2. \tag{10}$$

The weighting matrix $\boldsymbol{H}$ in (10) is referred to as the regularization matrix. The parameter μ is a Lagrange multiplier which controls the relative importance of the data misfit and the *a priori* information. Accurate estimates of the node positions were available during experimentation and were included in $\boldsymbol{m}'$. The regularization matrix was then held to be $\boldsymbol{H} = \mathrm{diag}[1/\sigma_{x1},\ 1/\sigma_{y1}, \ldots, 1/\sigma_{xN},\ 1/\sigma_{yN},\ 0,\ 0,\ 0]$, where σ_{xi} and σ_{yi} are the standard deviations of node coordinates (again treating the node locations as unknown, but with an estimated location of relatively small standard deviation). No information was available for the source position or source instant, therefore, their weights in the regularization matrix were held to be zero. Minimizing Φ in (10) with respect to $\boldsymbol{m}$ results in the regularized solution [10]

$$\boldsymbol{m} = [\boldsymbol{J}^T\boldsymbol{G}^T\boldsymbol{G}\boldsymbol{J} + \mu\boldsymbol{H}^T\boldsymbol{H}]^{-1}[\boldsymbol{J}^T\boldsymbol{G}^T\boldsymbol{G}(\delta\boldsymbol{T} + \boldsymbol{J}\boldsymbol{m}') + \mu\boldsymbol{H}^T\boldsymbol{H}\boldsymbol{m}']. \tag{11}$$

The parameter μ is generally chosen so that the χ^2 misfit achieves the expected value of $\chi^2 = M$, for M data. Although it is possible to compute an optimum μ at each iteration of the solution process, μ was held constant in this work. Prior to experimentation, simulations revealed that a constant value of $\mu = 100$ would produce sufficient χ^2 misfit and that the final model $\boldsymbol{m}$ would resemble the starting model $\boldsymbol{m}'$ that included the *a priori* estimates of node locations.

The χ^2 misfit of the linear inverse problem (9) was used to derive (11), however, convergence of the iterative process must be determined by the misfit to the nonlinear problem

$$\chi^2 = |\boldsymbol{G}(\boldsymbol{F}(\boldsymbol{m}) - \boldsymbol{T})|^2. \tag{12}$$

For this work, an iterative solution process was used to find source locations from the RI technique presented above. Convergence of the iteration process was determined by one of two criteria: (1) the change in the non-linear χ^2 statistic between iterations was less than 0.5%, or (2) the change in source location between iterations was less than 0.001 m.

3. Experimental platform

3.1. Hardware

One objective of this work is to produce a system that consists of readily available, commercial off-the-shelf (COTS) products. Accordingly, each of the system's nodes consists of a PC/104 module, a battery pack, and a microphone circuit. The PC/104 module used was a Diamond System's Prometheus that includes data acquisition circuitry, a 100 MHz CPU, 100 Mbps 10/100BaseT Fast Ethernet port, 32 MB of RAM and 128 MB flash disk storage.

Each node's microphone (Panasonic-ECG WM-34BY omni-directional) signal is amplified and fed through a 10 kHz low-pass filter. The resulting signal is then compared to a reference voltage by an electronic comparator whose output is sent to an external interrupt pin on the Prometheus. The external interrupt triggers a subroutine which records the TOA of the acoustic source. After recording the arrival time of the source on each node, arrival time information is collected and used to estimate the position of the source. Both LS and RI position estimates are found within seconds of the source arrival.

A starter pistol is used to generate impulsive acoustic sources that can be heard by all nodes in the network. Measuring the TOA of the source as the point at which the microphone output exceeded the voltage threshold proves to be a robust means of detection for this work because of the impulsive nature of the acoustic wave front. Miniature low-powered ICs have recently been proposed for bearing estimation [12,13]. With these dedicated hardware components it is possible to measure the TOA to within a few microseconds.

It should be noted that determining the TOA of the source by threshold detection is only effective for environments in which a single acoustic source louder than the ambient noise is present. For environments in which multiple sources are present, a sliding correlator [14], matched filter, or frequency domain method may be used to identify sources of interest, and determine their TOA.

Network nodes communicate via Ethernet ports and a 3Com router. A more practical sensor network would communicate wirelessly, but as it is not necessary for this work, wired communication is used.

3.2. Software

Nodes in the distributed system are directed by identical application programs written in C++ that run atop an embedded Linux OS. Network communication is facilitated with use of the Adaptive Communication Environment (ACE), and The ACE ORB (TAO) [15–17]. ACE is an open source framework developed for high-performance communication services, and TAO is an open source extension to ACE that arranges the client/server communication in an object-oriented fashion. Using ACE and TAO introduces slight performance reduction to the system, but the benefits of establishing a pattern-oriented structure of program design, while ensuring scalability, robustness and portability outweighs this loss.

3.3. Time synchronization

A distributed acoustic localization system will be accurate only when fine-grained time synchronization between node clocks is available. This is because TOA measurements are made relative to each node's local clock, not a global network reference. Reference Broadcast Synchronization (RBS) [18] provides time synchronization in the sensor network developed for this work. In RBS, an arbitrary node in the sensor network sends a general broadcast packet which is received by other nodes in the network. Receiving nodes mark the arrival time of the broadcast packet on their local clock. The general broadcast arrives at each of the receivers at approximately the same time and can be used as a reference for nodes to compare their clocks. Each node uses this information to setup a table of values representing the difference between their clock and the clocks of other nodes in the network.

Immediately after the reference broadcast is sent, and time synchronization is established, node clocks are synchronized to within a few microseconds. In time however, values of the time difference between node clocks will become inaccurate as the clocks tick at slightly different rates. The average clock drift between any two PC/104 modules was found to be 12 μs per second. RBS is performed between 5 and 8 s before the source instant during experimentation, resulting in 60–100 μs of error in time synchronization (average). A more practical clock skew correction method is described in Ref. [18] which estimates both the phase offset and the clock skew between nodes.

3.4. Grouping

In keeping with the scalable decentralized design objective, the sensor network is divided into subarrays, or sub-groups, of predetermined sizes. The TDOA method of source localization to be solved by LS requires a minimum of four TOA measurements to solve the resulting equations. Thus, a group size of four is the smallest considered for this work. Also considered are group sizes of five, six, seven, eight and nine nodes.

Grouping in this system is performed dynamically and based upon the spacing between nodes. Each node in the system is designated a group leader upon initialization. Leaders then select the $n - 1$ nodes furthest from themselves to be group members, where n is the group size. Grouping nodes in this manner ensures that groups maintain maximum inter-node spacing, effectively reducing each group's sensitivity to TOA measurement error. This grouping technique is sufficient for the small-scale sensor network developed. For a sensor network containing many nodes monitoring a large area, tradeoffs must be made between inter-node spacing and practical aspects of distributed systems, such as power requirements of wireless communication.

For the scenario in which numerous nodes are spread over a large area, grouping could be accomplished by having nodes choose the $n - 1$ nodes furthest from themselves within some limit. The limit could be in terms of distance (e.g. 20 m) or in terms of the number of hops required for two nodes to communicate (e.g. 3 hops). If the network is sparsely distributed, nodes could choose the $n - 1$ nodes nearest to themselves without concern for inter-node spacing.

3.5. Experimental procedure

Three randomly generated arrays consisting of nine nodes and covering a 2.5 by 2.5 m indoor area were considered in this work. The reason for the selection of this size of array field was for convenience of experimental set up, and limitations on available indoor space. An indoor venue was chosen to minimize the interference with experiments by extraneous noise sources.

Two of the arrays were used to localize 10 near-field sources positioned at random locations within the array area, and five far-field sources positioned outside of the array area. The third array was used to localize five near-field sources. Group sizes of four, five, six, seven, eight, and nine nodes were considered for each of the three random arrays. Group leaders estimated all source positions using both the LS and RI solution techniques previously discussed. The initial guess used with the RI technique was determined randomly, with the constraint that values used in the guess had to fall within the known boundaries of the array field. This was done to help assure that the RI method would converge. The result was 225 near-field and 90 far-field source position estimates for each group size/solution technique pair. One of the three random arrays is plotted in Fig. 1 with a set of near-field and far-field source locations.

Spatial coordinates used for comparison and calculation of results are referred to as expected values. The expected values of the source coordinates were what were supplied to the algorithm as *a priori* information. A set of expected coordinates denotes an expected position. Nodes were located to within 1 cm of their expected positions. The sources were located to within 4 cm of their expected position. The additional uncertainty in source position was due to the difficulty in holding the starter pistol steady while firing.

3.6. Measurement error

The ability of the experimental platform to localize sources is limited by TOA measurement error. This error is introduced by clock skew as well as delay in the microphone cir-

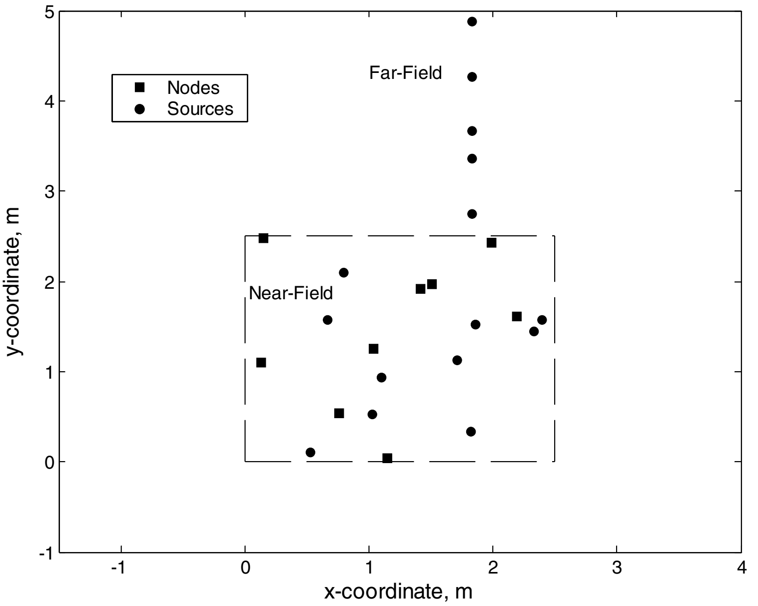

Fig. 1. Node and source locations for one random array.

cuit, threshold detection, and software interrupt. Time synchronization error between nodes at the time of firing was 60–100 μs, representing 2–3 cm in TOA measurement error. Time delay in the microphone circuit, threshold detection, and software interrupt are

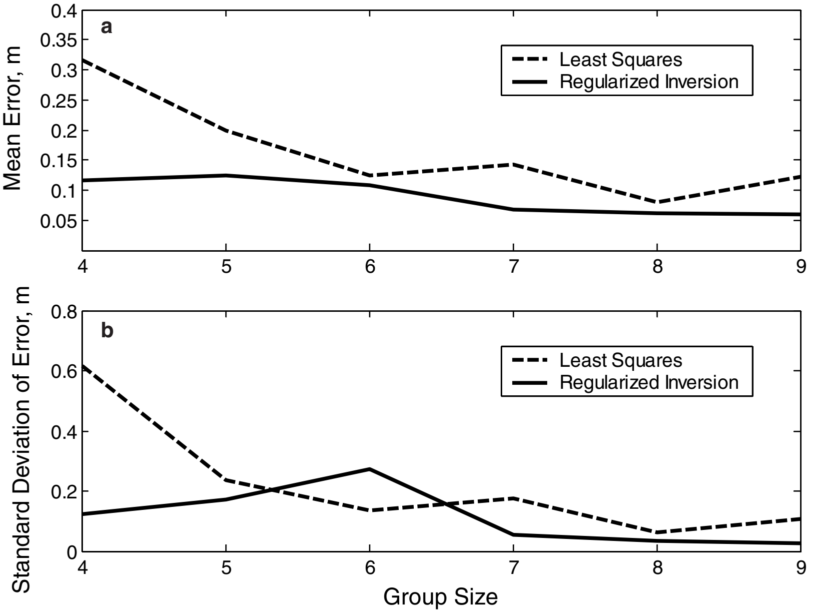

Fig. 2. The (a) average and (b) standard deviation of the RMS error in source position estimate as a function of group size. This includes all sources inside of the array area for the three arrays considered.

approximately the same for each node (within a few microseconds). This delay is subtracted out in the TDOA calculation used in the LS approach so that the measurement error introduced by time delay is on the order of a few microseconds. This delay remains in the RI calculations, but at an average of 8 μs was negligible compared to other sources of error.

Experimental results are also limited by node and source placement error which was 1 and 4 cm, respectively. Considering both TOA measurement error, and the error in experimental procedure, localization accuracy within 6–7 cm is achievable.

4. Results

The distributed platform developed for this work was successful in locating sources placed in the near-field using both LS and RI decentralized algorithms. Seen in Fig. 2 is the average root-mean-square (RMS) error in source position estimate as a function of group size. This plot shows that the accuracy in source position estimate improves significantly as the group size is increased, especially for the case of LS. When the system in Eq. (3) is exactly determined (4 nodes in each group), the average error in LS position estimate is 32 cm. This is because the LS matrix is frequently ill-conditioned. By adding two nodes to each group (resulting in an over-determined set of equations), the average error in source position estimate is reduced to about 12 cm.

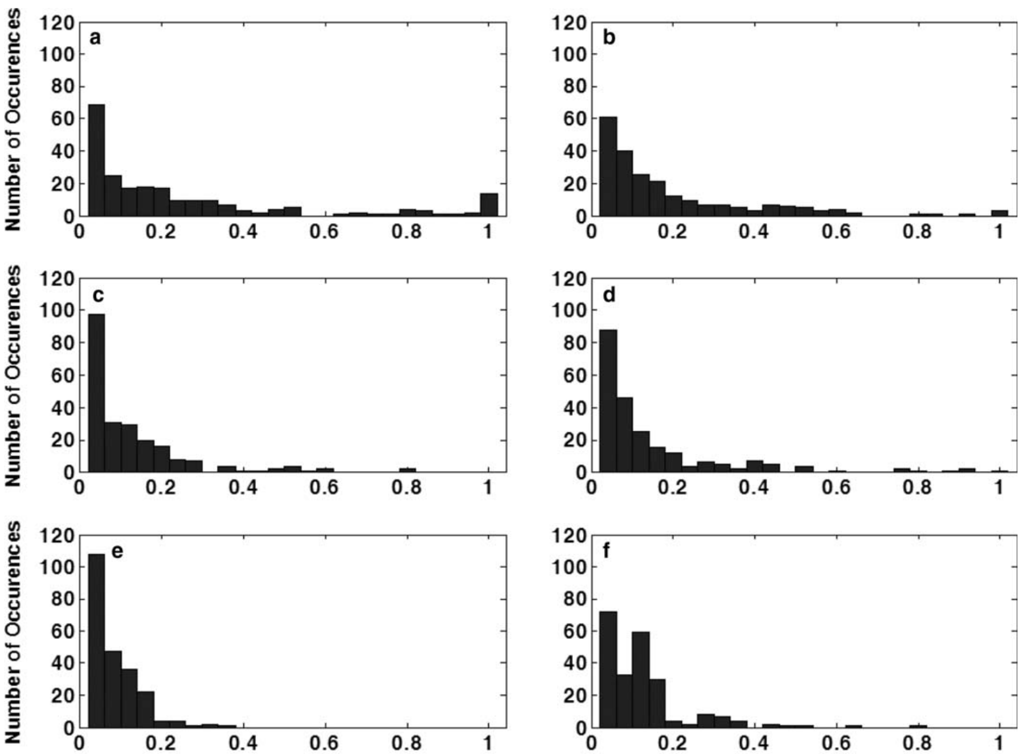

Fig. 3. Distribution of the error in source position estimate found by LS for group sizes of (a) four, (b) five, (c) six, (d) seven, (e) eight, and (f) nine.

The RI method of localization found accurate source positions for both small and large group sizes, and generally outperformed LS. The average RMS error in RI source position estimate for a group size of four is 12 cm, a significant improvement over the LS method. Increasing the group size improved source position estimates found by RI until a minimum average error of 6 cm was reached for a group size of nine nodes. These results are similar to those found in the literature. Chen reported an RMS localization error of about 7 cm for sources in the near field [5].

Error distribution for the LS and RI solution methods can be seen in Figs. 3 and 4. It is important to note that the large majority of position estimates found by RI and LS (group size of six or more) are accurate to within 15 cm. For example, 96% of position estimates found by RI for a group size of seven are accurate to within 15 cm. This is a desirable result when considering the decentralized nature of the localization algorithm, because estimated source positions do not have to be validated by other groups in the network, removing additional communication demands from the system. Outliers seen in Fig. 3a (exactly determined LS) occur when the system matrix in Eq. (3) is ill-conditioned.

The sensor array considered in this work was not successful in locating sources in the far field. Fig. 5 shows the average RMS error in far-field source estimates as a function of group size. The far-field source estimates improve slightly as the group size

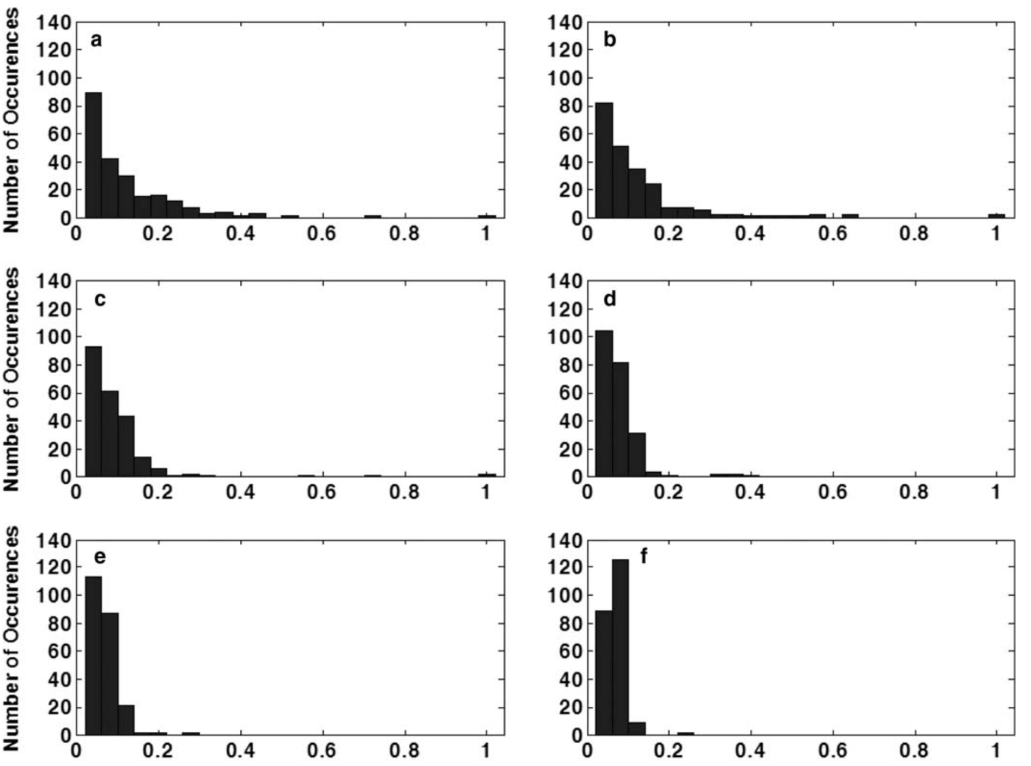

Fig. 4. Distribution of the error in source position estimate found by RI for group sizes of (a) four, (b) five, (c) six, (d) seven, (e) eight, and (f) nine.

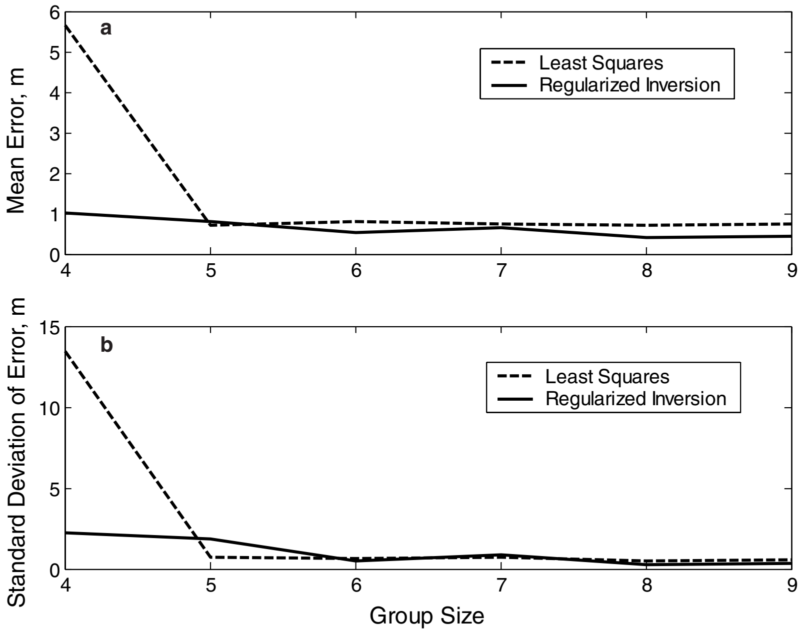

Fig. 5. The (a) average and (b) standard deviation of the RMS error in far-field source position estimate as a function of group size. This includes all sources outside of the array area for the three arrays considered.

is increased, but do not reach the accuracy level of the near-field source estimates. Sources in the far-field may be better localized using other methods, e.g. beamforming, and DOA [5,6,8].

5. Conclusions

A distributed sensor network capable of locating near-field sources via decentralized localization algorithms has been presented. Nodes may be added to the network without increasing the complexity of the system, or the computational workload of a central controller. Experimental results confirm that the LS method of localization performs poorly when the system is determined or slightly overdetermined. Increasing the group size of the subarrays improves the performance of the LS method by reducing the likelihood that the system matrix is ill-conditioned. The RI technique for localization was formulated with use of the regularization method and does not suffer from the ill-conditioned matrix problem as LS does. Accordingly, the RI method provided accurate source position estimates for small group sizes. In the future this approach could be applied to tracking a moving source in the near-field. The experimental setup is also being used to study the effectiveness of decentralized self-localization.

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