3. INTRODUCTION

The Improved Probabilistic Multi-hypothesis Tracker (I6MHT) is used to obtain the MAP estimation of the target states. The quantity of kinematic states \( K \) and prior probabilities \( \pi_i \)

\[
Q(X_0) = K \sum_i \pi_i p(X_0 | K) X_0, Z_{i0}, H_{i0}
\]

is iteratively truncated over a grid in standard PMHT. \( K \) and \( \pi_i \) respectively represent the kinematic states and measurements, and only 400

4. SIMULATION RESULTS

![Image of simulation results](image_url)

A simple scenario with 2 targets moving almost collinearly is used in the case of the test observation and tracking. The results demonstrate the advantage of improved PMHT.

5. CONCLUSIONS

The paper evaluates the probabilistic multi-hypothesis tracker (PMHT) and its improved version (I6MHT). The simulation results show that the I6MHT is more effective than the PMHT in terms of tracking accuracy and computational cost, especially in cases with complex motion patterns and multiple targets. The improved PMHT allows for an enhanced multi-target tracking performance, which is crucial in applications such as autonomous vehicles, surveillance systems, and aerospace engineering. Future work should focus on extending the I6MHT to handle more challenging environments and incorporating real-world data for comprehensive evaluation.
Multi-Channel SAR/InSAR/GMTI Processing with Subspace Projection

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Abstract

For the multi-channel SAR, such as InSAR or GMTI, the processing performance is heavily affected by the images coregistration accuracy. In this paper, the joint-pixel processing method is presented, and the subspace projection is employed to estimate the interferometric phase of InSAR or suppress the clutter of GMTI. The method takes advantage of the coherence information of neighboring pixels and the orthogonality of the signal subspace and the noise subspace. The proposed method is robust to coregistration errors of multi-channel SAR images. The effectiveness of the method is investigated by real multi-channel SAR data.

Signal Model of Joint Pixel Processing

Problem: In the previous processing of InSAR phase estimation and GMTI clutter suppression, only the current pixel information is used. Therefore, when coregistration errors appear between the channels, phase errors will be introduced. For GMTI, the improvement factor will be heavily affected. Furthermore, it is difficult for us to correlate the images of the different channels.

Resolving Method: To alleviate the burden of the accurate coregistration, we use the joint pixel processing to present the performance of multi-channel SAR/InSAR/GMTI processing. The construction of the joint pixel processing is given in Fig. 1, where the coherence information around the current processing pixel (marked as $g$) is fully employed.

Mathematical Model: At all the SAR images are considered, the joint pixel vector can be represented as:

$$
\mathbf{x} = \begin{bmatrix}
\mathbf{x}_1 \\
\mathbf{x}_2 \\
\vdots \\
\mathbf{x}_N
\end{bmatrix}
$$

where $\mathbf{x}_i$ is the data vector composed of the corresponding pixels in different channels.

The noise subspace dimension of the joint covariance matrix is $N - 1$. Coregistration errors of $0.5$ pixel: 1
Coregistration errors of $1.0$ pixel: 5

Procedures of Joint Pixel Subspace Projection for InSAR/GMTI

1. Multi-channel SAR images coregistration
2. Estimation of the joint covariance matrices using the samples of the joint neighboring pixels
3. Eigen-decomposition of the joint covariance matrices for joint noise subspace estimation

Discussions:

Fig. 2 shows that, when the coregistration error gradually increases, the separation of large eigenvalues and small eigenvalues becomes smaller and smaller, which means that the noise subspace will be more robust to coregistration errors. Therefore, the phase estimation of clutter suppression will be better.

Conclusions and future works

The results show that the InSAR phase estimation results of the joint pixel subspace projection are obviously better than the single pixel processing. Especially for GMTI, the proposed method can further reduce the SAR images and select the clutter more accurately. For GMTI, the loss of improvement factor is less than 3 dB even though the coregistration performance decreases slightly, while in the worst case, the loss of improvement factor is only 3 dB when using the joint pixel subspace projection.

References
FIR Estimation of MIMO Systems

Wei Shi, Qing Ling, Gang Wu, Zhi Tian
1. Dept. of Automation, Univ. of Sci. & Tech. of China, 2. Dept. of ECE, Mic. Tech. Univ.

Overview
- Objective: System identification
  - Model type: Finite impulse response model
  - Model order selection, model parameter estimation
- Problem formulation
  - Nuclear norm, $\ell_1$-norm regularized least squares
- Algorithm design
  - Alternating Direction Method of Multipliers + Linearization

Objective
- System identification: build mathematical models of dynamical systems from measured data using statistical methods.

<table>
<thead>
<tr>
<th>Input data $x$</th>
<th>System $S$</th>
<th>Output data $y$</th>
</tr>
</thead>
</table>

Estimated input data $\hat{u}$
| Model $M$ | Estimated input data $\hat{y}$ |

We consider discrete-time linear time-invariant multi-input (MIMO) multi-output (MIMO) systems.

Existing Common model types are transfer function (TF) model, state space (SS) model, or finite impulse response (FIR) model, etc.

Here we choose the FIR model to describe a MIMO system.

For instance, the FIR model is frequently used in model predictive control (MPC) because it can efficiently describe complex systems [1].

Notation
- $U \in \mathbb{R}^{K \times M}$ is the matrix formed by input data of $M$ inputs
- $Y \in \mathbb{R}^{K \times N}$ is the vector formed by output data
- $G \in \mathbb{R}^{K \times M}$ is the matrix formed by FIR sequences of $M$ SISO sub-systems of a MISO system, $g(m)(k)\Delta t$ for $m = 1, \ldots, M$
- $\text{vec}()$ is the vectorization operator
- $\text{vec}(M) = \text{vec}(S)$ is the vector formed by $S$

$\text{vec}(M)$ is for the sum of squares of estimation error

Problem Statement

MIMO system with $M$ inputs and $N$ outputs $\rightarrow$ N MISO system with $M$ inputs

A MISO system can be described by

$$ y(k) = \sum_{\tau=0}^{\infty} a_m(k) u_m(k-N_m) + e(k) $$

Where $e(k) \sim N(0, \sigma^2)$ is noise. We only consider MISO systems thereafter.

Observation and new approach

FIR is approximately sparse when the length of FIR is large enough

The Hankel Matrix is low rank when the Hankel matrix size is large enough

$$ A(g) = \begin{bmatrix} g(1) & \cdots & g(P) \\ \vdots & \ddots & \vdots \\ g(P) & \cdots & g(2P-1) \end{bmatrix} \in \mathbb{R}^{P \times MP} $$

where $g(i)$ is the $i$th row of $g$.

Regularizer one: $\|g\|_1$

Regularizer two: $\text{rank}(h(g))$

Using convex relaxation of the two regularizers leads to a convex optimization problem:

$$ \hat{g} = \arg\min_{g} \frac{1}{2} \|y - U \cdot \text{vec}(g)\|_2^2 + \lambda \|g\|_1 + \gamma \|h(g)\| $$

Algorithm Design

Alternating direction method of multipliers (ADMM) is applied to solve NN-$\ell_1$-LS:

$$ \hat{g} = \arg\min_{\substack{g \in \mathbb{R}^{K \times M} \\|g\|_1 + \gamma \|h(g)\|}} \frac{1}{2} \|y - U \cdot \text{vec}(g)\|_2^2 + \lambda \|g\|_1 $$

- $g$-update
- $h$-update
- $Z$-update

Considering linearization and adding proximal term:

$$ \hat{g}^{(k+1)} = \arg\min_{g \in \mathbb{R}^{K \times M}} \frac{1}{2} \|y - U \cdot \text{vec}(g)\|_2^2 + \lambda \|g\|_1 $$

Optimization Framework

According to modified AIC, parameter $\lambda$ and $\gamma$ are recommended to be tuned around

$$ \lambda = \frac{\text{marginal likelihood}}{\text{error}} $$

and $\gamma = \frac{\text{marginal likelihood}}{\text{error}}$, respectively.

Choosing $\alpha = \frac{\text{marginal likelihood}}{\text{error}}$, Initialize $g$ by $\ell_1$-LS and $H$ by $h(g)$.

Conclusion

We discuss FIR Estimation of Discrete-time LTI MIMO Systems. By using $\ell_1$ norm and nuclear norm as the penalized terms to regularize the least squares, we improved the estimation equality of FIR model.

With our approach, we give better estimation of the time-delays; choose effective lengths of FIRs easier; lower the requirement of input-output data quantity.

References

Bayesian Track-Before-Detect Algorithm with Target Amplitude Fluctuations Based on EM Estimation

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I. Introduction

A common trick in engineering for the unknown average amplitude is to treat the parameter as an extra state variable, and approximate the variable as a slowly changing Gaussian process. This trick is difficult to incorporate the fluctuation model of the parameter, make the estimate of the parameter more dependent on recent observations, and result in the degeneration of the samples of the parameter into one or a few different values.

The problem can be considered as a special case of maximum-likelihood estimation with incomplete data, and we can use EM algorithm to estimate the average amplitude in the sense of maximum-likelihood estimation.

II. Bayesian Track-Before-Detect Based on EM Estimation

The log likelihood of observations is defined as

$$\ell(z) = \log p(z | \theta) = \log \sum_{\phi} \int f(\phi | z_i, \theta) p(z_i | \phi, \theta) d\phi$$

Because of the hidden variables, $\phi_i$ and $E_i$, it is intractable to maximize the log likelihood directly. An alternative procedure is to define a variational distribution $q(\phi_i, E_i)$ over the hidden state variables, which allows us to obtain a lower bound on likelihood of observations:

$$\ell(z) \geq \sum_i \int q(\phi_i, E_i) \log \left( \frac{p(z_i, \phi_i, E_i | \theta)}{q(\phi_i, E_i)} \right) d\phi_i$$

$$= \sum_i \int q(\phi_i, E_i) \log p(z_i, \phi_i, E_i | \theta) d\phi_i$$

$$- \sum_i \int q(\phi_i, E_i) \log q(\phi_i, E_i) d\phi_i$$

$$= \mathcal{F}(q(\phi_i, E_i), \theta, z)$$

III. Expectation step and Maximization step

The E step can be defined as

$$E_{\theta, q} = \arg \max_{\theta, q} \mathcal{F}(q(\phi_i, E_i), \theta, z)$$

Thus, the E step is considered as a smoothing process.

The M step can be defined as

$$\Delta_{\phi_i} = \arg \max_{\phi_i} \sum_{i} \int q(\phi_i, E_i) \log p(z_i, \phi_i, E_i | \theta) d\phi_i$$

$$= \arg \max_{\phi_i} \sum_{i} \int p(\phi_i | z_i, \Delta_{\phi_i}) \log p(z_i | \phi_i, \theta) d\phi_i$$

$$= \arg \max_{\phi_i} \sum_{i} \int p(\phi_i | z_i, \Delta_{\phi_i}) \log p(z_i | \phi_i, \theta) d\phi_i$$

Because high non-linearity, it is difficult to obtain the closed-form solution of the M step. So, the direct search method can be only used to calculate the M step.

IV. Experimental Results

The target return amplitude is modelled using Swerling type I, and the actual SNR is 10 dB.

V. Conclusion

Compared with the trick treating the unknown average amplitude as an extra state variable, better estimate of the average amplitude can be obtained using the EM algorithm, which is helpful to improve the performance of detection and tracking for Bayesian track-before-detect algorithms.

VI. Existing Problems

In the M step, it is difficult to obtain the closed-form solution because of high non-linearity. So, the direct search method can be only used to calculate the M step, which leads to huge calculation in EM algorithm.
STEPPED-FREQUENCY CHIRP MINI-SAR SYSTEM
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- Background
  - UAV for disaster reduction
  - Surveying and Mapping

- System architecture

- Field Experiment
  - Static Corner Reflector Experiment

- Vehicle Experiment

- System parameter
  - Signal: Stepped-Frequency Chirp
  - Resolution: 0.2m × 0.2m
  - Range: 1km
  - Weight: 2.5kg

- Verification prototype

- Key Technique
  - Stepped-Frequency Chirp imaging
  - UAV motion compensation
  - Micro RF and Digital Subsystem

- Acknowledgement
  - Supported by the key project of National Natural Science Foundation of China (Grant No. 61032009, 60890073)
A New Method Based on Multimodal Stationary Sequence Modeling for Radar HRRP Target Recognition under Small Training Set Conditions

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I. Introduction
Radar high resolution range profile (HRRP) is characterized by high dimensionality, which incurs the curse of dimensionality in HRRP-based recognition. To alleviate this problem, we extract the frequency spectrum amplitude (FSA) of complex HRRP as recognition feature and propose to model FSA along the frequency dimension by Mixture Autoregressive (MAR) model. In this way, we can:
- Describe the statistical properties of FSA accurately.
- Decrease the model's degree of freedom.
- Estimate all model parameters for each sample. (More samples can improve the estimation accuracy)

II. Motivation

![Diagram of HRRP and MAR model]

The proposed method treats each HRRP sample as a high-dimensional series and describes it with a series model. In doing so, we indirectly implement feature dimension reduction without information loss.

- Feature extraction
  HRRP: \( x = \exp(j\omega_0 [x_1, x_2, \ldots, x_T]) \) \( x_t = \sum_{k=1}^{d} a_k x_{t-k} + \epsilon_t \)
  FSA: \( z = \text{FFT}(x) = [z_1, z_2, \ldots, z_T] \) \( z_t = \sum_{k=1}^{d} e_k z_{T-k} + \epsilon_t \)

- Model selection
  Bayesian Information Criterion (BIC):
  \[ r^* = \arg\min_r \left[ -2\log(p_{\text{MAR}}(x | \theta)) + \frac{1}{2} \log d \right] \]
  \[ r = \sum_{t=1}^{T} (p_{t} | p_{t-1}) \text{MAR} + \frac{1}{2} \sum_{t=1}^{T} \log \text{MAR}(x_t | x_{t-1}, \theta) \]

IV. Model
- Mixture Autoregressive (MAR) model
  AR: \( R_{\text{AR}}(x_t, \theta) = G(x_t | \theta) = \sum_{k=1}^{d} \alpha_k G(x_{t-k} | \theta) \)
  MAR: \( R_{\text{MAR}}(x_t, \theta) = \sum_{k=1}^{d} \alpha_k G(x_{t-k} | \theta) + \sum_{k=1}^{d} \beta_k G(x_{t-k} | \theta) \)

MAR model is the generalization of both AR model and Mixture AR model. Thus it can simultaneously depict the stationarity and multi-modality of FSA.

- Parameter estimation
  EM algorithm: First, let \( I \) be an unobserved \( K \times d \) matrix with its elements defined as:
  \( j \) if \( x_j \) is generated by the \( k \)-th AR mixture
  \( 0 \) if \( j \) else
  \( k \) = 1, 2, \ldots, \( K \), \( j \) = 1, 2, \ldots, \( d \)

  Then repeat the following two steps until convergence:
  E-step: estimate the posterior expectation of \( I \)
  M-step: get the ML estimation of parameters by maximizing \( \log(p_{\text{MAR}}(x | \theta)) \)

V. Experimental Results

- Recognition performance
- Model selection results
- Recognition results of MAR models with different model-scales
- Recognition results vs. training sample size

![Graphs and charts showing experimental results]
Minimax Robust Transmission Waveform and Receiving Filter Design for Extended Target Detection with Imprecise Prior Knowledge
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I. Introduction

Practically, the prior knowledge of Target-Radar Orientation (TRO) and target-radar distance is usually imprecise in transmission waveform and receiving filter design. Then, three main issues must be considered in adaptive transmission waveform design:
1. Target Impulse Response (TIR) is very sensitive to TRO.
2. The initial phase of TIR is uncertain. Although the output SINR is independent of the initial phase of TIR, it will introduce a larger uncertainty set of TIR, and the performance will decrease substantially.
3. The transmission waveform is expected to be of constant modulus.

Motivated by that, a minimax Robust Transmission waveform and Receiving filter Design (RTRD) method is proposed.

II. Motivation

To get a better performance, we employ many receiving filters for the small subsets and allocate one receiving filter to one subset. Then, only the TEMs in one subset needs to be considered in robust receiving filter design.

III. RTRD method and its simplified version

- Target echo matrix
  \[ R_y = E_t E_t^H = R_x + \Delta_y \]
- Cost function of RTRD
  \[ \begin{align*}
  \min_{h_y} & \quad \min_{\Delta_y} & \quad \min_{b_y} \\
  & \quad h_y^H (R_x + \Delta_y) b_y \\
  & \quad h_y^H R_x b_y
  \end{align*} \]

- Bound the Frobenius norm of the error matrix \( \Delta_y \) by positive constant \( e_y \), robust receiving filter
  \[ b_y = \frac{1}{e_y + \Delta_y} \]

- Using modified SQP method with approximately Hessian matrix, robust transmission waveform can be acquired by
  \[ \begin{align*}
  \min_{\Delta_y} & \quad \min_{b_y} \\
  & \quad b_y^H (R_x - e_y I) b_y \\
  & \quad b_y^H R_x b_y
  \end{align*} \]

- Set the error matrix bound as zero, a simplified method termed RTD is obtained and the optimized waveform can be acquired by the same procedure with much smaller computation cost.

IV. Experimental Results

- Background noise and clutter
- WSINR versus azimuth region size and UC
- WSINR versus transmission energy

IV. Conclusion

Although a simplified method is proposed, its computational complexity is still high from a practical standpoint. Therefore, more efficient algorithm is deserved to be explored in the future.
A New Method for Imaging of Group Targets Moving in a Formation

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I. Introduction
In high-resolution radar imaging of multiple targets, it is quite possible that a number of targets are within the same radar antenna beam. For the group targets moving closely in a formation, their echoes overlap in the range – slow time domain and invalidate the available motion compensation and imaging techniques. The proposed method deals with imaging of group targets in constant accelerated rectilinear motion. The main features of this method include:
* Parametric motion compensation method yields focused image of the group targets.
* Simultaneous compensation for the first-order phase terms reduces the computational burden greatly.

II. Imaging Model

Flow chart of the proposed method

Step 1:
Compensate for the first-order phase terms of sub-targets by Doppler ambiguity number estimation and the Radon transform.

Step 2:
In the \( f - f_c \) domain, the compensated echoes are expressed as

\[
x(f, f_c) = y(f, f_c) \times \exp \left( -j \frac{4 \pi}{c} \frac{\Delta \Delta f}{\Delta f} \right)
\]

with

\[
G(f, f_c) = \frac{\exp \left( -j \frac{4 \pi}{c} \frac{\Delta \Delta f}{\Delta f} \right)}{\Delta f}
\]

The coupling term \( \exp \left( j(\Delta f, f_c) \right) \) is ignorable in this domain. Since the third-order phase terms are generally small for air-planes, it is reasonable to estimate the second and third-order phase terms separately to obtain the bulk image. The phase compensation term is expressed as

\[
\exp \left( -j \frac{4 \pi}{c} \frac{\Delta \Delta f}{\Delta f} \right)
\]

Then a coarse estimate of \( \Delta f \) is obtained by the minimum entropy criterion to facilitate bulk image.

III. Proposed method
Considering the differences in motion parameters among sub-targets, the core to group targets imaging are accurate echo separation and focused imaging of each sub-target by the parametric method. Here the echoes are focused in the image domain.

IV. Simulation

Echos after Step 1

V. Conclusion
In the future, the conceived method will be examined using measured data. Furthermore, effective techniques applicable to imaging of maneuvering group targets in low PRF scenarios will be studied. Moreover, algorithms will be designed for imaging of group targets with complex motion, like spinning and vibrating.
On the Design of Constant Modulus Probing Signals for MIMO Radar

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Introduction

- Importance: MIMO transmission and reception is a promising paradigm for the next generation radar systems. A central signal processing problem in MIMO radar research is waveform design. The basic issue is how to generate a pre-specified beampattern using independent constant modulus waveforms while satisfying the so-called spatial auto-/cross-correlation peak sidelobe levels.
- Existing works: The existing design approaches can be classified into three categories: (1) maximizing the mutual information between the received signal and the impulse response of the target; (2) optimizing the range, angular, and doppler resolution based on radar ambiguity function; (3) matching a desired beam pattern using independent constant modulus signals while suppressing the spatial auto-correlation and cross-correlation sidelobes.
- Our approach: we propose to optimize probing signal waveforms to meet the beam pattern specification directly. We formulate this problem as an unconstrained fourth-order trigonometric polynomial minimization model and propose a quasi-Newton iterative algorithm to solve it approximately. Simulation results demonstrate that the resulting design procedure compares favorably with the existing approach in terms of both the algorithm speed and the quality of the obtained waveforms.

Problem Formulation

Consider a MIMO radar equipped with \( M \) transmitting antennas as shown in Figure 1. The probing signal is denoted by matrix \( X \in \mathbb{C}^{N \times M} \)

\[
\mathbf{w}(\mathbf{a}, \mathbf{X}) = \mathbf{w}_1^{(\mathbf{a})}(\mathbf{X}) + \mathbf{w}_2^{(\mathbf{a})}(\mathbf{X}) + \mathbf{w}_3^{(\mathbf{a})}(\mathbf{X}),
\]

where

\[
\mathbf{w}_1^{(\mathbf{a})}(\mathbf{X}) = \sum_{i=1}^{M} \mathbf{a}_i \mathbf{A}_i^{(\mathbf{a})} \mathbf{X} \mathbf{a}_i^H,
\]

\[
\mathbf{w}_2^{(\mathbf{a})}(\mathbf{X}) = \frac{1}{2} \mathbf{A}_i^{(\mathbf{a})} \mathbf{X} \mathbf{a}_i^H
\]

\[
\mathbf{w}_3^{(\mathbf{a})}(\mathbf{X}) = \frac{1}{2} \mathbf{A}_i^{(\mathbf{a})} \mathbf{X} \mathbf{a}_i^H
\]

Proposed L-BFGS Approach

The optimization model (1) involves minimizing a nonconvex fourth-order polynomial with some nonlinear equality constraints, which is numerically difficult to handle. Notice that the constant modulus constraints are equivalent to every entry of \( \mathbf{X} \) lying on the unit circle, i.e., \( x_{ij}^2 = 1 \). Using \( \theta \) as optimization variables and writing \( \mathbf{X} \) as \( \mathbf{X}(\theta) \), where \( \phi \) is an \( L \times M \) real matrix, we can drop the constant modulus constraints and formulate (1) as an unconstrained fourth order trigonometric polynomial minimization problem

\[
f(\theta) = \mathbf{w}_1^{(\mathbf{a})}(\theta, \mathbf{X}(\theta)) + \mathbf{w}_2^{(\mathbf{a})}(\mathbf{X}(\theta)) + \mathbf{w}_3^{(\mathbf{a})}(\mathbf{X}(\theta)).
\]

Then we obtain

\[
\mathbf{w}(\mathbf{a}, \mathbf{X}) = f(\theta).
\]

where both \( \theta \) and each entry \( \mathbf{w}(\mathbf{a}, \mathbf{X}) \) are real valued variables. Like (1), the unconstrained optimization model (4) is still nonconvex. However, the unconstrained formulation makes the problem amenable to the use of L-BFGS type iterative procedures which can be implemented efficiently. Moreover, the unconstrained formulation has a strong property that every local minimum is a 1/2-approximation of the global minimum.

Key references


Conclusions

In this paper, we have considered a direct way to synthesize constant modulus waveforms for a MIMO radar. Compared to the state-of-the-art design procedures (e.g., [1]), the proposed procedure (based on the L-BFGS algorithm) offers a comparable better performance and yet is substantially more efficient, especially for situations involving a large number of system parameters. (ycwang@mail.xjtu.edu.cn; luoq@umn.edu)
Covariance Matrix estimation for airborne STAP radar with limited range samples

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Abstract

Space-time adaptive processing (STAP) is an important technique in airborne radar signal processing. In many practical scenarios, the number of range secondary data used for covariance matrix estimation is insufficient due to the limited range of the radar. In this case, the conventional sample covariance matrix, on the other hand, has better performance. To improve the accuracy of covariance matrix estimation, a typical covariance matrix estimator, Bayesian covariance matrix estimation, structured covariance matrix estimation and sparse covariance matrix estimation are given.

Research questions

Space-time adaptive processing (STAP) has excellent performance on single-Doppler clutter suppression. The current methods' covariance matrix estimation is based on the conventional sample covariance matrix (SCM). Generally, secondary data are collected from range samples surrounding the cell under test (CUT), considering that range secondary data are also correlated and the radar's hardware limitation. However, considering that the covariance matrix estimation is based on correlated range secondary data, the performance of the covariance matrix estimation is no longer optimal. In addition, considering the hardware limitation of the radar, the covariance matrix estimation is no longer optimal. In this paper, we propose a method for estimating the covariance matrix based on the Bayesian framework and structured covariance matrix estimation. The introduced covariance matrix estimation method is denoted as the Bayesian covariance matrix estimation. The effectiveness and performance of the proposed method are evaluated through extensive simulations and experiments.

Signal Model

Consider a uniform linear array (ULA) with a separation of half the wavelength and a coherent planar wave propagated perpendicular to the ULA. The received signal at the nth antenna can be expressed as

\[ y_n = x_n + z_n \]

where \( y_n \) is the received signal at the nth antenna, \( x_n \) is the transmitted signal, and \( z_n \) is the noise signal.

Covariance matrix estimation methods

1. Covariance Matrix estimation
   - Cost function: \( \min_{R} \| W_{n} - (R + kI) \| \) subject to \( R \geq 0 \)
   - Where \( W_{n} = \{ y_n y_n^H \} \)
   - Where \( k > 0 \)
   - Return for the solution \( \hat{R} \)
   - Then the covariance matrix can be constructed as
     \[ R = \hat{W} \hat{W}^H + \sigma_n^2 I \]

2. Variance estimation
   - Cost function: \( \min_{R} \| W_{n} - (R + kI) \| \) subject to \( R \geq 0 \)
   - where \( \sigma_n^2 \) is the variance of the noise.

3. Bayesian covariance matrix estimation
   - Cost function: \( \min_{R} \| W_{n} - (R + kI) \| \) subject to \( R \geq 0 \)
   - where \( \sigma_n^2 \) is the variance of the noise.
A. SIMULATION RESULTS

![Simulation Results Diagram]

A simple scenario with 2 targets moving almost straightly is first considered. We compare PMHT-SF to standard PMHT and PMHT-C via 500 Monte Carlo runs in the case of the transition and observation matrix in the form of:

\[
A = \begin{bmatrix}
1 & \alpha \\
\alpha & 1 - \alpha
\end{bmatrix}
\quad \text{and} \quad
N = \begin{bmatrix}
\beta & 1 - \beta \\
1 - \beta & \beta
\end{bmatrix}
\]

To avoid the influence of turning, we only examine how well the state of target 1 is estimated. The performance is quantified by plotting the instantaneous RMS state estimation error. Both the standard PMHT and PMHT-C do poor jobs. As the feature states of both targets may change according to the transition matrix, the probability of the targets to take on different feature observations is actually 0.5. So the PMHT-C can provide little promotion even if its combination matrix updates adaptively. However, by estimating the feature states, PMHT-SF can improve the tracking performance. At some point, the position RMS can be even reduced by 26%.

We then investigate the performance gain obtained in different situations. The value of \(\beta\) varies from 0 to 0.5 and \(\alpha\) from 0.65 to 0.9. Simulation results show that when \(\alpha = \beta\), the number of incorrect feature state estimation increases at the same time, so is the RMS error. It means that the feature observations provide less information when \(\alpha = \beta\) are small.

![Simulation Results Graphs]

A more difficult situation is shown in the following figure. It is then considered. The standard PMHT and PMHT-C algorithms lose a track at the crossover point of the trajectories, while the improved PMHT successfully maintains tracking by using the attributes.

![Simulation Results Graphs]

B. CONCLUSIONS

It has been demonstrated how the probabilistic multi-hypothesis tracker can be extended to include discrete feature information when both the uncertainty of feature states and the instability of feature observing process should be taken into consideration. This extension was tested on a simulated scenario and compared with the standard PMHT and the PMHT-C. The PMHT-SF algorithm was found to give superior performance in terms of estimation error.
An Adaptive Network Selection Scheme Based on the Combination of User Mobility and Traffic Load

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Abstract

The integration of cellular and wireless local area networks (WLANs) has drawn much attention due to its non-backbone characteristics. Based on the combination of users' mobility and network load, this paper proposes an adaptive network selection scheme, called as DNMT (Dynamic Match of Mobility Traffic) scheme. By considering the mobility of the whole users’ movement character and arrival rate, we can get the Mobility Threshold (MT) from the statistics of the whole users’ movement character and arrival rate, and the traffic of the whole users’ movement character and arrival rate, which is the condition of the optimization problem, which minimizes the global network blocking probability. Then we use MT to differential mobile users to access different networks. Simulation results show that the proposed DNMT scheme can reduce cell-to-cell handoff probabilities compared to the referenced schemes.

Introduction

The urge generate wireless communication systems will be heterogeneous networks, which can provide ubiquitous and intelligent services for users by utilizing multiple radio access technologies (RATs). Having wireless networks, e.g., cellular/WLAN, are overlapped common, network selection scheme is needed to decide which network to access when a call arrives. Network selection scheme is one of key radio resource management (RRM) decisions to make the best use of the limited resource. Several papers have proposed network selection schemes that consider users’ mobility [1]-[3]. In [2], the authors use a permutation-based network selection scheme. "Common radio resource management (RRM)" scheme in [3] divides users into three classes: users outside the hotspot area, hotspot users and non-hotspot users by comparing the present threshold and individual users’ mobility characteristics. The threshold is pre-determined before network operation and is a constant to have the network context changes. In similar work of [4]-[5], propose network selection scheme based on prioritization of users. Users are classified as either vehicular or non-vehicular user based on a pre-defined speed threshold. However, scheme in [1][2] only consider individual user’s mobility rather than the multi users’ mobility characteristics. That is to say, none of the above proposals takes into account the distribution of whole users’ mobility and different traffic load levels. Therefore, these schemes will bring unnecessary call blockings and handoffs and can not achieve the performance optimization of the whole network.

Based on the combination of users’ mobility and network load, this paper proposes an adaptive network selection scheme, called as DNMT (Dynamic Match of Mobility Traffic Threshold) scheme. The proposed scheme uses the Mobility Threshold (MT) to differentiate mobile users to access different network. We can get the MT from the statistics of the whole users’ movement character and arrival rate, which is the condition of the optimization problem, which minimizes the global network blocking probability. The optimization problem incorporates the distribution of whole users’ mobility and different traffic load levels. Furthermore, the DNMT scheme takes into account the change of network context, so it provides the intelligent RRM to accommodate the dynamic network context.

System Model

The network is shown in Fig. 1. The whole network is divided into ultra-micro-cellular network, micro-cellular network and macro-cellular network. The ultra-micro-cellular network is characterized by high traffic density and fast user mobility, the micro-cellular network is characterized by low traffic density and fast user mobility, the macro-cellular network is characterized by high traffic density and slow user mobility. In this paper, we consider a three-tier cellular network, where each tier consists of one macro-cell and multiple micro-cells. Each tier is served by a base station (BS), which is connected to the core network through a backbone network. Each BS is equipped with multiple antenna elements and can support multiple users simultaneously. Each user is assumed to have a single antenna. The coverage area of each BS is circular and is determined by the transmission range of the BS. The BSs are arranged in a hexagonal pattern to minimize the overlap of the coverage areas.

Network Selection

When a call arrives in network 1, we have to perform network selection to decide which network to access. The proposed network selection scheme includes the following three steps:

1. **User Mobility and Traffic Load:**
   - The mobile terminal calculates its current location by using the GPS receiver.
   - The mobile terminal measures the signal strength of the competing access networks and calculates the network load, which is the number of active users in each network cell.

2. **Network Performance:**
   - The mobile terminal calculates the performance of each network cell by using the network load and the signal strength.

3. **Network Selection:**
   - The mobile terminal chooses the network with the highest performance and sends a request to the network to establish a connection.

Simulation Results

We compare the proposed scheme with three other network selection schemes, i.e., ÖRanien et al. [4], WLMN [5] and random scheme. The parameters used in all schemes are as follows: the average call holding time is 300s (5 minutes); the capacity of individual cell is C=10; the capacity of individual cell in WLMN is C=10; the call arrival rate is 0.01 per second; the call blocking probability is 0.01; the call cancellation rate is 0.01 per second; the call release rate is 0.01 per second. We compare the following metrics: call success rate, call blocking probability, call cancellation rate, call release rate, network load, and average cell throughput.

Conclusion

This paper proposes an adaptive network selection scheme (DNMT), which considers users' mobility in a multi-tier cellular network. This scheme provides better performance compared to other existing network selection schemes. The results show that the proposed scheme can improve the performance of the heterogeneous network and reduce the call blocking probability and the call cancellation rate. The DNMT scheme can be implemented in a multi-tier cellular network environment to improve its performance.
Maximizing Lifetime in Multi-Source Multi-Relay Non-Regenerative OFDM Networks

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Abstract

This paper presents an allocation strategy for maximizing the lifetime of amplify-and-forward (AF) dual-hop cooperative OFDM networks. The high computational complexity for this problem optimization necessitates our study of suboptimal approaches. We solve the optimization problem in two steps. Specifically, for each source-destination pair, source-relay selection and subcarrier pairing can be decided according to channel state information of the relay links and residual energy information at the relays. Numerical examples verify the effectiveness of our suboptimal algorithm.

Introduction

Recently, multiuser diversity (MUD)-based cooperative networks have attracted substantial research interest. Since many practical networks involve battery-powered nodes or terminals, extending the lifetime of such networks is crucial to guarantee uninterrupted data exchange without having to frequently replace batteries. There exists studies on lifetime maximization for physical-layer cooperative relays. In general, existing works tend to focus on scenarios with flat Rayleigh fading and do not sufficiently account for the gain provided by MUDs.

We propose that by combining orthogonal frequency division multiplexing (OFDM) with MUD-based cooperative relaying strategy, system lifetime can be further improved. To the best of our knowledge, there is no resource allocation approach which provides a solution for this problem. In this paper, we select the optimal relay and subcarrier strategy in each time slot (OSAS) technique to take into account energy power control. Specifically, we adopt subcarrier selection strategy as follows.

Problem Formulation

Consider an amplify-and-forward (AF) wireless network characterized by dual-hop cooperative OFDM links. There are $k_{sr}$ source nodes, $k_{sr}$ destination nodes and $k_{r}$ relays. $k_{sr} = k_{sr} + k_{sr}$. The channel on every hop is subject to orthogonal subcarriers, each approximately experiencing fast fade. A normalized unit power signal is loaded on every subcarrier. The transmission slot $S_{i}$ of each data frame can be divided into two phases equal in time. During the first phase, $S_{i}$, each source sends data to its relay partner $k_{sr}$ with power $P_{sr}$ in the second phase, we adopt the amplify-and-forward scheme where only one out of $k_{sr}$ subcarriers are selected, we introduce an amplified version of the received message at the relay by the destination power $P_{dr}$, and $k_{sr} > k_{sr}$. The channel coefficients of subcarriers $k_{sr}$ and $k_{sr}$ are denoted as $h_{sr}$ and $h_{sr}$, respectively, for the $k_{sr}$ $k_{sr}$, and $k_{sr}$, where $k_{sr}$ is a real random variable.

To maximize the network lifetime, it is of interest for us to solve the optimal strategy for the energy consumption of the network.

Solution

We study a cooperative network consisting of three source nodes and two relay nodes with initial energies $E_{sr}$ and $E_{dr}$.

Define $E_{sr} = E_{sr} + E_{dr}$ as the bandwidth efficiency. Further, the channel coefficients $h_{sr}$, $h_{sr}$, and $h_{sr}$ are independent of zero mean Gaussian noise $w_{sr}$ and $w_{sr}$. The channel model is given by $h_{sr} = h_{sr} + h_{sr}$, where $h_{sr}$ and $h_{sr}$ are zero mean Gaussian noise $w_{sr}$ and $w_{sr}$. The channel model is given by $h_{sr} = h_{sr} + h_{sr}$, where $h_{sr}$ and $h_{sr}$ are zero mean Gaussian noise $w_{sr}$ and $w_{sr}$.

We ensure that the network power is uniformly distributed across all subcarriers.

Numerical results

In this section, we present the numerical results to verify the performance of our proposed strategy.

Conclusion

This paper investigates resource allocation problem to maximize the lifetime of dual-hop multi-source multi-relay non-regenerative OFDM networks. The proposed scheme can be applied in various applications such as wireless video streaming, and wireless sensor networks. The simulation results show that the proposed scheme outperforms the baseline scheme in terms of energy efficiency.

Fig. 1: Bandwidth efficiency versus network lifetime

Fig. 2: Node load versus residual energy

References


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Resolution Enhancement for ISAR Imaging via Bayesian Compressive Sensing

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I. Introduction

In Inverse Synthetic Aperture Radar (ISAR) imaging, the cross-range resolution depends on the long coherent processing interval, which brings great contradiction between resolution and modern radar activities. ISAR image is generally constructed by limited strong scattering centers, representing strong spatial sparsity, which paves a way to resolution enhancement with limited observations by compressive sensing (CS). Assuming that the amplitude of the target scattered field follows an identical Laplace probability distribution, the resolution enhancement imaging is converted into a sparsity-driven optimization in Bayesian statistics sense. It is shown that improved performance is achievable by accounting the spatial structure of the scattered field with non-identical Laplace distribution.

II. Sparsity-driven Resolution Enhancement

Based on Gaussian noise, the likelihood of observations is

$$p(S|A,\sigma^2) = (2\pi\sigma^2)^{-K/2} \exp \left(-\frac{1}{2\sigma^2}(S - FA)\right)$$

where S is the observations, F is a partial Fourier matrix and \( A = [a] \) denotes the resolution enhanced image. For the complex-valued A, we have \( a = u \exp(i\phi) \), where \( u = |a| \) denotes the magnitude and \( \phi \in [0,2\pi] \) is the phase. To representing the sparsity of A, a half-Laplace distribution is imposed on \( u \). and the phase is modeled as complex Gaussian distribution, which leads to the following probability of A based on the assumption that the magnitude and phase are independent.

$$p(A|\gamma) = \prod_{i \in \Omega} \left( \frac{\gamma}{2} \exp \left( -\frac{\gamma}{2} |a_i| \right) + \frac{\gamma}{2\pi} \exp \left( -\frac{\gamma}{2\pi} |\phi_i| \right) \right)$$

According to Bayesian compressive sensing, the sparsity-driven estimator is

$$\hat{A}(S) = \arg \min_{\hat{A}} \left\{ \|S - FA\|_2 + \beta \|A\|_1 \right\}$$

where \( \beta = 2\sigma^2 \gamma \) is defined as the sparsity coefficient, which is directly related to the distributions of noise and image. In above optimization is named by Bayesian super resolution (BSR) method. In BSR, all the components of A are assumed to follow the identical Laplace distribution. However, in reality, the scattered field of a distributed target usually presents the spatial-assembling feature that most significant scattering centers are concentrated around a small region characterizing itself with a specific spatial organization. It is of great potential to substantially improve the performance by leveraging statistics models, which coincides with the target image better. Motivated by the re-weighting CS, we introduce the non-identical Laplace distribution that different scale parameters are used to different components of A, and BSR is transformed into the following form.

$$\hat{A}(S) = \arg \min_{\hat{A}} \left\{ \sum_{i} \left( |s_{i} - F_{i}a_{i}| + \beta \|W_{a_{i}}|a_{i}\|_{W_{a_{i}}} \right) \right\}$$

where \( a_{i} \) denotes the m-th column of A, and \( W_{a_{i}} \) is a diagonal matrix corresponding to the Laplace scale parameters of \( a_{i} \). The optimization is named by improved BSR (IBSR) method. Spectral analysis methods, such as bandwidth extrapolation method, are used as assistant tool to select optimal Laplace distributions.

III. Experimental Results

To study how the sample amount and noise affect the recovery performance, we compare BSR, IBSR and Burg’s BWE, CS and ICS by varying the sample numbers and SNRs.

Fig. 1 Resolution enhancement with 128, 64, 32 and 16 pulses

Fig. 2 Resolution enhancement with SNR 15, 10, 5 and 0dB

IBSR has been applied in ISAR imaging for “Tiangong-1” space station with “Shenzhou-8” spacecraft.

Fig. 3 IBSR imaging for “Tiangong-1” space station

IV. Conclusion

Resolution-enhanced ISAR imaging based on CS is presented. Based on the fact that the scattered field has distinctive spatial configuration, non-identical Laplace distribution is introduced in IBSR, to discriminate the prominent scattering centers from weak ones and noise in the \( \ell_1 \) penalty term, promoting the performance.
Maximizing Lifetime in Multi-Source Multi-Relay Non-Regenerative OFDM Networks

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Abstract

This paper presents a resource allocation strategy for maximizing the lifetime of amplify-and-forward (AF) dual-hop cooperative OFDM networks. The high-complexity (NP-hard) optimization problem is solved in two steps. Specifically, during each transmission interval, source-relay selection and relay-subcarrier assignment are performed to determine which subcarrier will be used. The goal is to maximize the total lifetime of the network. To achieve this, the energy consumption of the network is minimized by carefully selecting the subcarrier in each transmission interval. The proposed algorithm is shown to achieve a significant improvement in lifetime compared to existing methods, and the computational complexity is reduced through the use of convex optimization techniques.
Sparse Error Correction In Wireless Sensor Node Localization

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Overview
- Background: sensor node localization
  We consider non-Gaussian noise in measured distances
- Experimental Study: distance measurements
  We observe large sparse errors in distance measurements
- Objectives:
  Recover sparse errors in distance measurements and localize blind sensor nodes simultaneously
- Algorithm development:
  Norm approximation, SDP relaxation

Background
Sensor node localization: to determine the positions of blind sensor nodes
- Locations: anchors
- Distances: blind nodes

Common assumptions:
- Small dense Gaussian noise
- Measurement noise: most is small while a fraction is much larger
- Approximated as: small dense Gaussian noise + large sparse errors

Why erroneous? Multi-path effect, failure of transmissions, failure of RSSI modules, abrupt environmental interference, etc.

Experimental Study of Distance Measures
The receiver is located at different positions, collecting RSSI readings and computing distances to the transmitter. The estimated distances are compared with the true distances.

![Distance Measurement Diagram](image)

Problem Formulation
- D-dimensional area, N anchors (x_i, i = 1, 2, ..., N), 1 blind node (y)

Squared distance measurement model:
- Small noise
- Large error

Optimization criterion:
\[ \min_{\lambda, \omega, z} \sum_{i=1}^{N} \left[ d_i^2 - \|x_i - y\|^2 + \omega_i + \lambda \|\omega_i\|^2 \right] \]

Least squares of small noise
Sparsity of large errors

Algorithm Development
1. Norm approximation (\| \|
\[ \min_{\lambda, \omega, z} \sum_{i=1}^{N} \left[ d_i^2 - \|x_i - y\|^2 + \omega_i + \lambda \|\omega_i\|^2 \right] \]

2. SDP relaxation:
\[ \min_{\lambda, \omega, z} \sum_{i=1}^{N} \left[ d_i^2 - \|x_i - y\|^2 + \omega_i + \lambda \|\omega_i\|^2 \right] \]

Simulation
1 blind node, N=20 anchors, randomly distributed in a 100 x 100 area; the 20 measured squared distances are appended with i.i.d Gaussian noise \(\sim N(0, \sigma^2)\), randomly \(K=4\) out of them are further polluted by i.i.d Gaussian noise \(\sim N(0, \sigma^2)\), \(\sigma^2 >> \sigma^2\).

Algorithms:
- SDP-I in [1], SDP-I_k in [2], SGO in [3].

\[ \lambda_{opt}=0.085 \] is chosen based on cross-validation

Localization accuracy vs. \(\sigma\)
Localization accuracy vs. \(K\)

Conclusion
We demonstrate the existence of large sparse errors through experiments, and develop an algorithm by utilizing the sparse prior of errors and the technique of SDP relaxation.

References
ON THE LINEAR CONVERGENCE OF A PROXIMAL GRADIENT METHOD FOR A CLASS OF NONSMOOTH CONVEX MINIMIZATION PROBLEMS

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Introduction

Consider an unconstrained nonsmooth convex optimization problem of the form:

\[ \min_{x \in \mathbb{R}^n} J(x) = f(x) + g(x) = \sum_{j \in J} \alpha_j h_j(x) + g(x) \]

where \( J \) is a partition of \( \{1, \ldots, n\} \) and \( \alpha_j \in \mathbb{R}^+ \) some given nonnegative constants; \( f(x) = M_\alpha(x) \) where \( M_\alpha: \mathbb{R}^n \to \mathbb{R} \) is a continuously differentiable strongly convex function and \( A \in \mathbb{R}^{m \times n} \) is a given matrix. Notice that unless \( A \) has full column rank, the \( f(x) \) is not strongly convex.

Motivating Applications

Problem (1) arises in many contemporary statistical and signal processing applications including signal denoising, compressive sensing and sparse linear regression. For example,

\[ \min_{x \in \mathbb{R}^n} \frac{1}{2} \| Ax - b \|_2^2 + \lambda \| x \|_1 \]

where \( A \) is a group lasso, \( \lambda \) is a positive parameter, and \( \| \cdot \|_1 \) is the \( l_1 \) norm.

Proximal Gradient Method

A popular approach to solving Problem (1) is by proximal gradient method (PGM). The Moreau-Yosida proximal operator is defined as

\[ \text{prox}_{\lambda g}(x) = \arg \min_{y \in \mathbb{R}^n} \frac{1}{2} \| y - x \|_2^2 + \lambda g(y) \]

On the convergence of the PGM: Global convergence is given by [1]. The rate of convergence is typically sublinear \( O(1/k) \) [3]. The linear global rate is still unknown except for some special cases. When \( f(x) \) is the indicator function of the polyhedron and \( g(x) = h(x) \), the significance lies in the fact that it does not require strong convexity of \( f(x) \). Tseng [4] again without assuming the strong convexity.

In this paper, we extend Tseng's results of [5]. In particular, we establish the linear convergence of the PGM (2) for the problem (1). Our result significantly strengthens the sublinear convergence rate of PGM in the absence of strong convexity. The key step in the linear convergence proof lies in the establishment of a local error bound which provides an estimate of the distance to the optimal solution set in terms of the size of the proximal gradient vector. We derive and summarize PGM as the following:

**Step 1** Given initial guess \( x^0 \) and a small positive number \( \epsilon > 0 \), set \( k = 0 \).

**Step 2** Select a step size \( \alpha_k \) for some rule, for \( j \in \mathbb{N}_0 \),

\[ x_{k+1} = \left\{ \begin{array}{ll}
\text{argmin}_{x \in \mathbb{R}^n} & f(x) + \lambda \| x \|_1 \\
\quad \text{s.t.} & \| x - x_k \|_2 \leq 2 \alpha_k \|
\end{array} \right. \]

where \( \lambda = \frac{\beta_0}{\alpha_k} \),

\[ x_{k+1} = \left\{ \begin{array}{ll}
\text{argmin}_{x \in \mathbb{R}^n} & f(x) + \lambda \| x \|_1 \\
\quad \text{s.t.} & \| x - x_k \|_2 \leq 2 \alpha_k \|
\end{array} \right. \]

**Step 3** If \( \| x_{k+1} - x_k \|_2 \leq \epsilon \), then stop, else, set \( k = k + 1 \), go to Step 2.

Main Results

- The error bound condition holds for Problem (1).
- PGM (2) for Problem (1) generates a sequence of iterates that converges linearly to an optimal solution.

Conclusions & Extensions

- Developed a proximal gradient method for the problem whose subproblem can be solved efficiently (in closed form).
- Established linear convergence of this method, although the overall objective function is not strongly convex.
- The cases can be considered on the interaction proximal gradient methods or the matrix optimization problems further.
Degrees of Freedom for MIMO Two-Way X Relay Channel

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MIMO Two-Way X Relay Channel
- Two groups of source nodes with $N$ antennas each
- Relay node with $N$ antennas
- Each node in one group exchanges $N$ independent messages with the two source nodes in the other group via the relay node.

Signal Alignment with Joint Interference Cancellation

A Motivating example for $M=5$, $N=8$
We show that $d_1 = d_2 = d_3 = d_4 = d_5 = d_6 = d_7 = d_8 = 2$
can be achieved.

Main Results

Theorem 1: The total number of DoF for this system is upper bounded by

$$d \leq \min \{2M, N\}$$

Achievability: The DoF upper bound $2M$ is achievable by using our proposed transmission scheme, namely, signal alignment with joint interference cancellation when $N=2M$.

Numerical Examples

Simulation setup:
- Power: $P^1 = P^2 = P^3 = P^4 = P$
- Interference Rayleigh fading

For the general $M$ and $N$, we have the following theorem:

Theorem 2: When $M > N$, the necessary and sufficient condition for our proposed transmission scheme to achieve $N=2M$ is $N=2M$. Theorem 2 (Adapted) for $M=8$, $N=16$ is shown in the lower-right corner of the poster.
EXPERIMENTAL IMAGE FORMATION AND ANALYSIS FOR BISTATIC SAR SYSTEMS WITH THE SQUINT TRANSMITTER AND A FIXED RECEIVER
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1. INTRODUCTION
The BISTAR system based on the advantages of opportunities, which include navigation satellite and SAR satellite, has been the research hotspot for years. It has the advantages of agility configuration, abundant information, anti-interception, anti-interference etc.

Fig 1 geometry model

There are two features of BISTAR systems with squint transmitter and fixed receiver. Firstly, the target area is very small because the distance between the squint transmitter and target center is small by taking the power budget into account. Secondly, the squint transmitter will introduce a high order phase term, which is complex to cope with in the signal processing.

2. DISCRITION OF IMAGE FORMATION ALGORITHMS
The flow charts of both classic and extended NLOS algorithms are shown in Fig 2.

(a) classic NLOS    (b) extended NLOS

Fig 2 Block diagrams of the image formation algorithms

3. EXPERIMENTAL RESULTS
The experimental SAR images were acquired using the classic and extended NLOS algorithm, respectively. The final results are shown in the following.

4.1. Experimental images of classic and extended NLOS algorithm
The acquired bistatic images using different algorithms were shown in Fig 4. It is suggested from Fig 4 that the image with extended NLOS has better quality than the one with classic one, which becomes clearer when goes to the responses of strong single scatterer in red rectangles.

(a) Image with classic (left) and extended NLOS (right)

The profiles along range directions of two responses of artificial corner reflector are shown in (b) and the corresponding PNL-B and PSNRs are listed in Table 1.

Table 1 PNL-B and PSNR of single scatterer’s response

<table>
<thead>
<tr>
<th></th>
<th>Classic NLOS</th>
<th>Extended NLOS</th>
</tr>
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<tbody>
<tr>
<td>PNL-B (dB)</td>
<td>4.90</td>
<td>11.07</td>
</tr>
<tr>
<td>PSNR (dB)</td>
<td>20.34</td>
<td>23.56</td>
</tr>
<tr>
<td>SNR (dB)</td>
<td>-0.30</td>
<td>-0.06</td>
</tr>
</tbody>
</table>

After geometry correction, the bistatic image has a very good accordance with the optic one.

(a) Image after geometry correction (red: single scatterer)

4.2. Experimental images in different seasons
The bistatic, monostatic and optic images from the same target area are shown in Fig 6.

(a) winter       (b) summer       (c) winter

Fig 6 Experimental images in different seasons

The final results are given in Fig 8. As the top row from Fig 8, the collected scattering information of crops is acquired, and the corresponding result is shown in Fig 7.

3. CONCLUSION
This paper presents an extended NLOS algorithm for the bistatic SAR systems, with the squint transmitter and a fixed receiver. The experimental results were proved and analyzed to validate the algorithm. Furthermore, this experimental results suggest that the imaging algorithm has the ability to focus the single target acquired by the experimental system.

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Adaptive Beamforming for Nonstationary HF Interference Cancellation in Skywave Over-the-Horizon Radar

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I. Introduction
An adaptive degrees of freedom (DOFs) selection principle for notch-widening partially adaptive beamformer is proposed and a wide notch beam space adaptive multiple side-lobe canceller (MSLC) is developed for nonstationary interference cancellation.

- Nonstationarity of the interference:
  - Antenna motion and/or vibration;
  - Interference motion;
  - Nonstationary propagation medium (e.g., the ionosphere).
- Notch-widening technique:
  - Import robustness into adapted antenna pattern;
  - Alleviate the problem caused by the slow adapted weights relative to the time-varying interference spatial statistical characteristics;
  - Avoid temporal modulation caused by the conventional time-varying weights to the clutter echoes entered the receiver from side lobes of the adapted antenna pattern.
- Beam space adaptive MSLC:
  - Minimum required adaptive DOFs;
  - Robust side lobe structures.

II. Array Signal Processing Model

- Beam space MSLC
- Main beam output:
  \[ y(x) = \sum_{k=1}^{K} s_k(x) w_k(x) + n(x) \]
- Auxiliary beam outputs:
  \[ \tilde{y}(x) = \sum_{k=1}^{K} \tilde{s}_k(x) \tilde{w}_k(x) \]
- Beamforming matrix:
  \[ \mathbf{T} = \begin{pmatrix} w_1(x) & \cdots & w_K(x) \end{pmatrix} \]
- Wiener-Hoff solution:
  \[ \mathbf{w}^* = \mathbf{T}^\dagger \mathbf{S}^{-1} \mathbf{S}^\dagger \mathbf{T} \]

- Wide notch partially adaptive beamforming
  \[ \mathbf{y}(x) = \sum_{k=1}^{K} s_k(x) w_k(x) + n(x) \]

The required adaptive DOFs:
- \( K \times (N - 2) \)

III. Simulative and Experimental Results

- Simulations
  - Cluster Interference magnitude vs. frequency:
    - Magnitude of interference vs. frequency
    - Magnitude of interference vs. frequency
  - Clutter intensity vs. frequency:
    - Clutter intensity vs. frequency
    - Clutter intensity vs. frequency

- Measured data
  - Clutter intensity vs. frequency
  - Clutter intensity vs. frequency

- Normalized Doppler spectrum of the beam space adaptive MSLC output

IV. Conclusion

Wide notch adaptive beamforming is an efficient technique to suppress the nonstationary interference. Several notch widening techniques have been proposed to produce notches with desired width at the directions of the nonstationary interference in the adapted antenna pattern. To produce noise with desired width and depth, a sufficient number of adaptive DOFs are required. On the other hand, insufficient number of adaptive DOFs can not produce the notch with desired width and depth. In the other hand, too many adaptive DOFs may destroy the directive structure of the adapted antenna pattern and additional training samples and computational loads are required.

The relationship between the desired width of the notch and the number of required adaptive DOFs is derived, and the relationship can be used as a principle to allocate the number of adaptive DOFs, computational resources, and storage resources in designing and implementing the adaptive beamforming algorithms.
I. Introduction

It is always a challenging problem for marine surface surveillance radar to detect floating small targets in sea clutter. Due to their weak returns and unobservable Doppler offsets, incoherent integration and adaptive clutter suppression are ineffective. The prediction-based methods using nonlinear neural network learning and the fractal-based methods are difficult to attain satisfactory performance in short observation time of only several seconds. Here, the three features of received time series are extracted for detection and the detection problem boils down to the one-class classification in the anomaly detection. A fast convex hull learning algorithm is proposed to learn the decision region of the clutter-only pattern from the feature vectors of sea clutter in the 3D feature space. As a result, a tri-feature-based detector is proposed. The experimental results to the IPIX radar data sets show that the proposed detector attain good detection performance when the observation time is only ordered several seconds.

II. Problem Description and Analysis of Real Dataset

Problem Description of Sea-surface Floating Small Targets

Assume the radar transmit a coherent pulse train at a beam position. At each range cell, the radar receives a complex-value time series consisting of the I-channel and Q-channel data. As in adaptive detection, target detection in sea clutter can be formulated as the following binary hypothesis test:

\[ H_0: x(n) = c(n), n = 1, 2, ..., N \]
\[ H_1: x(n) = c(n) + e(n), n = 1, 2, ..., N \]

\[ x(n) \] is received time series at the range cell under test (CUT), \( x(n) \) are those at the reference cells around the CUT.

III. Feature Extraction and Detection Capability

Relative average amplitude (RAA) of time series

The denominator is the average value of the amplitude at the \( P \) reference cells and the numerator is the average amplitude of the received time series at the CUT. Because the sea clutter is inhomogeneous along range cells, the relative amplitude can fit the variance of sea clutter level with range to achieve CFAR detection capability.

Relative Doppler peak of Doppler amplitude spectrum

The maximal value and maximum of the Doppler amplitude spectrum

The relative peak height (RPH) of the Doppler spectrum

The RPH on the range-Doppler plane

By a complete analysis on the detection capability of the three features using 10 data sets at the four polarizations, we find the following facts. First, the detection capability of a single feature is quite different from one data set to another data set and at the four polarizations. Second, the detection capability of the three features are compensatory to each other. Each feature has a poor detection capability to a data set, another feature is probably good. Third, when the average SCR is small, the detection capability of the three features all degrade. Therefore, the three features must be jointly used to perform effective detection of sea-surface floating small targets.

Separability of sea clutter and returns with target in the 3D feature space

Sea clutter time series and returns with targets have much better separability in the 3D feature space than at a single feature.

Fig. 1 Average SCR of the ten sets of data at the primary cell and the four polarizations of the Doppler spectrum with relative amplitude on the common target.

Fig. 2 Histograms of the relative power under the null and hypothesis for the fourth data set at the HV polarization.

Fig. 3 Doppler amplitude spectra of sea-clutter time series and returns with target.

Fig. 4 Distributions of the feature vectors of sea clutter and returns with targets in the 3D feature space of the Doppler spectrum with different polarization pairs.
Improved Probabilistic Multi-Hypothesis Tracker
for Multiple Targets Tracking with Discrete Feature

1. INTRODUCTION

The P-MHT applies the GM filter to obtain the MAP estimation of the target states. The quantity of kinematic states $\mathbf{x}$ and prior probabilities $P(w)$ are

$$\mathbf{x}(k) = \mathbf{x}(k-1) + \mathbf{w}(k)$$

where $\mathbf{w}(k)$ is a process noise with zero mean and covariance $\mathbf{Q}$. The state transition functions are defined as

$$\mathbf{x}(k) = \mathbf{f}(\mathbf{x}(k-1), \mathbf{u}(k)) + \mathbf{w}(k)$$

where $\mathbf{f}$ is the state transition function and $\mathbf{u}$ is the control input. The control input is given by

$$\mathbf{u}(k) = \begin{bmatrix} \mathbf{v}(k) \end{bmatrix}$$

where $\mathbf{v}(k)$ is the control input vector. The control input is given by

$$\mathbf{v}(k) = \begin{bmatrix} v_x(k) \\ v_y(k) \end{bmatrix}$$

where $v_x(k)$ and $v_y(k)$ are the control inputs for the $x$ and $y$ directions, respectively.

2. PROBLEM FORMULATION

A. Kinematic Characterization

In the tracking scenario, the target is a moving object with a known motion model. The motion model is characterized by the state transition matrix $\mathbf{F}$ and the control input $\mathbf{u}$.

$$\mathbf{x}(k) = \mathbf{F} \mathbf{x}(k-1) + \mathbf{u}(k)$$

B. Measurement Model

The measurement model is given by

$$\mathbf{z}(k) = \mathbf{H} \mathbf{x}(k) + \mathbf{v}(k)$$

where $\mathbf{z}(k)$ is the measurement vector, $\mathbf{H}$ is the measurement matrix, and $\mathbf{v}(k)$ is the measurement noise.

C. Hypothesis Generation

The P-MHT uses a hypothesis tree to represent the possible target states. Each node in the hypothesis tree represents a possible state of the target. The hypotheses are generated by considering all possible state transitions from the previous state to the current state.

3. GENERATION RESULTS

A. Example of a Hypothesis Tree

B. Example of a Measurement Set

4. CONCLUSION

The P-MHT algorithm is shown to be effective in tracking multiple targets with discrete features. The algorithm is able to accurately track the targets and provide accurate state estimates. The results demonstrate the effectiveness of the P-MHT algorithm in real-world scenarios.
IV Convex Hull Training Algorithm and Tri-feature-based Detector

Problem formulation in the 3D feature space

Target returns are quite different from one radar to another and target returns are unavailable in designing detector. Only clutter vectors and their features are available. The problem boils down to the one-class classifier in anomaly detection. A mass of clutter vectors can be collected and their feature vectors form a training set of the clutter-only pattern $A^n$ such as $R^2 \times 1$. It can be regarded as the samples of the underlying unknown distribution $p(R^2|A^n, 0) = \{ \mathbf{R}_1, \mathbf{R}_2, \ldots, \mathbf{R}_N \} \subset R^2$. Designing a detector is to find the support (decision region) of the distribution $p(R^2)$ at a certain point value only from the training set $A^n$. When the feature vector of the clutter vector at the CUT fails into the support, then the CUT is declared as the clutter-only cell; otherwise, it is declared as a cell with target.

Here, we restrict the decision region to be a bounded convex set in the 3D feature space. In the radar terminology, the problem can be formulated as follows:

$$\max_{\mathbf{A}_n} \{ \mathbf{p}_1, \mathbf{p}_1(1:\mathbf{p}_1) \cdot \mathbf{p}_1(1:\mathbf{p}_1, \mathbf{p}_1(1:\mathbf{p}_1, \mathbf{p}_1(1:\mathbf{p}_1))$$

The problem is often unsolvable unless the two conditional densities have some special form. In fact, $p(R^2)$ is unavailable. Assume that it follows the uniform distribution in a large region $C^n$ covering the possible decision region $C$ of the clutter pattern. Then, the decision probability for the decision region $C$ of the clutter pattern requires $C^n \cap C = \emptyset$.

V Experimental Results and Analysis

Analysis of Experimental results

- In the low sea states, when the average SCR is over 5dB, detection probabilities are over 0.8 at the observation time 4.096 seconds and the false alarm level 0.001. The tri-feature-based detection method achieves satisfactory performance.
- Under the same sea state, detection performance highly depends upon the average SCR. The HV and VV polarizations have higher average SCR and better detection performance than the HH and WV polarizations. This can be interpreted from lower sea clutter level at the cross-polarization from backscattering mechanism of sea surface at a small grazing angle.
- In the moderate sea state, relative small detection probability at high average SCR is mainly because that the floating small target is sometime shadowed by sea waves. Fig. 9 illustrated the short-time average amplitudes at the primary cell and at ten clutter-only cells at the third dataset and the first dataset.

VI Conclusion

A tri-feature-based detection method is proposed to detect sea-surface floating small targets. The experimental results to the IPX dataset show that the tri-feature-based detector attains satisfactory detection performance at low sea states. Additionally, from the analysis of the experimental results, there are several comments on the radars for detection of sea-surface floating targets.

- Cross polarizations are better operation mode in floating small target detection than the linear-polarization mode.
- Detection performance highly depends upon the average SCR. Therefore, in floating small target detection, it is an efficient way to improve the resolution of radar to reduce the area of a resolution cell and lower sea clutter level.
- In the moderate sea states, the shadowing effect is an important factor to degrade detection performance. Because shadowing generally lasts for several strengthening observation time for a test that can reduce the influence of shadowing.
FIVE PROBLEMS ON SIGNAL PROCESSING

1. Clutter mitigation under range ambiguity condition for STAP

Clutter mitigation under range ambiguity condition for STAP

2. Matrix completion for DOA estimation

Matrix completion for DOA estimation

3. Noncooperative Wideband Spectrum Sensing

Noncooperative Wideband Spectrum Sensing

4. Can we solve LCMV-STAP by semidefinite relaxation program?

Can we solve LCMV-STAP by semidefinite relaxation program?

5. Welcome your discussion
Noise Robust Radar HRRP Target Recognition Based on Multitask Factor Analysis With Small Training Data Size

Lan Du, Hongwei Liu, Penghui Wang, Bo Feng, Mian Pan and Zheng Bao (National Lab. of Radar Signal Processing, Xidian University)

I. Introduction
A factor analysis model based on multitask learning (MTL) is developed to characterize the FFT-magnitude feature of complex high-resolution range profile (HRRP), motivated by the problem of radar automatic target recognition (ATR).

1. MTL mechanism:
- Share information among samples from different target aspects and learn the parameters collectively.
- Improve overall recognition performance with small training data size.
- Update the noise parameter in the classification stage: adaptively match the noise parameter of the test sample.
- Increase the recognition distance.

2. Efficient inference is performed via variational Bayes (VB).

II. Model Construction
- Feature extraction
- Complex HRRP samples
- Initial phase sensitivity
- Complex FFT spectrum
- FFT magnitude

III. Experimental Results
- Measured data
- Result analysis

- Recognition performance
- Recognition rate vs SNR
Noise Robust Radar HRRP Target Recognition Based on Multitask Factor Analysis With Small Training Data Size

Lan Du, Hongwei Liu, Penghui Wang, Bo Feng, Mian Pan and Zheng Bao (National Lab. of Radar Signal Processing, Xidian University)

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A factor analysis model based on multitask learning (MTL) is developed to characterize the FFT-magnitude feature of complex high-resolution range profile (HRRP), motivated by the problem of radar automatic target recognition (RATR).

- MTL mechanism: Share information among samples from different targets, and learn the parameters collectively.
- Improve the overall recognition performance with small training data size.
- Update the noise parameter in the classification stage: Adaptively match the noise parameter of the test sample, improve the noise robustness.
- Improve the recognition distance.
- Efficient inference is performed via variational Bayes (VB).

II. Model Construction

- Feature extraction
- Complex HRRP sample
- Complex FFT spectrum
- Measured data

III. Experimental Results

- Measured data
- Noise parameters
- Cross-frequency with DNN
- Cross-frequency with STIFA
- Cross-frequency with STIFA
- Cross-frequency with STIFA
- Cross-frequency with STIFA
- Cross-frequency with STIFA
Improved Probabilistic Multi Hypothesis Tracker for Multiple Targets Tracking with Discrete Feature

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1. INTRODUCTION

To efficiently handle the clutter environment and track multiple targets simultaneously, a multi-hypothesis tracker (MHT) is employed to perform state estimation and track generation. This has been extensively used in many applications such as surveillance, target tracking, and robotics. However, in real-world applications, the measurement model and prior motion have been extensively assumed to be Gaussian, while the real-world environment is often non-Gaussian. To address this, a more robust and flexible approach is needed. The probabilistic multi-hypothesis tracker (PMHT) is a powerful tool for tracking in non-Gaussian environments. However, it suffers from the curse of dimensionality and computational complexity as the number of targets increases. To overcome this issue, a discrete feature-based PMHT is proposed to reduce the computational burden.

2. PROBLEM FORMULATION

A. Model Formulation

The Bayesian filtering framework is used, where the multi-hypothesis filter is defined as the posterior probability of the target states given the measurements. The measurement model is given by

\[ p(y_t|x_t) = \sum_{i=1}^{N} p(y_t|x_t^{i}, z_t) p(x_t^{i}|x_{t-1}) p(x_{t-1}) \]

where \( N \) is the number of possible paths at time \( t \). The measurement model is given by

\[ p(y_t|x_t^{i}, z_t) = \prod_{j=1}^{J} p(y_{t,j}|x_{t,j}^{i}) \]

B. Algorithm Description

The proposed algorithm is a combination of the Kalman filter and the particle filter. The key idea is to use the Kalman filter to update the state estimate of the target, while the particle filter is used to adaptively adjust the number of particles and the state estimate. The algorithm works as follows:

1. Initialization:
   - Initialize the target state and motion model
   - Initialize the particle set

2. Prediction:
   - Update the state estimate using the Kalman filter
   - Propagate the particles according to the motion model

3. Update:
   - Compute the likelihood of each particle given the measurement
   - Resample the particles based on the likelihood

4. Repeat steps 2 and 3 until convergence

The proposed algorithm is effective in handling non-Gaussian environments and can adaptively adjust the number of particles to achieve a good balance between accuracy and computational cost. The algorithm is validated through simulations and real-world experiments, demonstrating its effectiveness in tracking multiple targets in complex environments.

3. CONCLUSIONS

The proposed probabilistic multi-hypothesis tracker is an effective tool for tracking multiple targets in complex environments. It efficiently handles non-Gaussian environments and can adaptively adjust the number of particles to achieve a good balance between accuracy and computational cost. The algorithm is validated through simulations and real-world experiments, demonstrating its effectiveness in tracking multiple targets in complex environments.
Waveform design for MIMO radar based on iterative FFT
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1. Introduction
MIMO radar can transmit different signals via different antennas, which can be flexibly deployed in various environments. Waveform design for MIMO radar aims to achieve the advantages of diversity and flexible designs of transmitted waveforms. Moreover, the working model of radar can be more flexible. In practice, most of methods for transmitted waveform design often take into account to get waveform design with appropriate correlation properties. In order to achieve the waveform with the desired properties, two-phase planar arrays are utilized based on a two-phase correlation property. In this paper, we consider the two-phase planar arrays to achieve the low auto-correlation properties of the desired waveforms. The signal from each antenna is shifted in time, and the desired properties of the transmitted signals are achieved by using a cyclic convolution matrix at an FFT to achieve the low auto-correlation properties of the desired waveforms.

II. Fast waveform design for MIMO radar

As for a MIMO radar system with a uniform linear array (ULA) comprising M transmit antennas with constant length $L = 2, 3, 5, 7$:

$$\text{The signal from each antenna is shifted in time, and the desired properties of the transmitted signals are achieved by using a cyclic convolution matrix at an FFT to achieve the low auto-correlation properties of the desired waveforms.}$$

$$\text{The relationship between MTF and the antenna vector}$$

The signal in the direction of $\theta$, can be written as:

$${\bf x}(t) = \sum_{i=1}^{M} a_i e^{j2\pi f_{\text{carrier}} t}$$

where $a_i$ satisfy the following conditions:

$$a_i = \begin{cases} 1, & \text{if } i \text{ is an even number}, \\ 0, & \text{if } i \text{ is an odd number}. \end{cases}$$

III. Experimental Results

The waveform design for the desired properties can be achieved by solving the following problem:

$$\min \sum_{i=1}^{M} \left| a_i \right|^2$$

subject to

$$\sum_{i=1}^{M} a_i = 1$$

where $\lambda$, $\mu$, and $\nu$ are the auxiliary variables. The waveform design problem can be solved by minimizing the cost function with respect to $a_i$ and $\lambda$.

The correlation function in the problem phase can be minimized cyclically with respect to the variables $\lambda$ and $\mu$. The correlation between the transmitted signals and the desired properties of the transmitted signals are achieved by using a cyclic convolution matrix at an FFT to achieve the low auto-correlation properties of the desired waveforms.
Joint Power and Bandwidth Allocation for Centralized Target Tracking in Multistatic Radar Systems
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I. Introduction

With the recent advances in centralized and cognitive signal processing, multistatic radar systems (MSRs) have become an attractive platform for centralized target tracking, where the definition of centralized is that a fusion center aggregates and processes information from all nodes in the network in real time. However, these systems commonly have limited resources, such as the total energy of each radar and the total time-processing capacity of the fusion center. For applications, it is advantageous to limit the total transmitted power and the number of the data collected in the fusion center at each time index, which, according to Nyquist sampling theory, is related to the maximum number of targets that can be tracked by each radar. Therefore, in this paper, a performance-driven resource allocation algorithm is proposed for single-target centralized tracking in MSRs. A general joint power and bandwidth allocation scheme is proposed to optimize the joint power and bandwidth allocation among the nodes.

II. The Resource Allocation Strategy

1. Performance Metric of Resource Allocation Strategy

As we know, the ROC performance depends on the performance of all estimated parameters of the target state. Generally, it can be derived as:

\[ J(\theta_0) \]

where \( J(\theta_0) \) is the RNN, which can be calculated as:

\[ J(\theta_0) = J_x(\theta_0) + J_y(\theta_0) \]

where \( J_x(\theta_0) \) and \( J_y(\theta_0) \) is the fitness of joint estimation and the observed data, respectively. \( \theta_0 \) is the covariance matrix of the estimated parameters. \( J_x(\theta_0) \) is the joint estimation of the observed parameters, and \( J_y(\theta_0) \) is the joint estimation of the observed parameters.

The diagonal elements of \( J_x(\theta_0) \) shows how well each target parameter is estimated and the observed data, respectively, \( \theta_0 \) is the covariance matrix of the estimated parameters. \( J_x(\theta_0) \) is the joint estimation of the observed parameters, and \( J_{\theta}(\theta_0) \) is the joint estimation of the observed parameters.

2. Metric Value Function for Joint Power and Bandwidth Budget

As the given total transmitted power \( P_{\text{total}} \) and a data processing capacity \( c_i \) of the fusion center, the aim of our work is to optimally allocate the power and bandwidth resources which can result in the maximization of the estimated RNN.

The general framework of the multistatic radar system is shown in Fig. 1. The problem of multistatic radar systems with non-linear time-varying channel models is formulated as follows:

\[ \min \left\{ \sum_{i=1}^{N} P_i \right\} \text{ subject to} \]

\[ \sum_{i=1}^{N} \sum_{j=1}^{M} B_{ij} \leq B_{\text{total}} \]

where \( P_i \) is the transmitted power of the \( i \)-th radar, \( B_{ij} \) is the bandwidth of the \( j \)-th channel of the \( i \)-th radar, \( B_{\text{total}} \) is the total bandwidth, and \( N \) is the number of radars.

It is shown that the above resource allocation problem is non-linear and non-convex and is solved by the CMA-ES algorithm.

III. Experimental Results

![Image of experimental results](image-url)
OUTAGE CONSTRAINED DISTRIBUTED MULTICELL COORDINATED BEAMFORMING: A DYNAMIC PRICING SCHEME

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\textbf{Abstract}

This work investigates the distributed coordinated beamforming design problem in multicell systems. We assume that only channel distribution information (CDI) is available at the transmitters, and aim to maximize the system throughput under individual power constraints and rate outage constraints. We devise a dynamic pricing mechanism by which the transmitters can optimize their beamformers in a fully parallel manner, using only local CDI and exchanging a few amount of messages with other transmitters. Simulation results demonstrate excellent performance of the proposed dynamic pricing algorithm.

\textbf{Non-Cooperative Game Formulation}

- Previously proposed SCA algorithm (U2021) is centralized and still complex.
- A naive strategy: Each user maximizes its own rate (utility) selfishly.
- Outage constraint is still complex.
- Observations:
  1) The outage constraint holds with equality at the optimum.
  2) The outage constraint function is strictly increasing with respect to $\frac{1}{w_i}$, $\sum_i w_i$.

\textbf{Dynamic Pricing Algorithm}

- Proposed Dynamic Pricing Algorithm:
  1) For all $i \in \{1, \ldots, K\}$, transmitter $i$ updates its beamformer by solving (PG).
  2) For all $i \in \{1, \ldots, K\}$, transmitter $i$ updates the prices $(\lambda_{i,x}, \lambda_{i,y})$ according to

\begin{align*}
\lambda_{i,x} &= \frac{1}{2} \left(1 - \frac{w_i}{w_{max}(Q_i)}\right)^2 \\
\lambda_{i,y} &= \frac{1}{2} \left(1 - \frac{w_i}{w_{max}(Q_i)}\right)^2
\end{align*}

where $w_{max}(Q_i)$ is the principal eigenvector of $Q_i$ (maximum ratio transmission (MRT)).

- Proposition 2: Any convergent point of the proposed dynamic pricing algorithm is a stationary point of (P).

\textbf{Problem Formulation}

- Outage constrained coordinated beamforming design:

$$
\min_{\bf{w}} \quad \sum_i w_i \\
\text{s.t.} \quad R_i \geq \frac{\lambda_i}{w_i}, \quad \sum_i w_i \leq 1
$$

- Closed-form expression of the outage constraint:

$$
\eta_i(w_i) = \frac{1}{\lambda_i} \left(1 - \frac{w_i}{w_{max}(Q_i)}\right)^2 \\
\sum_i \eta_i(w_i) \leq 1
$$

- Proposition 1: Problem (PG) can be optimally solved by convex relaxation.

\textbf{Interference Coordination}

- MRT does not handle the interference.
- Interference coordination by penalizing inter-cell interference.
- Pricing non-cooperative game (PG) [Huang2006]
An Approach to Network Transmit Beamforming by Noncooperative Game

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Motivation

• Interference management is one of the main tasks in a wireless communication system with multiple cells which share the same frequency band.
• To mitigate the mutual cell interference, the base station of each cell employs an M-element uniform circular arrays (UCA) for downlink transmit beamforming.
• We formulate this downlink network transmit beamforming by a noncooperative game and propose to solve the transmit beamforming vectors of all the cells by dynamic system methods.

Basic Principle

• Nash Equilibrium of Noncooperative Game

A noncooperative game is often performed in the form that player i ∈ ℤ = {1, 2, . . . , K} chooses its strategy from its own pure-strategy space Xi and gets the payoff u(i) [1], where each player’s objective is to maximize its own payoffs (utility function).

A pure strategy profile x* = {x1*, x2*, . . . , xK*} is defined as a Nash Equilibrium (NE) for all the players if for i, u(i)(x1*, . . . , xi, . . . , xK*) ≥ u(i)(x1*, x1*, . . . , xi, . . . , xK*), ∀xi ∈ Xi

Dynamic System

A dynamical system is a system that evolves in time through the iterated application of an underlying dynamical rule, which is often represented by a set of first-order differential equations (ODE’s) [2, 3, 4].

\[ x = f(x), \quad x(0) = x_0 \]

To approach the solution of ODE’s, the Runge-Kutta methods are important numerical iterative methods to be employed.

Relationship Between Nash Equilibrium and Stationary Points of Dynamic System

In a noncooperative game, under the assumption that each player’s payoff utility u(i) is twice continuously differentiable on X, and pseudoeconvex with respect to x, we have the following Propositions:

Proposition 1 [5]: x* is a Nash equilibrium if and only if x* ∈ X1 × X2 × . . . × XK ⊂ ℜN is the solution of the variational inequality

\[ (F(x*), x - x*) ≤ 0, \quad \forall x ∈ X, \]

where X is a given closed convex set and F is a given function from \( X \to \mathbb{R}^N \) i.e. \( F(x) = \left( \frac{\partial u_1}{\partial x}, \frac{\partial u_2}{\partial x}, \ldots, \frac{\partial u_K}{\partial x} \right) \).

The relationship between the variational inequality and the associated dynamical system is given by the following Proposition.

Proposition 2 [6]: Assume that x is a convex polyhedron, then the stationary points of the ODE’s

\[ \pi(x, - F(x)), \quad x(0) = x_0 \in X \]

coincide with the solutions of variational inequality

\[ (F(x*), x - x*) ≥ 0, \quad \forall x ∈ X, \]

where

\[ \pi(x, - F(x)) = \lim_{\varepsilon \to 0} P(x + \varepsilon F(x)) - x \]

\[ P(x) = \arg \min_{x' \in X} \| x' - x \|. \]

Notice that Proposition 2 implies that the Nash Equilibrium of a noncooperative game is consistent with the stationary point of the associated ODE’s.

System Model

Consider a wireless communication system of K cells, where each cell has one base station and a single user [6, 9].

Notation

• \( u_i(t) \) : the signal transmitted to k-th cell user with \( E[|u_i(t)|^2] = 1 \).
• \( w_i(t) \) : the transmit beamforming vector of k-th cell base station.
• \( \theta_k \) and \( \phi_k \) : the elevation and azimuth of the angle arrived at the k-th cell user from the j-th cell base station.
• \( \beta_j \) : the bit rate.
• \( \eta_j \) : the SNR.
• \( \gamma_j \) : the sum power of the interfering cell basestation.
• \( \gamma_k \) : the sum interference caused by the k-th base station to all other users.
• \( \lambda \) : the unit cost of the transmit power.
• \( \gamma \) : the unit cost of interference.

The transmit beamforming vector \( w_i(t) \) is given by

\[ w_i(t) = \left[ w_{i1}(t), \ldots, w_{iK}(t) \right]^T, \]

\[ \frac{\partial w_i(t)}{\partial x} = \left[ \frac{\partial w_{i1}(t)}{\partial x}, \ldots, \frac{\partial w_{iK}(t)}{\partial x} \right]^T. \]

Numerical Results

• Simulation parameters

  - \( M = 6 \) or \( M = 16 \) elements uniform circular array with half wavelength spacing and each cell user is with a single antenna element.
  - The location of cell users are random within the plane range with the semidiameter of \( \sqrt{C} \), where \( C \leq 3M \).
  - Choose all the initial transmit beamforming vector as \( w_i(0) = \left[ 1, 0, \ldots, 0 \right]^T \), and run 2000 iterations.

  - \( p_1 = 1 \).
Operative Game and Dynamical System Methods

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- Simulation Results for 8 elements UCA

1. $\alpha = 1$, $\beta = 0.1$, $p = 1$, $\gamma = 0$, $c_1^2 = 1.0e - 01$.
- $||w||$: 2.6639 2.5955 2.6058 2.6788 2.5767 2.6096 2.6456
- $\gamma$: 2.9732 1.9912 3.0375 3.7053 1.8191 2.0798 2.5359
- $w_1, w_2, w_3$: 6.2683 2.9793 3.7024 2.8150 10.2483 6.6988 3.4455

2. $\alpha = 1$, $\beta = 0.1$, $p = 1$, $\gamma = 0.1$, $c_1^2 = 1.0e - 01$.
- $||w||$: 2.0784 2.3802 2.3204 2.5688 1.7738 2.1293 2.3515
- $\gamma$: 3.0212 2.4109 3.7069 4.4082 2.7038 2.4737 2.8549
- $w_1, w_2, w_3$: 2.8465 1.2602 1.7615 0.9899 3.6760 2.5608 1.5463

User 1’s desired direction: 283°
Interference directions: 83°, 161°, 224°, 275°, 323°, 16°

User 2’s desired direction: 336°
Interference directions: 286°, 224°, 248°, 270°, 303°, 329°

User 3’s desired direction: 46°
Interference directions: 343°, 33°, 282°, 308°, 337°, 5°

User 4’s desired direction: 320°
Interference directions: 18°, 52°, 77°, 328°, 350°, 24°

- Simulation Results for 16 elements UCA

1. $\alpha = 1$, $\beta = 0.1$, $p = 1$, $\gamma = 0$, $c_1^2 = 1.0e - 01$.
- $||w||$: 2.6639 2.6712 2.6696 2.6463 2.6599 2.6487
- $\gamma$: 2.9025 3.2903 3.6507 3.6029 2.5013 2.7494 2.5949
- $w_1, w_2, w_3$: 3.5095 2.9165 1.9691 0.9419 6.2087 2.3662 1.1603

2. $\alpha = 1$, $\beta = 0.1$, $p = 1$, $\gamma = 0.1$, $c_1^2 = 1.0e - 01$.
- $||w||$: 2.6367 2.4167 2.5028 2.5097 2.2466 2.2809 2.6661
- $\gamma$: 3.7395 4.2850 4.7022 4.1334 2.9728 3.5728 3.2028
- $w_1, w_2, w_3$: 0.0099 0.5066 0.4511 0.4016 2.0493 0.7593 0.9161

References