Coherent Acoustic Array Processing and Localization on Wireless Sensor Networks

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Invited Paper

Advances in microelectronics, array processing, and wireless networking have motivated the analysis and design of low-cost integrated sensing, computing, and communicating nodes capable of performing various demanding collaborative space–time processing tasks. In this paper, we consider the problem of coherent acoustic sensor array processing and localization on distributed wireless sensor networks. We first introduce some basic concepts of beamforming and localization for wide-band acoustic sources. A review of various known localization algorithms based on time-delay followed by least-squares estimations as well as the maximum–likelihood method is given. Issues related to practical implementation of coherent array processing, including the need for fine-grain time synchronization, are discussed. Then we describe the implementation of a Linux-based wireless networked acoustic sensor array testbed, utilizing commercially available iPAQs with built-in microphones, codecs, and microprocessors, plus wireless Ethernet cards, to perform acoustic source localization. Various field-measured results using two localization algorithms show the effectiveness of the proposed testbed. An extensive list of references related to this work is also included.

Keywords*—*Ad hoc network, beamforming, distributed sensor network, microphone array, source localization, time synchronization, wireless network.

I. INTRODUCTION

Recent developments in integrated circuit (IC) technology has allowed the construction of low-cost small sensor nodes with signal processing and wireless communication capabilities that can form distributed wireless sensor network systems. These systems can be used to perform detection, localization, tracking, and identification of objects in diverse military, industrial, scientific, office, and home applications [1]–[5].

Beamforming is a space–time operation in which a waveform originating from a given source but received at spatially separated sensors are combined in a time-synchronous manner. If the propagation medium preserves sufficient coherency among the received waveforms, then the beamformed waveform can provide an enhanced signal-to-noise ratio (SNR) compared to a single sensor system. Beamforming can be used to determine the direction(s) of arrival and the location(s) of the source(s). Beamforming and localization are two interlinking problems, and many algorithms have been proposed to tackle each problem individually and jointly (i.e., localization is often needed to achieve beamforming, and some localization algorithms take the form of a beamformer).

In this paper, we consider coherent processing dealing with acoustic sources and sensors. The processing of seismic/vibrational sensor data is similar to that of acoustic sensors except for the propagation medium and unknown speed of propagation. Source types such as RF, magnetic, infrared, and visual have other distinct features and will not be considered here. Acoustic source localization and the beamforming problem is challenging due to its wide-band nature, near- and far-field geometry (relatively near/far distance of the source from the sensor array), and arbitrary array shape. In contrast, RF source can be considered to be narrow-band, far-field, and the array shape is often controlled. Many tutorial papers [6], [7] and books [8]–[10] have dealt with beamforming and localization. Recent developments in single-frame acoustic source localization can be categorized into two classes, namely, two-step methods (for single source only) with an intermediate time-delay estimation followed by a least-squares (LS) estimation [11]–[13] and

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a single-step maximum-likelihood (ML) approach that is capable of estimating multiple source locations and directly provide beamforming outputs [14], [15]. The ML approach has an obvious advantage (at the cost of computational complexity) over the time-delay LS-type methods, since in most practical scenarios multiple signals coexist and must be considered in order to achieve high performance in localization and signal-to-interference-and-noise-ratio (SINR) enhancement.

The design of acoustic localization algorithms mainly focuses on high performance, minimal communications load, and computationally efficient and robust methods to reverberant and interference effects. In [16], a robust method for relative time-delay estimation was proposed by reformulating the problem as a linear regression of phase data and then estimating the time delay through minimization of a robust statistical error measure. When several signals coexist, the relative time delay of the dominant signal was shown to be effectively estimated using a second-order subspace method [13]. A recent application of particle filtering to acoustic source localization using a steered beamforming framework also promises efficient computations and robustness to reverberations [15]. Another attractive approach using the integration (or fusion) of distributed microphone arrays can yield high performance without demanding data transfer among nodes [17]. Unlike the aforementioned approaches that perform independent frame-to-frame estimation, a tracking framework was also developed in [18] to provide power-aware, low-latency location tracking that utilizes the historical source information (e.g., trajectory and speed) with the single-frame updates.

Besides various physical phenomena, many system constraints also limit the performance of coherent array signal processing algorithms. For instance, the system performance may suffer dramatically due to sensor location uncertainty (due to unavailable measurement in random deployment), microphone response mismatch and directivity (which may be serious for some types of microphones in some geometric configurations), and loss of signal coherence across the array (i.e., widely separated microphones may not receive the same coherent signal) [7]. In a self-organized wireless sensor network, the collected signals need to be well time-synchronized in order to yield good performance. These factors must be considered for practical implementation of the sensor network. In the past, most reported sensor network systems performing these processing operations usually involve custom-made hardware. In this paper, we propose to use iPAQ 3760s by Compaq, which are handheld, battery-powered devices normally meant to be used as personal digital assistants (PDAs). We select the iPAQ for its compactness, reasonable battery life, Linux open-source operating system support, and its availability as a commercial off-the-shelf (COTS) product. Each iPAQ has a built-in microphone and codec for sound acquisition, and it supports a spread-spectrum wireless Ethernet card for the transmission of data. As will be described later in more detail, the CPU clocks of the iPAQs are synchronized using the reference-broadcast synchronization (RBS) method [30], and the synchronized collected data is processed offline using Matlab to provide various localization and beamforming results. Extensive experiments using the wireless iPAQ testbed have been conducted to demonstrate the effectiveness of the RBS algorithm and localization/beamforming algorithms in various scenarios.

The paper is organized as follows. In Section II, we introduce the general framework of acoustic source localization and beamforming. Some practical coherent array processing issues, including fine-grained time synchronization, are considered in Section III. In Section IV, the testbed setup is described and the experimental results are demonstrated. Finally, in Section V we make some conclusions.

II. Array Signal Processing Algorithms

A. Acoustic Source Localization

For an array of R microphones simultaneously receiving M independent, spatially separated sound signals $(M < R)$, the acoustic waveform arriving at the rth microphone is given by

$$x_r(t) = \sum_{m=1}^{M} h_r^{(m)}(t) * s_m(t) + n_r(t) \qquad (1)$$

for $r = 1, \ldots, R$, where s_m is the mth source signal, $h_r^{(m)}$ is the impulse response from the mth source to the rth sensor (i.e., a delta function in free space corresponding to the time delay or a filtered response to include the reverberation effect), n_r is the additive noise, and $*$ denotes the convolution operation. For each chosen frame time (a function of the source motion and signal bandwidth), the received signal is appropriately digitized and collected into a space–time data vector $\mathbf{x} = [x_1(0), \ldots, x_1(L-1), \ldots, x_R(0), \ldots, x_R(L-1)]^T$ of length RL. The corresponding frequency spectrum data vector is then given by $\mathbf{X}(\omega_k) = [X_1(\omega_k), \ldots, X_R(\omega_k)]^T$, for $k = 0, \ldots, N-1$, where N is the number of fast Fourier transform (FFT) bins.

Denote $\boldsymbol{\Theta}$ as the estimation parameter, which in the near-field case is the source location vector $[\mathbf{r}_{s_1}^T, \ldots, \mathbf{r}_{s_M}^T]^T$ and $\mathbf{r}_{s_m}$ is the mth source location, and in the far-field case is the angle vector $[\phi_s^{(1)}, \theta_s^{(1)}, \ldots, \phi_s^{(M)}, \theta_s^{(M)}]^T$, and $\phi_s^{(m)}$ and $\theta_s^{(m)}$ are the azimuth and elevation angles of the mth source, respectively. In general, the ML estimation with additive white Gaussian noise is given by

$$\widehat{\boldsymbol{\Theta}}^{\mathrm{ML}} = \arg\max_{\boldsymbol{\Theta}} \sum_{k=1}^{\frac{N}{2}} W(k) \left\|\mathbf{P}(k, \boldsymbol{\Theta})\mathbf{X}(\omega_k)\right\|^2 \qquad (2)$$

where $W(k)$ is the weighting function by design (e.g., zero for insignificant bins and stronger weighting on dominant bins and/or high-frequency bins), $\mathbf{P}(k, \boldsymbol{\Theta}) = \mathbf{D}(k, \boldsymbol{\Theta})\mathbf{D}^\dagger(k, \boldsymbol{\Theta})$ is the projection matrix that projects the data vector into the parameter space, $\mathbf{D}^\dagger(k, \boldsymbol{\Theta}) = (\mathbf{D}(k, \boldsymbol{\Theta})^H \mathbf{D}(k, \boldsymbol{\Theta}))^{-1}\mathbf{D}(k, \boldsymbol{\Theta})^H$ is the pseudoinverse of the steering matrix $\mathbf{D}(k, \boldsymbol{\Theta})$ [14], and only the positive frequency bins are considered (negative frequencies are simply mirror images for real-valued signals). Note that no closed-form solution is available for (2), and efficient iterative computational methods have been proposed, including the alternating projection [14], particle filtering [15], and the SAGE method [20]. For the actual implementation of the approximate maximum-likelihood (AML) algorithm in the experiments shown in Section IV-B, we select the 100 highest frequency bins of the received sensor data for processing. A finite grid search [with equal vertical and horizontal spacing of 0.001 m for source localization and 0.3° for direction-of-arrival (DOA) estimation] is then conducted to find the global maximum of the log-likelihood function. Note that a refinement of the estimation can be performed using iterative methods, but is not considered in this paper.

In the case of a single source, the time-delay-LS methods can also be applied [11]–[13]. The time difference of arrival (TDOA) can be estimated by using various correlation operations among sensors [16] or a blind beamforming method proposed in [13]. Without a loss of generality, we choose $r = 1$ as the reference sensor for differential time delays. Let the reference sensor be the origin of the coordinate system for simplicity. The TDOA for R sensors satisfies

$$t_{r1} = t_r - t_1 = \frac{\|\mathbf{r}_s - \mathbf{r}_r\| - \|\mathbf{r}_s - \mathbf{r}_1\|}{v} \tag{3}$$

for $r = 2, \ldots, R$, where $\mathbf{r}_s = [x_s, y_s, z_s]^T$ and $\mathbf{r}_r = [x_r, y_r, z_r]^T$ are the source location and rth sensor location, respectively, and v is the speed of propagation. This is a set of $R - 1$ nonlinear equations, which after some manipulations can be formulated as a closed-form LS solution (with or without constraints) [11]–[13] of the form $\mathbf{A}\mathbf{y} = \mathbf{b}$, where the system matrix $\mathbf{A}$ contains the sensor locations and measured TDOAs, the unknown vector $\mathbf{y}$ contains the source location, source range, and v (if unknown), and the vector $\mathbf{b}$ is a function of sensor locations. An overdetermined LS solution can be given in the case of six or more sensors (for three-dimensional localization and unknown v). For a two-dimensional scenario, the constrained LS (CLS) solution to estimate the source location has the form of

$$\mathbf{A} = \begin{bmatrix} \mathbf{r}_2^T & t_{21} \\ \mathbf{r}_3^T & t_{31} \\ \vdots & \vdots \\ \mathbf{r}_R^T & t_{R1} \end{bmatrix}$$

$$\mathbf{y} = \begin{bmatrix} \mathbf{r}_s \\ v\|\mathbf{r}_s\| \end{bmatrix}$$

$$\mathbf{b} = (1/2) \begin{bmatrix} (vt_{21})^2 + \|\mathbf{r}_2\|^2 \\ (vt_{31})^2 + \|\mathbf{r}_3\|^2 \\ \vdots \\ (vt_{R1})^2 + \|\mathbf{r}_R\|^2 \end{bmatrix}.$$

The constraint of the previous equations is given by $v^2\|\mathbf{B}\mathbf{y}\| = \|\mathbf{f}^T\mathbf{y}\|$, where

$$\mathbf{B} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \text{ and } \mathbf{f} = [0\ 0\ 1]^T.$$

The CLS solution can be obtained by the Lagrangian multiplier method. The solution of the unknown vector $\mathbf{y}$ can be given by $\mathbf{y} = (\mathbf{A}^T\mathbf{A} + \lambda v^2\mathbf{B} - \lambda\mathbf{f}\mathbf{f}^T)^{-1}\mathbf{A}^T\mathbf{b}$. The Lagrangian multiplier λ can be obtained by substituting $\mathbf{y}$ back to the previous constraint equation. The resulting equation is a fourth-order equation. We then select the root which gives estimate the most physical meaning. A similar LS formulation is also available for DOA estimation [19].

B. Wide-Band Beamforming

The main purpose of beamforming is to improve the SINR, which is often performed after a desired source location is obtained (except for the blind beamforming methods). In the most general sense of digital wide-band beamforming in the time-domain, the digitized received array signal is combined with appropriate delays and weighting to form the beamformer output

$$y(n) = \sum_{r=1}^{R} \sum_{\ell=0}^{L-1} w_{r\ell} x_r(n - \ell), \tag{4}$$

where $w_{r\ell}$ is the chosen beamforming weight to satisfy some criterion, and x_r here denotes the digitized version of the received signal. Numerous criteria exist in the design of the beamforming weight, including maximum SINR with frequency and spatial constraints. Other robust blind beamforming methods have also been proposed to enhance SINR without the knowledge of the sensor responses and locations. For instance, the blind maximum power (MP) beamformer in [13] obtains array weights from the dominant eigenvector (or singular vector) associated with the largest eigenvalue (or singular value) of the space–time sample correlation (or data) matrix. This approach not only collects the maximum power of the dominant source, but also provides some rejection of other interferences and noise.

In some cases, especially for multiple sources, frequency-domain beamforming may be more attractive for acoustic signals due to their wide-band nature. This is especially advantageous when a ML localization algorithm is used *a priori*, since the beamforming output is a direct result of the ML source signal vector estimate $\widehat{\mathbf{S}}^{\mathrm{ML}}(\omega_k)$ given by

$$\mathbf{Y}(\omega_k) = \widehat{\mathbf{S}}^{\mathrm{ML}}(\omega_k) = \mathbf{D}^{\dagger}\left(k, \widehat{\mathbf{\Theta}}^{\mathrm{ML}}\right)\mathbf{X}(\omega_k) \tag{5}$$

where $\mathbf{Y}(\omega_k)$ is the beamformed spectrum vector for the M sources [14]. The ML beamformer in effect performs signal separation by utilizing the physical separation of the sources, and for each source signal, the SINR is maximized in the ML sense. When only a single source exists, $\mathbf{D}^{\dagger}(k, \widehat{\mathbf{\Theta}}^{\mathrm{ML}})$ degenerates to a vector and only the SNR is maximized.

III. Practical Coherent Array Processing Issues

Practical coherent array processing design must consider ill effects of the propagation medium and channel disturbances and the imperfections of the sensor array system. ML array processing under reverberation and various types of non-Gaussian channel noises have been considered in

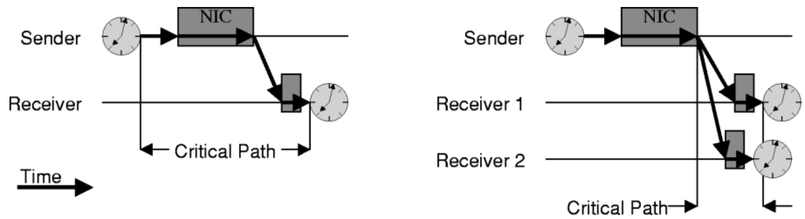

Fig. 1. A critical path analysis for traditional time synchronization protocols (*left*) and RBS (*right*). For traditional protocols working on a LAN, the largest contributions to nondeterministic latency are the send time (from the sender's clock read to delivery of the packet to its network interface card (NIC), including protocol processing) and access time (the delay in the NIC until the channel becomes free). The receive time tends to be much smaller than the send time because the clock can be read at interrupt time, before protocol processing. In the RBS, the critical path length is shortened to include only the time from the injection of the packet into the channel to the last clock read.

[21]–[23], under imperfect spatial coherence across the array [24], and uncalibrated/partially calibrated sensor array [25], [26]. Equalization of the mismatched sensor responses under known conditions [27] and blind conditions [28] using various blind equalization methods proposed for wireless communication systems [29] can also be used here.

Another important issue for coherent array processing is the need for fine-grain time synchronization among the sensors. Time synchronization comes easily for a sensor array connected by wires to a multichannel A/D converter. However, precise time synchronization becomes a critical performance limiting factor when low-cost sensor nodes digitize their signals locally and are used for coherent processing in a digital wireless network. Over the years, many protocols have been designed for maintaining synchronization of physical clocks over computer networks. Most share the same basic design: a server periodically sends a message containing its current clock value to a client. A simple one-way message suffices if the typical latency from server to client is small compared to the desired accuracy. A common extension is to use a client request followed by a server's response. By measuring the total round-trip time of the two packets, the client can estimate the one-way latency. This allows for more accurate synchronization by accounting for the time that elapses between the server's creation of a timestamp and the client's reception of it. The network time protocol (NTP) [31] is a ubiquitously adopted protocol for Internet time synchronization that exemplifies this design.

Synchronization algorithms that measure round-trip delay have one major weakness: their one-way latency estimate is confounded by differences in the forward and reverse path delays. Of course, this is very likely in the Internet, where time-varying cross traffic causes differences in queueing delay from message to message. However, such effects are also seen in LANs, where jitter on the order of tens to thousands of microseconds can be introduced by the medium-access control (MAC) layer. The value of nondeterministic delay varies depending on the specific type of network in use. For example, contention-based MACs (e.g., Ethernet) must wait for the channel to be clear before transmitting, and retransmit in the case of a collision. Wireless request to send/clear to send (RTS/CTS) schemes such as those in 802.11 networks require an exchange of control packets before data can be transmitted. Time-division multiple access channels require the sender to wait for its slot before transmitting. The jitter introduced is significant compared to our order-μs synchronization precision goal.

The RBS scheme [30] is based on the observation that jitter introduced within a LAN is dominated by these MAC delays, unlike the Internet, where propagation delay dominates. RBS, therefore, takes a different approach to reducing error: nodes periodically send a message to their neighbors using the network's physical-layer broadcast. Recipients use the message's arrival time as a point of reference for comparing their clocks. The message contains no explicit timestamp, nor is it important exactly when it is sent. RBS, therefore, does not synchronize a sender with a receiver, but rather synchronizes *a set of receivers with one another*. By using only receiver-to-receiver relations, the largest sources of nondeterministic latency are removed from the critical path, as seen in Fig. 1. While the delay incurred might vary unpredictably from message to message, the nature of a broadcast dictates that for a *particular* message, these quantities are *the same for all receivers*. In addition, because the residual error is often a well-behaved distribution (e.g., Gaussian), multiple reference broadcasts can be sent over time, allowing both improved precision of the phase offset estimate and correction for clock skew.

IV. Testbed Setup and Experimental Results

A. Wireless iPAQ Testbed

We selected the Compaq iPAQ 3760 Pocket PC as the testbed node for the following reasons. It has a built-in microphone and audio codec that supports sampling at 8 to 48 kHz in signed 16-b integer. Its 206-MHz StrongARM-1110 CPU, 32-MB ROM, and 64-MB RAM provide reasonable resources for signal processing. In addition, we insert an 11-Mb/s ORiNOCO PC card into each iPAQ for 802.11 wireless LAN connection. Thus, each node has integrated sensing, processing, and communication capabilities. We also chose the FAMILIAR distribution of the Linux operating system [32] for the testbed. The combination of COTS hardware and open-source operating system makes a powerful and convenient development platform.

In the testbed, fine-grained network time synchronization is realized by a daemon implementation of the RBS algo-

Table 1
Rms Error Result of the Source Localization Experiments Using AML and TDOA-CLS Methods

Result in figure no.	Configuration in figure no.	Type of source(s)	No. of frames evaluated	AML RMS Error	TDOA-CLS RMS Error
2	Not shown	vehicle	40	0.07m	0.05m
3	Not shown	music	40	0.07m	0.08m
5	4	vehicle	30	0.6m at S1, 0.3m at S4	0.7m at S1, 0.2m at S4
7	6	music	30	1.4m at S1, 0.4m at S5	1.6m at S1, 0.6m at S5
9	8	vehicle	20	0.3m	Not available
10	8	music and vehicle	20	source 1: 0.4m, source 2: 0.8m	Not available

rithm to reconcile the acoustic codecs' sample clocks with each other. The daemon simultaneously acts in both "sender" and "receiver" roles. Every 10 s (slightly randomized to avoid unintended synchronization), each daemon emits a reference broadcast pulse packet with a sequence number and sender ID. The daemon also watches for such packets to arrive; it timestamps them and periodically sends a report of these timestamps back to the pulse sender along with its receiver ID. The pulse sender collects all of the pulse reception reports and computes clock conversion parameters between each pair of nodes that heard its broadcasts. These parameters are then broadcast back to local neighbors. The RBS daemons that receive these parameters make them available to users. RBS never sets the nodes' clocks, but rather provides a user library that converts UNIX `timevals` from one node ID to another.

To test the precision of the time synchronization on our platform, we connected a general purpose input/output (GPIO) output from each of two iPAQs to an external logic analyzer. The analyzer was programmed to report the time difference between two pulses seen on each of its input channels. In each trial, we used RBS clock conversion parameters to command each iPAQ to raise their GPIO lines high at the same time. We ran a total of 325 trials, each separated by about 8 s, for a total test period of about 45 min. RBS achieved a mean 1.26 ± 1.11 μs synchronization error. We believe this is primarily limited by the iPAQ's clock resolution under Linux, which is 1 μs.

All nodes are organized into clusters. The cluster head commands other nodes to collect the same number of acoustic data samples starting from the same time. However, the low-end consumer-grade audio codecs on iPAQ 3760s have large nondeterministic latencies when they are asked to start recording. Simply starting recording at the same time on all sensor nodes does not guarantee getting audio data starting from the same time even if all sensor nodes' CPUs are perfectly synchronized. We can avoid this problem by using the "audio server" [33]. The audio server is a daemon that continuously runs the audio codec for sampling. In addition, it timestamps and buffers the most recent 10 s of audio data, and makes the data available to user applications through a library function. The cluster head picks a recent local timestamp, converts it to each sensor node's local timestamp, and then sends each sensor node a data request with the specified sample numbers and the specified starting time in terms of the sensor node's local time. The sensor node simply requests from the audio server the specified number of audio data samples starting from the specified local time, then sends them back to the cluster head. In this way, the cluster head collects from all sensor nodes the same number of audio data samples starting from the same time.

Data requests and replies between cluster head and sensor nodes are realized by a client-server model. A server continuously runs on each sensor node. When the cluster head requests data, it creates one client thread targeting each sensor node. Requests specify the starting time and duration of the requested data. When the server receives a data request, it requests data from the audio server according to the specification, and then sends them back to the cluster head. All data request threads run concurrently; thus, data request and reply between the cluster head and each sensor node proceeds concurrently and independently.

B. Experimental Results

Using the wireless iPAQ testbed described previously, we conducted several experiments to demonstrate its effectiveness in localization/beamforming applications. At this stage, the testbed is not completely automated and does not perform real-time signal processing for localization/beamforming due to the following challenges. First, the testbed requires accurate sensor location recordings to yield accurate results, and these measurements need to be inputted to the software prior operation. Second, efficient processing algorithm software needs to be installed in the iPAQ nodes to generate real-time results. In the following experiments, the time-synchronized acoustic data is collected by the testbed and processed offline using Matlab for the purpose of algorithm verification. The experiments are conducted outdoors to avoid severe reverberation encountered in a room environment.

We considered two scenarios: direct localization for sources in the near field and DOA estimation for sources in the far field. When several subarrays are available to obtain independent DOA estimation of the same source, bearing crossings from the subarrays is used to obtain the location estimate. In the near-field case, we also assume the received signal is highly coherent across the array. Two types of algorithms tailored for both the near- and far-field cases are considered, namely, the approximated ML (AML)

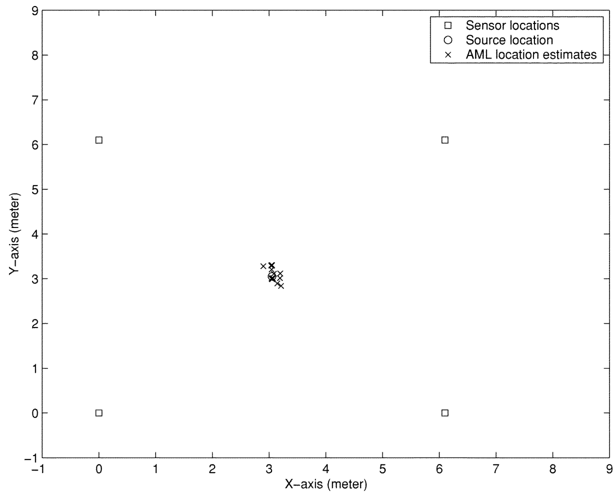

Fig. 2. AML source localization of a vehicle source.

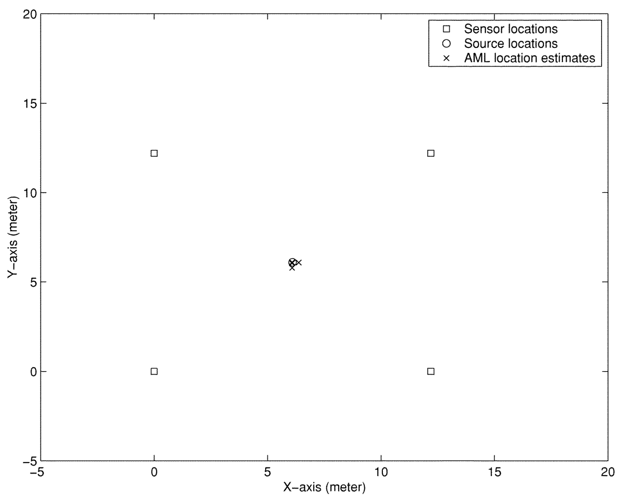

Fig. 3. AML source localization of a music source.

[14] and TDOA-CLS (constrained LS) [19]. The AML is in the form of (2) with finite frame length (limited due to possible movement of the source) and the TDOA-CLS uses the LS solution of $\mathbf{Ay} = \mathbf{b}$ with a constraint to improve the accuracy of estimation. In the case of multiple sources, only the AML method can perform estimation and the alternating projection procedure is applied. The results of the experiments are shown in Table 1 as well as the following figures.

In the first experimental setting, the source (a computer speaker) is placed in the middle of a wirelessly connected square array (each side of length L) of iPAQs. In this near-field case (relative to the array), the four nodes act as one array with intersensor spacing L of 20 ft (6.1 m). The sound of a moving light-wheeled vehicle is played through the speaker and collected by the microphone array embedded in the iPAQs. Fig. 2 shows the direct localization results of the speaker using the AML method. Then, a similar experiment is conducted using the same configuration except that L is set to be 40 ft (12.2 m). This time the loudspeaker plays prerecorded organ music, whose spectrum has a 2-kHz bandwidth with a central frequency at 1.75 kHz. The AML source localization result is shown at

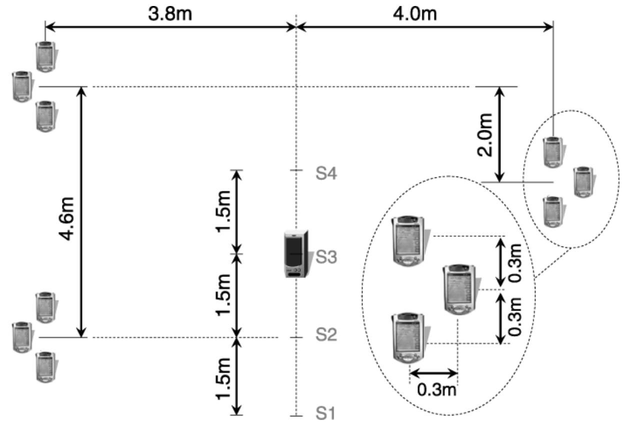

Fig. 4. Experimental setting 2: triangular subarray configuration.

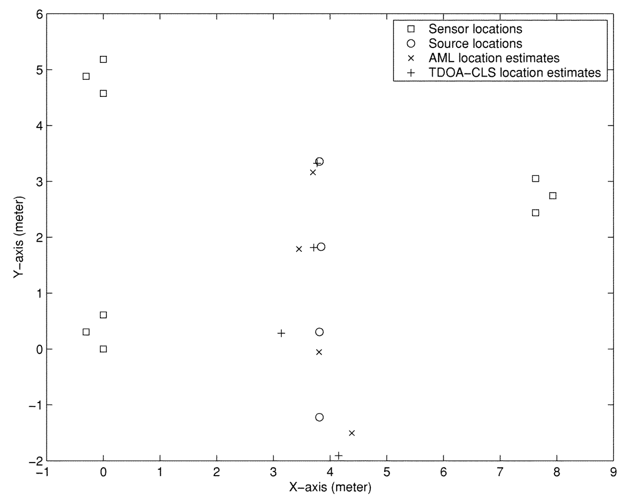

Fig. 5. Cross-bearing results of a vehicle source at different locations.

Fig. 3. From the rms errors of the previous two experiments, both algorithms show comparably promising results.

The second experimental setting is depicted in Fig. 4, where three triangular subarrays each with three iPAQs form the sensor network. In this far-field case (relative to each subarray), the DOA of the source is independently estimated in each subarray, and the bearing crossing is used to obtain the location estimate. The speaker is placed at four distinct source locations $\mathrm{S1}, \ldots, \mathrm{S4}$, simulating source movement, and the same vehicle sound is played each time. Fig. 5 depicts one snapshot (for clear illustration) of the AML and TDOA-CLS results at the four locations. We note that better results are clearly obtained when the source is inside the convex hull of the overall array. Moreover, the rms errors of Figs. 2 and 3 are much less than the rms error result here. The rms errors of direct source localization are much less because of the favorable geometry, shorter ranges, and fully coherent process in contrast to coherent DOA estimation and noncoherent cross-bearing process.

A few more far-field cases are considered. The third experimental setting is depicted in Fig. 6, where three linear subarrays each with three iPAQs form one sensor network. The speaker, this time playing the organ music sound, is placed at six distinct locations. Fig. 7 shows the one-snapshot results of

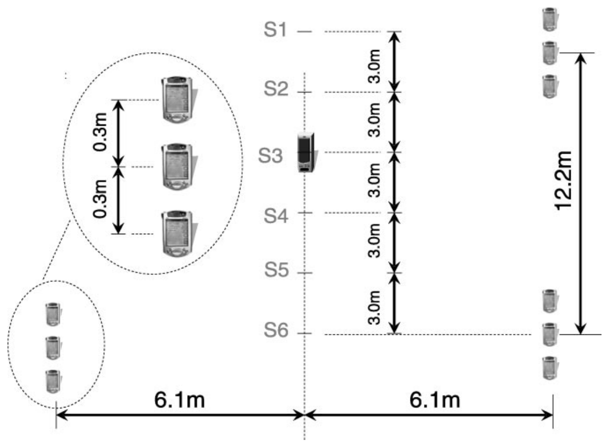

Fig. 6. Experimental setting 3: linear subarray configuration.

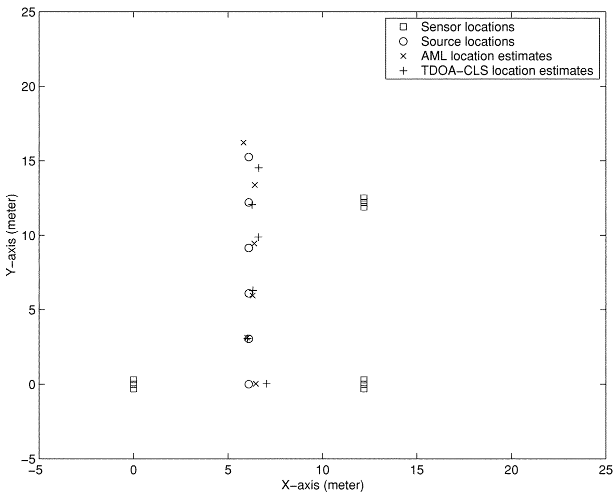

Fig. 7. Cross-bearing localization of a music source at different locations.

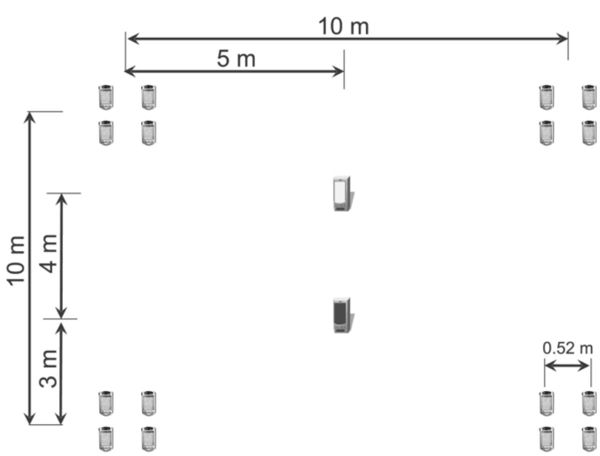

Fig. 8. Experimental setting 4: square subarray configuration.

the two algorithms at the six locations. The rms error calculation shows performance similar to the second experiment, which demonstrates that both AML and TDOA-CLS algorithm can locate different sources. The fourth experimental setting is depicted in Fig. 8, where four square subarrays each with four iPAQs form a single network. Two speakers, one

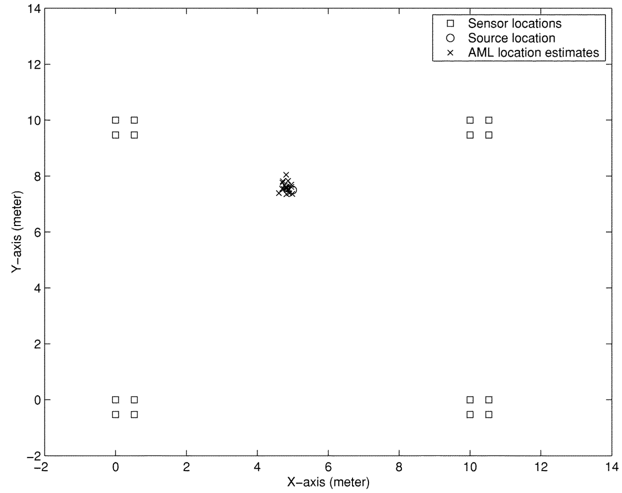

Fig. 9. AML cross-bearing localization of a vehicle source.

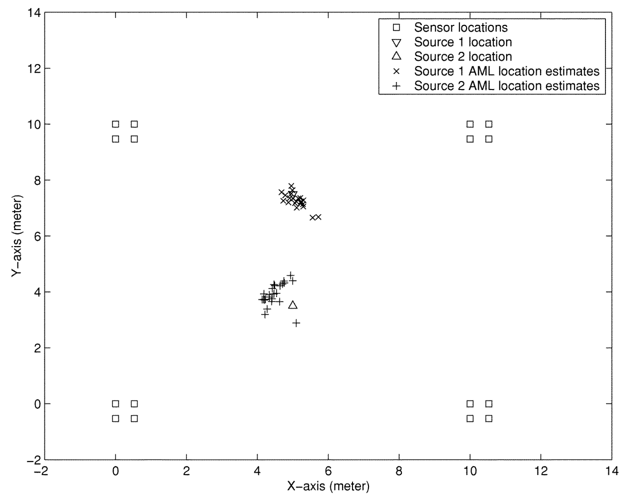

Fig. 10. AML cross-bearing localization of two sources using alternating projection.

playing the vehicle sound and the other one playing the music sound simultaneously, are placed inside the convex hull of the overall array—first, when only speaker one is playing, as shown in Fig. 9; then, when both sources are playing simultaneously, as shown in Fig. 10. Comparing Figs. 9 and 10, we see good multisource localization, but not as good as the performance with only a single source.

Note when the number of subarray element increases, the localization accuracy of the results reported above improves, which agrees with the Cramer–Rao bound analysis reported in [34].

V. CONCLUSION

In this paper, a wireless sensor network testbed is successfully implemented using COTS products. Promising localization results are shown in the offline processing of the collected data. The experiments show the effectiveness and proper joint operation of the localization/beamforming and time synchronization algorithms to yield good results. Future work includes real-time processing on the iPAQ nodes.

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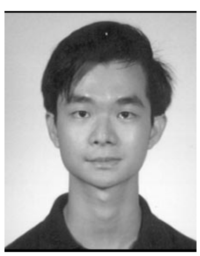

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