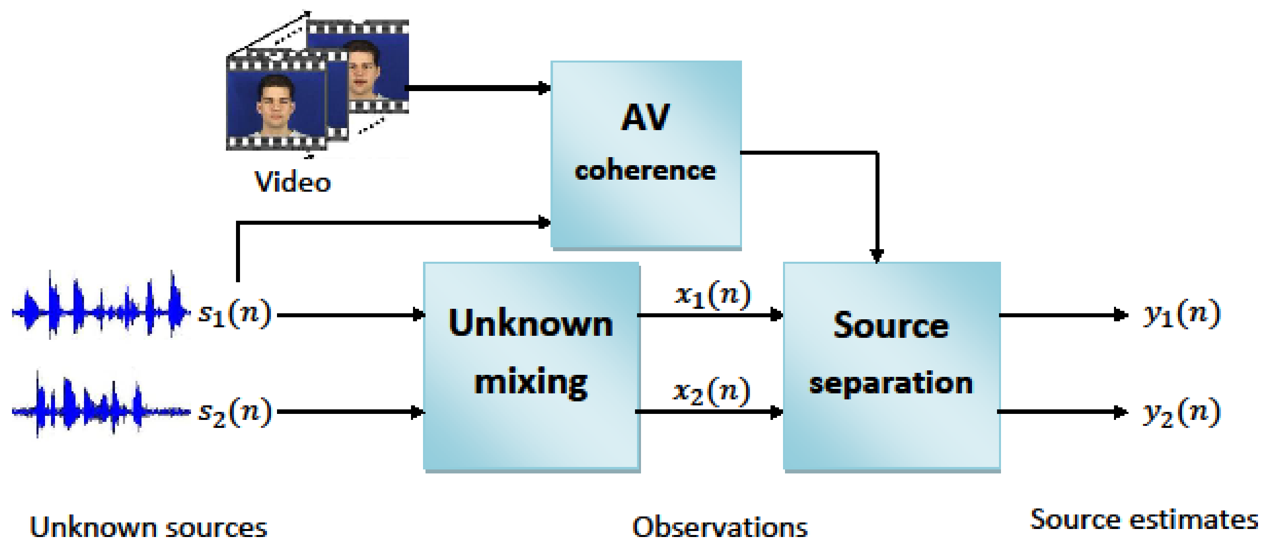
Audio-Visual Dictionary Learning and Probabilistic Time-Frequency Masking in Convolutive and Noisy Source Separation



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Acknowledgement

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➢Collaborators: Dr Philip Jackson, Dr Mark Barnard, Prof Josef Kittler, Prof Jonathon Chambers (Loughborough University), and Dr Wei Dai (Imperial College London)

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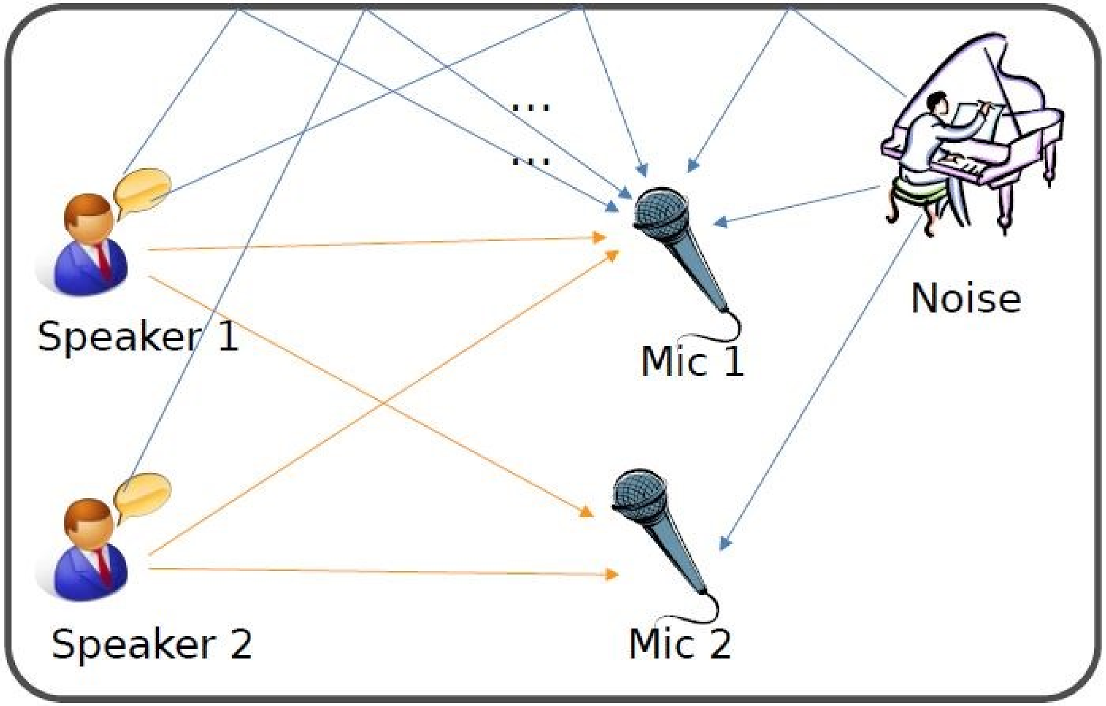
Outline

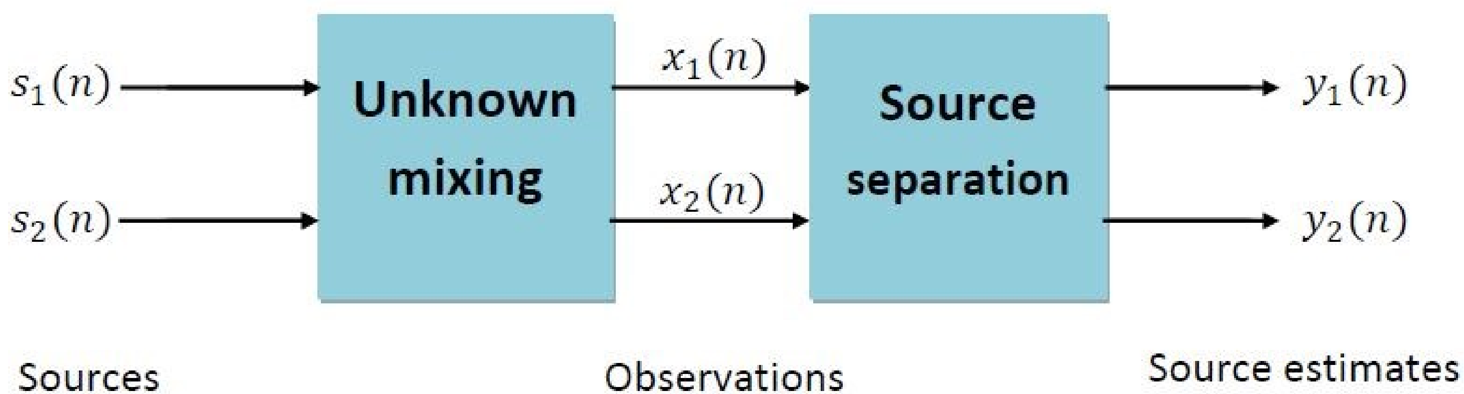
- Introduction
  - Cocktail party problem, source separation, time-frequency masking
  - Why audio-visual BSS (AV-BSS)
- Dictionary learning (AVDL) based AV-BSS
  - Audio-visual dictionary learning
  - Time-frequency mask fusion
- Results and demonstrations
- Conclusions and future work

Introduction----Cocktail party problem

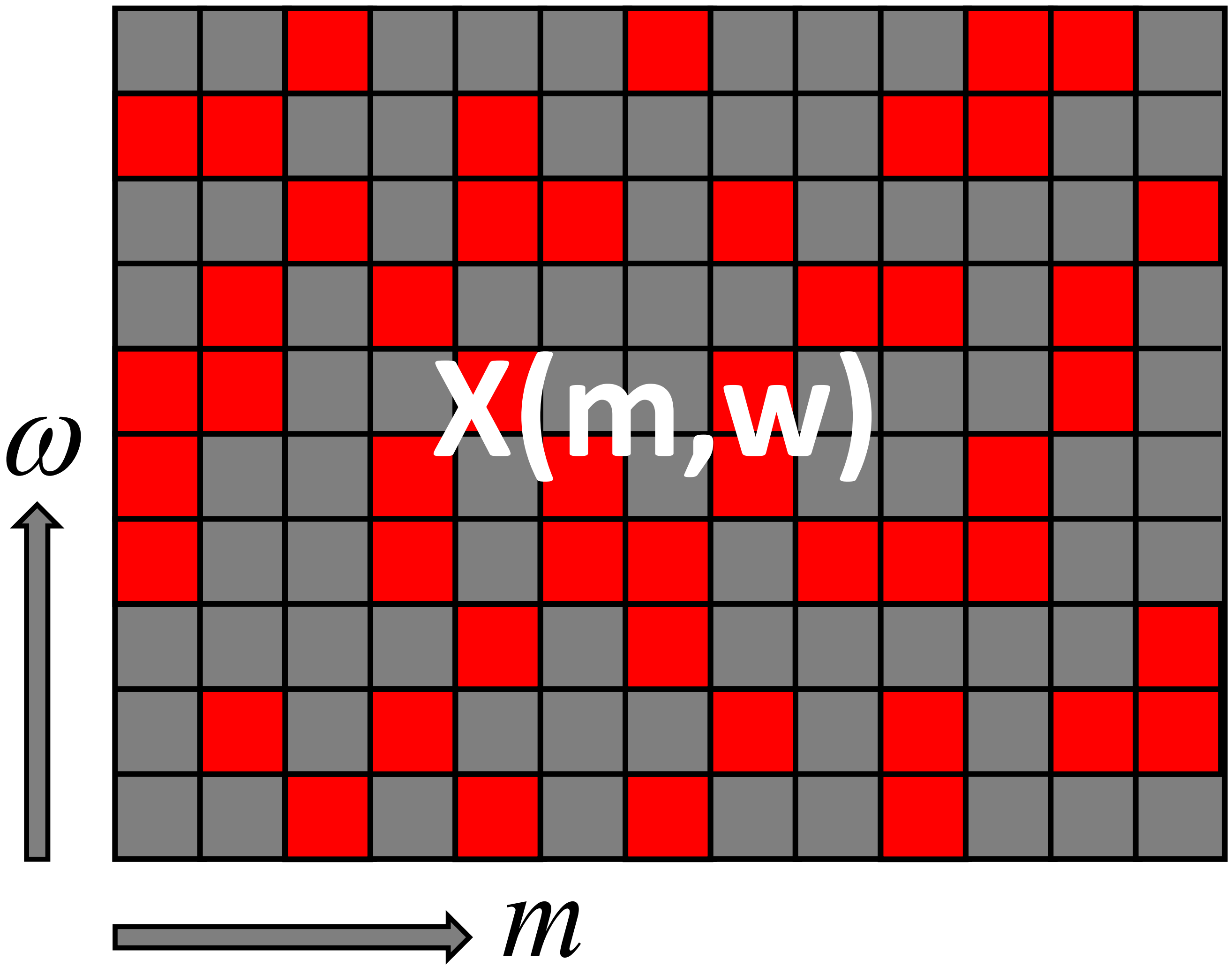


- Independent component analysis (ICA)
- Time-frequency (TF) masking

"Blind" source separation
BSS



BSS using TF masking

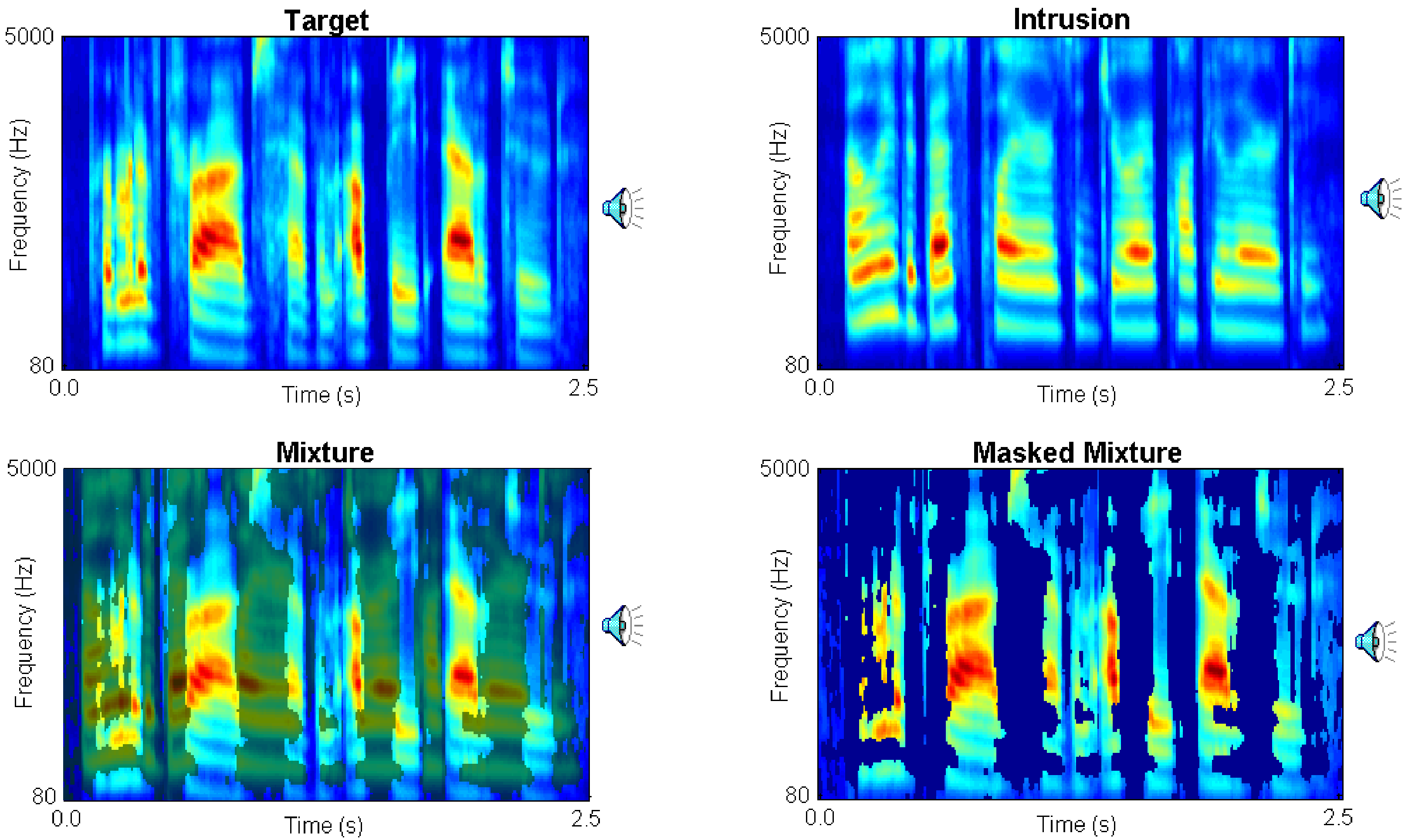


CASA

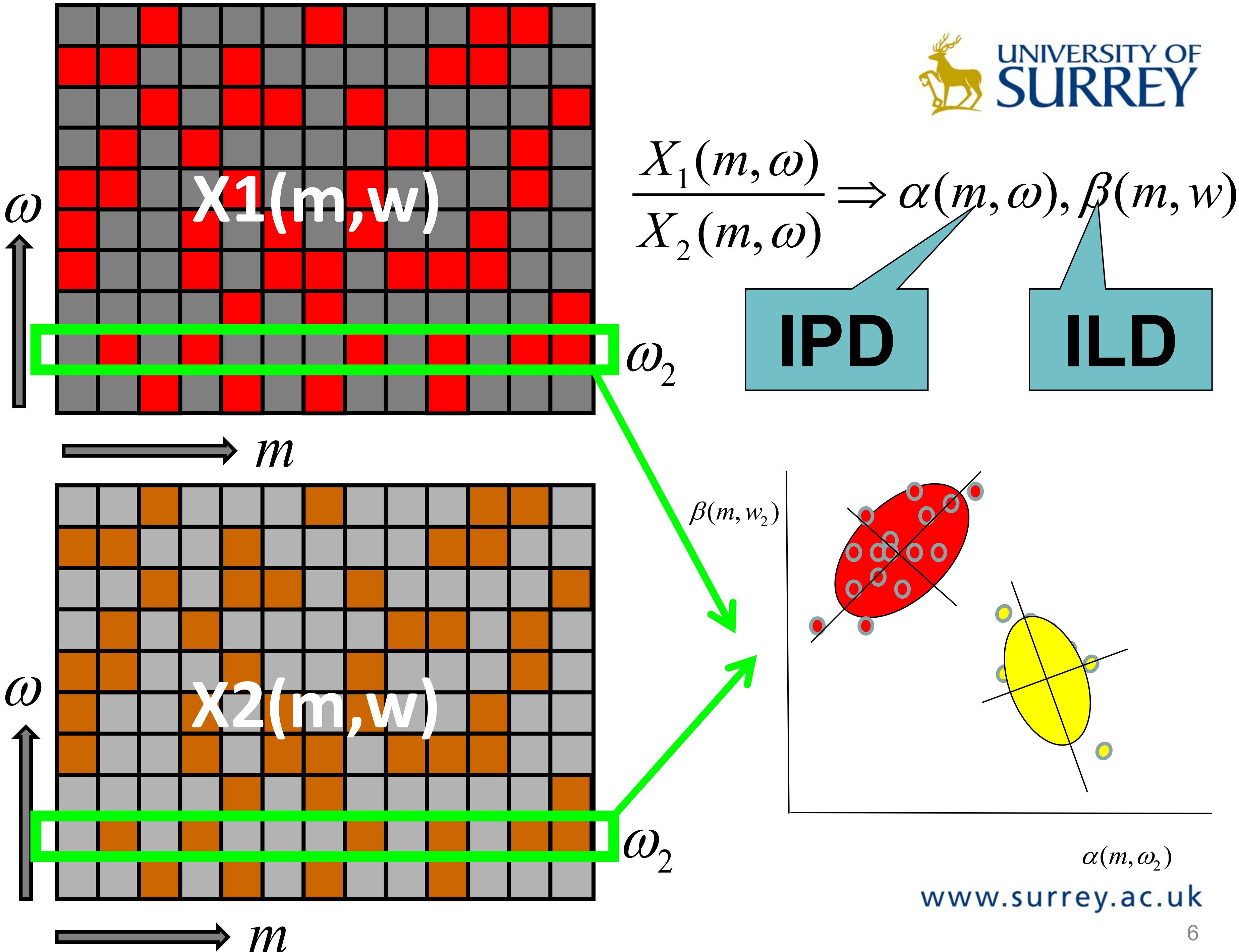
Onset
Periodicity
Harmonicity
Locations
Binarual cues

Sparsity assumption ------ each TF point is dominated by one source signal.

Benchmark: ideal binary mask (IBM)



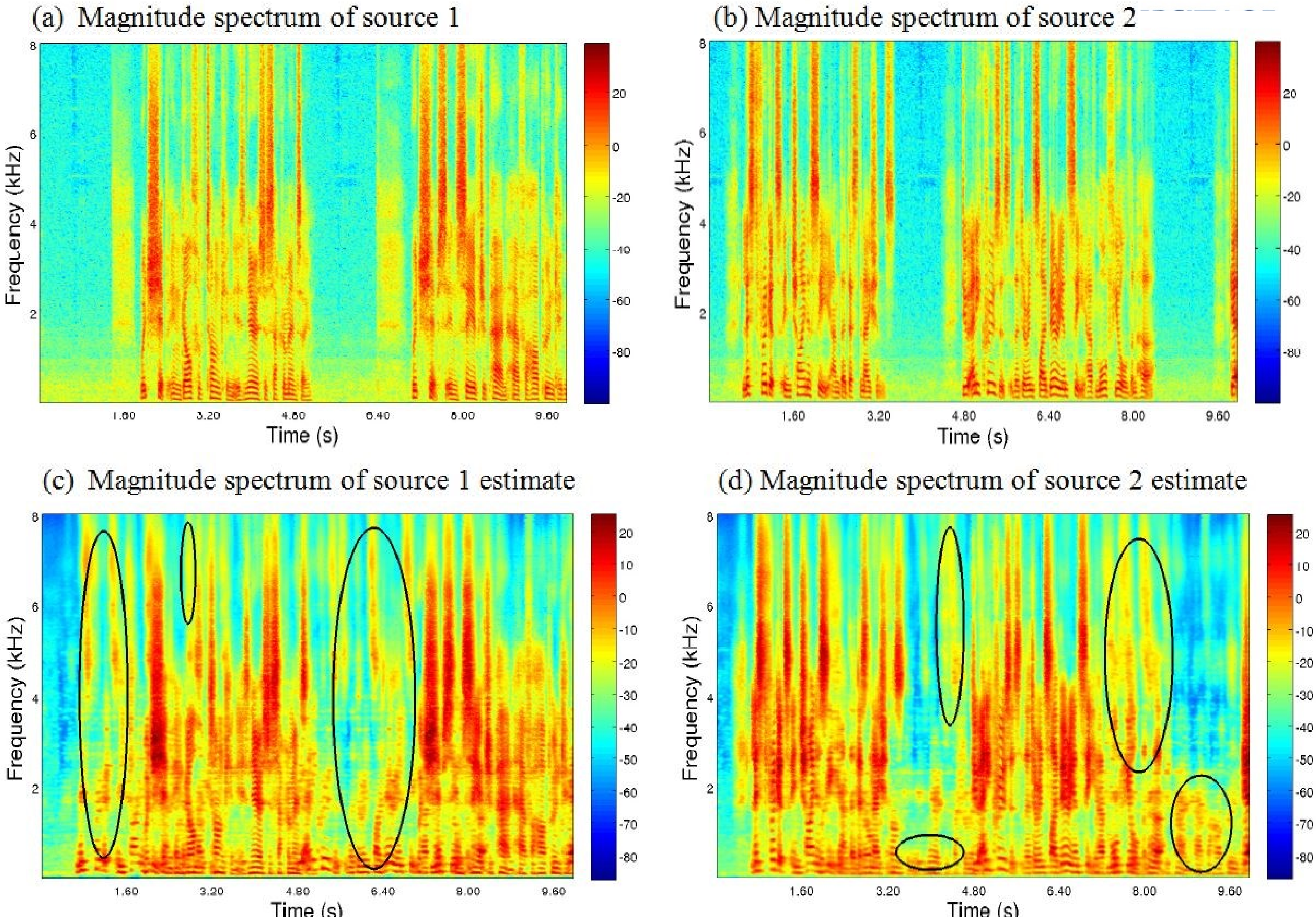
Demonstrations by DeLiang Wang, The Ohio State Univ.



X1(m,w)
X2(m,w)
ω
m
ω_2
$\frac{X_1(m,\omega)}{X_2(m,\omega)} \Rightarrow \alpha(m,\omega), \beta(m,w)$
IPD
ILD
$\beta(m,w_2)$
$\alpha(m,\omega_2)$

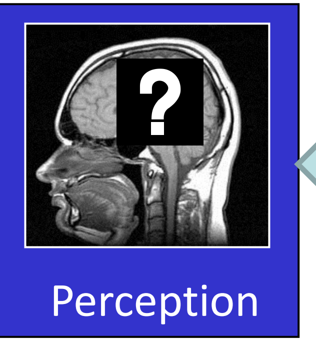
Adverse effects

- Acoustic noise
- Reverberations


(a) Magnitude spectrum of source 1
(b) Magnitude spectrum of source 2
(c) Magnitude spectrum of source 1 estimate
(d) Magnitude spectrum of source 2 estimate
Frequency (kHz)
Time (s)
1.60
3.20
4.80
6.40
8.00
9.60
20
0
-20
-40
-60
-80
10
-10
-30
-50
-70

Why AV-BSS?----AV coherence

Audio-visual (AV) coherence



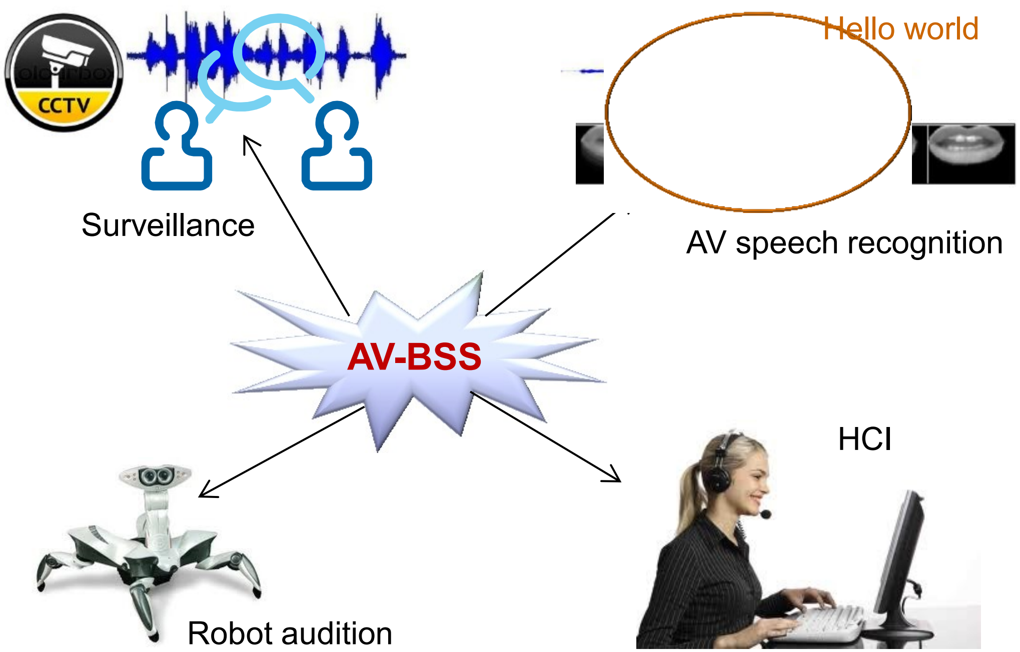
Why AV-BSS?

- The audio-domain BSS algorithms **degrade in adverse conditions**.
- The visual stream contains **complementary information** to the coherent audio stream.

Objective

How can the visual modality be used to assist audio-domain BSS algorithms in noisy and reverberant conditions?

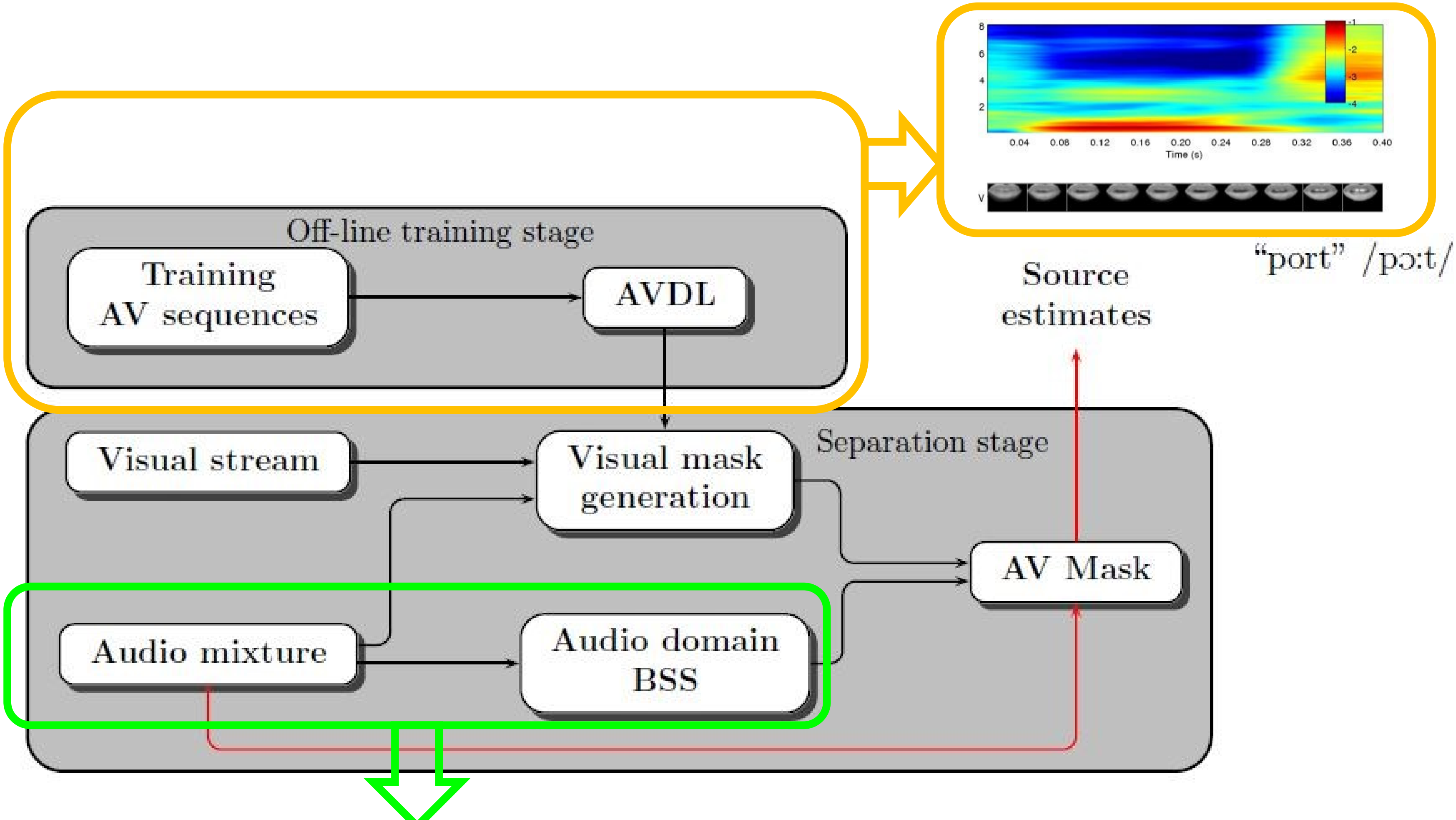
Potential applications



Key Challenges

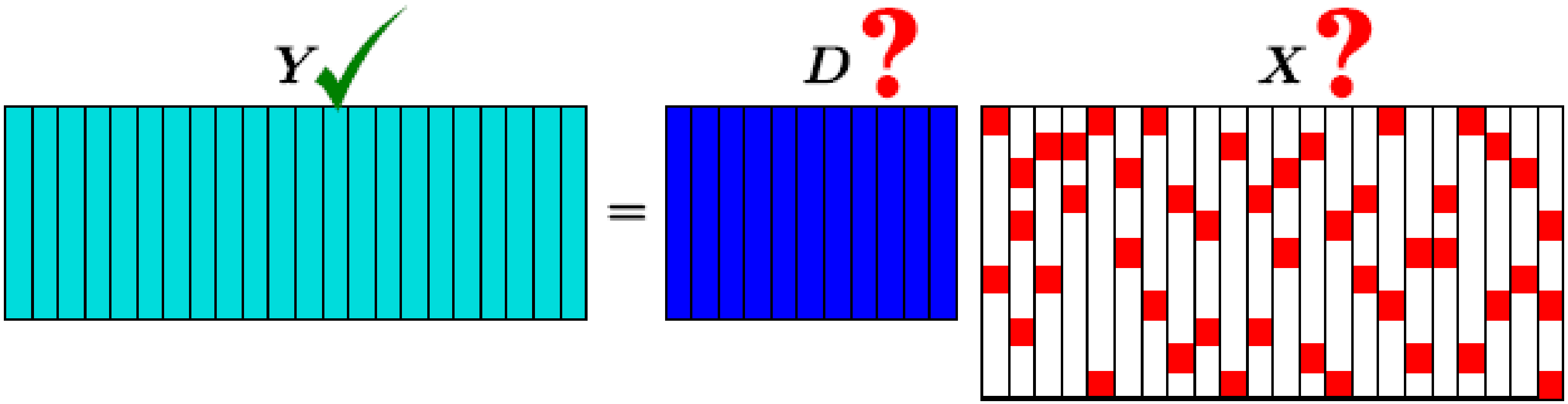
- Reliable **AV coherence modelling**
- **Bimodal differences** in size, dimensionality and sampling rates
- **Fusion of AV coherence** with audio-domain **BSS** methods

AVDL based BSS



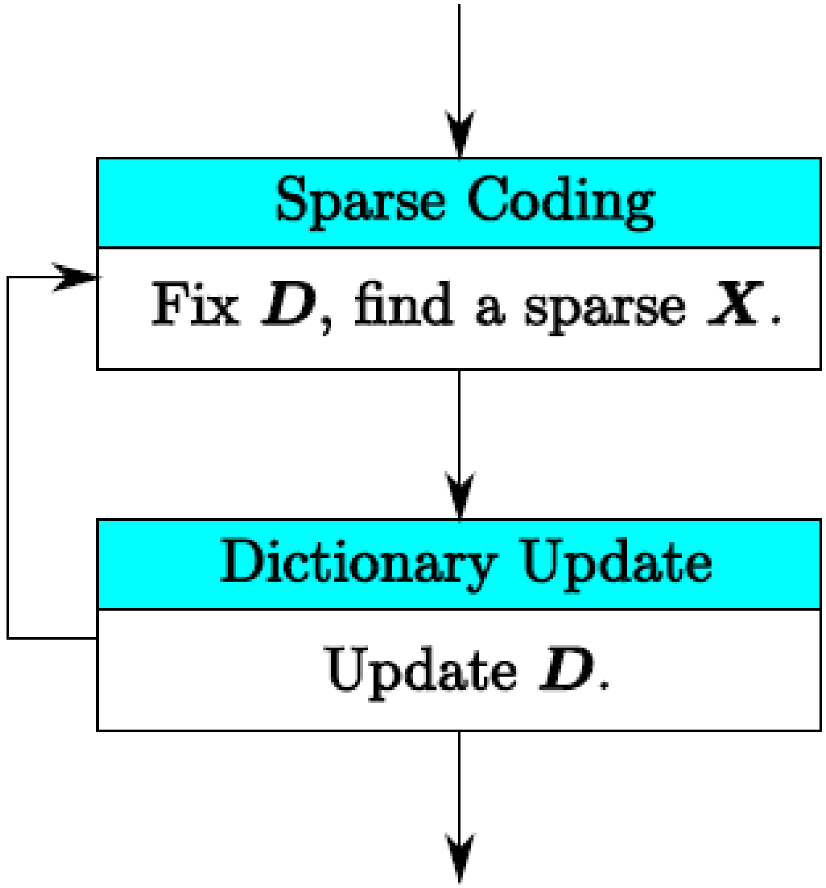
TF masking, Mandel et al. 2010.

Dictionary learning

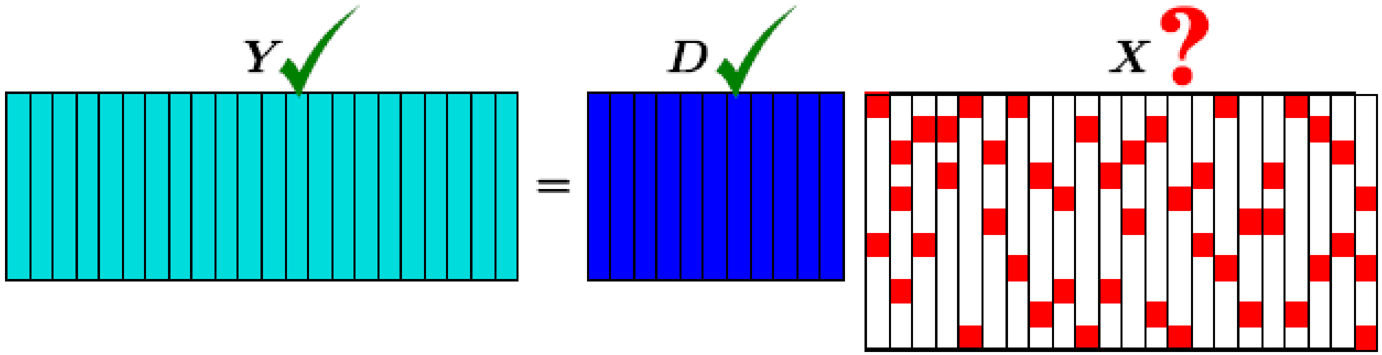


Figures taken from ICASSP 2013 Tutorial 11, by Dai, Maihe and Wang. Likewise for next four pages. Acknowledgement to Wei Dai for making these figures.

A two-stage procedure



Sparse coding (approximation)



$$\min \|X\|_0 \text{ s.t. } \|Y - DX\|_F^2 \leq \epsilon.$$

Greedy algorithms:

- OMP Y. Pati, et al. 1993; J. Tropp 2004
- Subspace pursuit (SP) W. Dai and O. Milenkovic 2009 CoSaMP D. Needell and J. Tropp 2009
- IHT T. Blumensath and M. Davies 2009

Dictionary update: the formulation

- Constraints:
  - Fixed sparsity pattern

$$\begin{aligned} \Omega &= \{(i,j): \boldsymbol{X}_{i,j} \neq 0\}, \\ \mathcal{X}_\Omega &= \{\boldsymbol{X}: \boldsymbol{X}_{i,j} = 0, \ \forall (i,j) \in \Omega^c\}. \end{aligned}$$

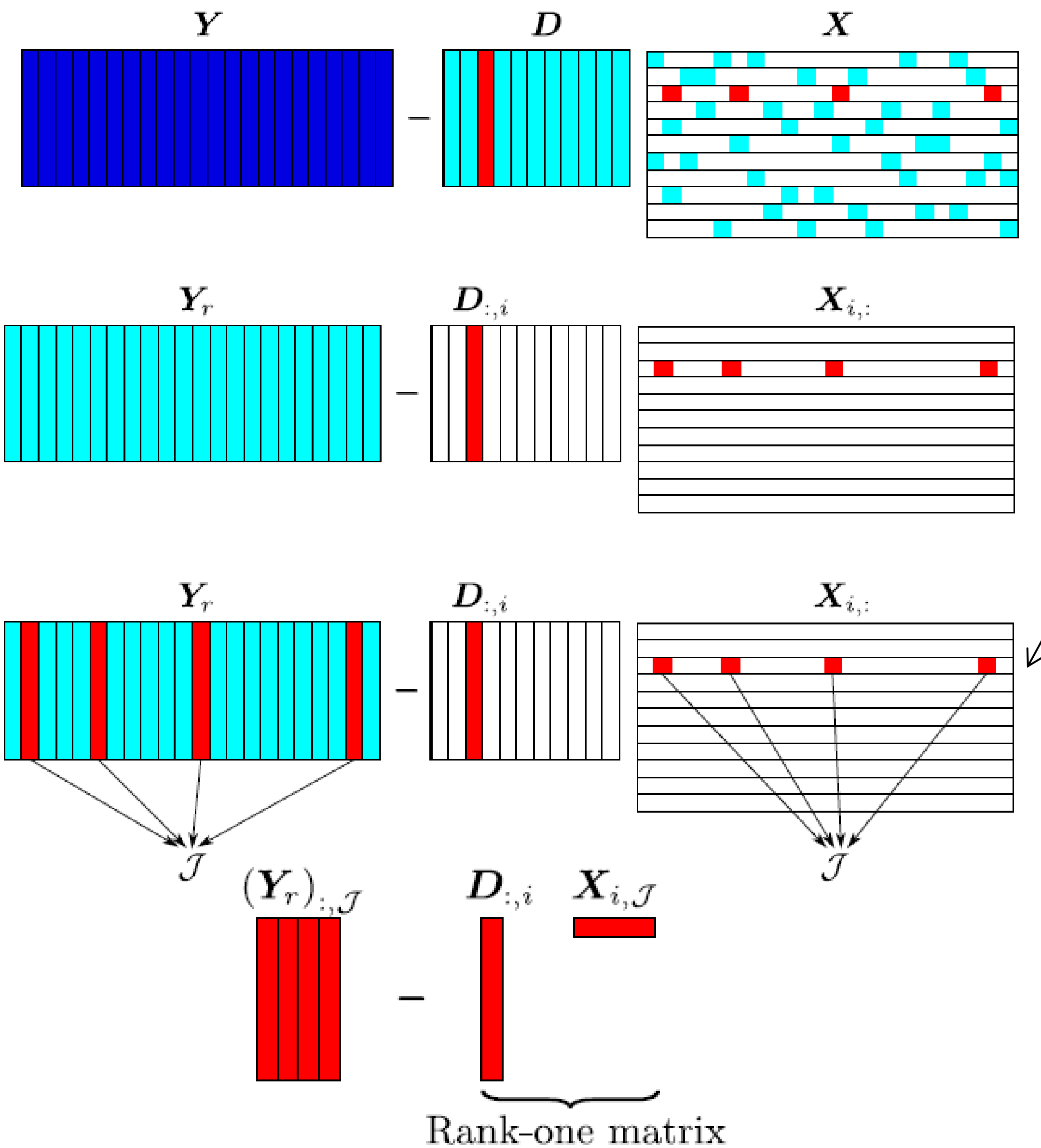
  - Unit norm codewords

$$\mathcal{D} = \left\{\boldsymbol{D}: \ \|\boldsymbol{D}_{:,j}\|_2 = 1, \ \forall j \in [d]\right\}.$$

- Dictionary Update:

$$\min_{\boldsymbol{D}\in\mathcal{D}, \ \boldsymbol{X}\in\mathcal{X}_\Omega} \|\boldsymbol{Y} - \boldsymbol{D}\boldsymbol{X}\|_F^2 .$$

Dictionary update: K-SVD algorithm

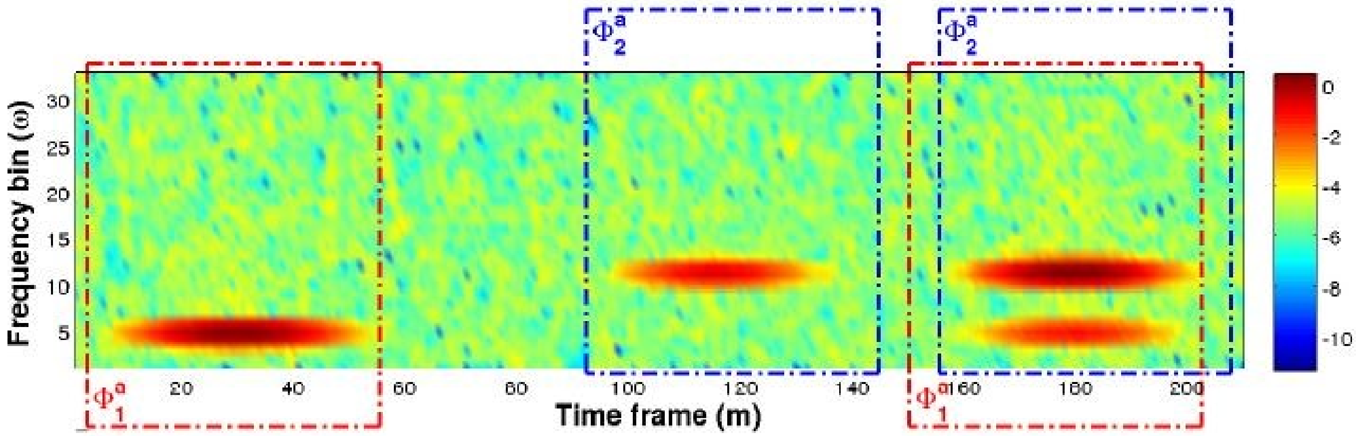


$$\|Y - DX\|^2$$
$$= \|Y - D_{:,j\neq i}X_{j\neq i,:} - D_{:,i}X_{i,:}\|^2$$
$$= \|Y_r - D_{:,i}X_{i,:}\|^2$$
$$= \left\|(Y_r)_{:,\mathcal{J}} - D_{:,i}X_{i,\mathcal{J}}\right\|^2 + c$$

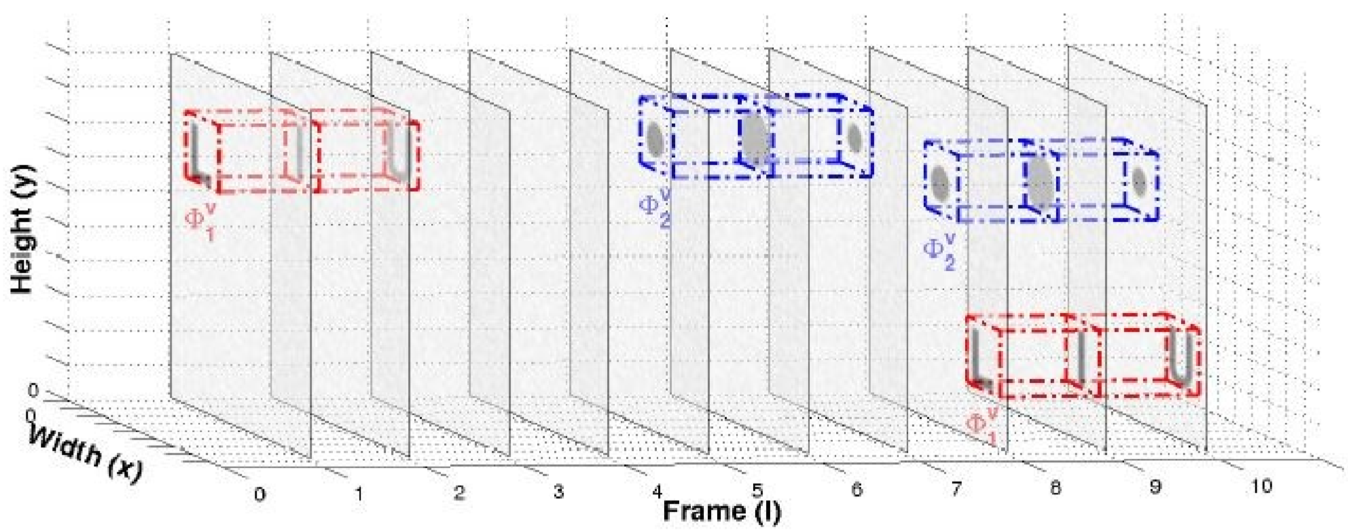
Audio-visual dictionary learning: a generative model

$$\begin{pmatrix} \psi^a(m) \\ \psi^v(y,x,l) \end{pmatrix} \approx \begin{pmatrix} \hat{\psi}^a(m) \\ \hat{\psi}^v(y,x,l) \end{pmatrix} = \sum_{d=1}^{D} \begin{pmatrix} \sum_{\breve{m}=1}^{M_s} c_{d\breve{m}} \phi_d^a(m-\breve{m}) \\ \sum_{\breve{y}=1,\breve{x}=1,\breve{l}=1}^{Y_s,X_s,L_s} b_{d\breve{y}\breve{x}\breve{l}} \phi_d^v(y-\breve{y}, x-\breve{x}, l-\breve{l}) \end{pmatrix}$$

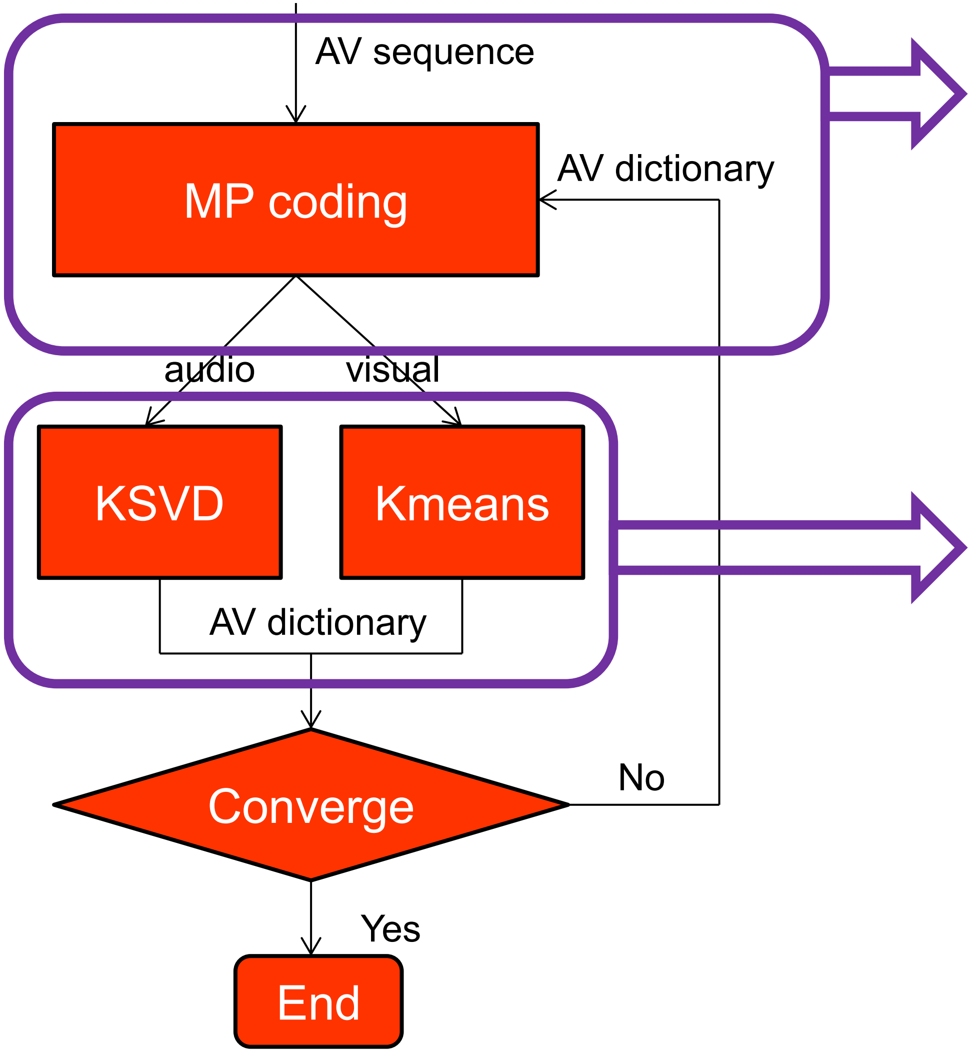
Sparse assumption of AVDL



(a) Audio stream ψ^a



Flow of the AVDL



The coding process relies on the matching criterion, how well an atom fits the signal in the MP algorithm

A **scanning index** is proposed to reduce the computational complexity.

The learning process uses two different update methods, to accommodate different bimodality sparsity constraints.

By mapping the AV sequence to the learned dictionary, a visual mask can be achieved.

The overall algorithm

Algorithm 1: Framework of the Proposed AVDL

Input: A training AV sequence $\boldsymbol{\psi} = (\boldsymbol{\psi}^a; \boldsymbol{\psi}^v)$, an initial $\mathcal{D}$ with K atoms, and the number of non-zero coefficients N

Output: An AV dictionary $\mathcal{D} = \{\boldsymbol{\phi}_k\}_{k=1}^{K}$

Initialization: $iter = 1$, $MaxIter$
while $iter \leq MaxIter$ **do**
%Coding stage
Given $\mathcal{D}$, decompose $\boldsymbol{\psi}$ using **(1)** to obtain Ω.
%Learning stage
Given Ω and the residual $\boldsymbol{\upsilon}$, update $\mathcal{D} = \{\phi_k\}$ for $k = 1, 2, \ldots, K$ to fit model **(1)**.
$iter = iter + 1$

The coding process

$$J^{av}(\bar{\boldsymbol{v}}_{\breve{y}\breve{x}\breve{l}\breve{m}}, \boldsymbol{\phi}_k) = J^a(\bar{\boldsymbol{v}}^a_{\breve{m}}, \boldsymbol{\phi}^a_k) J^v(\bar{\boldsymbol{v}}^v_{\breve{y}\breve{x}\breve{l}}, \boldsymbol{\phi}^v_k),$$

$$J^a_{\mathrm{Mon}} = |\langle \bar{\boldsymbol{v}}^a_{\breve{m}}, \boldsymbol{\phi}^a_k \rangle|$$

$$J^v(\bar{\boldsymbol{v}}^v_{\breve{y}\breve{x}\breve{l}}, \boldsymbol{\phi}^v_k) = \exp\left\{ \frac{-1}{YXL} \left\| \bar{\boldsymbol{v}}^v_{\breve{y}\breve{x}\breve{l}} - \boldsymbol{\phi}^v_k \right\|_1 \right\}.$$

$$[k_n, y_n, x_n, l_n, m_n] = \arg\max_{[k, \breve{y}, \breve{x}, \breve{l}, \breve{m}]} J^{av}(\bar{\boldsymbol{v}}_{\breve{y}\breve{x}\breve{l}\breve{m}}, \boldsymbol{\phi}_k),$$

$$B(k_n, y_n, x_n, l_n) = 1$$

$$C(k_n, m_n) = J^a(\bar{\boldsymbol{v}}^a_{m_n}, \boldsymbol{\phi}^a_{k_n}).$$

$$\bar{\boldsymbol{v}}^a_{l_n} \leftarrow \bar{\boldsymbol{v}}^a_{l_n} - C(k_n, l_n)\boldsymbol{\phi}^a_{k_n}.$$

The coding process (algorithm)

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Algorithm 2: The Coding State of the Proposed AVDL

Input: An AV sequence $\boldsymbol{\psi}$, the dictionary $\mathcal{D} = \{\boldsymbol{\phi}_k\}_{k=1}^{K}$, the threshold δ, the number of non-zero coefficients N

Output: The coding parameter set $\Omega = \{\mathbf{B}, \mathbf{C}\}$ and residual $\boldsymbol{\upsilon}$

Initialization: Set Ω with zero tensors, $\boldsymbol{\upsilon} = \boldsymbol{\psi}, n = 1, J_{opt} = J_{\max} = 0$

Calculate $\mathcal{S}^{av}$ using **(10)** to **(13)**.

while $n \leq N and\ J_{opt} \geq \delta J_{\max}$ **do**

  % Projection

  $\mathcal{L} = \begin{cases} \{1 : L_s\}, & \text{n=1} \\ l_{n-1} + \{1 - L : L - 1\}, & \text{otherwise} \end{cases}$

  for $\boldsymbol{k} \leftarrow$ **1to** K do

    foreach $\breve{l} \in \mathcal{L}$ **do**

      Calculate $J^a(\bar{\boldsymbol{\upsilon}}^a_{\breve{m}}, \boldsymbol{\phi}^a_k)$, where $\breve{m}$ is tied with $\breve{l}$ via set **(2)**.

      foreach $(\breve{y}, \breve{x}), \breve{y} \in \{1 : Y_s\}, \breve{x} \in \{1 : X_s\}$ **do**

        if $\mathcal{S}^{av}(\breve{y}, \breve{x}, \breve{l}) = 1$ **then**

          Obtain $J^v(\bar{\boldsymbol{\upsilon}}^v_{\breve{y}\breve{x}\breve{l}}, \boldsymbol{\phi}^v_k)$ via **(6)** and $J^{av}(\bar{\boldsymbol{\upsilon}}_{\breve{y}\breve{x}\breve{l}\breve{m}}, \boldsymbol{\phi}_k)$ via **(5)**.

  % Selection

  Obtain $[y_n, x_n, l_n, k_n, m_n]$ via **(7)**.

  Update Ω via **(8)**.

  Residual calculation via **(9)**.

  $J_{opt} = J^{av}(\bar{\boldsymbol{\upsilon}}_{y_n x_n l_n m_n}, \boldsymbol{\phi}_{k_n})$

  if $n = 1$ **then**

  $J_{\max} = J^{av}(\bar{\boldsymbol{\upsilon}}_{y_1 x_1 l_1 m_1}, \boldsymbol{\phi}_{k_1})$

  $n = n + 1$

The learning stage

Algorithm 3: The Learning Stage of the Proposed AVDL.

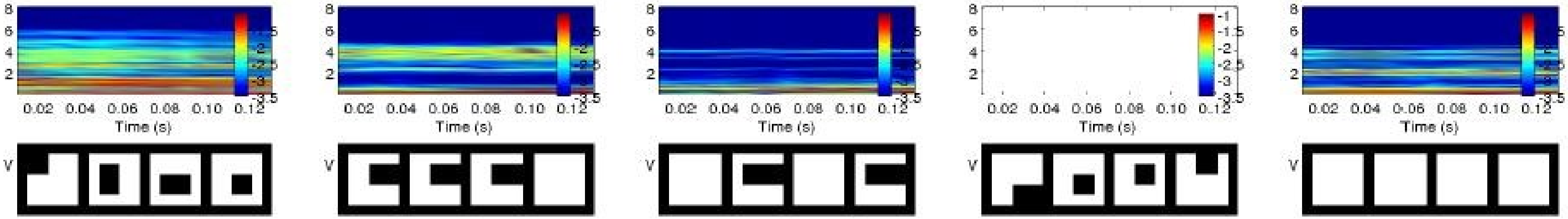
Input: The parameter set $\Omega = \{\mathbf{B}, \mathbf{C}\}$, the residual $\boldsymbol{\upsilon}$, the old dictionary $\mathcal{D} = \{\boldsymbol{\phi}_k\}_{k=1}^{K}$
Output: A new dictionary $\mathcal{D}$
1 **Initialization:** $k = 1$
2 **while** $k \leq K$ **do**
3 Update $\boldsymbol{\phi}_k^a$, $\mathbf{C}$ and $\boldsymbol{\upsilon}$ via K-SVD using **(14)** to **(17)**.
4 Update $\boldsymbol{\phi}_k^v$ via the K-means algorithm
5 $\boldsymbol{\phi}_k^v = \text{Mean}\ (b_{k\breve{y}\breve{x}\breve{l}}\bar{\boldsymbol{\upsilon}}^v_{k\breve{y}\breve{x}\breve{l}})$, subject to $b_{k\breve{y}\breve{x}\breve{l}} \neq 0,\ \forall(\breve{y}, \breve{x}, \breve{l})$
6 $k = k + 1$

$$\bar{\boldsymbol{\upsilon}}^a_{\breve{m}} \leftarrow \bar{\boldsymbol{\upsilon}}^a_{\breve{m}} + c_{k\breve{m}}\boldsymbol{\phi}^a_k,\ \forall\breve{m}. \qquad \boldsymbol{\phi}^a_k \leftarrow \mathbf{ivec}(\mathbf{u}_k|\boldsymbol{\phi}^a_k).$$

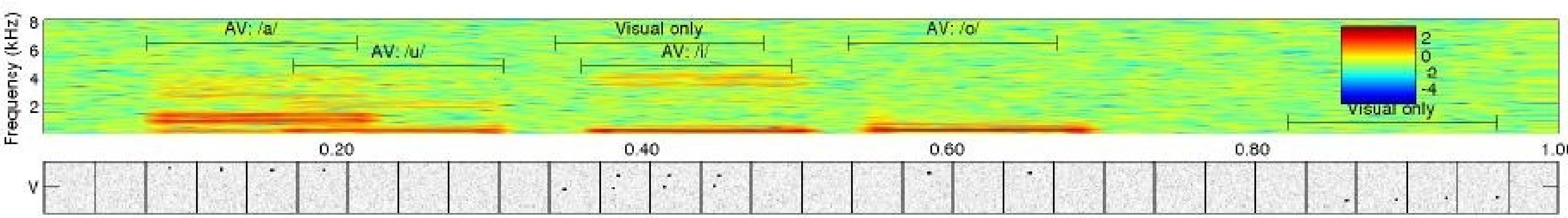
$$\Upsilon_k \approx \lambda_k \mathbf{u}_k \mathbf{v}_k^T, \qquad \bar{\boldsymbol{\upsilon}}^a_{\breve{m}} \leftarrow \bar{\boldsymbol{\upsilon}}^a_{\breve{m}} - c_{k\breve{m}}\boldsymbol{\phi}^a_k,\ \forall\breve{m}.$$

AVDL evaluations

Synthetic data



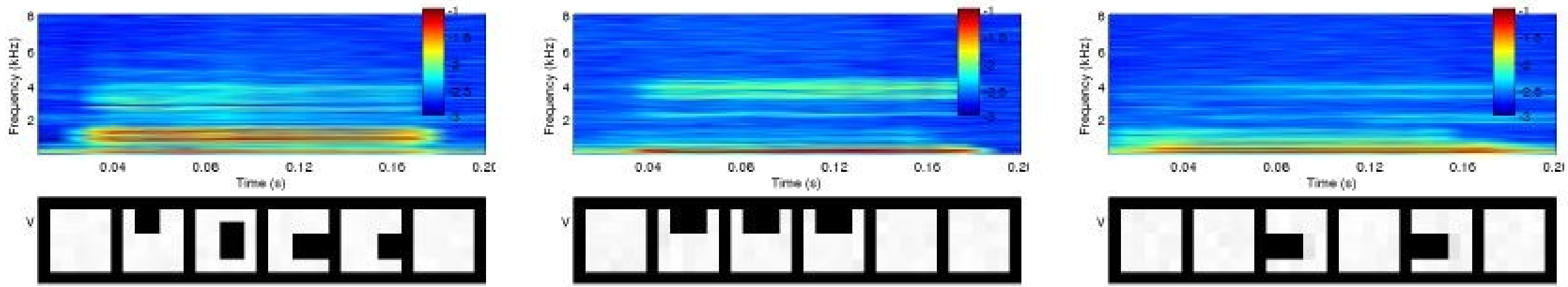
(a) AV: /a/ (b) AV: /i/ (c) AV: /o/ (d) Visual only (e) Audio only:



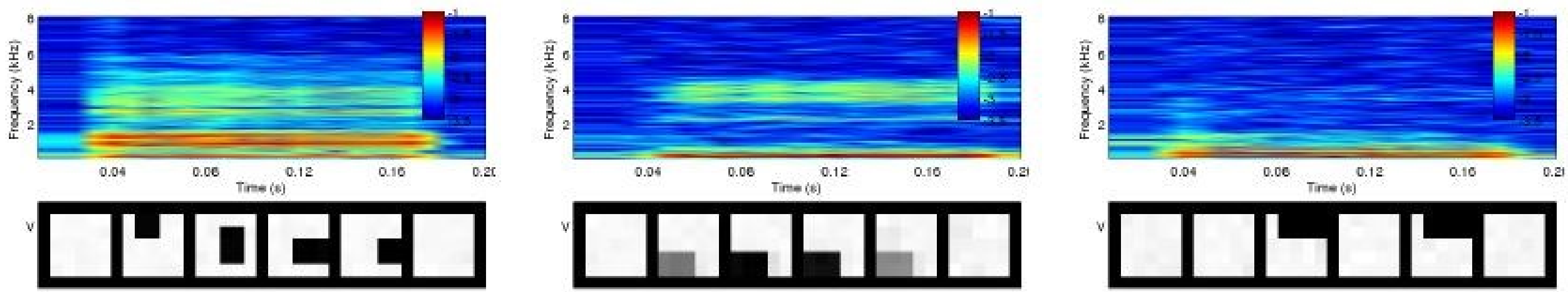
(f) The generated AV synthetic sequence (only one second data is shown)

AVDL evaluations

Additive noise added



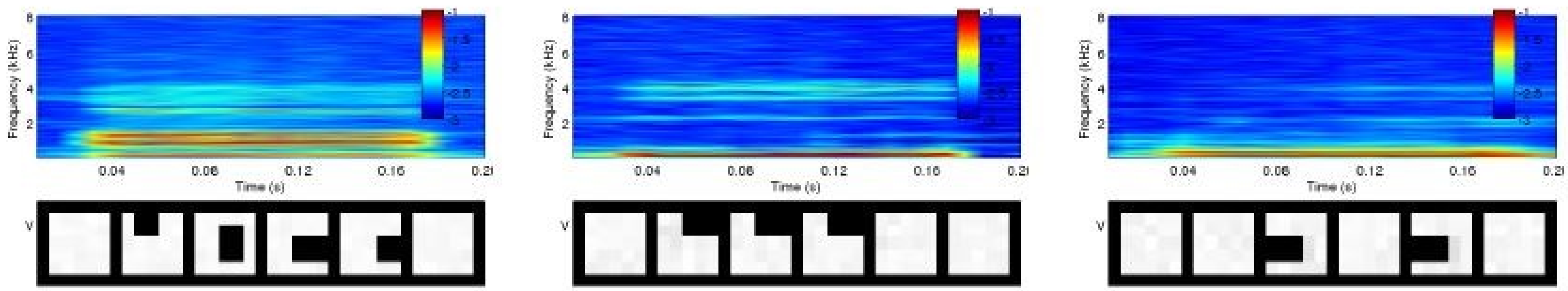
(a) AVDL: /a/ (b) AVDL: /i/ (c) AVDL: /o/



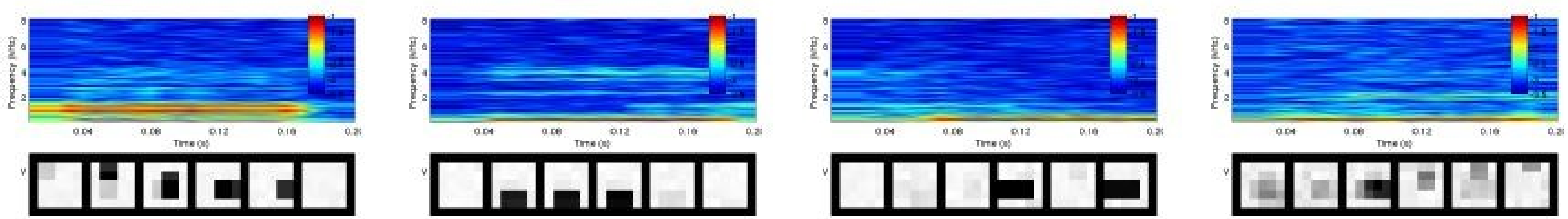
(d) Monaci: /a/ (e) Monaci: /i/ (f) Monaci: /o/

AVDL evaluations

Convolutive noise added



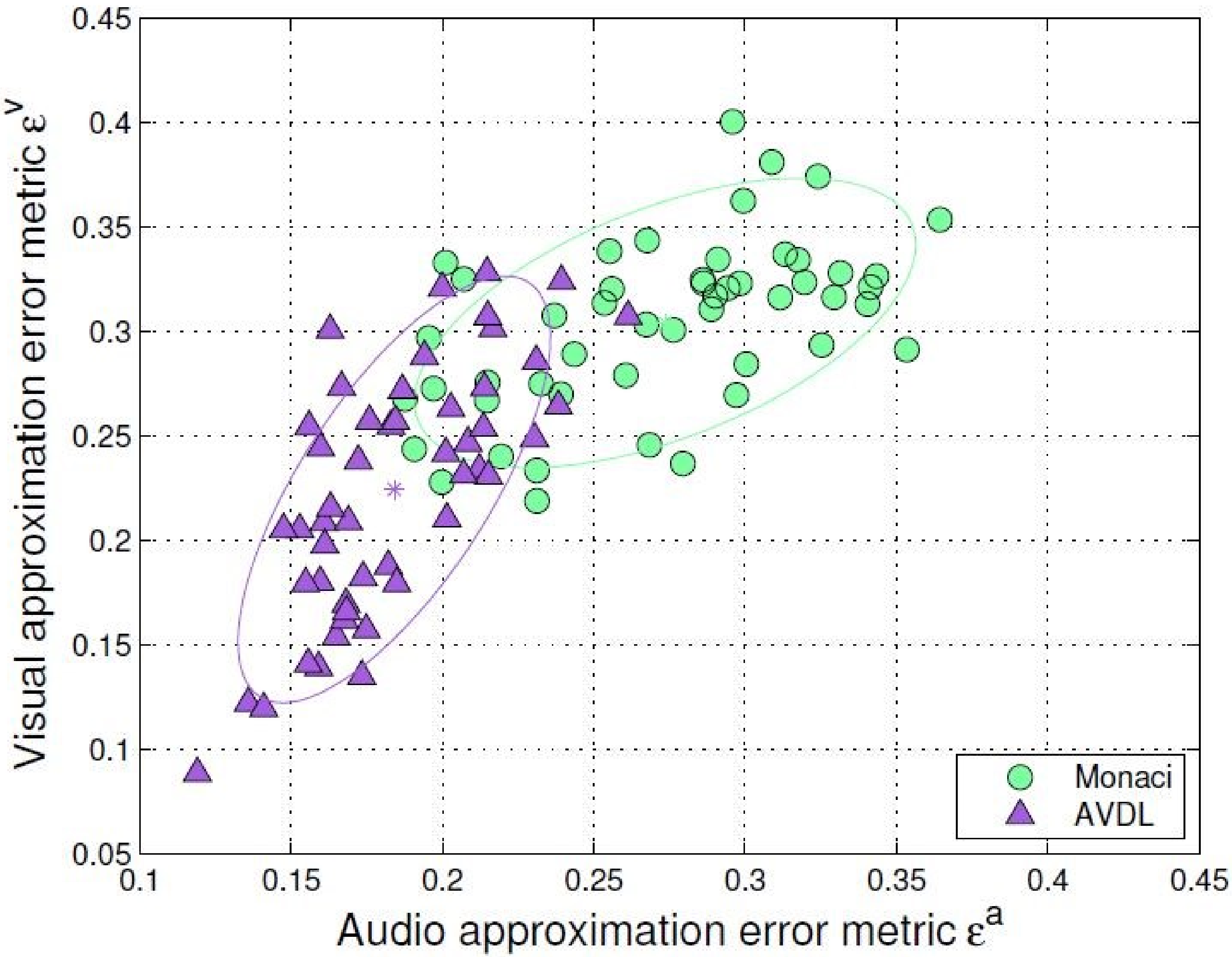
(a) AVDL1 (b) AVDL2 (c) AVDL3



(d) Monaci1 (e) Monaci2 (f) Monaci3 (g) Monaci4

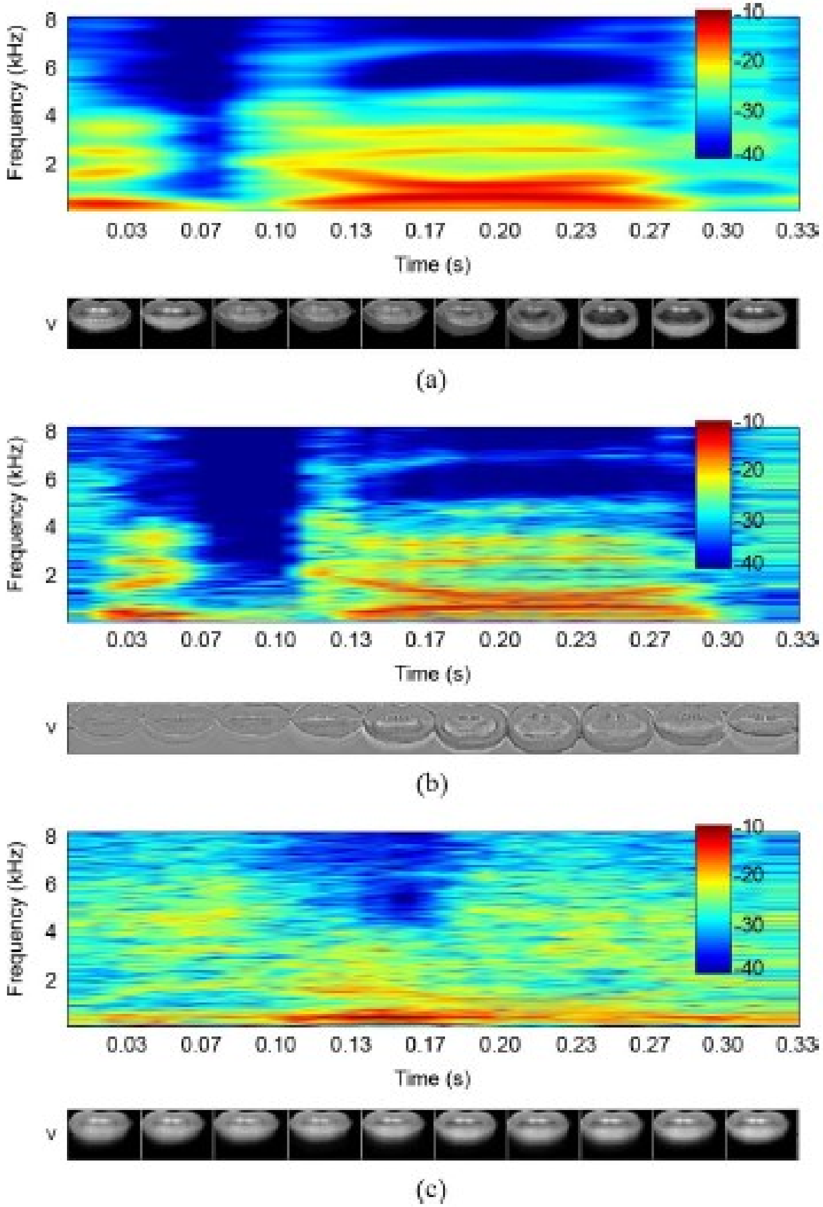
AVDL evaluations

The approximation error metrics comparison of AVDL and Monaci's method over 50 independent tests over the synthetic data



The proposed AVDL outperforms the baseline approach, giving an average of 33% improvement for the audio modality, together with a 26% improvement for the visual modality.

AVDL evaluations



AV mask fusion for AVDL-BSS

$$\mathcal{M}^{av}(m,\omega) = \boxed{\mathcal{M}^{a}(m,\omega)}\, r\, \boxed{(\mathcal{M}^{v}(m,\omega))}$$

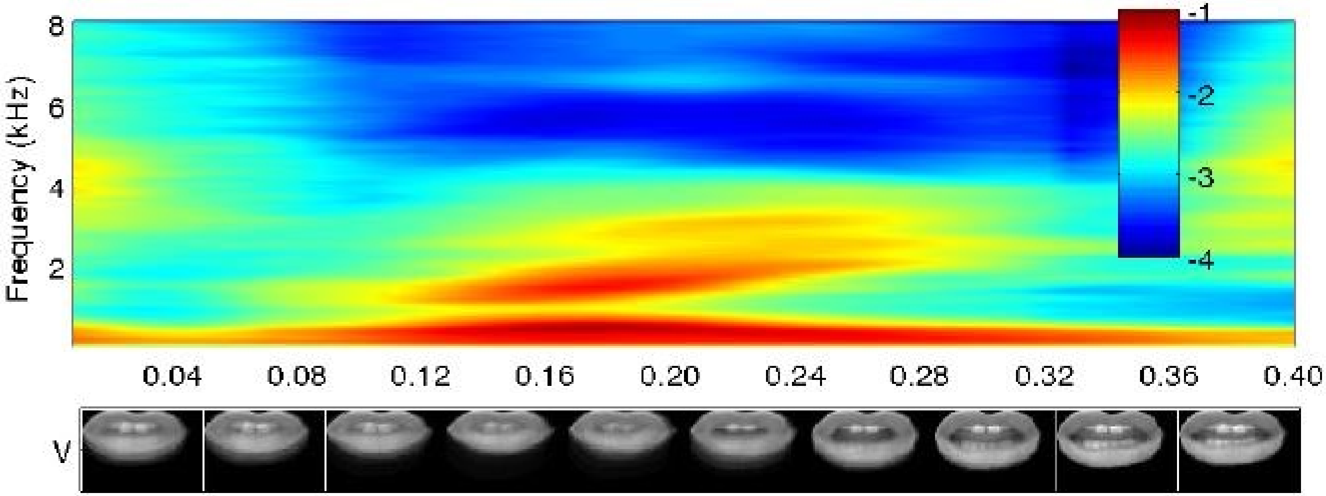
Audio mask
Statistically generated by evaluating the IPD and ILD of each TF point.

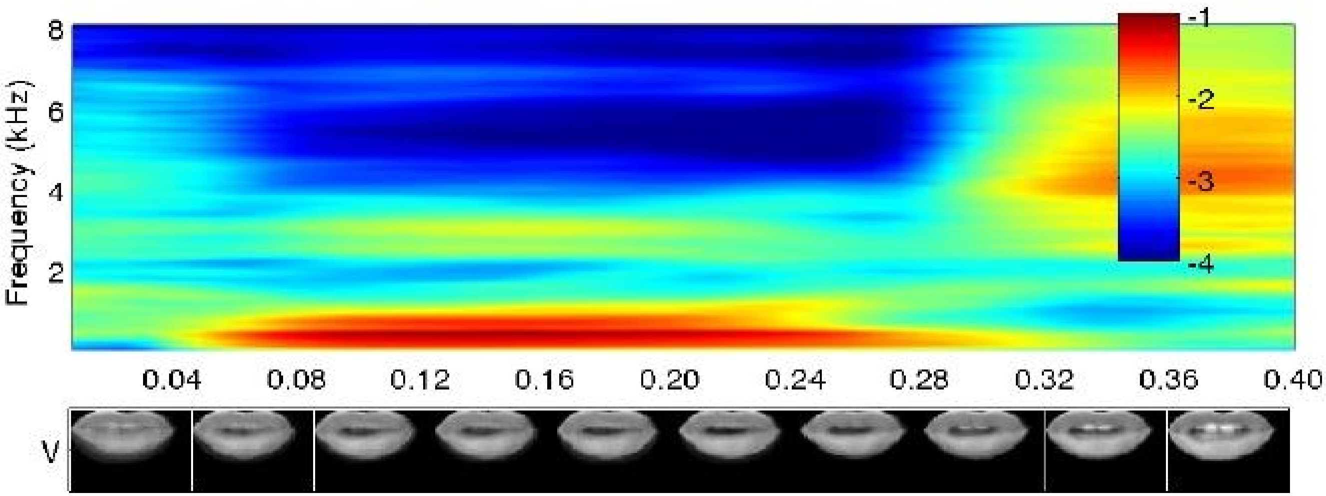
Visual mask
Mapping the observation to the learned AV dictionary via the coding stage in AVDL.

Visual mask generation

$$\mathcal{M}^v(m,\omega) = \begin{cases} 1, & \text{if } \hat{\psi}^a(m,\omega) > \psi^a(m,\omega) \\ \hat{\psi}^a(m,\omega)/\psi^a(m,\omega), & \text{otherwise.} \end{cases}$$

AVDL evaluations





Long Speech

Sheerman-Chase et al.
LILiR Twotalk database
2011

Lip tracking,
Ong et al. 2008

The first AV atom represents the utterance “**marine**" /m^{ə}ri:n/ while the second one denotes the utterance “**port**" /p^{ɔ}:t/.

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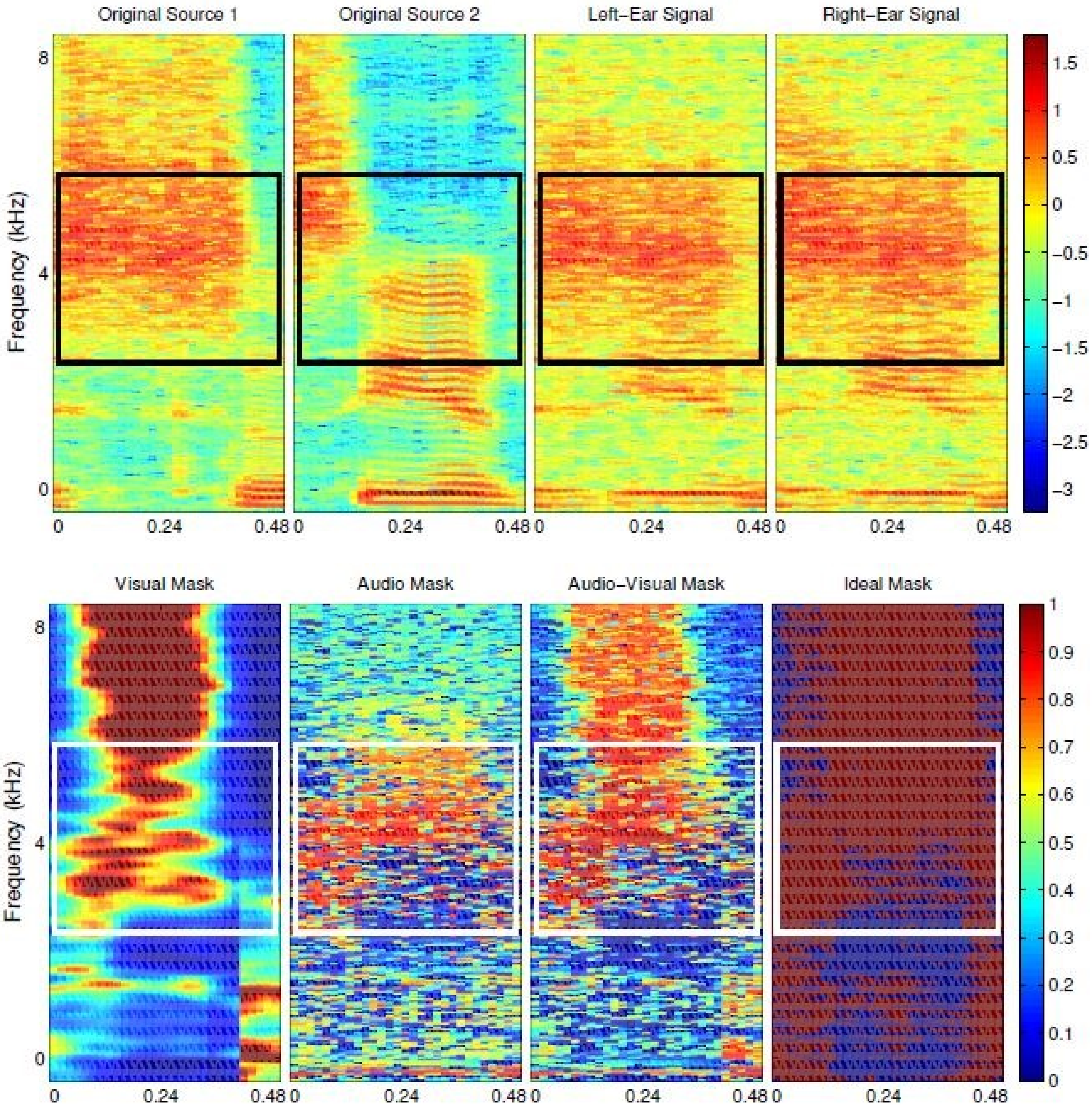
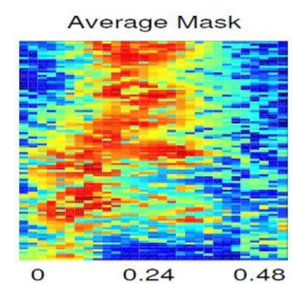
Demonstration of TF mask fusion in AVDL-BSS



Why do we choose the power law combination, instead of, e.g., a linear combination?



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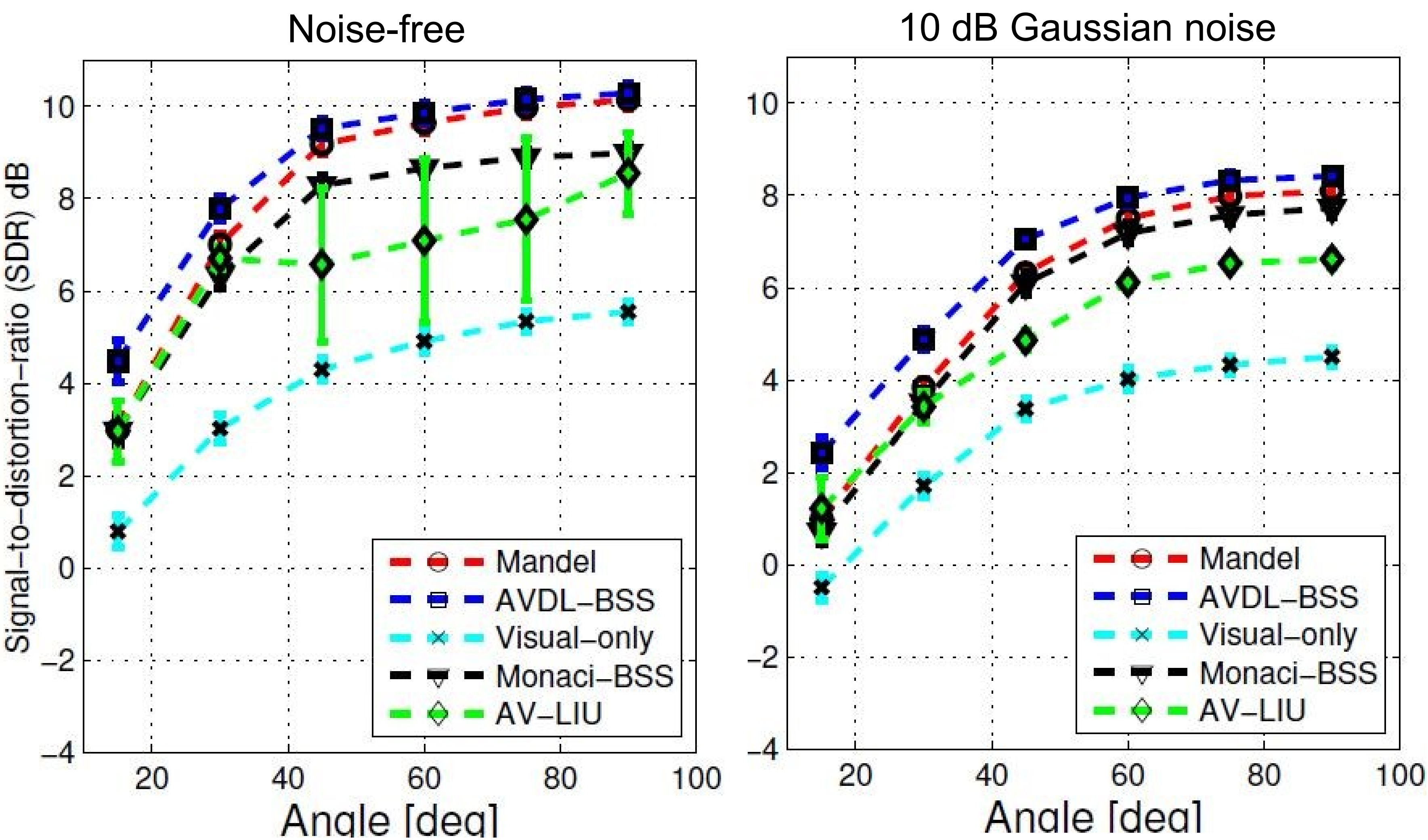
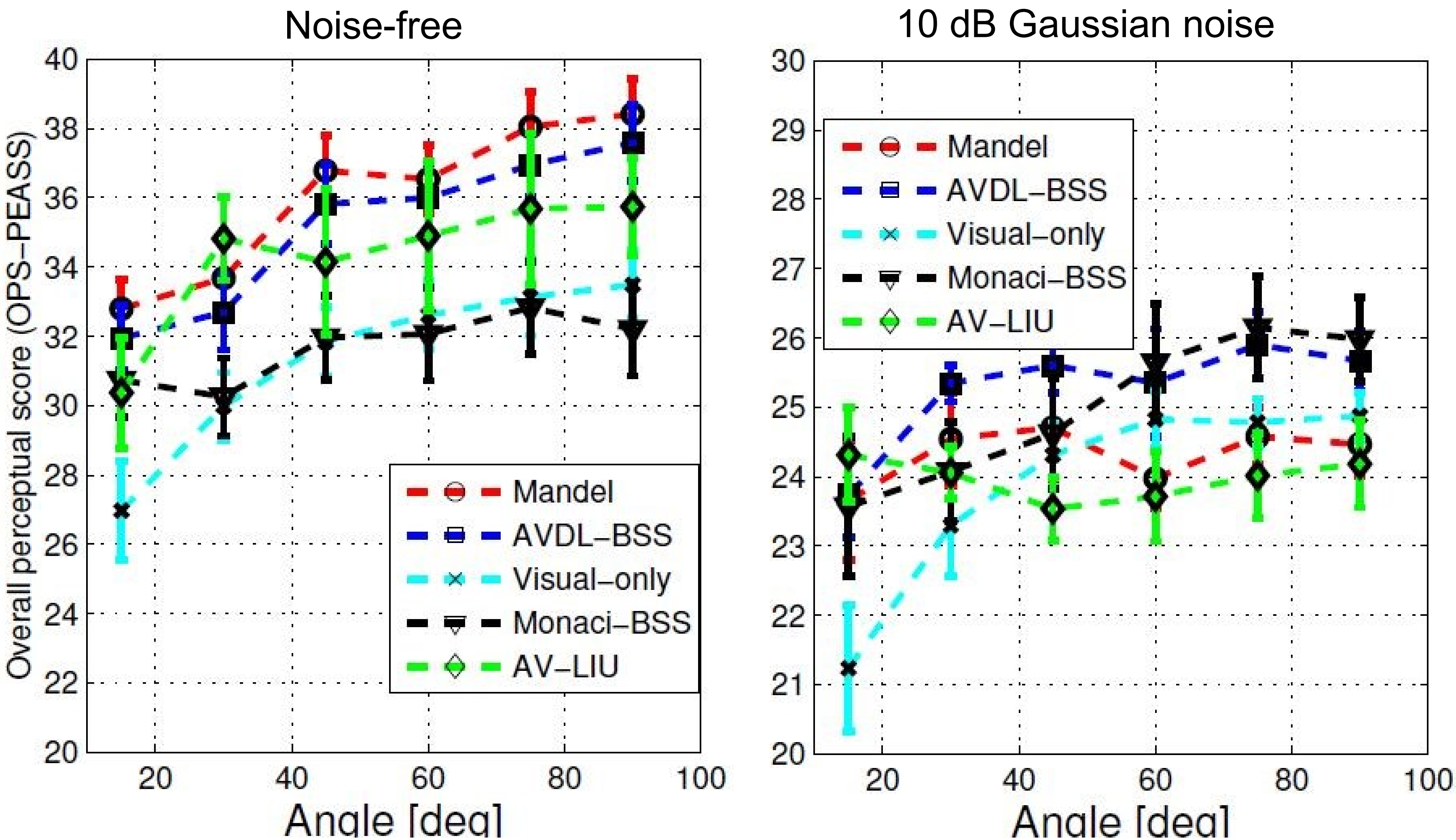
AVDL-BSS evaluations----SDR



AVDL-BSS evaluations----OPS-PEASS



Some examples

	Mixture	Ideal	Mandel	AV-LIU	AVDL-BSS	Rivet	AVMP-BSS
A							
B							
C							
D							

Conclusions

- AVDL offers an alternative and effective method for modelling the AV coherence within the audio-visual data.
- The mask derived from AVDL can be used to improve the BSS performance for separating reverberant and noisy speech mixtures

Future work

- To achieve dictionary adaptation and source separation simultaneously

Thank you

Q & A

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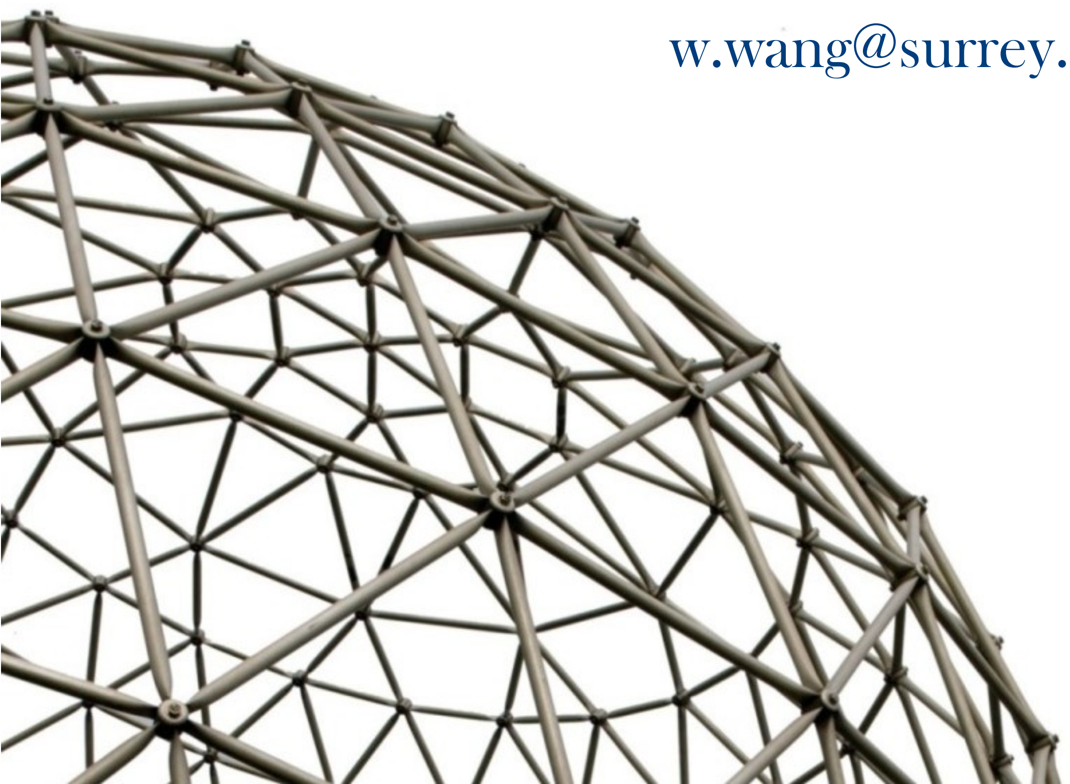

References

Q. Liu, W. Wang, P. Jackson, M. Barnard, J. Kittler, and J.A. Chambers, "Source separation of convolutive and noisy mixtures using audio-visual dictionary learning and probabilistic time-frequency masking", IEEE Transactions on Signal Processing, vol. 61, no. 22, pp. 5520-5535, 2013.

Q. Liu, W. Wang, and P. Jackson, "Use of bimodal coherence to resolve spectral indeterminacy in convolutive BSS", Signal Processing, 92(8):1916-1927, 2012.

Q. Liu, W. Wang, P. Jackson, and M. Barnard, "Reverberant speech separation based on audio-visual dictionary learning and binaural cues", in Proc. SSP, 2012.