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

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\section*{Problem Statement & Applications:} a unified scheme for existing tasks

Audio inpainting scheme: an inverse problem where
- a set of reliable audio data $y$ 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 $s$ from $y$ given $M$

\begin{equation}
\begin{aligned}
(1) \; y = Mx \text{ with } & s \in \mathbb{R}^N, y \in \mathbb{R}^{N-M}, M \in \mathbb{R}^{N-M \times N} \forall \mathbb{R}^N
\end{aligned}
\end{equation}

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.

\section*{Proposed Approach:} audio inpainting using sparse representations

Since the problem (1) is ill-posed, additional \textit{a priori} is required.

\textbf{Sparsity assumption on audio data}

\begin{equation}
\begin{aligned}
(2) \; s = Dx \text{ with } & D \in \mathbb{R}^N \times \mathbb{R}^K \text{ (dictionary)} \quad x \in \mathbb{R}^K \text{ (sparse coefficients)} \\
\end{aligned}
\end{equation}

\textbf{Noisy ideal estimation}

\begin{equation}
\begin{aligned}
(3) \; \hat{x} = \arg\min_{x} \|x\|_1 \text{ s.t. } y = MDx
\end{aligned}
\end{equation}

\textbf{Inpainting algorithms}

\textbf{Algorithm 1 inpainting with $l_1$ minimization (L1)}

Using sparse representation:

\begin{equation}
\begin{aligned}
\hat{x} = \arg\min_{x} \{ |x|_1 \text{ s.t. } \|y - MDx\|_2 \leq \delta \}
\end{aligned}
\end{equation}

\textbf{Algorithm 2 OMP-based inpainting (OMP)}

Dictionary $D = [d_1, \ldots, d_K] \rightarrow M = D \cdot W_{DM}$ (W: diag. matrix of norms of MD columns)

Residual $m = y - MDx$

Iteration counter $k = 1$, support set $\emptyset$

\textbf{while} $k \leq K_{max}$ AND $\|y - MDx\|_2 \geq \delta_{OMP}$ \textbf{do}:

Select atom $j = \arg\min_{l \in \emptyset} \|x_l\|_2$; $\frac{|d_j|}{\|d_j\|_2} > 1$

Update support $\emptyset \leftarrow \emptyset \cup j$

Update current solution $\hat{x} \leftarrow \hat{x}_{LM} + x_j$

Update residual $r = y - MDx$

Increment iteration counter $k = k + 1$

\textbf{end while}

\begin{equation}
\begin{aligned}
x = DW_{LM}^{\hat{x}}
\end{aligned}
\end{equation}

\textbf{Specific inpainting algorithms for restoring clipped signals}

\textbf{Algorithm 3 ($l_1$)}

Using sparse representation, do:

\begin{equation}
\begin{aligned}
\hat{x} = \arg\min_{x} \{ |x|_1 \text{ s.t. } \|y - MDx\|_2 \leq \delta \}
\end{aligned}
\end{equation}

\begin{equation}
\begin{aligned}
x = DW_{LM}^{\hat{x}}
\end{aligned}
\end{equation}

\textbf{Algorithm 4 (OMPc)}

After the while loop in Alg. 1, refine $s_k$ as:

\begin{equation}
\begin{aligned}
s_k = \arg\min_{x} \{ |x|_1 \text{ s.t. } \|y - D_k x_k\|_2 \leq \delta_{OMPc} \}
\end{aligned}
\end{equation}

\begin{equation}
\begin{aligned}
x_k = DW_{LM}^{\hat{x}}
\end{aligned}
\end{equation}

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

\section*{Experiments:} declipping audio signals

\textbf{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, Lc 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

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{experiments.png}
\caption{Average SNR improvement (dB) across datasets.}
\end{figure}