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# Audio inpainting: problem statement, relation with sparse representations and some experiments

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## PROBLEM STATEMENT & APPLICATIONS: a unified scheme for existing tasks

**Audio inpainting scheme:** an inverse problem where

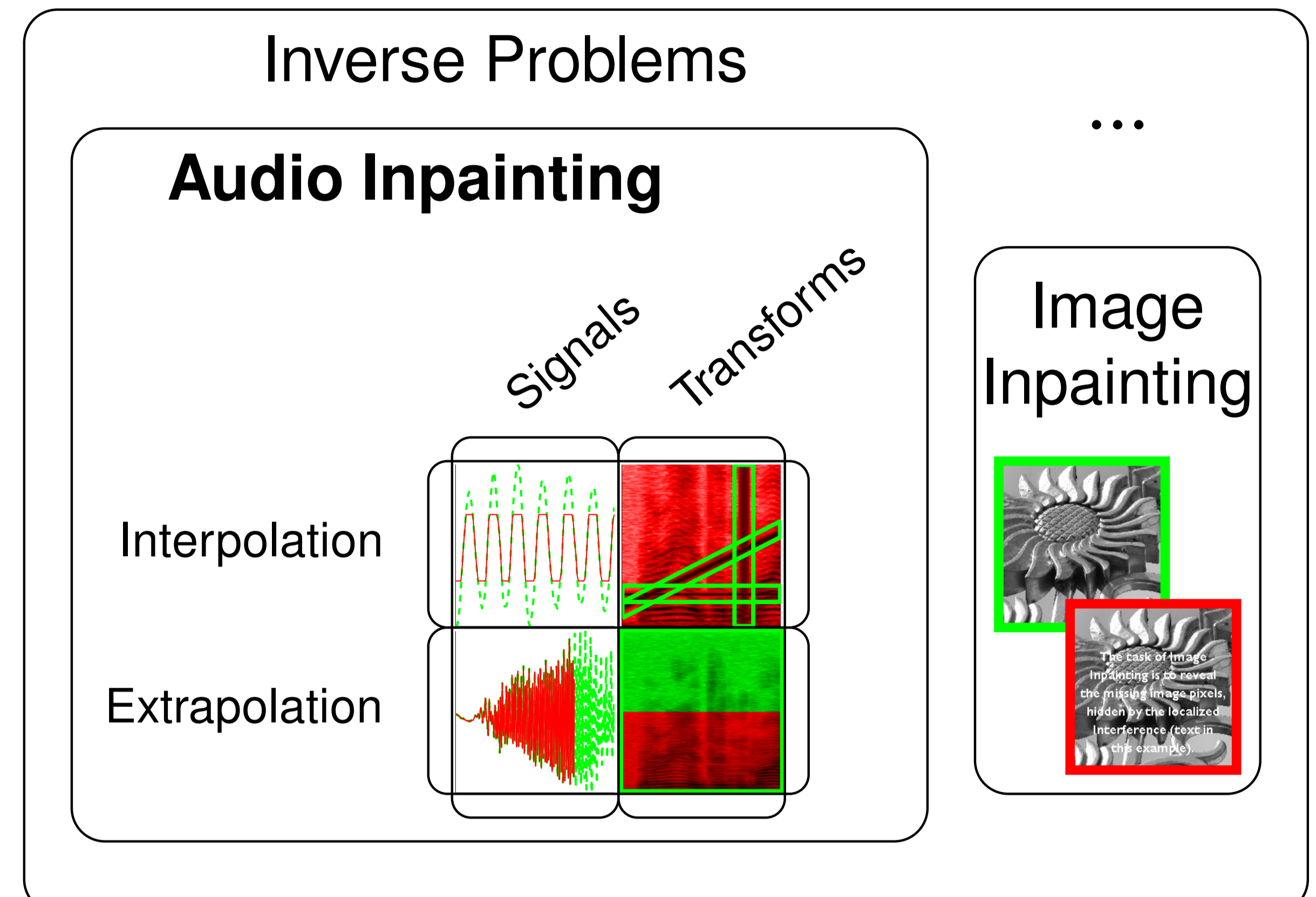
- a set of reliable audio data  $\mathbf{y}$  is observed,
  - one must estimate the remaining missing or highly corrupted data.
- A unified scheme covering existing subproblems referred to as interpolation, extrapolation, imputation, (bandwidth) extension.

**Formulation:** estimate the original data  $\mathbf{s}$  from  $\mathbf{y}$  given  $M$

$$(1) \mathbf{y} = M\mathbf{s} \text{ with } \begin{cases} \mathbf{s} & \in \mathbb{R}^N \\ \mathbf{y} & \in \mathbb{R}^{N-M} \\ M & \in \mathbb{R}^{N-M} \times \mathbb{R}^N \end{cases} \text{ and } \begin{matrix} M \\ \text{---} \\ \end{matrix} \begin{matrix} 1 \\ 0.8 \\ 0.6 \\ 0.4 \\ 0.2 \\ 0 \end{matrix}$$

**Several kinds of audio data:** waveforms [1,2], transforms or mid-level representations [3].

**A number of applications:** removing clicks in old recordings, declipping, packet loss concealment in VoIP or P2P networks, bandwidth extension, recovery of TF coefficients masked by interfering sources/noise.



## PROPOSED APPROACH: audio inpainting using sparse representations

Since the problem (1) is ill-posed, additional *a priori* is required.

**Sparsity assumption on audio data**

$$(2) \mathbf{s} = D\mathbf{x} \quad \text{with } \begin{cases} D \in \mathbb{R}^N \times \mathbb{R}^{K_D} \text{ (dictionary)} \\ \mathbf{x} \in \mathbb{R}^{K_D} \text{ (sparse coefficients)} \\ \|\mathbf{x}\|_0 \ll N \leq K_D \end{cases}$$

**Noiseless ideal estimation**

$$(3) \hat{\mathbf{x}} \triangleq \arg \min_{\mathbf{x}} \|\mathbf{x}\|_0 \text{ s.t. } \mathbf{y} = M\mathbf{D}\mathbf{x}$$

**Inpainting algorithms**

**Algorithm 1** Inpainting with  $l_1$ -minimization ( $L_1$ )

Using convex minimization, do

$$\hat{\mathbf{x}} \leftarrow \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 \text{ s.t. } \|\mathbf{y} - M\mathbf{D}\mathbf{x}\|_2^2 \leq \theta^2$$

$$\hat{\mathbf{s}} \leftarrow D\hat{\mathbf{x}}$$

**Algorithm 2** OMP-based inpainting (OMP)

Dictionary  $\tilde{D} = [\tilde{\mathbf{d}}_1, \dots, \tilde{\mathbf{d}}_{K_D}] \leftarrow M \times D \times W_{MD}^{-1}$  ( $W_{MD}$ : diag. matrix of norms of MD columns)

Residual  $\mathbf{r}_0 \leftarrow \mathbf{y}$

Iteration counter  $k \leftarrow 1$ , support set  $\Omega_0 \leftarrow \emptyset$

**while**  $k \leq K_{max}$  **AND**  $\|\mathbf{r}_k\|_2 \geq \theta_{OMP}$  **do**

Select atom:  $j \leftarrow \arg \max_j |\langle \mathbf{r}_{k-1}, \tilde{\mathbf{d}}_j \rangle|$

Update support  $\Omega_k \leftarrow \Omega_{k-1} \cup j$

Update current solution  $\mathbf{x}_k \leftarrow \arg \min_{\mathbf{x}} \|\mathbf{y} - \tilde{D}_{\Omega_k} \mathbf{x}\|_2$

Update residual  $\mathbf{r}_k \leftarrow \mathbf{y} - \tilde{D}_{\Omega_k} \mathbf{x}_k$

Increment iteration counter  $k \leftarrow k + 1$

**end while**

$$\hat{\mathbf{s}} \leftarrow D\mathbf{W}_{MD}\mathbf{x}_k$$

**Specific inpainting algorithms for restoring clipped signals**

→ Constrain the restored samples to be beyond the clipping threshold  $\theta_{clip}$

**Algorithm 3** ( $L_1$ -C)

Using convex minimization, do

$$\hat{\mathbf{x}} \leftarrow \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 \text{ s.t. } \begin{cases} \|\mathbf{y} - M\mathbf{D}\mathbf{x}\|_2^2 \leq \theta^2 \\ M^+ \mathbf{D}\mathbf{x} \geq \theta_{clip} \\ M^- \mathbf{D}\mathbf{x} \leq -\theta_{clip} \end{cases}$$

$$\hat{\mathbf{s}} \leftarrow D\hat{\mathbf{x}}$$

**Algorithm 4** (OMPc)

After the while loop in Alg. 1, refine  $\mathbf{x}_k$  as

$$\mathbf{x}_k \leftarrow \arg \min_{\mathbf{x}} \|\mathbf{y} - \tilde{D}_{\Omega_k} \mathbf{x}\|_2 \text{ s.t. } \begin{cases} M^+ \mathbf{D}\mathbf{x} \geq \theta_{clip} \\ M^- \mathbf{D}\mathbf{x} \leq -\theta_{clip} \end{cases}$$

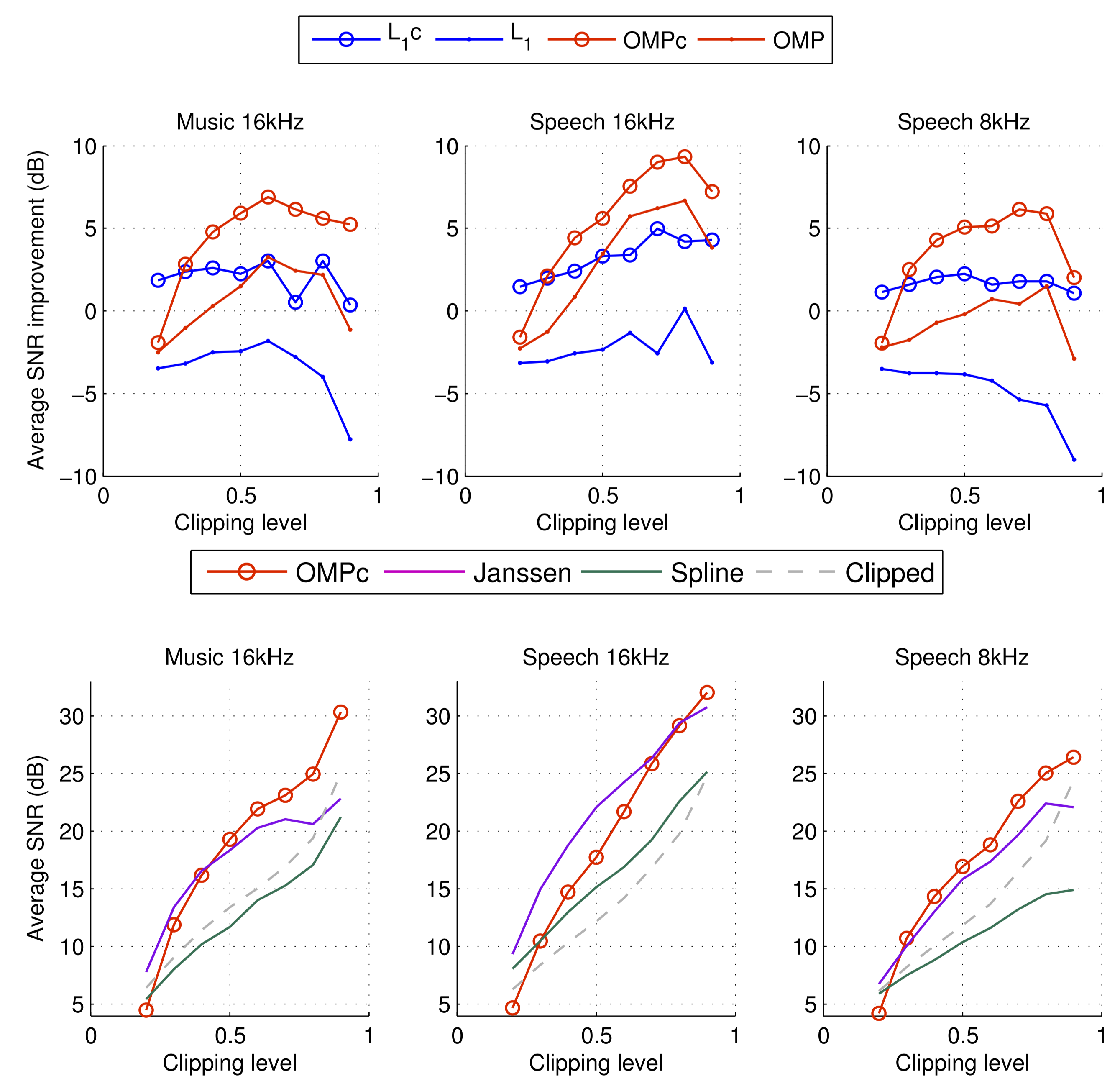
$$\hat{\mathbf{s}} \leftarrow D\mathbf{W}_{MD}\mathbf{x}_k$$

where  $M^+$  and  $M^-$  are the projectors onto the subspace of positive and negative clipped samples respectively.

## EXPERIMENTS: declipping audio signals

**Experimental settings**

- 3 datasets with 10 5-seconds signals
- Frame-by-frame processing with OLA reconstruction: 75% overlap, 64ms frames, sine weighting windows
- Algorithms OMP, OMPc,  $L_1$ ,  $L_1$ c are applied in each frame
- OMPc is compared to spline interpolation and Janssen's algorithm [1] based on autoregressive models.
- Algorithm parameters are fixed (tuned on a separate database)
- Dictionary D: redundant sine-windowed DCT
- SNR is computed on the corrupted samples only



[1] A. Janssen, R. Veldhuis, L. Vries, Adaptive interpolation of discrete-time signals that can be modeled as autoregressive processes, in IEEE Trans. on Acoustics, Speech and Signal Proc., 34 (2), 1986.

[2] S. J. Godsill, P. J. W. Rayner, Digital audio restoration - A statistical model-based approach, Springer-Verlag London, 1998.

[3] J. Le Roux, H. Kameoka, N. Ono, A. de Cheveigné, S. Sagayama, Computational auditory induction by missing-data non-negative matrix factorization, Proc. of SAPA, 2008.

