BARCLAY SHAW

Source Localization and Beamforming

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Distributed sensor networks have been proposed for a wide range of applications. The main purpose of a sensor network is to monitor an area, including detecting, identifying, localizing, and tracking one or more objects of interest. These networks may be used by the military in surveillance, reconnaissance, and combat scenarios or around the perimeter of a manufacturing plant for intrusion detection. In other applications such as hearing aids and multimedia, microphone networks are capable of enhancing audio signals under noisy conditions for improved intelligibility, recognition, and cuing for camera aiming. Recent developments in integrated circuit technology have allowed the construction of low-cost miniature sensor nodes with signal processing and wireless communication capabilities. These technological advances not only open up many possibilities but also introduce challenging issues for the collaborative processing of wideband acoustic and seismic signals for source localization and beamforming in an energy-constrained distributed sensor network. The purpose of this article is to provide an overview of these issues. Some prior systems include: WINS at RSC/UCLA [1], AWAIRS at UCLA/RSC [2]-[4], Smart Dust at UC Berkeley [5], USC-ISI network [6], MIT network [7], SensIT systems/networks [8], and ARL Federated Laboratory Advanced Sensor Program systems/networks [9].

In the first section, we consider the physical features of the sources and their propagation properties and discuss the system features of the sensor network. The next section introduces some early works in source localization, DOA estimation, and beamforming. Other topics discussed include the closed-form least-squares source localization problem, iterative ML source localization, and DOA estimation.

Microsensor Networks

Physical Features

We first characterize the basic physical characteristics and features of the sources and their propagation properties as shown in Table 1. These features are outside the control of

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the designer of the architecture and algorithm for the sensor network. In this article, we will deal with these features in terms of acoustic or seismic (i.e., vibrational) sources. While these two sources have some common features, they also have some distinct differences. Radio frequency (RF), visual, infrared, and magnetic sources have other distinct features but will not be considered here. The movement of personnel, car, truck, wheeled/tracked vehicle, as well as vibrating machinery can all generate acoustic or seismic waveforms. These waveforms are referred to as wideband signals since the ratio of highest to lowest frequency component is quite large. For audio waveforms (i.e., 30 Hz-15 kHz), the ratio is about 500, and these waveforms are wideband. Dominant acoustical waveforms generated from wheeled and tracked vehicles may range from 20 Hz-2 kHz, resulting in a ratio of about 100. Similarly, dominant seismic waveforms generated from wheeled vehicles may range from 5 Hz-500 Hz, also resulting in a ratio of about 100. Thus, the acoustic and seismic signals of interest are generally wideband. On the other hand, most propagated RF waveforms are narrowband, since the ratio of the highest frequency f_H to the lowest frequency f_L is usually very close to unity (e.g., for the 802.11b ISM wireless LAN system, the ratio is 2.4835 GHz/2.GHz = 1.03). Narrowband signals have a well-defined nominal wavelength, and time delay can be compensated by a simple phase shift. For wideband signals there is no characteristic wavelength and time delays must be obtained by interpolation of the waveform.

When an acoustic or seismic source is located close to the sensors, the wavefront of the received signal is curved, and the curvature depends on the distance, then the source is in the near-field. As the distance becomes large, the wavefront becomes planar and parallel, then the source is in the far-field. For a far-field source, only the direction-of-arrival (DOA) in the coordinate system of the sensors is observable. A simple example is when the sensors are placed on a line with uniform intersensor spacing, then all adjacent sensors have the same time delay, and the DOA of the far-field source can be estimated readily from the time delay. For a near-field source, the collection of all relative time-delays of the source can be used to determine the source location.

For an acoustic source, the propagation speed in air is a known constant of approximately 345 m/s. Measurable atmospheric parameters such as the temperature and the component of the wind velocity along the direction of propagation from the source to the sensors have only second-order effects, but can be used to determine a more accurate propagation speed. It is also known that turbulent atmospheric conditions can cause loss of coherency of acoustical wavefronts [10] and degrade coherent processing of these wavefronts beyond distances of few tens of feet [11]. On the other hand, for a seismic source, the propagation speed is unknown and depends strongly on the propagation medium. The propagation speed of the Rayleigh surface wave, over a medium (e.g., from dry sand to hard rocks), can be from 0.7 to 15 times the speed of sound in air [12]. In most practical situations, the seismic propagation medium is highly variable. Thus, there appears to be no simple model for the estimation of seismic propagation speed over an outdoor field based on physically measurable quantities such as characterizing the medium type (e.g., sandstone, limestone, etc.) or mechanical properties of the medium (e.g., Young's modulus, bulk modulus, density, etc.). Least squares (LS) estimation techniques based on collected sensor data can be used to estimate the unknown seismic propagation speed.

Another related issue is that of free space versus reverberant propagation. Most indoor rooms are fairly reverberant, and the reflection of sound wave energy upon striking a surface may vary from 10-90% depending on the material. In an ideal empty outdoor field, there is no sound reverberation. Then the generated sound energy decreases ideally as the inverse of the distance squared. For outdoor open fields, reflection of sound from nearby walls, hills, and large objects can result in some reverberations. On the other hand, for seismic propagation, the inhomogeneity of the medium with different medium densities results in considerable reverberation and a highly frequency-dependent source to sensor(s) transfer function(s). These reverberation phenomena make the estimation of DOA and location of a single physical source appear to be like multiple sources. This makes these localization problems much more difficult since a false DOA estimate can be in the direction of the dominant reflected path instead of the direct path. To effectively remove the reverberation effect, the acoustic channel impulse response needs to be estimated and inverted [13]. Studies have shown a frequency-dependent loss of seismic energy and the received seismic energy which may decrease much more rapidly than distance squared [12], [14]. This means a seismic sensor is generally only sensitive to a nearby source. This leads to the need for a high density of seismic sensors to characterize the movement of a seismic source. Nevertheless, the rapid attenuation with range may provide a simplification in that among a large number of seismic sensors, only a very small set of sensors near the seismic source is acti-

Table 1. Physical Features.
1) Acoustic versus seismic source
2) Narrowband versus wideband signal
3) Far-field versus near-field source
4) Known versus unknown propagation speed
5) Free-space versus reverberant space propagation
6) Single versus multiple source

vated. This small effective seismic propagated region may provide a simple way to tackle the multiple source detection, identification, and tracking problem based upon simple spatial separation of these propagated regions [14].

Basic System Features

Given the physical characteristics and features of the sources and their propagation properties considered above, we want to discuss the various system concepts and features under the control of the system designer. The list in Table 2 includes power source, sensing, data transmission, processing, and decision features used to perform source localization and beamforming. In many fixed-site sensor network scenarios, power lines and data cable interconnections are available at all the nodes. Thus, there is essentially unlimited energy for sensing, processing, and decision, and reliable data transmission capability is also available. In this article, however, the sensor network is assumed to be ad hoc and has to work in an arbitrary physical environment. Thus, all operations are assumed to be powered by batteries of limited energy, and all data communications among the nodes are provided by low-power and low-data rate wireless RF links. For low-cost and low-energy consumption, we assume passive sensors. These sensors only operate on the received acoustic and seismic waveforms from the noncooperative source. This is in contrast to a complex active radar or sonar system in which a very sophisticated receiver is used to find some information of interest from the reflected target return.

An important system issue is whether the sensors in the network perform collaborative sensing of the observed waveforms. By this we mean information collected by one sensor is used together with information collected by other sensors. Clearly, this approach is more effective than each sensor working independent of others. In this article, we will assume and discuss various challenges and costs of collaborative sensing and processing. We note there are many degrees of collaboration. Furthermore, we can also consider whether the sensors perform synchronous or nonsynchronous sensing. By synchronous sensing, we mean the sensor data are collected with time tags and thus some common features at a given time instant can be exploited. Synchronous sensing implies timing errors must be controlled. Coherent processing must be performed with precise synchronization. For instance, a group of sensors may perform spatial (coherent) processing to provide the source location or DOA estimate. The synchronous data must be shared within the group, but may not need to be transmitted synchronously to other parts of the network. On the contrary, noncoherent processing techniques may not need to share data with other sensors; thus, the synchronization requirement is relaxed. A fully synchronous sensing system imposes considerable precision at the network control level as well as great demand on the network data transmission requirement. The use of synchronous subarray sensing without requiring full synchronous sensing of all the sensors is a practical way to attack this issue.

Table 2. System Features.
1) Power-line versus battery power supply
2) Wired versus wireless RF links
3) Passive versus active sensor
4) Collaborative versus noncollaborative sensing
5) Coherent versus noncoherent processing
6) Synchronous versus nonsynch. sensing
7) Known versus unknown sensor response
8) Known versus unknown sensor location
9) Wideband versus narrowband processing
10) Distributed versus central processing

Another issue is whether the sensor spatial gain response is known or needs to be calibrated. Still another sensor issue is whether the sensor locations are known. There are situations in which some of the sensor locations are known (or estimated), other unknown sensor locations can be estimated from all the sensor data [15]. All of these issues have great practical sensor network implications with respect to collaboration.

In general, not to suffer significant degradation, complicated wideband array processing, beamformation, and equalization algorithms must be used to process the wideband acoustic and seismic signals of interest (see Fig. 6). This means the simpler one-tap equalizer and beamformer commonly used for narrowband RF communication/avionic system processing is not generally applicable here. Another important system issue is whether the processing can be distributed to each node (or at least at some nearby nodes) or performed at a central processor node. In the model of [16], a radio transmitting 1 kb of data over a distance of 100 m operating at 1 GHz using a binary phase-shift keying modulation with an error probability of 10^{-6} and fourth-power distance loss with Rayleigh fading, requires approximately 3 joules of energy. The same energy can then perform 300 millions instructions for a 100 MIPS/watt general processor. This results in a ratio of 30,000 processing instructions per transmission bit with equal energy consumption. Other practical sensor networks [17] have yielded ratios in the 1,000-2,000 values. These results show if the application and the sensor architecture permit, it is much more energy efficient to perform distributed local processing then to do central processing that requires extensive communications. Of course, not all algorithms can use distributed processing as shown in Table 2.

Self-Organization and Ad Hoc Sensor Network

Traditional computer/communication LAN has a fixed network topology and number of nodes. These networks are usually designed to maximize the throughput rate of the data. On the other hand, the purpose of most sensor networks as already mentioned earlier is to detect, identify, localize, beamform, and track one or more stationary or moving sources in unknown environments. Thus, traditional computer/communication network design rules are generally not applicable here. A node is defined to consist of one or more sensor(s) of the same type or different types (e.g., acoustic or seismic), an associated processor, and a transceiver. These nodes can be distributed in various manners. They may be placed around the perimeter of a plant or near the intersection of several roads (as shown in Fig. 1) in some controlled manner. They may be rapidly deployed by the users near the paths of their travel, or maybe even scattered randomly out of a truck or airplane.

Clearly to use such a sensor system, we need to have these nodes self-organize into a usable ad hoc network in minimum time and minimum energy from some initially given near-arbitrary placements [18]-[19]. After proper organization, the network should be able to pass data packets from various nodes of the network to the next-level user. Since the transmission and reception distances of these transceivers are low, energy efficient multihop routing needs to be used [20]. As part of the multihop routing procedure, the concept of adjacent nodes must be determined [18]. Furthermore, since the energy used by the receiver is almost as much as that used by the transmitter, these transceivers should be off for as long as possible. The receiver initially listens only in some low time duty factor manner [14]. However, when a node enters into more demanding roles, the transceiver may transmit, receive, and relay information packets in multihop stages needing higher time duty factors.

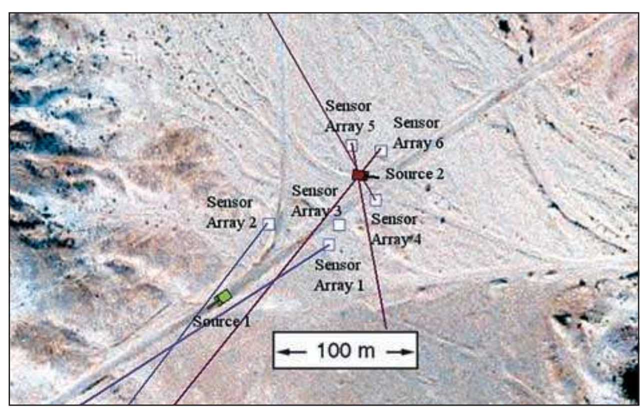
Layered Architecture for Energy Constraint Communication and Processing

In many sensor networks (e.g., AWAIRS [2]), the node operates in different modes to perform different tasks, and these tasks require different power consumptions. Distinct operations of the nodes that depend on their roles result in a layered architecture for the sensor network [14]. Normally, the relatively low-power sensors and the associated electronics are always on and have their thresholds set above some nominal ambient background noise level. When a source of sufficient strength enters the sensor network, one or more of these nodes may be triggered. If a sensor of a different type in the node was also activated, then their combined result increases the true detection and decreases a false detection. The processor of

In many sensor networks, the node operates in different modes to perform different tasks, and these tasks require different power consumptions.

these nodes may also perform the source identification task. Furthermore, if two or more sensors of the same type are in the same node, then we may be able to perform DOA estimation of the source from that node. We should note that all these operations mentioned above are done at the individual node level. There is no need to transmit the raw data collected by the sensor(s) in a node to another node or to the next-level user. Of course, the detection of a source (possibly with some information on the confidence of the detection), the possible identification of the source, the DOA estimation of the source, and the time of occurrence of these events need to be transmitted from each active node to the next-level user. In this case, the amount of information transmitted over the sensor network is relatively low. In Fig. 2, these operations are shown at the lower levels of the layered architecture labeled intranode collaboration sensing and processing.

Various higher levels of collaborations with other nodes are possible. An activated node may inform adjacent nodes of a recent detection to possibly lower their thresholds to investigate the disturbing event. If the original event is not a false alarm, then other nearby sensors should have also detected that source. The next-level user can then have a quite crude estimation of the location of the source assuming some information about the locations (even if approximate) of the sensors is known. Relevant features extracted from sensor(s) in each node may be sent to the next-level-user for fusion purpose to enhance detection. One simple form of fusion is to compare the amplitude values of different sensors (of the same type). By using the closest-point-of-approach (CPA), which is one type of noncoherent processing, one may provide an estimation of the source location [21]. An-



▲ 1. A generic scenario of sources and sensors in a sensor network.

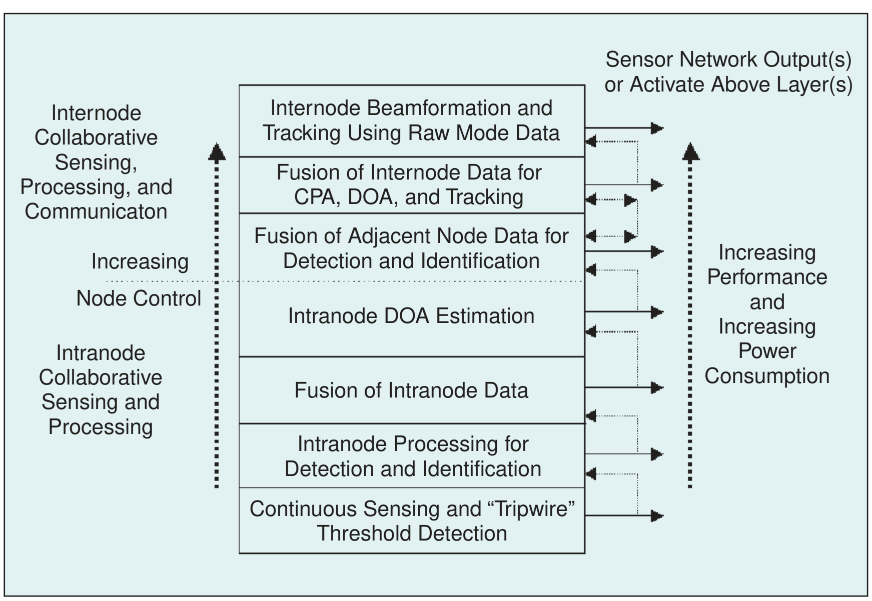
The purpose of a sensor network is to monitor an area, including detecting, identifying, localizing, and tracking one or more objects of interest.

other form of fusion is to use the DOA estimate from each subarray of sensors of similar type. Then the triangulation process of determining the intersection of these cross bearing DOA angles can be used to estimate the source location (see the generic scenario of Fig. 1). We note in both the CPA and the DOA triangulation methods, processing is performed locally and only small amount of information from each node needs to be transmitted to the next-level user for processing. On the other hand, for full coherent processing and beamforming applications, data from selected dominant frequency bands of interest or the whole raw data from the sensors in various relevant nodes need to be sent to other nodes or to the next-level-user. All of these collaborations among the sensors require varying amount of costly data transmission in the sensor network. These operations are shown in the upper levels of Fig. 2 labeled internode collaborative sensing, processing, and communication.

Source Localization, DOA Estimation, and Beamforming

The earliest development of space-time processing was spatial filtering or beamforming dating back to World War II. Advances in radar, sonar, and wireless communications followed using arrays of sensors. In radar and wireless communications, the information signal is modulated on the RF waveform at the transmitter and then demodulated to a complex envelope at the receiving sensor. This is the narrowband signal model where the DOA information is contained in the phase differences among the sensors. The conventional beamformer is merely a spatial extension of the matched filter [22]. In classical time-domain filtering, the time-domain signal is linearly combined with filtering weight to achieve high/low/bandpass filtering. A beamformer combines the spatially distributed sensor collected array data linearly with the beamforming weight to achieve spatial filtering. Beamforming enhances the signal from the desired spatial direction and reduces the signal(s) from other direction(s) in addition to possible time/frequency filtering. The beamformer output is a coherently enhanced estimate of the transmitted signal, with one set of weights for each source. In many cases, the desired signal direction may need to be estimated.

In [22], Krim and Viberg have provided an excellent review and comparison of many classical and advanced parametric narrowband techniques up to 1996. Early work in DOA estimation includes the early version of maximum-likelihood (ML) solution, but it did not become popular due to its high computational cost. Concurrently, a variety of suboptimal techniques with reduced computations have dominated the field. The more well-known techniques include the minimum variance method of Capon [23], the multiple signal classification (MUSIC) method of Schmidt [24], and the minimum norm of Reddi [25]. The MUSIC algorithm is perhaps one of the most popular suboptimal techniques. It provides super resolution DOA estimation in a spatial pseudospectral plot by utilizing the orthogonality between the signal and noise subspaces. However, a well-known problem with some of these suboptimal techniques occurs when two or more sources are highly correlated. This may be caused by multipath or intentional jamming, and most of the suboptimal techniques have difficulties without reverting to advanced processing or constraints. Many variants of the MUSIC algorithm have been proposed to combat signal correlation and to improve performance.



▲ *2. Layered architecture showing increasing communication, computation, and energy cost.*

Closed-Form Least Squares Source Localization

For various acoustic/seismic sensor array problems, a wideband signal model may be more appropriate. Since acoustic and seismic signals are unmodulated and may contain a wider bandwidth, the array data is real valued and hence the beamforming weights are also real. In many cases we are interested in locating the source in the near-field. As the source approaches the array, both the angle and range become parameters of interest. Note that unlike the radar and communications problems where the signal may be a random process with known statistics or drawn from a known finite alphabet, the acoustic/seismic source signals are most likely to be deterministic but unknown (e.g., waveform generated by a passing vehicle). An additional factor that arises in the near-field scenario is that each sensor may have a different gain as opposed to equal gain in the far-field case. The sensors are assumed to be omnidirectional, and the gain variation is due to differences in the propagation paths in the near-field geometry. For a randomly distributed array of R sensors, the data collected by the pth sensor at time n can be given by

$$x_p(n)=\sum_{m=1}^{M} a_p^{(m)} s_0^{(m)}\left(n-t_p^{(m)}\right)+w_p(n), \tag{1}$$

for $n=0,\ldots,L-1$, $p=1,\ldots,R$, and $m=1,\ldots,M$, where M is the number of sources ($M<R$), $a_p^{(m)}$ is the signal gain level of the mth source at the pth sensor (assumed to be constant within the block of data), $s_0^{(m)}$ is the source signal, $t_p^{(m)}$ is the fractional time-delay in samples (which is allowed to be any real-valued number), and w_p is zero-mean white Gaussian noise with variance σ^2. The time-delay is defined by $t_p^{(m)}=\left\|\mathbf{r}_{s_m}-\mathbf{r}_p\right\|/v$, where $\mathbf{r}_{s_m}$ is the mth source location, $\mathbf{r}_p$ is the pth sensor location, and v is the speed of propagation in length unit per sample. Define the relative time-delay between the pth and the qth sensors by

$$t_{pq}^{(m)}=t_p^{(m)}-t_q^{(m)}=\left(\left\|\mathbf{r}_{s_m}-\mathbf{r}_p\right\|-\left\|\mathbf{r}_{s_m}-\mathbf{r}_q\right\|\right)/v.$$

Note, in the wideband problem, time delays are exploited as opposed to phase differences in the narrowband case.

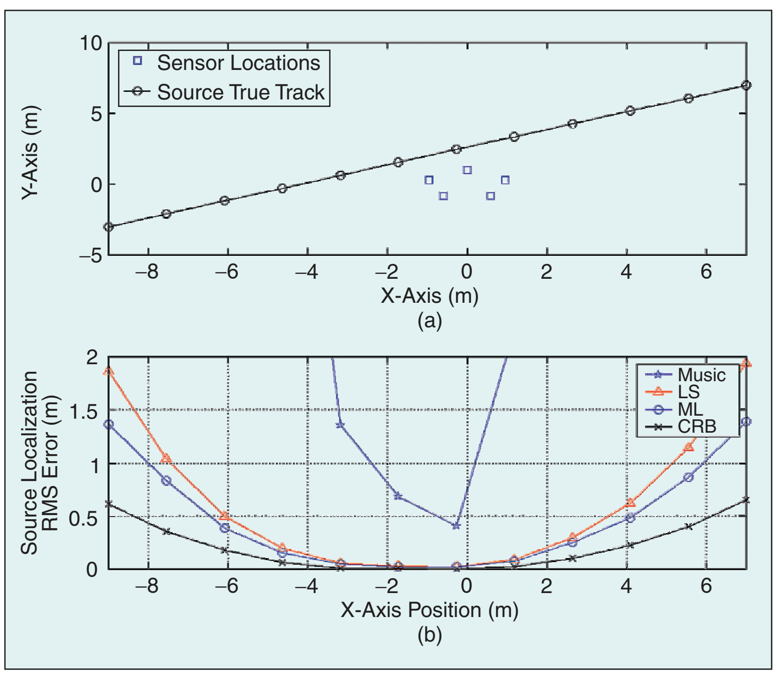
One class of near-field source localization algorithm is based first on using time-delay techniques. These algorithms provide closed-form solutions to estimate the location of a single source based on spherical intersection [26], hyperbolic intersection [27], or linear intersection [28], from the measured relative time-delays. Nevertheless, these algorithms require known speed of propagation. In [4] and [29], a closed-form LS and constrained least-squares (CLS) solutions are derived for unknown speed of propagation. The CLS solution improves the location estimate from that of the LS solution by forcing an equality constraint on two components of the solution. The closed-form source location estimate is given by the solution of a set of linear equations [29], expressed as

$$\mathbf{A}\mathbf{y}=\mathbf{b}, \tag{2}$$

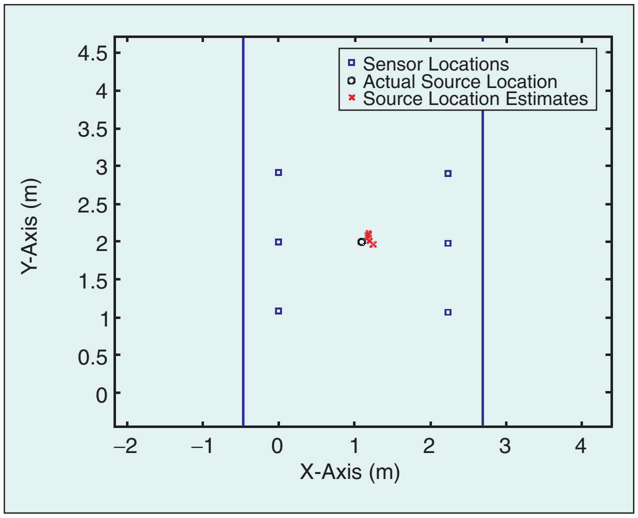
where the system matrix $\mathbf{A}$ contains the sensor locations and relative time delays, the unknown vector $\mathbf{y}$ contains the source location, source range, and the speed of propagation, and the vector $\mathbf{b}$ is a function of sensor locations. An overdetermined LS solution can be given by evaluating the pseudoinverse $\mathbf{A}^{\dagger}$ of the matrix $\mathbf{A}$ in the case of six or more sensors (for three-dimensional (3-D) localization) resulting in $\mathbf{y}=\mathbf{A}^{\dagger}\mathbf{b}$. The earliest time-delay estimation is based on maximizing the cross-correlation between sensor data [30]. Other phase transform (PHAT) methods [31] or second-order subspace methods [4] have been proposed to improve time-delay estimation under Gaussian noise assumption. Other robust time-delay estimation methods have been proposed for impulsive noise with "heavy-tailed" distribution [32], and higher-order statistics have even been exploited to estimate time-delays of multiple sources [33].

Iterative Maximum-Likelihood Source Localization and DOA Estimation

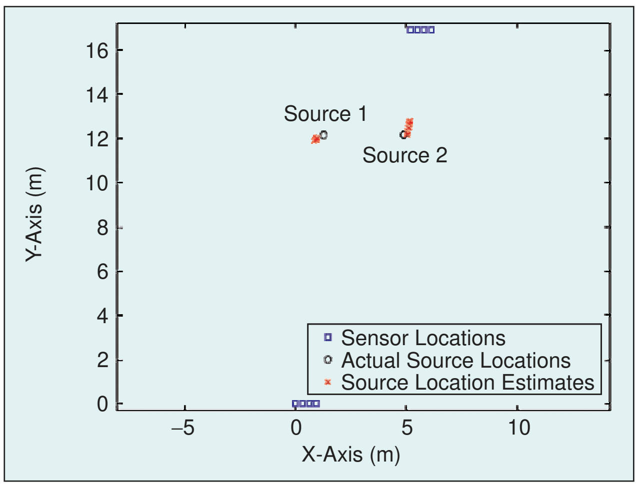
Another class of source localization algorithm is based on parameter estimation, where only iterative solutions are available. Despite the possible increase in computational complexity, this class of algorithms generally offers greater estimation accuracy. The fundamental difference between the parametric and closed-form solutions depends on the use of the optimization criterion. The closed-form solution is indeed optimized in two independent steps, namely, estimating relative time delays between sensor data and then source location based on the time-delay estimates. On the other hand, the parametric solution, which is based on the maximum-likelihood criterion, is optimized in a single step directly from the data without needing time-delay estimation. The parametric ML method has been shown to outperform the closed-



▲ *3. (a) A moving source scenario with five sensors; (b) source localization RMS error comparisons.*



▲ *4. Localization of an indoor near-field source using the LS method.*



▲ *5. Two-source localization via bearing crossing of the DOAs obtained by the ML alternating projection method.*

form methods [15] for the single source case. In the case of multiple sources, using even more advanced time-delay estimation techniques, the closed-form methods do not seem to guarantee solutions in all cases. Thus, the closed-form methods in general cannot estimate multiple source locations, while the parametric method can do so by expanding the parameter space.

To obtain the parametric solution, it is best to transform the wideband data to the frequency-domain, where a narrowband signal model can be given for each frequency bin. A block of L samples is collected from each sensor and transformed to the frequency-domain by a discrete Fourier transform of length N. In the frequency domain, the array signal spectrum vector is given by $\mathbf{X}(k)$, which contains the phase-shifted (a function of source location or DOA) version of the source signal spectrum plus the noise spectrum vector, for $k=0,\ldots,N-1$. The noise spectrum vector is zero-mean complex white Gaussian distributed with variance $L\sigma^2$. By combining the data spectrum vectors in the positive frequency bins, the ML solution can be given by

$$\arg\max_{\Theta} \sum_{k=1}^{N/2} \left\| P(k,\Theta) X(k) \right\|^2, \tag{3}$$

where Θ is the unknown parameter vector which may either be the source locations or the DOAs, and $P(k,\Theta)$ is an orthogonal projection matrix [15]. An efficient alternating projection (AP) procedure was proposed in [15] for the ML method to avoid a multidimensional search by sequentially estimating the location of one source while fixing the estimates of other source locations from the previous iteration. Once the source locations are estimated, the ML estimate of the source signals (ML beamformer output) can be obtained. It is interesting to note that in the near-field case, the ML beamformer output is the result of forming a focused spot (or area) on the source location rather than a beam since range is also considered. Another possible parametric solution is the wideband extension of the MUSIC algorithm; however, it has been shown to be highly suboptimal in the near-field case [15].

Cramér-Rao Bound Analysis

Besides the development of the estimation algorithms, it is useful to consider their theoretical performance limits. The Cramér-Rao bound (CRB) is a well-known statistical method to obtain the theoretical lower bound of the estimation variance for the performance of any unbiased estimator [34]. The CRBs for DOA and source localization are derived based on the time-delay model in [35], and the CRBs based on the data model of (1) are given in [15]. More physical properties of the problem can be found from the CRBs based on the data model. In particular, the source localization variance, denoted as the variance matrix Σ, is lower bounded by the CRB, i.e., $\Sigma \geq \mathbf{G}/S$, which can be broken down into two separate parts, a scalar factor S that depends only on the signal and a matrix $\mathbf{G}$ that depends only on the array geometry. This suggests separate performance dependence of the signal and the geometry. Thus, for any given signal, the CRB can provide the theoretical performance of a particular geometry and helps the design of an array configuration for a particular scenario of interest. The signal dependence part shows that theoretically the source location RMS error is linearly proportional to the noise level and speed of propagation and inversely proportional to the source spectrum and frequency. Thus, better source location estimates can be obtained for high frequency signals than low frequency signals. In further sensitivity analysis, large range estimation error is found when the source signal is unknown, but such unknown parameter does not affect the angle estimation.

Simulation and Experimental Results

Consider the simulation of a moving source on a straight line near a circular array of five sensors as shown in Fig. 3(a). At each position, the array data is simulated using an acoustic waveform of a measured vehicle signature. The speed of propagation is assumed to be 345 m/s. In Fig. 3(b), the source localization RMS errors are plotted using the wideband MUSIC, LS, and ML algorithms and the CRB. Both the LS and ML algorithms are shown to approach the CRB asymptotically, but the ML algorithm uniformly outperforms the LS algorithm. However, the wideband MUSIC yields much worse estimates than those of the LS and ML methods, especially when the source is far from the array.

To demonstrate the usefulness of the localization algorithms, an experiment was conducted inside a semi-anechoic chamber where six microphones simultaneously collect the sound (prerecorded moving light wheeled vehicle) driven by an omni-directional loud speaker placed in the middle of the room. As depicted in Fig. 4, the location of the sound source can be estimated with high accuracy (RMS error of 127 cm) using the LS algorithm under 12 dB SNR. For the same data set, the ML algorithm can even improve the accuracy to an RMS error of 73 cm. Then, another experiment was conducted outdoor with two linear arrays collecting the sound (two distinct prerecorded moving light wheeled vehicles) simultaneously coming from two different omni-directional loud speakers placed between the two arrays. The DOAs of the two sources are separately estimated for the two arrays using the ML alternating projection algorithm. The source locations are then estimated via the triangulation of bearing crossings of the DOAs. In Fig. 5, accurate location estimates (RMS error of 36 cm for source 1 and RMS error of 45 cm for source 2) are shown for the dataset with 11 dB SNR. In this case, the closed-form methods have difficulties separating the time-delays of the two sources.

Blind Beamforming

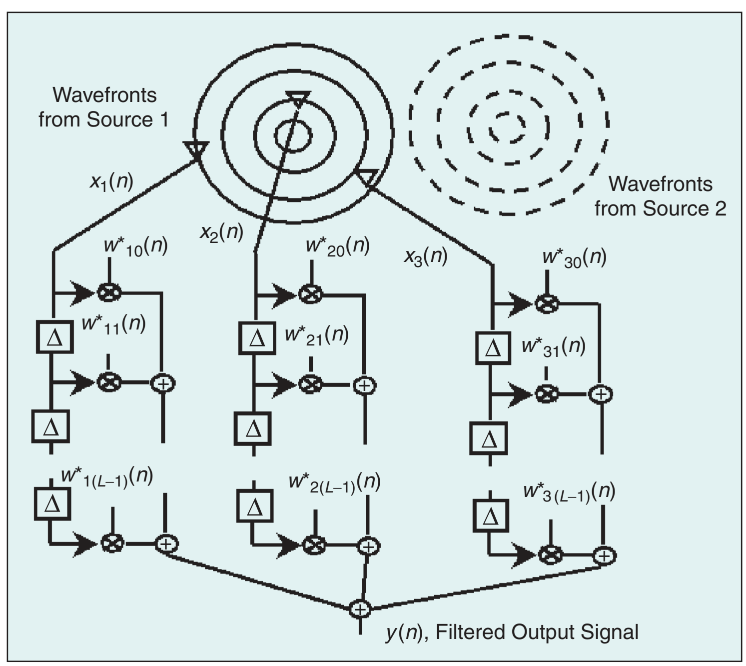
Despite the existence of many calibrating techniques, another approach in array signal processing is blind beamforming. In general, blind beamforming is an operation similar to conventional beamforming except without the knowledge of sensor responses and locations. In other words, blind beamforming enhances the signal by processing only the array data without much information about the array. A cumulant-based blind beamforming algorithm was proposed in [36] for the narrowband problem. The cumulant, or the higher order statistics (HOS), of the data is utilized to estimate the steering vector of the source up to a scale factor. This can be viewed as a form of online calibration using HOS, which often requires longer data lengths. In some practical scenarios, the data length needs to be quite short for a moving source.

Another blind beamforming that uses the second-order statistic (SOS) was proposed in [4] for wideband signals. A tap delay line of weights is applied to each sensor to perform space-time processing as depicted in Fig. 6. The blind maximum power (MP) beamformer in [4] 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. Theoretical justification of this approach uses a generalization of Szegö theory of the asymptotic distribution of eigenvalue of the Toeplitz form. The relative phase information among the weights yields the relative propagation time delays from the dominant source to the array sensors. We should also mention considerable blind beamforming, source localization, and tracking results from measured seismic sources requiring internode collaboration have also been reported [37].

In many sensor networks, the node operates in different modes to perform different tasks and these tasks require different power consumptions.

Conclusions

Research in distributed sensor network requires integrating multidisciplinary concepts and technologies from many areas. In signal processing, various sensor array processing algorithms and concepts have been adopted, but must be further tailored to match the communication and computational constraints. With advances in inte-



▲ *6. Block diagram of blind beamforming with two sources and three sensors.*

grated cuircuit technology, the processing power of the node constantly improves, thus allowing the use of more computationally demanding optimal signal processing algorithms. With advances in wireless radio hardware and software network protocol and control, reliably movement of sensor data for demanding processing algorithms becomes feasible. However, concerns of instantaneous power and total energy for computations and communications of battery-driven sensor network are always present. These factors influence greatly the intra- and internode collaboration and the relevant signal and array processing algorithms and architectures. Active research problems remain for the design of sensor array algorithms that are robust and adaptive to environmental changes and under demanding weather, wind, reverberation, impulsive noise, and strong interference conditions. While analytical algorithmic development and verification by simulations are important, reliable measured sensor array data taken over realistic field conditions under appropriate applications are crucially needed to truly verify and test these concepts and algorithms. It is only through alternating series of designs, tests, and verifications can the full potentials of the sensor network arrays be realized.

Acknowledgments

This work is partially supported by DARPA-ITO SensIT program under contract N66001-00-1-8937 and AROD-PSU contract S01-26.

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