The IEEE 82nd Vehicular Technology Conference (Boston, USA)

Opportunistic User Selection in Network MIMO Systems with Limited Feedback

Khalil Elkhalil[1], Mohammed E. Eltayeb[2] , Hayssam Dahrouj[1,3], and Tareq Al-Naffouri[1]

[1]King Abdullah University of Science and Technology, Thuwal, Saudi Arabia.
[2]The University of Texas at Asutin, Texas, USA.
[3]Effat University, Jeddah, Saudi Arabia.

E-mails: {khalil.elkhalil, hayssam.dahrouj, tareq.alnaffouri}@kaust.edu.sa, meltayeb@utexas.edu.

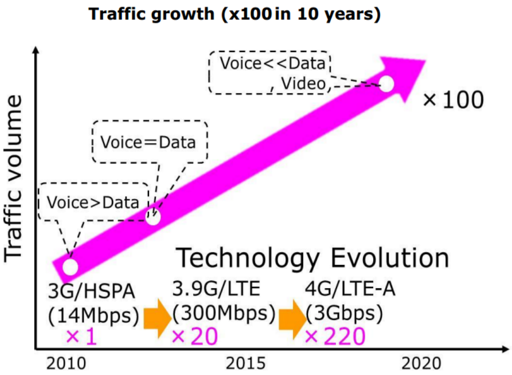


Figure 1: Explosive growth of traffic (1).

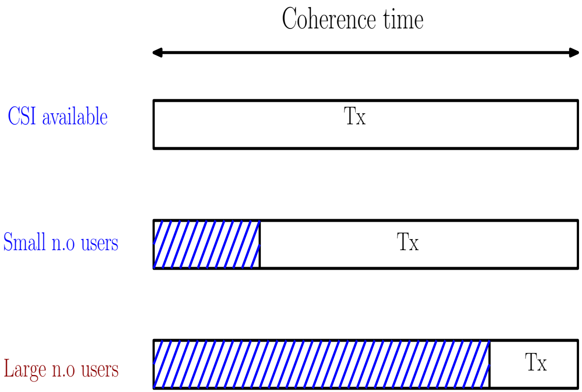
(1): Ericsson Mobility Report, June 2013.

- To cope with the increasing demand, new solutions can be used such as
  - Higher-order modulation.
  - MIMO.
- Exploit randomness in the channel (MUD).

idea: Assign network resources to strong users.

Challenge channel state information (CSI).

Feedback is a key issue !



Challenge How to reduce feedback ?

User Selection in NW-MIMO

System Model

- M BSs with L antennas each and K users ($K \geq LM$).
- $\mathbf{h}_k = [h_{k,1}, h_{k,2}, ..., h_{k,LM}]$ channel from the BSs to the kth user.
- $\mathcal{K} = \{\pi(1), \pi(2), ..., \pi(|\mathcal{K}|)\}$

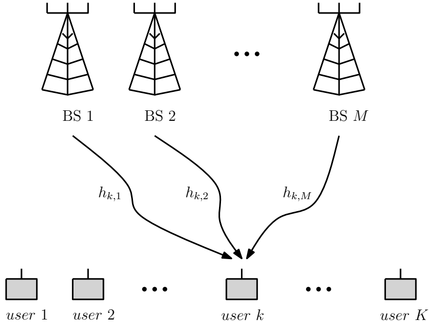
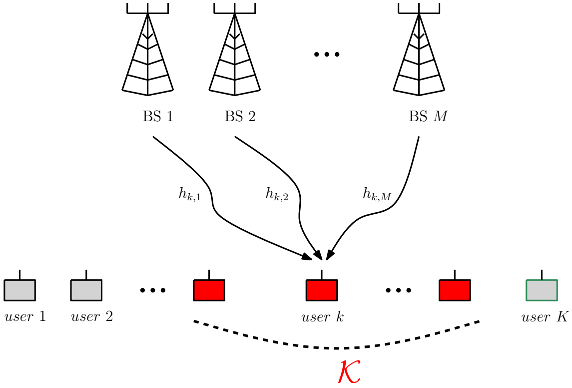


Figure 2: Network Model

User Selection



Challenge What's the optimal set $\mathcal{K}$?

Optimal set $\mathcal{K}$

$$\mathbf{W}(\mathcal{K}) = \mathbf{H}(\mathcal{K})^H \left(\mathbf{H}(\mathcal{K}) \mathbf{H}(\mathcal{K})^H \right)^{-1} \quad (1)$$

$$R_{ZFBF}(\mathcal{K}) = \max_{P_i : \sum_{i \in \mathcal{K}} \gamma_i^{-1} P_i \leq P} \sum_{i \in \mathcal{K}} \log(1 + P_i), \quad (2)$$

$$\gamma_i = \frac{1}{||w_i||^2}$$

$$R_{ZFBF} = \max_{\mathcal{K} \subset \{1, \cdots, K\} : |\mathcal{K}| \leq M} R_{ZFBF}(\mathcal{K}) \quad (3)$$

Problem Computationally unfeasible for large K !

Semi-orthogonal user selection (SUS) [3]

idea: choose users to be nearly orthogonals

1. $$\pi(1) = \underset{k \in \{1,2,\ldots,K\}}{\text{argmax}} \|\mathbf{h}_k\|^2 \tag{4}$$

2. $$\pi(i+1) = \underset{k \in \mathcal{A}_i}{\text{argmax}} \|\mathbf{h}_k\|^2, \tag{5}$$

   where $\mathcal{A}_i = \left\{1 \le k \le K : \frac{\left|\mathbf{h}_k \mathbf{h}_{\pi(j)}^H\right|}{\|\mathbf{h}_k\| \left\|\mathbf{h}_{\pi(j)}\right\|} \le \epsilon, 1 \le j \le i\right\}$ and $i \le M-1$

3. repeat until $|\mathcal{K}| = M$ or $\mathcal{A}_i = \emptyset$

Problem Full CSI needed or Fb. load $\sim \mathcal{O}(K)$

[3] T. Yoo, N. Jindal and A. Goldsmith. "Finite-Rate Feedback MIMO Broadcast Channels with Large Number of Users," *in Proc. IEEE ISIT*, 2006.

CS Approach

1. CDI and CQI for each user (training).
2. Sparsify users (thresholding).
3. Two fback info (CQI and ch. gain).
4. Assign two Gaussian codes for each user.

For the ith user selection,

if $\|\mathbf{h}_k\|^2 \geq \gamma_i$ **then**

transmit $(a_{m,2k-1} pilot + a_{m,2k} CQI)$,

for $m = 1, 2, ..., J$

else

be silent

lth BS receives

$$\mathbf{y}_l = \mathbf{A}(\mathbf{g}_l \circ \mathbf{X}) + \mathbf{z}_l \quad (6)$$

Feedback Recovery

$$\begin{bmatrix} h_{1,l} \\ h_{1,l} \\ h_{2,l} \\ h_{2,l} \\ \vdots \\ h_{K,l} \\ h_{K,l} \end{bmatrix} \circ \begin{bmatrix} pilot \\ CQI_1 \\ pilot \\ CQI_2 \\ \vdots \\ pilot \\ CQI_K \end{bmatrix} \tag{7}$$

- recover $CQI_{\pi(i)} \rightarrow h_{\pi(i),l}$
- Transmit $h^*_{\pi(i),l} / \left\|\mathbf{h}_{\pi(i)}\right\|$
- user j receives

$$c_j = \sum_{l=1}^{LM} \frac{h_{j,l} h^*_{\pi(i),l}}{\|\mathbf{h}_j\| \left\|\mathbf{h}_{\pi(i)}\right\|} = \frac{\mathbf{h}_j \mathbf{h}^H_{\pi(i)}}{\|\mathbf{h}_j\| \left\|\mathbf{h}_{\pi(i)}\right\|} \tag{8}$$

- compare c_j with ϵ.

Important Result on Block-Sparse Recovery

- Robust recovery for a sparse vect. with size N and sparsity S: $M = \mathcal{O}(S \log N/S)$.
- Similarly to recover a block sparse vect. with block size J and sparsity S: $M = \mathcal{O}(JS \log N/S)$.

Structure in the sparse signal [2]

Baraniuk *et al* (2010), showed that robustness guarantees can be achieved with

$$M = \mathcal{O}(JS + S \log N/S) \tag{9}$$

$\rightarrow$ substantial improvement over $\mathcal{O}(JS \log N/S)$

[2] R. Baraniuk, V. Cehver, M. Duarte and C. Hegde. "Model-Based Compressed sensing," *IEEE Transactions on Information Theory*, 2010.

Timer approach

idea: set timer for each user

$$\tau_k \propto \frac{1}{\left\|\mathbf{h}_j\right\|^2} \tag{10}$$

→ First expired, First feedback (FEFF).

Problem Collision !

Numerical Results

$M = 6$ BSs, $\epsilon = 0.25$

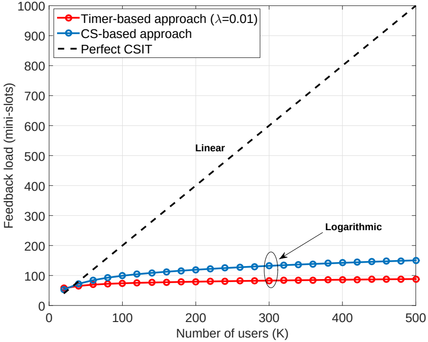


Figure 3: Feedback load versus the number of users K.

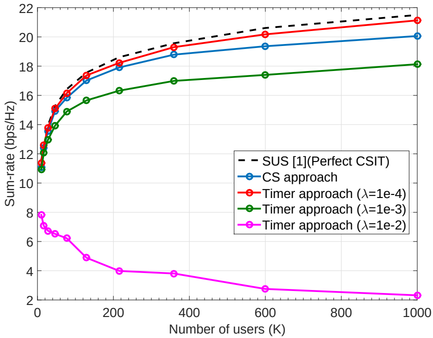


Figure 4: Sum-rate versus the number of users K.

Conclusions

- A compressed sensing based feedback algorithms has been established for different scenarios
- The feedback load grows logarithmically with the number of users/relays.
- The proposed feedback algorithms permit a substantial reduction in the feedback load with tolerable performance hit
- The proposed algorithms offer a practical framework that can be implemented in practice for various scenarios.

Thank you for your attention