

# Efficient Beamforming for Over-the-Air Federated Learning Model Aggregation

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## Abstract

In this paper, we propose low algorithms to minimize MSE for over-the-air computation (AirComp) federated learning (FL), improving aggregation accuracy, convergence, and robustness.

## I. Introduction

Centralized aggregation in Internet of Things (IoT) networks suffers from prohibitive latency, bandwidth, and privacy issues. Although AirComp-based FL reduces uplink load, it incurs aggregation MSE from channel noise and misalignment. This paper presents low complexity joint beamforming algorithms to minimize MSE.

## II. System Model and Beamforming Vector Design

We consider a wireless FL framework where  $K$  devices each perform  $E$  local updates and send a unit-power signal  $\mathbf{x}_k$  over channel  $\mathbf{h}_k \in \mathbb{C}^N$  to a Base station (BS) with  $N$  antennas using AirComp. The BS receives  $\mathbf{y} = \sum_{k=1}^K \mathbf{h}_k b_k \mathbf{x}_k + \mathbf{n}$ , with  $|b_k|^2 \leq P_{\max}$  and  $\mathbf{n} \sim \mathcal{CN}(0, \sigma^2 \mathbf{I})$ . Applying beamformer  $\mathbf{a} \in \mathbb{C}^N$ , it estimates the average update via  $\frac{1}{K} \mathbf{a}^H \mathbf{y} = \frac{1}{K} \sum_{k=1}^K \mathbf{a}^H \mathbf{h}_k b_k \mathbf{x}_k + \frac{1}{K} \mathbf{a}^H \mathbf{n}$ . The MSE is defined as  $\mathbb{E} \left[ \left| \frac{1}{K} \mathbf{a}^H \mathbf{y} - \frac{1}{K} \sum_{k=1}^K \mathbf{a}^H \mathbf{h}_k \mathbf{x}_k \right|^2 \right]$ . Minimizing MSE under  $|b_k|^2 \leq P_{\max}$ , yields

$$\begin{aligned} \text{(P1)} \quad & \min_{\mathbf{a}, \mathbf{b}} \sum_{k=1}^K |\mathbf{a}^H \mathbf{h}_k b_k - 1|^2 + \sigma^2 \|\mathbf{a}\|^2 \\ \text{s.t.} \quad & |b_k|^2 \leq P_{\max}, \forall k. \end{aligned} \quad (1)$$

Using the misalignment allowed optimization (Miso) approach and, since the constraint is not convex, we employ a majorization minimization (MM) algorithm to derive a series of convex subproblems

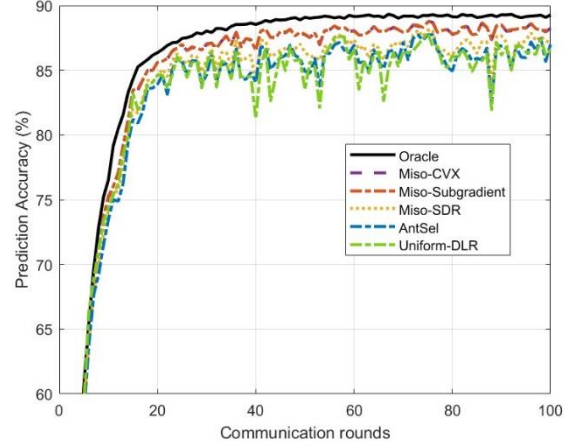
$$\begin{aligned} \text{(P2)} \quad & (\mathbf{a}^{(l+1)}, \mathbf{t}^{(l+1)}) = \underset{\mathbf{a}, \mathbf{t}}{\operatorname{argmin}} \sum_{k=1}^K (t_k - 1)^2 + \sigma^2 \|\mathbf{a}\|^2 \\ \text{s.t.} \quad & t_k^2 \leq P_{\max} \psi_k(\mathbf{a}, \mathbf{a}^{(l)}), \forall k. \end{aligned} \quad (2)$$

where  $\psi_k(\mathbf{a}, \mathbf{a}^{(l)}) \equiv 2\operatorname{Re}\{\mathbf{a}^{(l)H} \mathbf{h}_k \mathbf{h}_k^H \mathbf{a}\} - |\mathbf{h}_k^H \mathbf{a}^{(l)}|^2$ .

Since (P2) is a convex problem, we solve it with the interior point method using the CVX toolbox, which is called Miso-CVX. Since its complexity is  $\mathcal{O}(N^3)$ , we propose a low-complexity algorithm based on the projected subgradient method, called Miso-Subgradient

$$\begin{aligned} & \text{Repeat} \\ & \mathbf{a} \leftarrow \frac{P_{\max}}{\sigma^2} \mathbf{H} \operatorname{diag}(\boldsymbol{\lambda}) \mathbf{H}^H \mathbf{a}^{(l)} \\ & t_k \leftarrow \frac{1}{1 + \lambda_k}, \forall k \\ & \lambda_k \leftarrow \max(\lambda_k - \xi(P_{\max} \psi_k(\mathbf{a}, \mathbf{a}^{(l)}) - t_k^2), 0), \forall k \\ & j \leftarrow j + 1 \\ & \text{Until convergence} \end{aligned} \quad (3)$$

where we define  $\mathbf{H} = [\mathbf{h}_1 \cdots \mathbf{h}_K] \in \mathbb{C}^{N \times K}$  and  $\lambda_k$  is the dual variable associated with the  $k$ -th inequality



**Fig. 1.** The prediction accuracy of CNN with SVHN datasets ( $K = 10$ ,  $N = 20$ ,  $\text{SNR} = -15\text{dB}$ ).

We compare our proposed algorithm with Oracle-AirComp, without aggregation error, Miso-SDR[1], AntSel[2], and Uniform-DLR[3]. Fig. 1 shows that the proposed algorithm exhibits at most a 2% point deviation from the Oracle algorithm, but the other algorithms deviate up to 5% point.

## III. Conclusion

In this paper we proposed efficient beamforming vector design algorithm for AirComp federated learning. The proposed algorithm shows superior robustness and learning performance than existing algorithms.

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