Array Signal Processing in Wireless Sensor Networks

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Editorial

Recent advances in Integrated Circuits (IC) and Micro Electro Mechanical Systems (MEMS) technologies have allowed the design and construction of low-cost low-power smart sensor nodes with sensing, computing, signal processing and wireless communication capabilities that can form distributed wireless sensor network systems. Wireless sensor networks have been recognized as one of the most important technologies in the 21st century, and the systems hold the promise to revolutionize the sensing paradigm and can be used to perform detection, localization, tracking, and identification of objects in a broad spectrum of military, scientific, industrial, and home applications like infrastructure health monitoring, disaster management, and battlefield surveillance [1].

An essential problem in wireless sensor networks is localization or position determination, which consists of two categories of requirements: localization of the sensor nodes or the mobile units themselves and localization of intruders or objects [2]. In general, location estimates are derived from two types of measurements: angle and range. The widely used range estimation models include Received Signal Strength (RSS), Time of Arrival (TOA) and Time Difference of Arrival (TDOA), where the synchronization and cooperation between the transmitter and the receiver are required. These techniques are well suited to the problem of sensor node self-localization because the direct communication links between each other in a neighborhood region are available; however, will find difficulties in a passive configuration to localize the intruders or objects. Estimation of the incident signals' directions, or Angle of Arrival (AOA) estimation, is potentially able to locate the signal sources in a non-cooperative, stealthy and passive manner, which is highly desirable in surveillance applications. The benefits of AOA measurements for location estimation in wireless sensor networks have been widely investigated and a couple of AOA-alone and AOA-range hybrid systems have been developed [3-5].

In addition to location estimation, AOA measurements can be exploited to enhance communication efficiency and network capacity, and support location-aided routing, dynamic network management, and many location-based services [6-8]. A chief goal of wireless communication research has long been to enhance the network capacity, data rate and communication efficiency. In comparison with solutions to increasing the spectrum usage, smart antenna technology provides a more practical and cost-efficient solution. With smart antennas, the sender can focus the transmission energy towards the desired user while minimizing the effect of interference, and the receiver can form a desired beam towards the sender while simultaneously placing nulls in the directions of the other transmitters. This spatial filtering capability potentially leads to improved user capacity; reduced power consumption, lower Bit Error Rates (BER), and extended range coverage [9]. A key component that aids the sensor array to be smart and adaptive to the environment is AOA estimation of the desired emitters and co-channel interferers. To fully exploit the AOA capability, various Medium Access Control (MAC) protocols have been developed.

A standard data model for the problem of AOA estimation is a narrow-band model with far-field geometry. Assume the sources having the same known center frequency illuminate a sensor array, and the sources are located sufficiently far from the array such that in homogenous isotropic transmission media, the wave fronts are planar. An AOA problem is classified as narrow-band if the signal bandwidth is small compared to the inverse of the transit time of a wave front across the array aperture, and the array response is not a function of frequency over the signal bandwidth. The number of sources is assumed known (given or estimated from the signal detection algorithms [10]) and less than the number of sensors, this is to guarantee the uniqueness of AOA estimation [11]. Additive stationary white Gaussian noise is present at all sensors. Regarding the source signals, there are two different types of models in current use: conditional model, which assumes the signals to be deterministic (i.e. the same in all realizations) and unconditional model, which assumes the signals to be random [12,13]. Noting that the narrow-band assumption implies that for all possible propagation delays caused by the space extent of the array, the effect of a time delay on the received waveforms is a simply a phase shift.

In the recent decades, AOA estimation with a sensor array has received considerable attention from a variety of research communities like radar, sonar, radio astronomy, mobile communications, and wireless sensor networks, and a range of useful and complementary algorithms have been developed, such as delay-and-sum beam forming, Multiple Signal Classification (MUSIC), Estimation of Signal Parameters via Rotational Invariance Technique (ESPRIT), Minimum Variance Distortion less Response (MVDR), Maximum Likelihood (ML), and others [14-27]. In general, the AOA estimation algorithms explore the statistical information and structure of the data covariance matrix computed from a batch of array snapshots or data samples.

Delay-and-sum beam forming, or known as Digital Beam Forming (DBF) is one of the oldest and simplest array processing algorithms [18]. The underlying idea is quite simple: when a propagating signal is present in an array's aperture, if the sensor element outputs are delayed by appropriate amounts and added together, the signal will be reinforced with respect to noise or waves propagating in different directions. The delays that reinforce the signal are directly related to the length of time it takes for the signal to propagate between sensor elements. The AOA measurement process is similar to that of mechanically steering the array in different directions and measuring the output power. When a set of data samples is given, the DBF power spectrum is evaluated, and the AOA estimates are obtained by viewing the peaks in the spectrum.

The Minimum Variance Distortion less Response (MVDR) approach is also known as the Capon's algorithm [26,27]. Since it explicitly produces an optimal weight vector, it can be used as a beam former as well as an AOA estimator. The AOA measurement is performed similarly to that of delay-and-sum beam forming or mechanically scanning, however, the weight vector is the solution to a constrained optimization problem, where the array output power is minimized while the signal coming from the array looking direction is passed to the beam former's output undistorted. Solving this optimization problem leads to finding the set of weights that result in the lowest-power array output subject to the directional constraint, while minimizing power presumably reduces the deleterious effects of noise and unwanted interference.

The Multiple Signal Classification (MUSIC) algorithms [28] exploit the eigen-structure of the data covariance matrix, and can be classified as eigen-based methods. The rationale for this category of algorithms is related to the division of information in the covariance matrix of the data received by the array elements into two vector subspaces, namely, the signal subspace and the noise subspace. These algorithms assume that the signal of interest lies in a lower dimensional signal space than the full dimensional space spanned by the vectors of data samples received by the sensor elements. It assumes that the principal eigenvectors are linear combinations of the array steering vectors associated with the sources, and vice versa. Equivalently, the principal eigenvectors and the source steering vectors span the same vector subspace – the signal subspace. And the noise eigenvectors span the noise subspace, which is orthogonal to the signal subspace. Once the noise subspace has been estimated, a search for AOA estimates is made by looking for steering vectors that are as orthogonal to the noise subspace as possible.

The Maximum Likelihood (ML) AOA estimation method is a nearly optimal technique. In theory, it gives a superior performance compared to other methods, providing asymptotically unbiased and efficient estimates, especially in the threshold region [14,16,17]. The AOA estimates are obtained by solving a multi-dimensional unconstrained optimization problem. However, the complexity and computational load of maximizing the complex, multi-model, and highly nonlinear likelihood function has prevented it from popular use for a long time. Several researchers have proposed various schemes to optimize the likelihood function, with an aim to obtain global convergence with less computing cost. It proves that for uncorrelated sources, the statistical performances of maximum likelihood estimators with Conditional (CML) data model (assuming the signals to be the same in all realizations) and the maximum likelihood estimators with Unconditional (UML) data model (assuming the signals to be random) are similar; while for highly correlated or coherent sources, UML is significantly superior [29].

In summary, array signal processing has been a fundamental and essential problem in numerous applications like radar, sonar and mobile communications, and will be a promising area in wireless sensor networks with significant practical interests. A variety of high-resolution algorithms have been investigated and evaluated in different scenarios and settings. The development of this theme will benefit and enable more research on detection, localization, tracking, communication, networking, and next-generation sensor platforms.

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