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Model-based Compressive Sensing for Distant Multi-party Speech Recognition

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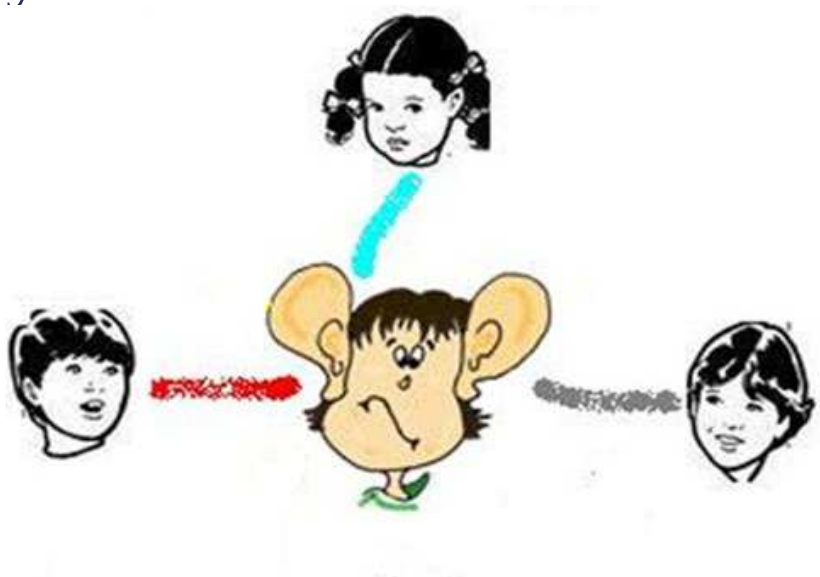
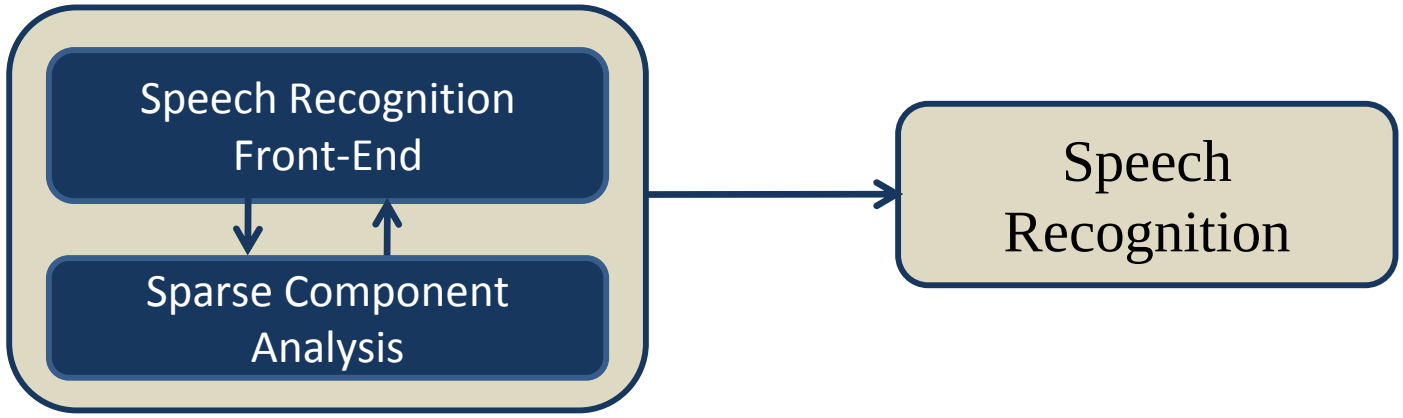
Problem of competing speech sources

- **Goal:** Speech separation to perform speech recognition
- **Challenge:** Fewer measurements than unknown sources
- **Approach:** Sparse Component Analysis



Key idea

- **We cast the under-determined speech separation problem as a sparse signal recovery where we leverage compressive sensing theory to solve it**
  - Integrate sparse component analysis into front-end processing of speech recognition system



Distant Speech Recognition Front-End

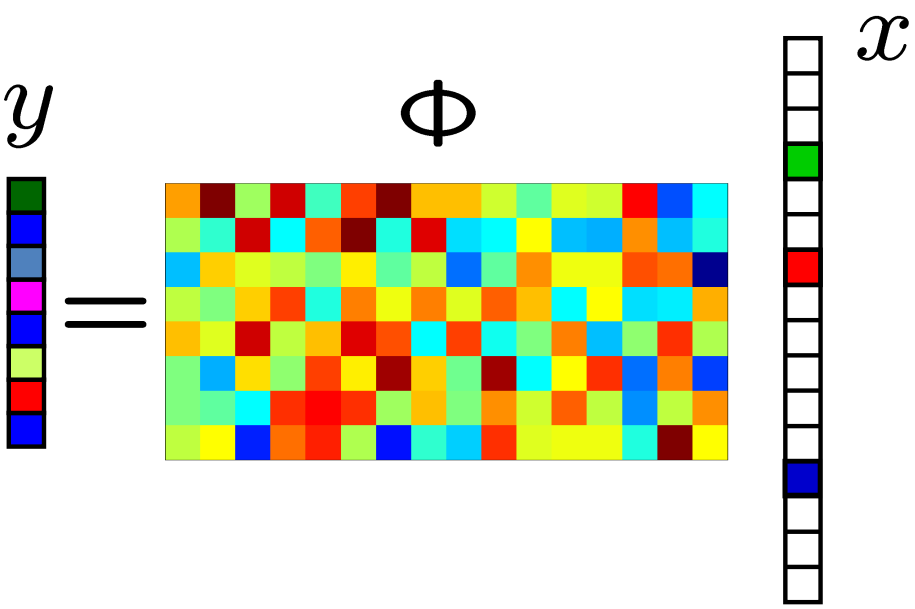
Agenda

- **A short review of compressive sensing**
- **Blind source separation via model-based compressive sensing (BSS-MSR)**
- **Speech recognition experiments**
- **Conclusion**

Compressive Sensing (CS)

In a nutshell

- **CS is sensing via dimensionality reduction**
  - Dimensionality reduction naturally happens in many problems. So, we can leverage the CS theory and algorithms.



CS Premises, in theory …

I. Sparse representation

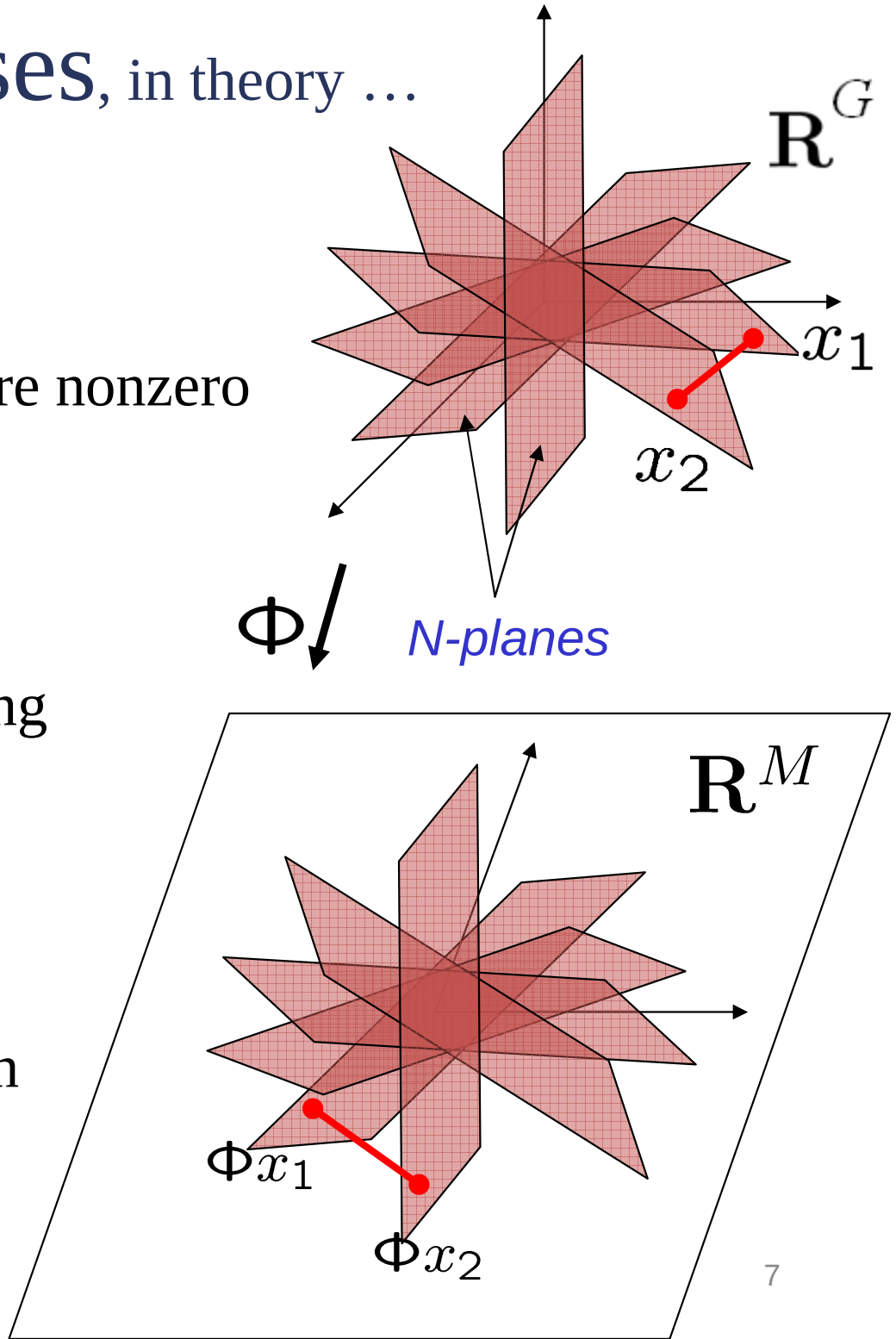
- Only *N* out of *G* coordinates are nonzero

II. Incoherent measurements

- Distance/information preserving

III. Signal recovery

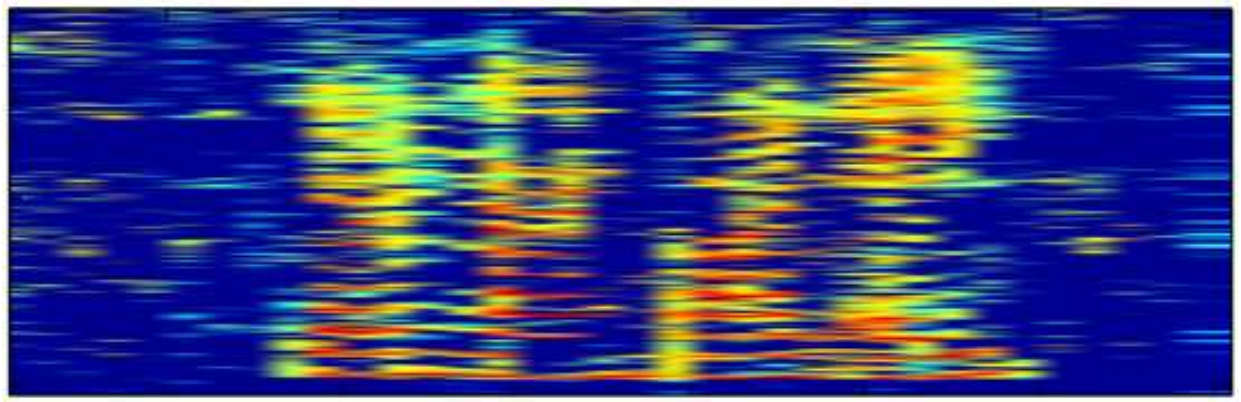
- Search for the sparsest solution

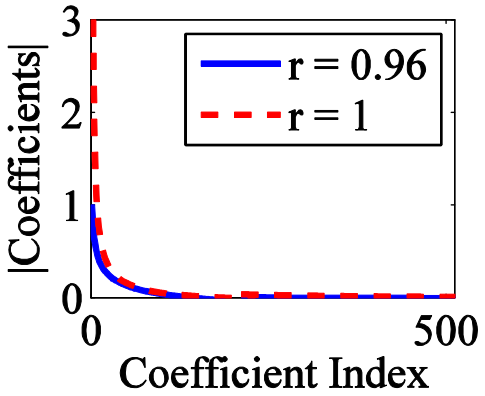


Model-based CS, in practice …

➢ Compressible representation

- Sorted coordinates decay according to the power-law with the rate $r < 1$
  - Sparse representation of speech is obtained by Gabor expansion





➢ Model-based signal recovery

- Leveraging the structure underlying the sparse coefficients improve the recovery performance and reduces the number of required measurements

Blind Source Separation via Model-based Sparse Recovery (BSS-MSR)

Insights from 2000's

➢ Sparse component analysis

[*Yilmaz , Rickard ; IEEE TSP'04* | Zibulevsky, Bofill; SP'01 | Saab et al. IEEE TSP'07 | Gribonval, ICASSP'02 | O'Grady, Pearlmutter; ICA'04 | Georgiev et al.; IEEE TNN'05]

➢ Source localization by sparse recovery

[*Cevher et al. IPSN'09* | Model and Zibulevsky; SP'06 | Malioutov, Cetin, and Willsky; IEEE TSP'05 | Guo et al. MSSP'10 | Chen et al.; Proc. of IEEE'03]

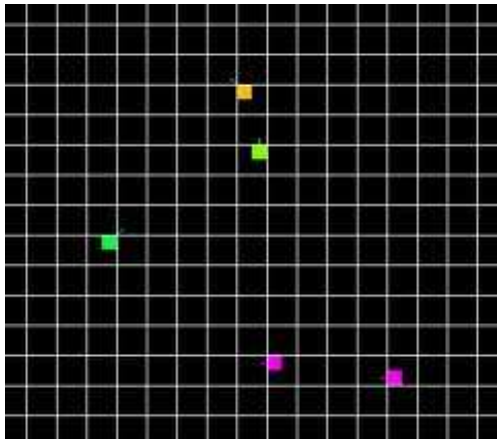
What is new about BSS-MSR?

- Model-based sparse recovery
- Convolutive mixtures
- New efficient and accurate recovery algorithm (ALPS)

I. Spatio-spectral sparse representation

➢ Spatial sparsity

- We discretize the room into G dense grids: only very few have speech activity



➢ Spectral sparsity

- We work with the time-frequency representation of speech

➢ Spatio-spectral representation

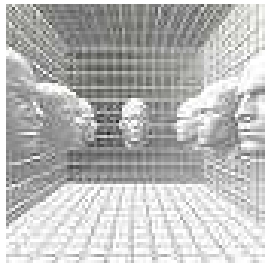
- It holds a **block-sparsity model**

$$X(\omega,\tau)=\begin{bmatrix} X_1(\omega,\tau) \\ \cdot \\ \cdot \\ X_N(\omega,\tau) \end{bmatrix}$$

II. Incoherent Measurement

- **Natural CS measurements are manifested by the media Green's function [Carin'09]**

- Image Model of multi-path effect



source at υ ; sensor at μ

$$\xi^{\omega}_{\upsilon\to\mu} : Y(\omega,\tau) = \sum_{r=1}^{R} \frac{\iota^{r}}{\left\|\mu-\upsilon_{r}\right\|} \exp(-j\omega \frac{\left\|\mu-\upsilon_{r}\right\|}{c}) X(\omega,\tau)$$

ι : Reflection coefficient $\quad$ c : Speed of sound

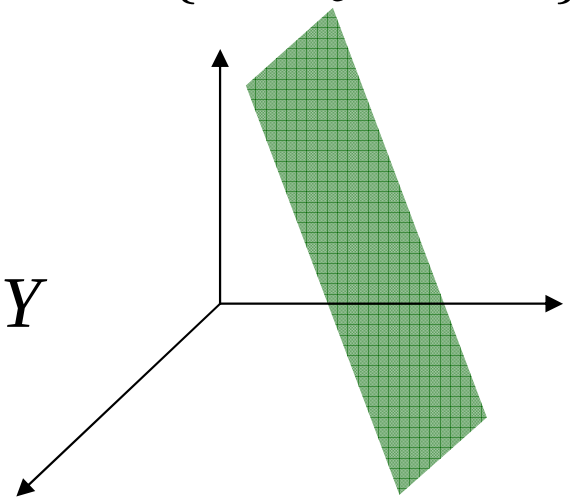
- Microphone array measurement matrix $\quad \Phi = \begin{bmatrix} \xi^{\Omega}_{\upsilon_1\to\mu_1} \cdots \xi^{\Omega}_{\upsilon_1\to\mu_N} \\ . \\ \xi^{\Omega}_{\upsilon_M\to\mu_1} \cdots \xi^{\Omega}_{\upsilon_M\to\mu_N} \end{bmatrix}$

III. Sparse signal recovery

- **Objective:** recover K-sparse signal $X_{G\times 1}$, $N << G$
  - Array observation: $Y_{M\times 1}$
  - Measurement matrix: $\Phi_{M\times N}$, $M < G$

Challenge: nullspace of Φ

$\forall V \in \text{kernel}(\Phi), X' = X + V \Rightarrow Y$



Sparsity gives enough prior information to overcome the ill-posed nature of the inverse problem

$\Rightarrow$ The recovery algorithm seeks the sparsest solution

III. Model-based Sparse Recovery

- **We estimate the signal using ALPS sparse recovery algorithm***
  - A model approximation is performed along with a gradient calculation at each iteration by thresholding (H_N) the energy of the blocks

$$X_{i+1} = H_N\left(X_i + \kappa \Phi^t (Y - \Phi X_i)\right)$$

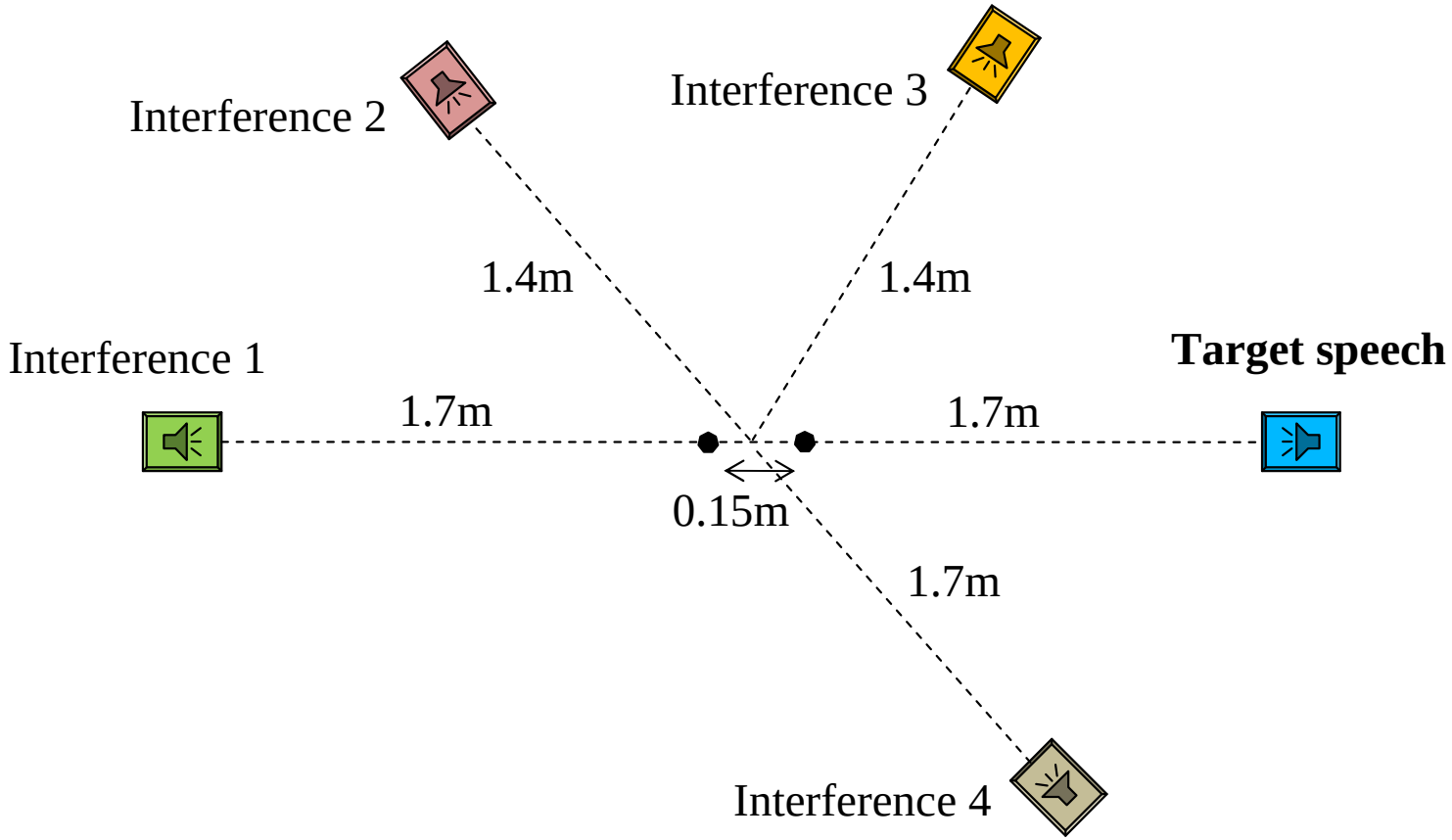
- Volkan Cevher, "An ALPS View of Sparse Recovery", *ICASSP'2011*.

  Codes available at http://lions.epfl.ch/ALPS

Speech Recognition Experiments

Experiments

- Reverberation time: 200ms
- Grid resolution: 0.5m×0.5m
- Speech Corpus: AURORA2 overlapping with HTIMIT interferences



Speech recognition performance

- Word accuracy of the separated speech for stereo echoic mixtures of 3 sources

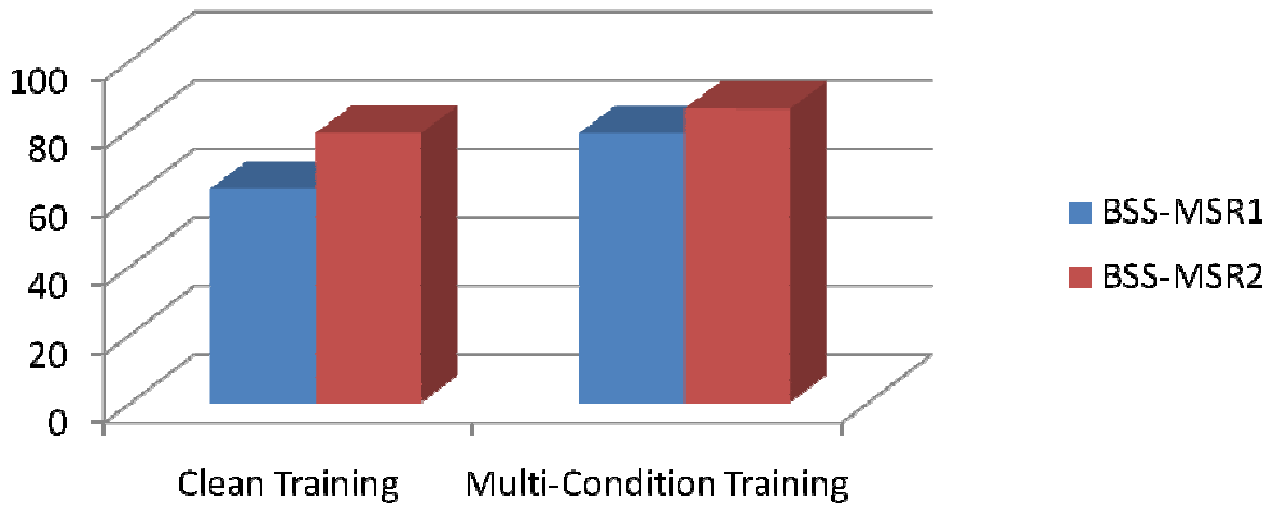
Training Condition	Aurora2 baseline	BSS-MSR
Clean	59.3	89.3
Multi-condition	61.78	92.7

- Relative improvement for recognition of 3 competing sources would be **73.7**% for clean-training and **80.9**% for multi-condition-training

Speech recognition performance

➢ Word accuracy of the separated speech for echoic mixtures of 5 sources
BSS-MSR[1] refers to the stereo recording and BSS-MSR[2] refers to 4-channel array

Training Condition	Aurora2 baseline	BSS-MSR[1]	BSS-MSR[2]
Clean	47.3	81.7	88.7
Multi-condition	58.19	91	94



Conclusion

- **Information bearing components for ASR are sparse**
- Sparse component analysis is a potential approach to deal with the problem of overlapping speech for realistic applications of ASR
- Model-based sparse recovery goes beyond sparsity
- Block-sparsity model exists in
  - Microphone array signal ensemble
  - Virtual source images due to multi-path effect

It motivates new approaches in multi-channel sparse component analysis in reverberant condition

Thank you!

Good … Bad

- **The good things about BSS-MSR are**
  - No constraint on the number of microphones, but
    - ✓ the more, the better
  - No restriction on the geometry of the array, but
    - ✓ the array must provide a reasonable spatial information
- **The bad things about BSS-MSR are**
  - Requires knowledge of microphones, but
    - ✓ automatic calibration is possible with the same framework
  - Requires knowledge of the room acoustic, but
    - ✓ initial evaluations on the simple Image model was promising