velocity-field information removes all ambiguities such as grating lobes. This allows the use of simple structures for which fast direction estimation algorithms exist, e.g., a uniform linear array, to determine both the azimuth and elevation of a source. It also means that spatially undersampled arrays of vector sensors can be used to increase aperture and hence performance. A fast estimation algorithm that makes uses of this property was developed in [455] and another algorithm for arbitrary array shapes appears in [484].

In [184] the effect of sensor placement on the direction estimation performance of an array of acoustic vector sensors has been considered. Using the Cramer-Rao bound on the parameters of a single source, conditions were derived that minimize the lower bound on the asymptotic mean-square angular error, and that it is isotropic. The increase in estimation accuracy obtained by vector sensors is greatest for linear or planar arrays (as opposed to 3D), small number of sensors, and low SNRs. By exploiting velocity and pressure information, any vector-sensor array, a popular linear array, can be used to unambiguously determine both the azimuth and elevation of a single source.

Vector sensors have been successfully applied in other areas such as hull-mounted applications, where they overcome serious problems in detecting low-frequency emitting targets [189]. (At low frequency the vessel’s hull is acoustically flexible, leading to a very low pressure signal but a strong velocity signal.)

Chemical Sensors

Chemical sensors are useful for detecting explosives, drugs, and leakage of hazardous chemicals, and for monitoring the environment. They are manufactured by companies such as Cynano Sciences, Inc.; Science Applications International Corporation (SAIC); and Jaycor in San Diego, California. Array-processing techniques using chemical sensors have been proposed in [184], [288], and [319]. Compared with animal chemoreception, these techniques have the advantage that they share information and can be optimized.

Methods for detecting and localizing vapor-emitting sources were developed in [288]. Based on the diffusion equation, distributions of vapor concentration in time and space were derived for various environments. The results were used to develop statistical models of the array measurements. Maximum-likelihood estimates and general-likelihood ratio tests were derived to estimate the unknown source parameters and detect the existence of a source. The performance was analyzed using Cramer-Rao bounds and probabilities of detection and false alarm.

Employment of moving sensors was proposed in [319]. A single moving sensor can achieve the task of multiple stationary sensors by taking measurements at different locations and times. Its path can be planned in real time to optimize a performance criterion. The criterion used in [319] was to reduce the expected location error, which was accomplished by moving the sensor in directions opposite to the gradients of the Cramer-Rao bound.

Monitoring of disposal sites on the ocean floor using chemical sensor arrays was considered in [184]. Such sites have been suggested as suitable for the relocation of dredge materials from harbors and shipping channels, where their buildup has a detrimental impact upon economy and military security. Algorithms for detecting possible release of pollutants near these sites were developed, and their performance was analyzed. The results were used to optimally design arrays with respect to the numbers of sensors and time samples as well as sensor locations.

Superconducting Quantum Interference Devices (SQUIDs)

SQUIDS are the most sensitive detectors of magnetic flux currently available. They find broad application, from measurements of magnetic fields induced by brain activity to nondestructive evaluation of materials and the location of underground objects and structures. Their most important commercial use is in magnetoencephalography (MEG). MEG is concerned with mapping electrical activity in the brain by measuring the induced external magnetic field [151]. MEG sensor arrays measure extracranial magnetic fields of only a few hundred femtoTesla—a billion times smaller than the Earth’s steady magnetic field. Together with electroencephalography (EEG), which measures electric potentials on the scalp, MEG has emerged as a powerful noninvasive tool for the localization and tracking of electrical sources in the brain. The solution to this problem is of great importance in the diagnosis and evaluation of various brain disorders such as epilepsy, and for furthering understanding of brain function.

In [274] the MUSIC algorithm was applied for localizing brain sources modeled as current dipoles. Maximum-likelihood techniques have been developed in [98] to account for unknown spatially correlated noise, predominantly due to sporadic background activity in neurons. The optimization of MEG sensor arrays to minimize the mean-square error of dipole location estimates has been proposed in [176]. SQUIDs have opened other new applications of signal processing, such as detecting the wake of a ship using an airborne system [282].

In conclusion, it is expected that the use of novel sensors will continue to be a source of new applications and further developments in signal processing.

A WWW link to the author of the above section:
http://www.eecs.uc.edu/~nehora/

Sensor-Array Signal Processing

A. Lee Swindlehurst, Brigham Young University

The processing and manipulation of data received by a spatially distributed array of sensors has been an active area of research in the signal-processing community for well over
30 years. The long-lasting attention devoted to this area can be traced to the large number of applications where data is collected in both space and time. Figure 5 depicts a generic scenario in which energy (possibly acoustic, electromagnetic, seismic, etc.) from two sources is received by a sensor array. There are a number of possible objectives of such a system, with the most important being:

- **Source Localization**—determine the azimuth and elevation angles to the sources, and possibly the range to the sources as well if they are located in the near-field of the array; information on source velocity can be obtained by measuring frequency shifts, or angle and range rates of change.

- **Source Separation**—determine the signal waveforms transmitted by each source; the fact that the energy from each source arrives from different directions allows these waveforms to be separated even if they overlap in time and frequency.

- **Channel Estimation**—determine the space-time propagation effects between the sources and the array; estimate where reflections occur or how much the transmitted signal is spread in time and angle.

Which of the above three objectives is most important depends on the application. In active radar and sonar, the received waveforms are approximately scaled and delayed versions of a known signal, so it is the location (and motion) of the sources that is most important. In a communications system, it is the information-bearing waveform and not the location of the sources that is crucial. For seismic applications, the source signals arise from explosive charges. The received energy is used to characterize the propagation channel, which in this case provides information about the structure of the ground.

To be more precise, and to aid the discussion that follows, we introduce some simple mathematical notation. Referring to Fig. 5, in the simplest case the sources and array lie in the same plane, and the sources are far enough from the array so that the arriving signals have planar wavefronts. For this case, if the signals are assumed to be "narrowband" and there are a total of 2 signals, then the output of array element \( p \) is given by:

\[
\mathbf{x}_p(t) = \mathbf{a}(\theta_p) \mathbf{s}(t)
\]

where \( \theta_p \) represents the DOA of the waveform from source \( p \), and \( \mathbf{a}(\theta) \) is the (complex) response of element \( p \) to a signal arriving from that direction. In the general case, we would treat the reflection of source \( p \)'s signal in Fig. 5 as a separate term in the above sum; i.e., we would let \( s_1(t) = s_1(t - T) \). The outputs of an array of \( m \) elements can be stacked in a vector, as follows:

\[
\mathbf{x}(t) = \begin{bmatrix} x_1(t) \\ \vdots \\ x_m(t) \end{bmatrix} = \sum_{p=1}^{m} \mathbf{a}(\theta_p) s_p(t) + \mathbf{n}(t)
\]

where \( \mathbf{a}(\theta) = [a_1(\theta), a_2(\theta), \cdots, a_m(\theta)]^T \) denotes the vector array response, and we have added a term, \( \mathbf{n}(t) \), to account for unmodeled measurement noise and interference. Using this notation, we can give concrete examples of the three objectives listed above. For example, in source localization, we would use samples of the array output \( \mathbf{x}(t) \) to estimate the DOAs \( \theta_1, \theta_2, \cdots, \theta_m \) of the sources. Source separation involves extracting samples of one (or more) of the signals, \( \mathbf{s}_1, \mathbf{s}_2, \cdots, \mathbf{s}_m \), from the array data. In channel estimation, we may look for \( \mathbf{s}_1(t) = \mathbf{n}(t - T_1) \), in which case we are interested in the amplitudes, \( a_p \), and delays, \( T_p \), of the various arrivals (perhaps as well as the DOAs).

Early research in sensor-array signal processing, conducted mainly in the 1960s and 70s, was based on the observation that if the array is composed of identical uniformly spaced elements (i.e., a uniform linear array, or ULA for short), then a direct analogy exists with temporal sampling. The array elements perform a uniform one-dimensional spatial sampling of the wavefield, and the spacing between elements determines what spatial frequencies can be uniquely represented. Signals whose wavefronts are nearly parallel to the ULA, \( \theta = 0^\circ \), have low spatial frequencies; as \( \theta \rightarrow 90^\circ \) increases, the spatial frequency of the signal increases and reaches a maximum at \( \theta = 90^\circ \). A spatial version of the Nyquist criterion states that the array response vector \( \mathbf{a}(\theta) \) of a ULA is unique provided that the elements of the array are separated by no more than one-half the wavelength of the signal. Using this analogy with temporal sampling, it is possible to design spatial filters that pass signals with certain spatial frequencies (i.e., that arrive from certain directions) and attenuate others. However, unlike temporal filtering, it is usually not known a priori what spatial fre-
The further integration of computational wave-equation solutions and signal-processing techniques will pose many challenges and rewards in the future.

The sources are often noncooperative and little may be known about the signals they generate. In such situations, discrimination based only on the spatial properties of the received signals is necessary, which in turn requires that the response of the array be accurately calibrated with respect to $\theta$. The sensitivity of subspace based methods to array calibration errors limited their usefulness to some degree; particularly in underwater environments where the propagation medium is severely nonuniform. As military funding has waned, and as the field of personal wireless communications has emerged, interest in applications of array signal processing to communication systems has blossomed in the past few years. The use of multiple antennas at the base station of a wireless network offers a processing gain that can increase base station range and improve coverage. By exploiting the spatial selectivity of an antenna array, co-channel interference may be reduced, which in turn can be traded for increased system capacity. In addition, communication channels can be multiplexed in the spatial dimension just as in the frequency and time dimensions. This is often referred to as spatial-division multiple access (SDMA).

A distinguishing aspect of using antenna arrays in communications applications is that, due to the cooperative nature of such systems, significant information about the source signals is available and can be exploited for spatial processing. For example, it may be known that training sequences are present in the data, or that the signal is digitally modulated with a known symbol constellation and pulse-shaping filter, or that the signal has a constant amplitude envelope, etc. Each of these properties can be used by a system employing multiple antennas to achieve source separation without the need for explicit array calibration data. Algorithms that use this approach are referred to as “blind” source separation methods (see the sections by Cardoso and Tong). Such techniques can also be extended to perform blind equalization of propagation channels with significant delay spread. A breakthrough in this area came in the early 1990s, when it was shown that if a pulse-amplitude modulated signal is received by an array of antennas, then the channel can be identified using only second-order cyclostationary statistics.

Although blind methods can eliminate the need for calibration information, significant performance improvement can be achieved if reasonably accurate calibration is available. Techniques that exploit both the spatial
and temporal properties of the received signals are thus of high interest at the present time. Joint space-time processing in radar and sonar applications is also receiving added attention, as the speed and throughput of multi-channel DSP processors continues to increase. Further advances in computing power will bring other difficult array processing problems to the forefront, such as source localization and separation for wide-band signals, parameter estimation for sources with distributed spatial spectra, and matched-field processing for sonar applications.

There is a large body of published literature in the area of sensor array signal processing available to the interested reader. The references listed below are good starting points because of their tutorial nature and their extensive bibliographies:

- General books: [161], [311], [185]
- General papers: [197], [382]
- Adaptive beamforming [27], [439]
- Applications to radar systems [104], [163]
- Subspace methods [299], [34], [24]
- Applications in communications [298], [34], [306]

Blind Source Separation

Jean-Francois Cardoso, Ecole Nationale Superieure des Telecommunications (ENST)

Objectives

Source Separation

Source separation consists of recovering a set of “source signals” from the observation of several mixtures of these signals. This problem typically arises when the available signals are obtained at the output of an array of sensors that temporally and spatially sample signals emitted at different locations in space. In general, each sensor receives a mixture of all the source signals, if there are fewer sources than sensors, the received mixture of signals is in general, linearly inseparable. This is the case of spatially separated signals, which are discussed in the following section by L. Tong.

Figure 6 shows an example of separation of electrocardiography (EKG) signals. The left panel shows the output of one EKG electrode located on the abdomen of a pregnant woman; the fetus heart beat cannot be easily distinguished. The data set [38] contains the outputs of seven other sensors placed on the mother’s chest and abdomen. A source separation technique allows the contributions from the mother (middle) and from the fetus (right panel) to be separated.

Blind Source Separation

Exploring an array of sensors to focus on a particular source while rejecting other “interferers” is a standard task in array processing (see the sections by Swindlehurst and Krokidis in this article). The blind source separation (BSS) problem consists in recovering all the sources without using prior information about the channels, i.e., about the transfer function between the sources and the sensors. BSS is a “output-only” technique in the sense that neither source signals nor training sequences are available. All of the available information is contained in the observed data themselves. Two seminal papers on this topic are those by Jutten et al. [188] and Comon [74].

The major strength of the blind approach to source separation stems precisely from the fact that a precise model of the underlying physical phenomena, e.g., wave generation, propagation, and transduction, is not required. Thus, for example, BSS can be applied to uncalibrated arrays in situations where calibration is difficult or impossible or when physical modeling is overly complicated or unreliable.

The basic idea of BSS is that one makes up for the lack of information about the channels by assuming that the source signals are (statistically) independent. Statistical independence is a relatively strong assumption but it is plausible in many contexts because it arises from a lack of physical relationship between the various sources.

The simplest source separation model assumes an m-sensor array receiving signals $s_1(t), \ldots, s_m(t)$, from as many sources $x_1(t), \ldots, x_n(t)$ and an instrument matrix $A$:

$$
\begin{bmatrix}
s_1(t) \\
s_2(t) \\
\vdots \\
s_m(t)
\end{bmatrix}
= A
\begin{bmatrix}
x_1(t) \\
x_2(t) \\
\vdots \\
x_n(t)
\end{bmatrix}
$$

The mixture coefficients $a_{ij}$ can be collected in an $n \times n$ “mixing matrix” A. The $n$ source signals and the $m$ array outputs into an $n \times 1$ column vectors, the BSS model reads more concisely as $x(t) = As(t)$.
Such approaches involve a tight coupling between the physics of wave propagation and signal processing. They also rely on the availability of sufficiently accurate estimates of the environmental parameters. Numerous results obtained with real data in very different settings, however, suggest that "sufficiently accurate" should be understood as "perfect knowledge" of the environment. Indeed, in some situations, robust signal processing methods have been developed that facilitate matched-field processing with almost "common knowledge" of the environment. Clearly, the further integration of computational wave-equation solvers and signal-processing techniques will pose many challenges and rewards for the future.

A WWW link to the author of the above section:
http://www.ee.duke.edu/people/ghkim/

References


