Compressive Massive Access for Internet of Things: Cloud Computing or Fog Computing?

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Outline

- System Model
- Proposed Solutions
  - Cloud Computing-based Massive Access
  - Fog Computing-based Massive Access
- Simulation Results

System Model

Centralized AP cooperation

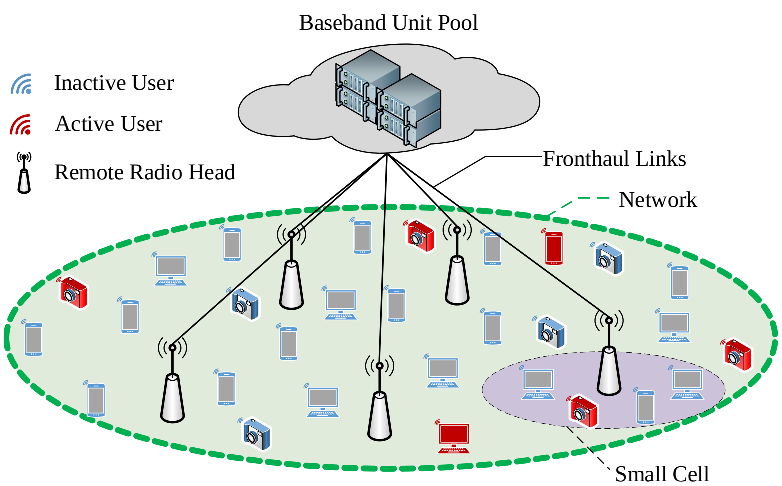

Fig. 1. C-RAN for cloud computing.

- The APs are only designed for receiving and transmitting signals.
- All APs are connected in a BBU pool.
- The signals received at all APs are jointly processed in the BBU.

Distributed AP cooperation

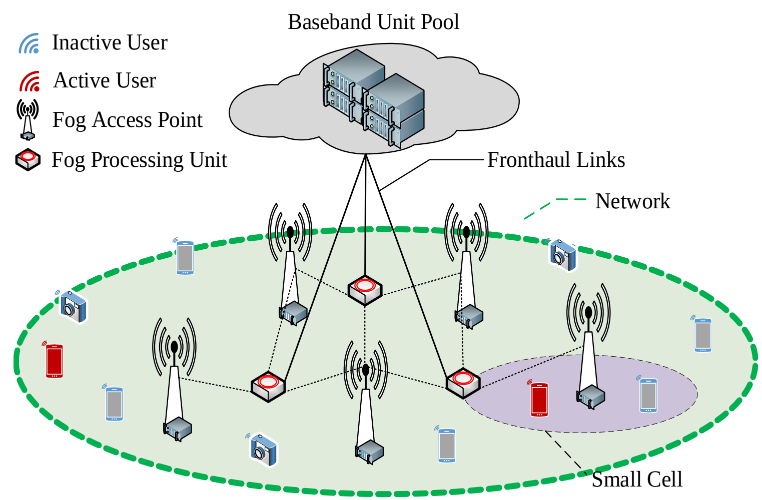

Fig. 2. Fog-RAN for fog computing.

- Fog-APs have computation capabilities.
- Several neighboring Fog-APs are connected to a fog processing unit for cooperation.
- The processing tasks are performed at the Fog-APs and fog processing units.

System Model

Received Signal Model

- The network serves BK_c users distributed in B hexagonal cells.
- Each cell contains one AP serving K_c single-antenna user.
- The AP is equipped with M_c-antenna uniform linear array.

For the *t*-th time slot, the signal received at the *b*-th AP is

$$\begin{aligned}\mathbf{r}_b^t &= \sum_{k\in\mathcal{A}} \sqrt{P_k}\mathbf{h}_{b,k}s_k^t + \mathbf{n}_b^t \\ &= \sum_{k=1}^{K} \alpha_k \sqrt{P_k}\mathbf{h}_{b,k}s_k^t + \mathbf{n}_b^t.\end{aligned} \tag{1}$$

Here, α_k is the activity indicator of users, and The massive MIMO channel is modeled as $\mathbf{h}_{b,k} = \rho_{b,k}\widetilde{\mathbf{h}}_{b,k}$, where $\rho_{b,k} = 128.1 + 37.6\lg(d_{b,k})$ and

$$\widetilde{\mathbf{h}}_{b,k} = \sum_{l=1}^{L} \beta_{b,k}^l \mathbf{a}_{\mathrm{R}}\left(\phi_{b,k}^l\right) \tag{2}$$

System Model

Frame Structure

- A frame consists of T time slots, T is smaller than the channel coherence time.
- The first G time slots are used to transmit pilots.
- The remaining (T - G) time slots are used for data transmission only.

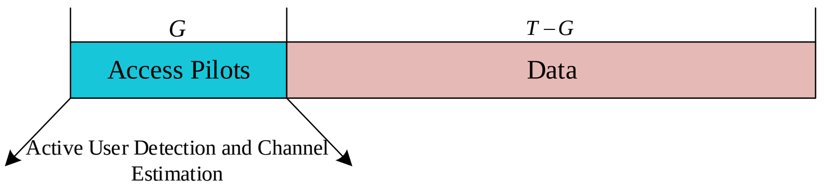

Fig. 3. The frame structure of the uplink signals.

For facilitating AUD and CE, the received signals in successive time slots are collected as

$$\mathbf{R}_b = \mathbf{S}\mathbf{H}_b + \mathbf{N}_b, \forall b \in [B] \tag{3}$$

where $\mathbf{R}_b = \left[\mathbf{r}_b^1, \mathbf{r}_b^2, \cdots, \mathbf{r}_b^G\right]^{\mathrm{T}} \in \mathbb{C}^{G\times M_c}$, $\mathbf{S} = \left[\mathbf{s}^1, \mathbf{s}^2, \cdots, \mathbf{s}^G\right]^{\mathrm{T}} \in \mathbb{C}^{G\times K}$, $\mathbf{s}^t = \left[s_1^t, s_2^t, \cdots, s_K^t\right]^{\mathrm{T}} \in \mathbb{C}^{K\times 1}$,
$\mathbf{H}_b = \left[\alpha_1\sqrt{P_1}\mathbf{h}_{b,1}, \alpha_2\sqrt{P_2}\mathbf{h}_{b,2}, \cdots, \alpha_K\sqrt{P_K}\mathbf{h}_{b,K}\right]^{\mathrm{T}} \in \mathbb{C}^{K\times M_c}$, and $\mathbf{N}_b = \left[\mathbf{n}_b^1, \mathbf{n}_b^2, \cdots, \mathbf{n}_b^G\right]^{\mathrm{T}}$.

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Cloud Computing-based Massive Access

Procedure of Cloud Computing-Based Scheme

- **Step 1:** In pilot phase, all active users directly transmit their access pilots to the RRHs without permission.
- **Step 2:** Each RRH collects the received signals and sends them to the cloud via fronthaul links.
- **Step 3:** The BBU performs AUD and CE for the whole network by jointly processing the received signals from all RRHs.

At BBU, the received signals from all RRHs are concentrated as

$$\begin{aligned} \mathbf{Y} &= [\mathbf{R}_1, \mathbf{R}_2, \cdots, \mathbf{R}_B] \\ &= \mathbf{S}\mathbf{X} + \mathbf{N}, \end{aligned} \tag{4}$$

where $\mathbf{X} = [\mathbf{H}_1, \mathbf{H}_2, \cdots, \mathbf{H}_B] \in \mathbb{C}^{K \times M}$ and $\mathbf{N} = [\mathbf{N}_1, \mathbf{N}_2, \cdots, \mathbf{N}_B]$.

The AUD and CE can be simultaneously realized by estimating $\mathbf{X}$ based on the noisy measurements $\mathbf{Y}$ and known pilot matrix $\mathbf{S}$.

Cloud Computing-based Massive Access

Problem Formulation

The channel vector observed at a specific receive antenna of the RRHs is sparse as

$$\left|\mathrm{supp}\left\{[\mathbf{X}]_{:,m}\right\}\right|_c = K_a \ll K \qquad (5)$$

Moreover, all RRH antennas exhibit the same sparsity

$$\mathrm{supp}\left\{[\mathbf{X}]_{:,1}\right\} = \mathrm{supp}\left\{[\mathbf{X}]_{:,2}\right\} = \cdots = \mathrm{supp}\left\{[\mathbf{X}]_{:,M}\right\} \qquad (6)$$

Leveraging the structured sparsity in (5) and (6), AUD and CE can be formulated as a MMV CS problem.

Cloud Computing-based Massive Access

MMV-AMP Algorithm for CS Recovery

- An intuitive explanation of AMP: in the large system limit, i.e., $K \to \infty$, while $\gamma = Ka/K$ and $\kappa = G/K$ are fixed, we have

$$\mathbf{Y} = \mathbf{S}\mathbf{X} + \mathbf{N} \to C_{k,m}^{q} = x_{k,m} + n_{k,m}^{q}, \forall k, m, \tag{7}$$

where $C_{k,m}^{q} \sim CN\left(C_{k,m}^{q}; x_{k,m}, D_{k,m}^{q}\right)$ is the equivalent measurement, $n_{k,m}^{q} \sim CN\left(n_{k,m}^{q}; 0, D_{k,m}^{q}\right)$ denotes the effective noise.

- The marginal posterior probabilities of channel matrix $\mathbf{X}$:

$$\begin{aligned} p\left(x_{k,m} \mid \mathbf{Y}\right) &\approx p\left(x_{k,m} \mid C_{k,m}^{q}, D_{k,m}^{q}\right) \\ &\approx \frac{1}{Z} p_0\left(x_{k,m}\right) \mathcal{CN}\left(x_{k,m}; C_{k,m}^{q}, D_{k,m}^{q}\right), \ \forall k, m. \end{aligned} \tag{8}$$

- The a priori distribution of channel matrix $\mathbf{X}$: a spike and slab a priori distribution

$$\begin{aligned} p_0(\mathbf{X}) &= \prod_{m=1}^{M} \prod_{k=1}^{K} p_0\left(x_{k,m}\right) \qquad \boxed{f\left(x_{k,m}\right) = \mathcal{CN}\left(x_{k,m}; \mu, \tau\right)} \\ &= \prod_{m=1}^{M} \prod_{k=1}^{K} \left[(1-\gamma_{k,m})\delta(x_{k,m}) + \gamma_{k,m} f(x_{k,m})\right]. \end{aligned} \tag{9}$$

Cloud Computing-based Massive Access

- The marginal posterior probabilities of channel matrix **X**:

$$p\left(x_{k,m} \mid C_{k,m}^q, D_{k,m}^q\right) = \left(1-\pi_{k,m}^q\right)\delta\left(x_{k,m}\right) + \pi_{k,m}^q CN\left(x_{k,m}; A_{k,m}^q, B_{k,m}^q\right), \tag{10}$$

- The posterior mean and variance of channel matrix **X**:

$$g_a\left(C_{k,m}^q, D_{k,m}^q\right) = \pi_{k,m}^q A_{k,m}^t \tag{11}$$

$$g_c\left(C_{k,m}^q, D_{k,m}^q\right) = \pi_{k,m}^q\left(\left|A_{k,m}^q\right|^2 + B_{k,m}^q\right) - \left|g_a\right|^2 \tag{12}$$

- The EM algorithm is employed to learn the unknown hyper-parameters:

$$\gamma_{k,m}^{q+1} = \pi_{k,m}^{q+1} = \frac{\gamma_{k,m}^q}{\gamma_{k,m}^q + (1-\gamma_{k,m}^q)\exp\left(-L\right)}, \tag{13}$$

$$\sigma_{k,m}^{q+1} = \frac{1}{G}\sum_g\left[\frac{\left|y_{g,m} - Z_{g,m}^q\right|^2}{\left|1+V_{g,m}^q / \sigma_{k,m}^q\right|^2} + \frac{\sigma_{k,m}^q V_{g,m}^q}{\sigma_{k,m}^q + V_{g,m}^q}\right] \tag{14}$$

- Refine the update rule of the sparsity ratio:

$$\gamma_{k,m}^{q+1} = \frac{1}{\left|\mathcal{N}_{k,m}\right|_c}\sum_{(o,u)\in\mathcal{N}_{k,m}} \pi_{o,u}^{q+1} \text{ with } \mathcal{N}_{k,m} = \left\{(o,u) \mid o = k; u = 1,\cdots,M\right\} \tag{15}$$

Cloud Computing-based Massive Access

Algorithm 1 MMV-AMP Algorithm

Input: Noisy observation $\mathbf{Y}$, pilot matrix $\mathbf{S}$, the maximum number of iterations $T_{\max}$ and termination threshold ε.

Output: Estimated channel matrix $\widehat{\mathbf{X}}$ and the related belief indicators $\pi_{k,m}, \forall k, m$.

1: $\forall k, m$: Set iteration index q to 1, initialize the hyper-parameters, $\gamma_{k,m}$ and $\sigma_{k,m}$, as in [12], and initialize other parameters as $V_{g,m}^{0} = 1$, $Z_{g,m}^{0} = y_{g,m}$, $\hat{x}_{k,m}^{1} = 0$, $v_{k,m}^{1} = \tau$.

2: **repeat**

3: $\forall g, m$: Update $V_{g,m}^{q}$ and $Z_{g,m}^{q}$ according to (13) and (14) at the factor nodes.

4: $\forall k, m$: Update $D_{k,m}^{q}$ and $C_{k,m}^{q}$ according to (11) and (12) at the variable nodes.

5: $\forall k, m$: Compute the posterior mean and variance as $\hat{x}_{k,m}^{q+1} = g_a(C_{k,m}^{q}, D_{k,m}^{q})$, $v_{k,m}^{q+1} = g_c(C_{k,m}^{q}, D_{k,m}^{q})$.

6: $\forall k, m$: Update the hyper-parameters $\gamma_{k,m}^{q+1}$ and $\sigma_{k,m}^{q+1}$ as in (22) and (23).

7: $\forall k, m$: Refine the update rule for the sparsity ratio, $\gamma_{k,m}^{q+1} = \frac{1}{|\mathcal{N}_{k,m}|_c} \sum_{(o,u)\in\mathcal{N}_{k,m}} \pi_{o,u}^{q+1}$.

8: $q = q + 1$.

9: **until** $q > T_{\max}$ or $\left\|\widehat{\mathbf{X}}^{q} - \widehat{\mathbf{X}}^{q-1}\right\|_{\mathrm{F}}^{2} < \varepsilon \left\|\widehat{\mathbf{X}}^{q-1}\right\|_{\mathrm{F}}^{2}$.

10: **return** $\widehat{\mathbf{X}}^{q}$ and $\pi_{k,m}, \forall k, m$.

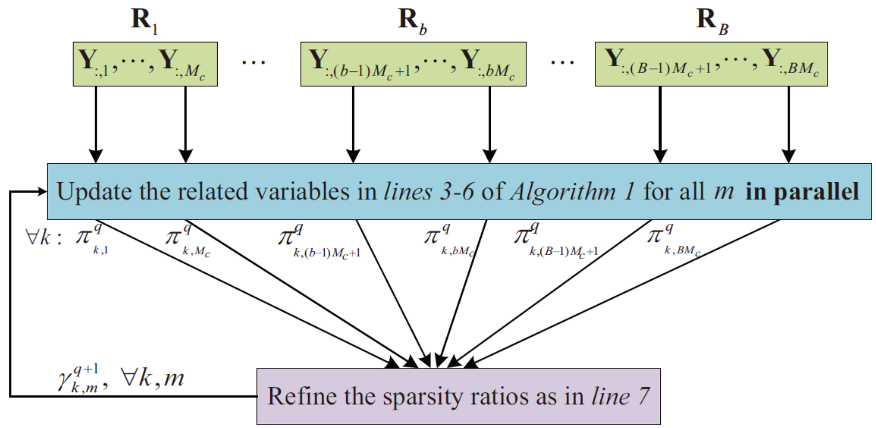

Fig.4 The procedure of MMV-AMP algorithm applied to the model (5).

- In lines 3-6, the signals received at B RRHs are processed in parallel.
- In line 7, the signals received at B RRHs are jointly processed.

Fog Computing-Based Massive Access

Algorithm 2 Fog Computing Deployment

Set iteration index q to 1, and initialize related parameters.
repeat
  $\forall b$: Replacing $\mathbf{Y}$ with $\mathbf{R}_b$, the b-th F-AP executes *lines 3-6* of *Algorithm 1* locally based on its own received signal $\mathbf{R}_b$ and known pilot matrix $\mathbf{S}$.
  $\forall b$: At the b-th F-AP, refine the sparsity ratios locally, $\widetilde{\pi}_{k,b}^{q+1} = \frac{1}{M_c} \sum_{m=(b-1)M_c+1}^{bM_c} \pi_{k,m}^{q+1}$, $\forall k \in [K]$.
  $\forall k$: At the fog processing units, jointly refine the sparsity ratios, $\gamma_{k,m}^{q+1} = \frac{1}{|\mathcal{B}_k|_c} \sum_{b \in \mathcal{B}_k} \widetilde{\pi}_{k,b}^{q+1}$.
  $q = q + 1$.
until $q > T_{\max}$.
$\forall b$: With $\widehat{\mathbf{X}}_{\mathcal{K}_b,\mathcal{M}_b}^{q}$ and $\pi_{k,m}^{q}$, $\forall k \in \mathcal{K}_b, \forall m \in \mathcal{M}_b$, the b-th F-AP performs AUD and CE for the users in its coverage as in (24). Here, $\mathcal{K}_b = \{(b-1)K_c + 1, \cdots, bK_c\}$ and $\mathcal{M}_b = \{(b-1)M_c + 1, \cdots, bM_c\}$.

For a specifically iteration of MMV-AMP algorithm:

- Each F-AP updates the related messages locally based on its own received signal.

- Several neighboring Fog-APs cooperate at a fog processing unit.
- The results obtained at multiple F-Aps are jointly processed to refine the update rule of $\gamma_{k,m}$.

- The cloud capabilities are extended closer to the edge of the network.
- The estimation of user activity and related channels for the whole network is split.
- Several neighboring Fog-APs cooperate at a fog processing unit.
- The corresponding computations are executed at Fog-APs and fog processing units.

Fog Computing-Based Massive Access

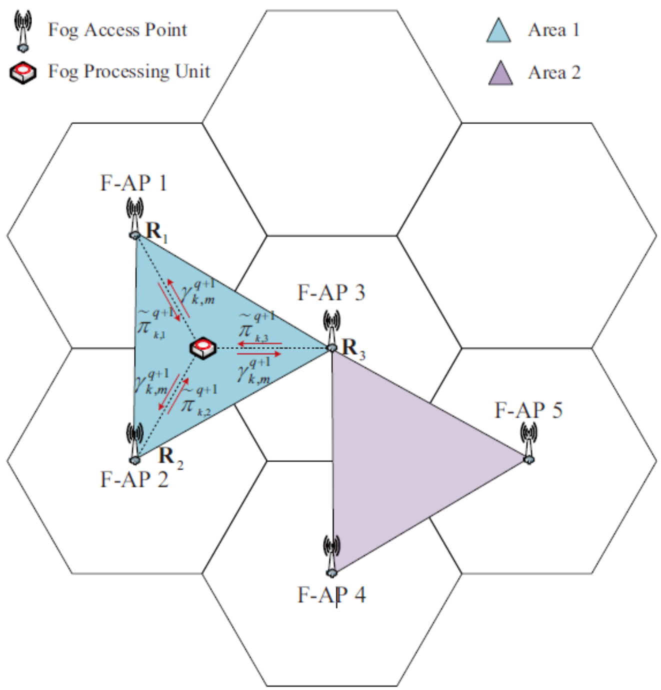

Fig. 5. An illustration of F-APs cooperation for fog computing deployment, in which $N_{co} = 3$ is considered.

- A huge size of network to serve a vast area.
- The channel strengths from a specific active user to far away F-APs are approximate zero due to path loss.
- Forwarding signals received at all APs to a function node for jointly processing is not an efficient way.
- Fog computing provide a more flexible AP cooperation.

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Simulation Results

System Parameters

number of cells	radius of cell	users in each cell	active ratio	transmit power
$B = 7$	1 km	$K_c = 500$	5%	23 dBm
noise power	**bandwidth**	**path gain**	**number of paths**	maximum number of iterations
-174 dBm/Hz	10 MHz	$\beta_{b,k}^{l} \sim \mathcal{CN}(\beta_{b,k}^{l}; 0,1)$	8~14	200

Baseline Scheme

Massive access solution under traditional network architecture, where each BS only seeks to detect the users from its own cell while treating the intercell interference as noise.

Simulation Results

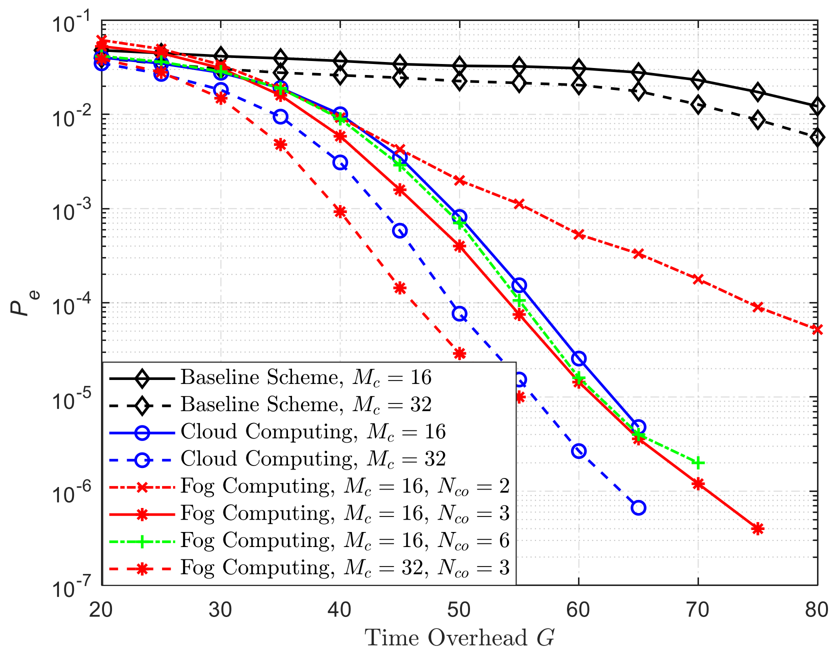

Fig. 6. Comparison of detection error probability.

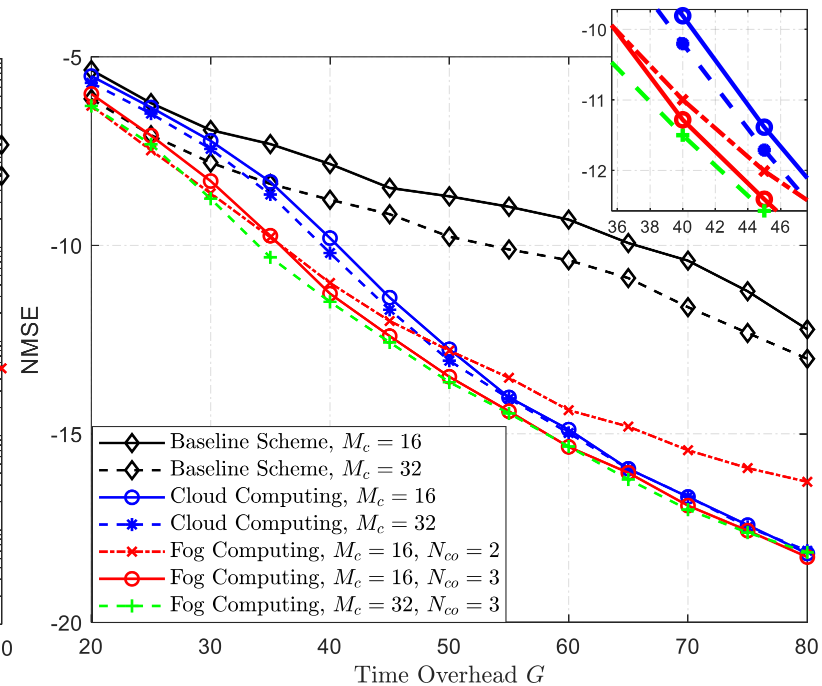

Fig. 7. NMSE performance comparison for CE.

- ✓ The proposed solutions outperform the baseline scheme.
- ✓ The performance can be improved by equipping more antennas at APs.
- ✓ The fog computing will approach the performance of cloud computing by increasing the number of APs for cooperation.

THANKS!

Q&A