Title
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Acoustic Source DOA Estimation using
the Cross Entropy Method

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Introduction: In this paper, we propose a novel implementation for the Maximum-Likelihood DOA estimator based on the Cross Entropy (CE) method. Simulation results show the proposed algorithm converges to the CRB within a few iterations, and the convergence speed is insensitive to the coherence of sources.

Features of AML DOA Estimator

- Optimal in the ML sense
  - Achieves CRB at high SNR.
- Superior performance over many other suboptimal DOA estimators
  - TDOA methods can only estimate single source DOA.
- Subspace methods degrade severely when sources are strongly coherent.
- High Complexity
  - Multiple dimensional grid search is generally required.
  - Iterative maximization algorithms have been proposed in the literature.

Introduction to ML Criterion for wideband DOA Estimation:

Data received by the pth sensor at time n:
\[ x_p(n)=\sum_{\alpha=1}^{M} s_\alpha(n-t_\alpha(n)) + w_p(n) \]

After N point DFT
\[ X(w_i)=D(w_i,s_j(w_i)) + q(w_i) \]

where \( R(w_i)=X^H(w_i)X(w_i) \)
\[ P(w_i,\theta)=D(w_i)D^H(w_i) \]
\[ \bar{D}(w_i)=|D(w_i)D^H(w_i)|^2D^H(w_i) \]

By techniques of separating variables, we can estimate DOA as:
\[ \hat{\theta} = \arg \max \sum_{i=1}^{N} \log |P(\omega_i,\hat{\theta})R(\omega_i)| \]

In multiple sources case, AML requires multi-dimensional search.

Various numerical solutions (AP, GN, CG) have been proposed.

CE algorithm for wideband DOA estimation:

A summary of the proposed algorithm
1. Initialize parameters \( \rho, \beta, \alpha, \beta, \theta(0) \) can be chosen to incorporate the a priori knowledge of the DOAs.
2. Generate \( N \) samples \( \theta(0), \ldots, \theta(N) \) from the proposal distribution
\[ f(\theta, v) = \prod_{n=1}^{N} f_n(\theta_n, v_n) \]
\[ f_n(\theta_n, v_n) = \frac{1}{\sqrt{2\pi \sigma_n}} e^{-\frac{(v_n-\theta_n)^2}{2\sigma_n^2}} \]
3. Compute \( J(\theta(0), \ldots, \theta(N)) \). Set \( \hat{\theta}(t) \) as the order statistic \( J_{(t-N,v)} \).
4. Use the same samples \( \theta(0), \ldots, \theta(N) \) to estimate the parameters \( \bar{\theta}(t)=\left[\bar{\theta}^T(t), \bar{\sigma}^2(t)\right]^T \) through the following update equations:
\[ \bar{\mu}_n(t) = \frac{1}{N} \sum_{n=1}^{N} H(\theta^{(n)}, \hat{\theta}(t)) \exp(\rho^{(n)}) \]
\[ \bar{\sigma}_n^2(t) = \frac{1}{3} \left[ \sum_{n=1}^{N} H(\theta^{(n)}, \hat{\theta}(t)) \cos(\rho^{(n)} - \bar{\theta}(t)) \right] \]
5. Stop the algorithm when it converges; otherwise set \( t=t+1 \) and reiterate Step 2

Simulation Results

Scenario 1: Incoherent Sources:
DOAs=30, 90, 180 degrees
8-element UCA with radius=0.25 m
Np=200

Scenario 2: Coherent Sources:
DOAs=30, 90, 180 degrees
8-element UCA with radius=0.25 m
Np=200