Direction of Arrival Estimation for Sensor Networks via Approximate Message Passing

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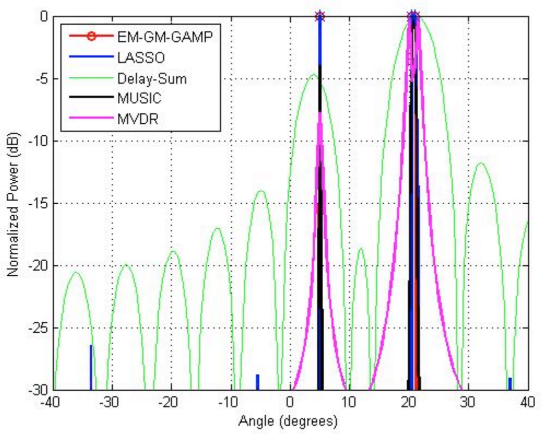
Abstract:

Direction-of-Arrival (DOA) estimation, an active research area for decades, lies at the heart of many real-time, modern, big data and internet-of-things applications such as acoustic, seismic, and electromagnetic sensing and wireless communication networks. Conventional DOA estimation methods, such as delay-and-sum beamforming, MUSIC, MVDR etc., are based on L2 techniques. However, the underlying sparsity inherent in DOA signals has recently motivated researchers to tackle the problem from the compressed sensing (CS) perspective via L1 minimization or the LASSO [2]. Despite considerable improvement, the LASSO solves the minimization in the minmax sense, by assuming a Laplacian prior for the data. We here focus on a recently proposed approximate message passing (AMP) algorithm [1] where the signal prior can be estimated and used as extra information for the DOA estimation.

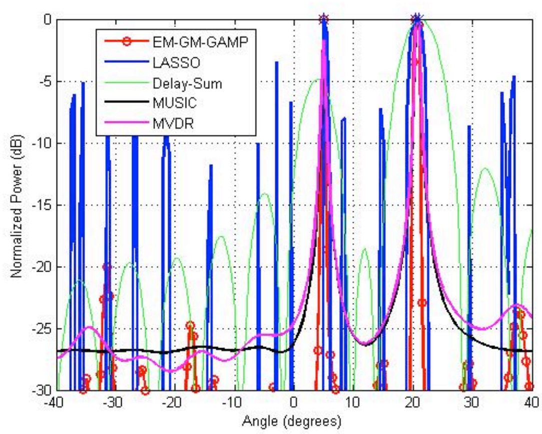
An unknown but limited number of source signals are assumed to be distributed in bearing $\theta \in [-90^{o}, 90^{o}]$ For a linear array with arbitrary inter-element spacing, the propagation delay from the potential source at bearing θ_i to each element of the array can be characterized by the steering vector

$a(\theta_i) = \frac{1}{\sqrt{M}}\left[1, e^{j\frac{2\pi f d_1}{c}\sin\theta_i}, \cdots, e^{j\frac{2\pi f d_M}{c}\sin\theta_i}\right]^T$, where M is the number of sensors in the array. Defining a fine angular grid and concatenating the steering vectors, we have $A = [a(\theta_1), \cdots, a(\theta_N)]$. Then the received signal at the sensor array can be modelled as $y = Ax + n$ where n is the noise and x is the sparse signal. In this way the DOA estimation problem is transformed as a sparse signal recovery problem as in the CS setting. Given y and A, the reconstruction of x is achieved by the EM-AMP algorithm [1]. As an iterative algorithm, AMP can be casted as a Gaussian denoising problem at each step. With the signal prior being approximated as a Gaussian mixture model, the denoising is conducted by the appropriate MMSE estimator, which leads to an improved reconstruction.

For validation, the three aforementioned conventional beamformers, LASSO, and EM-GM-GAMP algorithm are applied to the synthetic data with 3 separated DOAs at [5, 20.5, 21] degrees under two noise level SNR =10, 50dB. The receiver is a 16 elements linear array. Our experiments show that, in both scenarios, the AMP algorithm successfully identified the 3 targets with a signal snapshot while the rest either fails at high noise environment or requires multiple snapshots to achieve the same accuracy.



(a) SNR = 50 dB



(b) SNR = 10 dB

Reference:

[1]. Vila, Jeremy P., and Philip Schniter. "Expectation-maximization Gaussian-mixture approximate message passing." *IEEE Transactions on Signal Processing,* 61.19 (2013): 4658-4672.

[2]. Gerstoft, Peter, and Angelliki Xenaki. "Compressive beamforming with LASSO." *The Journal of the Acoustical Society of America* 137.4 (2015): 2388-2388.