Fast Distributed Beamforming without Receiver Feedback

Kushal Chakrabarti, Amrit S. Bedi, Fikadu T. Dagefu, Jeffrey N. Twigg, and Nikhil Chopra

University of Maryland College Park U.S. Army Research Laboratory, Adelphi

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Distributed Beamforming

Objective

- Wireless Communication in Presence of Near-peer Adversaries
- Increasing Operational Tempo of Future Battles (Requires Autonomy)
- Reliability in Complex Environments (e.g., Dense Urban, Indoors, Forests)

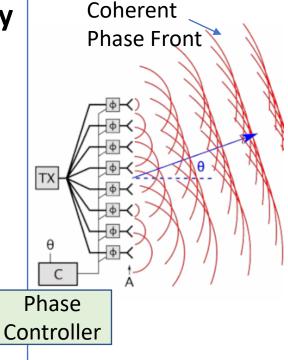
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Inspiration: Phased Antenna Array

- Creates coherent signal using multiple antennas
- ☐ Directional, Controlled Pattern
 - Covert Communications
 - Targeted Jamming
 - Radar
- ☐ Electronically steerable
- ☐ Gain is N^2
 - 5 Element Array @2W
 - = 1 50W Tx



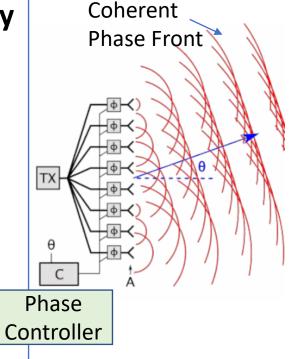
Distributed Beamforming

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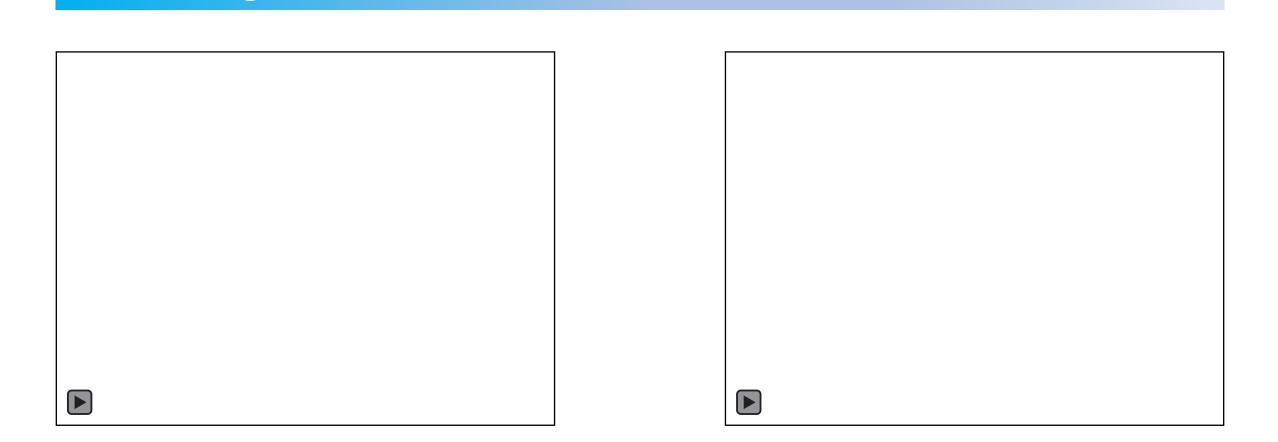
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Distributed Robotic Beamforming Distributed **Across** Robots ☐ Distributed, resilient to singleagent failure ☐ Agile, composed of evolving robot swarm ☐ Adapt to environment and nearpeer adversary



Controlling Covert Directional Communication

How do we autonomously control signal strength (signature management) in different desired directions simultaneously?

Existing Works

	Prior Works
[1]- [4]	objective: maximizing gain or steering nulls at specific locations
[5]- [7]	utilize receiver feedbacks
[8] <i>,</i> [9]	sparse beamforming, mobile agents
[7] <i>,</i> [10]	channel model-free [7], probabilistic channel prediction and path planning for minimizing power [10]
[11]	receiver feedback-free

[1] D Richard Brown, Upamanyu Madhow, Patrick Bidigare, and Soura Dasgupta. Receiver-coordinated distributed transmit nullforming with channel state uncertainty. In 2012 46th Annual Conference on Information Sciences and Systems (CISS), pages 1–6. IEEE, 2012.

[2] Yongsheng Fan, Yuanping Zhou, Donglin He, and Wenlong Xia. Fast transmit beamforming with distributed antennas. IEEE Antennas and Wireless Propagation Letters, 16:121–124, 2016.

[3] Sairam Goguri, Ben Peiffer, Raghu Mudumbai, and Soura Dasgupta. A class of scalable feedback algorithms for beam and null-forming from distributed arrays. In 2016 50th Asilomar Conference on Signals, Systems and Computers, pages 1447–1451. IEEE, 2016.

[4] Justin S Kong, Fikadu T Dagefu, and Brian M Sadler. Distributed adaptive beamforming and nullforming for secure wireless communications, March 31 2022. US Patent App. 17/205,355.

[5] Amy Kumar, Raghuraman Mudumbai, Soura Dasgupta, Upamanyu Madhow, and D Richard Brown. Distributed MIMO multicast with protected receivers: A scalable algorithm for joint beamforming and nullforming. IEEE Transactions on Wireless Communications, 16(1):512–525, 2016.

[6] Jemin George, Anjaly Parayil, Cemal Tugrul Yilmaz, Bethany L Allik, He Bai, and Aranya Chakrabortty. Multi-agent coordination for distributed transmit beamforming. In 2020 American Control Conference (ACC), pages 144–149. IEEE, 2020.

[7] Jemin George, Cemal Tugrul Yilmaz, Anjaly Parayil, and Aranya Chakrabortty. A model-free approach to distributed transmit beamforming. In ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 5170–5174. IEEE, 2020.

[8] Anjaly Parayil, Amrit Singh Bedi, and Alec Koppel. Joint position and beamforming control via alternating nonlinear least-squares with a hierarchical gamma prior. In 2021 American Control Conference (ACC), pages 3513–3518. IEEE, 2021.

[9] Tzanis Anevlavis, Jonathan Bunton, Anjaly Parayil, Jemin George, and Paulo Tabuada. To beam or not to beam? beamforming with submodularity-inspired group sparsity. In 2020 59th IEEE Conference on Decision and Control (CDC), pages 390–395. IEEE, 2020.

[10] Arjun Muralidharan and Yasamin Mostofi. Energy optimal distributed beamforming using unmanned vehicles. IEEE Transactions on Control of Network Systems, 5(4):1529–1540, 2017.

[11] Samer Hanna, Enes Krijestorac, and Danijela Cabric. Destination-feedback free distributed transmit beamforming using guided directionality. arXiv preprint arXiv:2108.01837, 2021

Comparison with Existing Works

Prior Works	Our Work
objective: maximizing gain or steering nulls at specific locations	objective: beampattern matching advantages: precise control over power at multiple locations, inherent beamforming and nullforming in constructive manner, can include additional constraints (limited transmit power, derivative constraints)
utilize receiver feedbacks	does not require receiver feedbacks
sparse beamforming, mobile agents	fixed number of agents, stationary agents
channel model-free, probabilistic channel prediction for minimizing power	feedback-free, objective: beampattern matching
receiver feedback-free	does not assume line of sight (LOS) channels

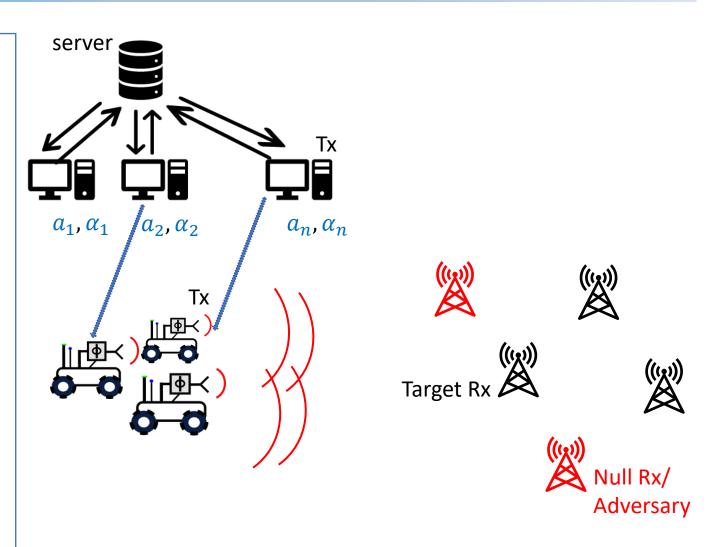
Our Contributions

proposed a novel algorithm: Iteratively Pre-conditioned Gradient-descent for		
Distributed Beamforming (IPG-DB)		
significantly faster than the gradient-descent (GD) based methods		
☐ does not rely on receiver feedbacks		
\square does not assume channel fading parameters: significantly robust to channel noise		
☐ replace slower GD with faster IPG-DB for position, sparsity, and excitation in [1]		

[1] Anjaly Parayil, Amrit Singh Bedi, and Alec Koppel. Joint position and beamforming control via alternating nonlinear least-squares with a hierarchical gamma prior. In 2021 American Control Conference (ACC), pages 3513–3518. IEEE, 2021.

Proposed Setting of Beamforming Agents

- ☐ server-agent based setting
 - agents communicate with server
 - no peer-to-peer communication
- what is a server?
 - can be an auxiliary node, located close to the agents
 - can exchange information with the agents
 - can process information
 - need not know the beamforming problem

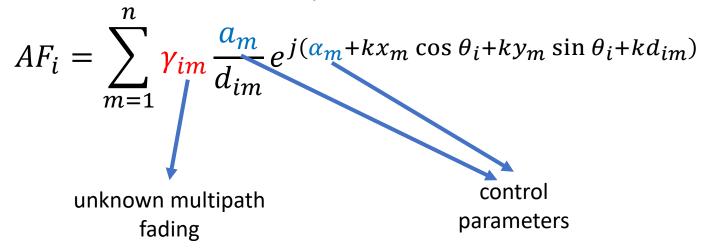


Problem Formulation: Notation

```
beamforming agents: m = 1, ..., n
receivers: i = 1, ..., s
location of agent m:(x_m,y_m)
location of receiver i:(\rho_i,\theta_i)
desired array factor amplitude at receiver i: f_i
distance between agent m and receiver i:
                   d_{im} = \sqrt{(x_m - \rho_i \cos \theta_i)^2 + (y_m - \rho_i \sin \theta_i)^2}
excitation signal amplitude and phase of agent m:(a_m,\alpha_m)
synchronized carrier frequency : f
wavenumber: k = \frac{2\pi f}{3 \times 10^8} metre^{-1}
```

Problem Formulation: Optimization

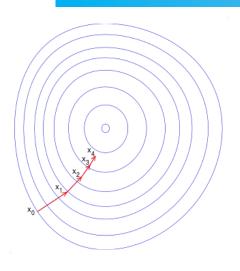
constructed array factor at receiver i:



$$(a_m^*, \alpha_m^*)_{m=1}^n = \underset{(a_m, \alpha_m)_{m=1}^n}{\arg\min} \sum_{i=1}^s w_i ||f_i - |AF_i|||^2$$

[1] Jemin George, Anjaly Parayil, Cemal Tugrul Yilmaz, Bethany L Allik, He Bai, and Aranya Chakrabortty. Multi-agent coordination for distributed transmit beamforming. In 2020 American Control Conference (ACC), pages 144–149. IEEE, 2020.

Intuition behind Proposed Algorithm IPG-DB

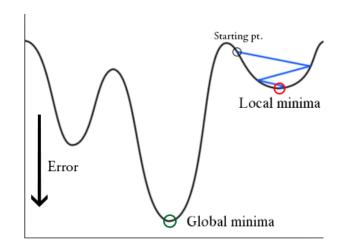


$$\min_{x \in \mathbb{R}^d} f(x)$$

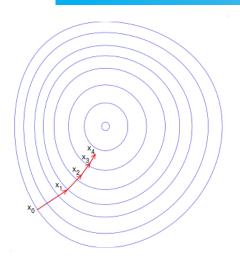
Gradient-Descent:

$$x(t+1) = x(t) - \delta \nabla f(x(t)), \qquad t = 0,1, \dots$$

- \Box convergence guaranteed to $\nabla f(x^*) = 0$
- ☐ slow convergence for ill-conditioned problems



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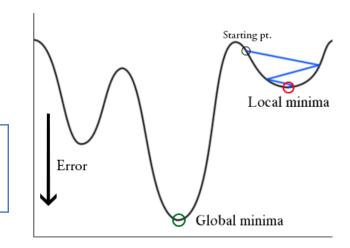


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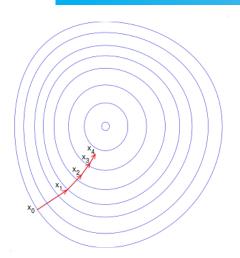
Newton's Method:

$$x(t+1) = x(t) - \nabla^2 f(x(t))^{-1} \nabla f(x(t)),$$

t = 0,1,...

- ☐ fast quadratic convergence
- □ vulnerable to channel noise

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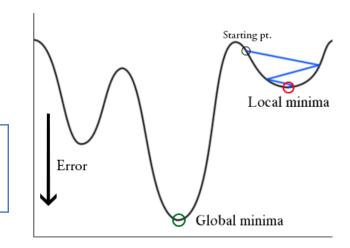


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Iteratively Pre-conditioned Gradient-Descent (IPG) [1]:

stabilization parameter for non-convex costs

$$K(t+1) = K(t) - \varepsilon(t)(\nabla^2 f(x(t))K(t) + \beta K(t) - I), \qquad t = 0,1, \dots$$
$$x(t+1) = x(t) - \delta K(t)\nabla f(x(t)), \qquad t = 0,1, \dots$$

$$K^* \text{ s. t. } \nabla^2 f(x^*) K^* + \beta K^* = I \equiv K^* = (\nabla^2 f(x^*) + \beta I)^{-1}$$

From IPG to IPG-DB

$$x(t) = \begin{pmatrix} a_1(t), \dots, a_n(t), \alpha_1(t), \dots \alpha_n(t) \end{pmatrix}^T$$

$$x(t+1) = x(t) - \delta K(t) \nabla f \big(x(t) \big), \qquad t = 0,1, \dots$$

$$a_m(t+1) = a_m(t) - \delta k_m(t) \nabla f \big(x(t) \big), \qquad m = 1, \dots, n$$
 depends on
$$x(t) = \begin{pmatrix} a_1(t), \dots, a_n(t), \alpha_1(t), \dots \alpha_n(t) \end{pmatrix}^T$$

How to distribute?

Description of IPG-DB Algorithm

agent $m: (a_m(t), \alpha_m(t))$, server: $K(t) \in \mathbb{R}^{2n \times 2n}$

server broadcasts to each agent: ϵ , β , δ , K(0)

For each iteration $t \geq 0$:

$$\zeta_{im} = kx_m \cos \theta_i + ky_m \sin \theta_i + kd_{im}$$

$$u_{im}(t) = \frac{1}{d_{im}} \cos(\alpha_m(t) + \zeta_{im}), v_{im}(t) = \frac{1}{d_{im}} \sin(\alpha_m(t) + \zeta_{im}), y_{im}(t) = a_m(t)(u_{im}(t) + jv_{im}(t))$$
 agent m

at each agent m

agent
$$m$$
 to server

$$\{u_{im}(t), v_{im}(t), y_{im}(t), i = 1, \dots, s\}, k_m(t), k_{m+n}(t)$$
 server
$$y_i(t) = \sum_{m=1}^n y_{im}(t)$$

 $k_j(t)$: j-th row of K(t) $H_j(t)$: j-th row of Hessian, locally computed

$$\begin{aligned} u_i(t) &= [u_{i1}(t), \dots, u_{in}(t)]^T, v_i(t) = [v_{i1}(t), \dots, v_{in}(t)]^T, Y_i(t) = [y_{i1}(t), \dots, y_{in}(t)]^T \\ &\{y_i(t), i = 1, \dots, s\}, \{u_i(t), v_i(t), Y_i(t), i = 1, \dots, s\}, K(t) \end{aligned}$$

server to each agent *m*

$$a_{m}(t+1) = a_{m}(t) - \delta k_{m}(t) \sum_{i=1}^{s} w_{i} \frac{|y_{i}(t)| - f_{i}}{|y_{i}(t)|} (\Re y_{i}(t)u_{i}(t) + \Im y_{i}(t)v_{i}(t))$$

$$\alpha_{m}(t+1) = \alpha_{m}(t) - \delta k_{m+n}(t) \sum_{i=1}^{s} w_{i} \frac{|y_{i}(t)| - f_{i}}{|y_{i}(t)|} (-\Re y_{i}(t)\Im Y_{i}(t) + \Im y_{i}(t)\Re Y_{i}(t))$$

$$k_{j}(t+1) = k_{j}(t) - \epsilon (H_{j}(t)K(t) + \beta k_{j}(t) - I_{2n,j}), j = m, m+n$$

at each agent m

Empirical Results: Synthetic Data

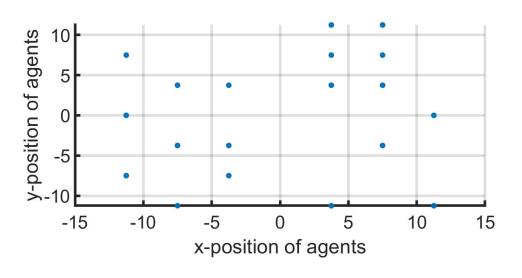
problem settings

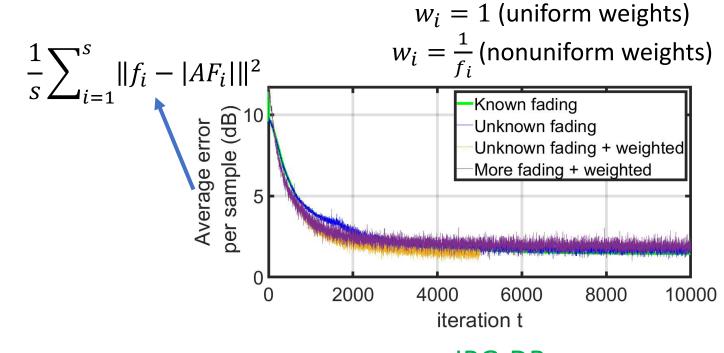
- \square # beamforming agents: n = 19
- \blacksquare # receivers: s = 49
- \Box location of receivers: $\rho_i = 5\lambda$, uniform θ_i in (0.2π)
- \Box synchronized carrier frequency : $f = 40 \, MHz$
- lacksquare unknown i.i.d. Rayleigh fading $\gamma_{im}\epsilon\mathbb{R}$

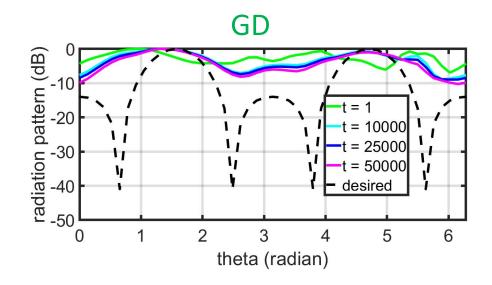
algorithm parameters

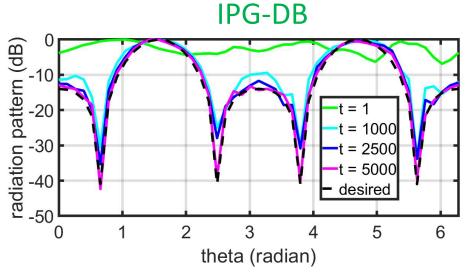
$$\epsilon(t) = \frac{1}{\lambda_{max}(H(t)) + \beta}$$
$$\beta = 0.1 \text{ (IPG-DB)}$$
$$\beta = 0 \text{ (GD)}$$
$$\delta = 1$$

Empirical Results: Synthetic Data









Summary

