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1. MISO Channel Estimation and Tracking from Received Signal Strength Feedback

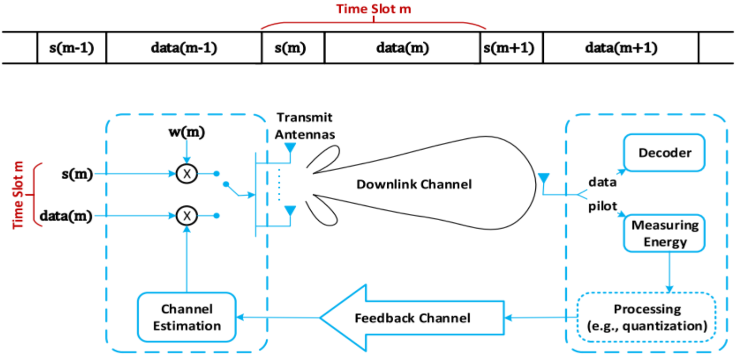
Authors: Tianyu Qiu , Xiao Fu , Nicholas D. Sidiropoulos , and Daniel P. Palomar

Goal: Estimate the channel using Received Signal Strength (RSS) / Channel Quality Indicator (CQI) feedback.

- All existing and emerging wireless communication systems provide basic Received Signal Strength (RSS) / Channel Quality Indicator (CQI) feedback to compensate for temporal channel variations.
- It can track the vector MISO channel from RSS/CQI feedback alone if one employs time-varying beamforming and phase modulation together with phase retrieval ideas from optics and crystallography..
- Three efficient algorithms that cover different model assumptions are proposed to track the vector MISO channel on the transmitter side using only RSS/CQI feedback.

1. Problem Statement

We first consider a MISO channel.



$$z(m) = \mathbf{w}^H(m)\mathbf{h}(m)s(m) + v(m) \in \mathbb{C}$$

$$y(m) = |z(m)| = |z(m)s^*(m)| = |\mathbf{w}^H(m)\mathbf{h}(m) + v(m)s^*(m)|, \forall m$$

1. Proposed Algorithms

Here, $v(m) \sim \mathcal{CN}(0, \sigma_v^2)$. RSS is given by $|z(m)|^2$ and is related to CQI by $(|z(m)|^2 - \sigma_v^2)/\sigma_v^2$.

$$y(m)e^{j\phi(m)} = \mathbf{w}^H(m)\mathbf{h}(m) + n(m), \ \forall m$$

$$\min_{\{\mathbf{h}(m),\phi(m)\}_{m=1}^M} \sum_{m=1}^{M} |y(m)e^{j\phi(m)} - \mathbf{w}^H(m)\mathbf{h}(m)|^2$$

- Recursive Phase Retrieval

  A. Forgetting Factor Based Formulation

$$\min_{\mathbf{h},\{\phi(m)\}_{m=1}^M} \sum_{m=1}^{M} \lambda^{M-m}|y(m)e^{j\phi(m)} - \mathbf{w}^H(m)\mathbf{h}|^2$$

  B. An Efficient Recursive Algorithm

$$\min_{h,\varphi_M} \|\mathbf{D}_M^\lambda \mathbf{D}_M^y e^{j\varphi_M} - \mathbf{D}_M^\lambda \mathbf{W}_M \mathbf{h}\|_2^2$$

1. Proposed Algorithms

$$\mathbf{h}(m) = \alpha \mathbf{h}(m-1) + \mathbf{u}(m),\ \forall m = 1, 2, ...$$

$$(h(M), \{\phi(m)\}_m) = arg\ \min_{h, \varphi_M} \|\mathbf{C}_M^{-1/2}(\mathbf{D}_M^y e^{j\varphi_M} - \mathbf{D}_M^\alpha \mathbf{W}_M \mathbf{h})\|_2^2$$

- Generalized Maximum Likelihood Estimation-One step Gradient (GMLE-G)

$$\boldsymbol{\varphi}_M^{(t+1)} \leftarrow \arg\min_{\boldsymbol{\varphi}_M} g\left(\mathbf{h}^{(t)}, \boldsymbol{\varphi}_M\right),$$

$$\mathbf{h}^{(t+1)} \leftarrow \arg\min_{\mathbf{h}} g\left(\mathbf{h}, \boldsymbol{\varphi}_M^{(t+1)}\right),$$

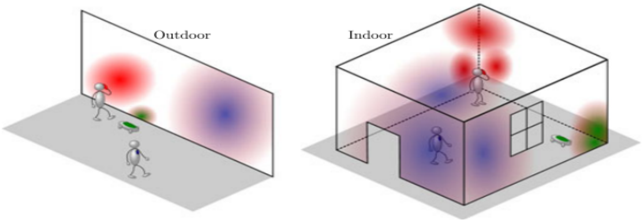
- Generalized Maximum Likelihood Estimation-One step Gradient (GMLE-D)

$$\mathbf{u}^{(t+1)} \leftarrow \arg\min_{|u_m|=1, \forall m} g\left(\mathbf{h}^{(t)}, \mathbf{u}\right)$$

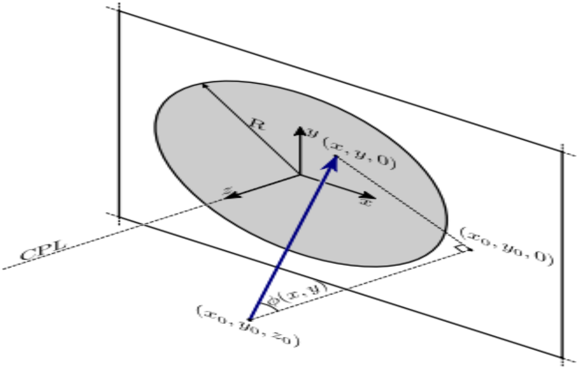
2. Beyond Massive MIMO: The Potential of Positioning With Large Intelligent Surfaces

Authors: Sha Hu , Fredrik Rusek , and Ove Edfors

- It considers the potential for positioning with a system where antenna arrays are deployed as a large intelligent surface (LIS), which is a newly proposed concept beyond massive multi-input multi-output (MIMO).



2.Signal Model



$$\hat{s}_{x_0,y_0,z_0}(x,y) = s_{x_0,y_0,z_0}(x,y) + n(x,y),$$

$$s_{x_0,y_0,z_0}(x,y) = \frac{\sqrt{z_0}}{2\sqrt{\pi}\eta^{\frac{3}{4}}} \exp\left(-\frac{2\pi j\sqrt{\eta}}{\lambda}\right),$$

2. CRLB

We denote an useful parameter, $\tau = (R/z_0)^2$,

- Terminal on the CPL

$$C_{x,y}([0,\ 0,\ z_0], R) = 16\tau^{-2}\left(\frac{1}{z_0^2} + \frac{4\pi^2}{\lambda^2}\right)^{-1} + o(\tau^{-2}),$$

$$C_z([0,\ 0,\ z_0], R) = 16\tau^{-1}\left(\frac{13}{z_0^2} + \frac{16\pi^2}{\lambda^2}\right)^{-1} + o(\tau^{-1})$$

- Terminal not on the CPL

$$C_{x,y} \approx \frac{4\lambda^2 z_1^5}{\pi^2 z_0 R^4},$$

$$C_z \approx \frac{\lambda^2 z_0^2}{\pi^2 R^2} + \frac{4\lambda^2 (x_0^2 + y_0^2) z_1^5}{\pi^2 z_0^3 R^4}.$$

- Phase uncertainity in analog circuits of the LIS

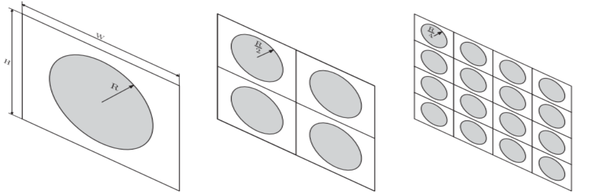
$$\tilde{s}_{x_0,\, y_0,\, z_0}(x, y) = \frac{\sqrt{z_0}}{2\sqrt{\pi}\eta^{3/4}} \exp\left(j\left(-\frac{2\pi\sqrt{\eta}}{\lambda} - \varphi\right)\right)$$

2. CRLB

$$C_z \approx \frac{48\lambda^2}{\pi^2\tau^3}\left(1+\frac{12\lambda^2}{\pi^2 z_0^2\tau^2}\right)^{-1},$$

$$C_\varphi \approx \frac{4}{\tau\lambda^2}\left(\lambda^2+4\pi^2 z_0^2\right).$$

- Deployment of the LIS



(a) Centralized: Single LIS. (b) Distributed: 4 half-scale LISs. (c) Well distributed: 16 quarter-scale LISs.

$$I_{x,y} \approx \frac{\pi^2 z_0 R^4}{16\lambda^2(z_0^2+D^2)^{5/2}} + \frac{\pi^2 D^2 z_0 R^2}{2\lambda^2(z_0^2+D^2)^{5/2}},$$

$$I_z \approx \frac{\pi^2 R^2 z_0^3}{\lambda^2(z_0^2+D^2)^{5/2}},$$

3. Atomic Norm Minimization for Modal Analysis From Random and Compressed Samples

Authors: Shuang Li, Dehui Yang, Gongguo Tang, and Michael B. Wakin

- Modal analysis is the process of estimating a system modal parameters, such as its natural frequencies and mode shapes.
- There is a growing interest in developing automated techniques for structural health monitoring (SHM) based on data collected in a wireless sensor network.
- In order to conserve power and extend battery life, however, it is desirable to minimize the amount of data that must be collected and transmitted in such a sensor network.
- The paper highlights the fact that modal analysis can be formulated as an atomic norm minimization (ANM) problem, which can be solved efficiently and in some cases recover perfectly a structure mode shapes and frequencies.

3. Atomic Norm

Suppose a data matrix $\mathbf{X} = [\mathbf{x}_1, \ldots, \mathbf{x}_N]$ of size $M \times N$.

$$x_i = \sum_{k=1}^{K} c_{k,i} a(f_k)$$

$$a(f) = [e^{j2\pi f 0}, \ldots, e^{j2\pi f(M-1)}]^T$$

$$A(f, b) = a(f) b^*$$

$$\mathcal{A} = \{A(f, b) : f \in [0, 1), \|b\|_2 = 1\}$$

$$\|\mathbf{X}\|_{\mathcal{A}} = inf\{t > 0 : \mathbf{X} \in t\, conv(\mathcal{A})\}$$

$$x^*(t) = \sum_{k=1}^{K} A_k \psi_k^* e^{j2\pi F_k t}$$

$$T = \{t_1, \ldots, t_M\} = \{0, T_s, \ldots, (M-1)T_s\}$$

$$\mathbf{X}^\star = \sum_{k=1}^{K} A_k \begin{bmatrix} \psi_{1,k}^\star e^{j2\pi F_k t_1} & \cdots & \psi_{N,k}^\star e^{j2\pi F_k t_1} \\ \vdots & \ddots & \vdots \\ \psi_{1,k}^\star e^{j2\pi F_k t_M} & \cdots & \psi_{N,k}^\star e^{j2\pi F_k t_M} \end{bmatrix}$$

$$= \sum_{k=1}^{K} |A_k| \begin{bmatrix} \psi_{1,k} e^{j2\pi f_k 0} & \cdots & \psi_{N,k} e^{j2\pi f_k 0} \\ \vdots & \ddots & \vdots \\ \psi_{1,k} e^{j2\pi f_k (M-1)} & \cdots & \psi_{N,k} e^{j2\pi f_k (M-1)} \end{bmatrix}$$

$$= \sum_{k=1}^{K} |A_k| \boldsymbol{a}(f_k) \boldsymbol{\psi}_k^\top = \sum_{k=1}^{K} |A_k| \mathbf{A}(f_k, \boldsymbol{b}_k),$$

3. Measurement Schemes

A. Modal Analysis for noiseless signals:-
It considers five measurement schemes:-

- uniform sampling

$$\hat{X} = arg \min_X \|X\|_{\mathcal{A}} \, s.t., X = X^*$$

- synchronous random sampling

$$\hat{X} = arg \min_X \|X\|_{\mathcal{A}} \, s.t., X_{\Omega_S \times [N]} = X^*_{\Omega_S \times [N]}, \, \Omega_S \subset T$$

- asynchronous random sampling

$$\Omega_A \subset T \times [N]$$

- random temporal compression

$$y_n = \Phi_n x_n^*,\ n = 1, \ldots, N.$$

$$\hat{X} = arg\ \min_X \|X\|_{\mathcal{A}},\ s.t.$$

$$y_n = \Phi_n x_n^*,\ n = 1, \ldots, N,$$

$$X = [x_1, \ldots, x_N],$$

- random spatial compression

$$y_m = \langle {X^*}^T(:, m), \tilde{b}_m \rangle = \langle {X^*}^T(:, m), \tilde{b}_m\, \tilde{e}_m^T \rangle,\ m = 1, \ldots, M, \tilde{b}_m \in \mathbb{C}^{N\times 1},$$

$$\hat{X} = arg\ \min_X \|X\|_{\mathcal{A}},\ s.t.\ y_m = \langle X^T(:, m), \tilde{b}_m\, \tilde{e}_m^T \rangle, 1 \leq m \leq M$$

3. Modal Analysis for Noisy Signals

$$Y = X^* + W,$$

entries of W satisfy $\mathcal{CN}(0, \sigma^2)$ and we consider the following atomic norm denoising problem:

$$\min_X \frac{1}{2}\|Y - X\|_F^2 + \lambda\|X\|_{\mathbb{A}}$$

4. Sketched Subspace Clustering

- The immense amount of daily generated and communicated data presents unique challenges in their processing.
- Subspace clustering (SC) is a relatively recent method that is able to successfully classify nonlinearly separable data in a multitude of settings.
- SC methods incur prohibitively high computational complexity when processing large volumes of high-dimensional data.
- The paper introduces a randomized scheme for SC, termed as Sketch-SC, tailored for large volumes of high-dimensional data.

4. Problem Statement

Consider the following optimization problem

$$\min_{A \in \mathcal{C}} h(A) + \lambda L(X - BA)$$

B is an appropriate $D \times n$ basis matrix (dictionary), $h(A)$ is a a regularization function of the $n \times N$ matrix A. L(.) is an appropriate loss function, and $\mathcal{C}$ is a constraint set for A.
For SSC, LSR and LRR, $B = X$, $n = N$ and $h(.)$ is $\|.\|_1, \frac{1}{2}{}^2_F, \|.\|_*$, and $L(.)$ is $\frac{1}{2}\|^2_F, \frac{1}{2}\|^2_F$ and $\frac{1}{2}\|^2_F$ or $\frac{1}{2}\|_{2,1}$ respectively. Constraint for SSC is $\mathbb{C} = \{A \in \mathbb{R}^{N \times N} : A^T 1 = 1; diag(A) = 0\}$, while for LSR and LRR, we have $\mathcal{C} = \mathbb{R}^{N \times N}$.

$\hat{X} = \hat{R}X$ and $\hat{B} = \hat{X}R$

$$\min_A h(A) + \lambda L(\hat{X} - \hat{B}A)$$

Here, $\hat{R}$ be a $d \times D$ JLT matrix, where $d << D$

Other Papers

- Self-Interference Cancelation Through Advanced Sampling ... *M. Bernhardt, F. Gregorio, J. Cousseau, and T. Riihonen*
- Low-Complexity Massive MIMO Subspace Estimation and Tracking From Low-Dimensional Projections ... *S. Haghighatshoar and G. Caire*
- Sparse Activity Detection for Massive Connectivity ... *Z. Chen, F. Sohrabi, and W. Yu*
- High-Dimensional MVDR Beamforming: Optimized Solutions Based on Spiked Random Matrix Models ... *L. Yang,M. R.McKay, and R. Couillet*