ROBUST SPEAKER IDENTIFICATION USING MATRIX COMPLETION UNDER A MISSING DATA IMPUTATION FRAMEWORK

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Overview

- Design and development of efficient speaker recognition algorithms characterized by increased robustness in diverse environments and conditions
- Focus is given on *noise robust text-independent speaker identification* (SID) using *short training/testing* sessions
  - speech signals are often corrupted by noise due to, *e.g.*, the environment where the speaker is present, the voice transmission medium etc.
  - it is often not feasible to obtain large amounts of training data from all speakers
  - speaker utterance to be identified should be as short as possible to reduce the SID response time
- Reduce noise corruption adopting *matrix completion* under a missing data imputation framework
  - exploit low-rank features' property

Low-rank matrix completion

- Let $\mathrm{M} \in \mathbb{R}^{p\times q}$ be the *data matrix*
  - in general, one cannot recover the pq entries of M from a smaller number of k entries, where $k \ll pq$
  - such recovery is possible when rank $r = \mathrm{rank}(\mathrm{M})$ of the matrix is small compared to its dimensions
    - possible recovery of M from $k \geq O(nr\log(n))$, where $n = \max\{p,q\}$
  - consider the following assumptions:
    - the known entries of matrix M are denoted as $\mathrm{M}_{i,j}$, where $(i,j) \in \Omega \subset \{1,\dots,p\} \times \{1,\dots,q\}$ and Ω is the set of sampled values
    - linear map $\mathcal{A} : \mathbb{R}^{pq} \to \mathbb{R}^k$ is defined as a sampling operator recording a small number of entries from the matrix

$$(\mathcal{A}_\Omega(\mathrm{M}))_{i,j} = \begin{cases} M_{i,j}, & (i,j) \in \Omega \\ 0, & \text{otherwise} \end{cases}$$

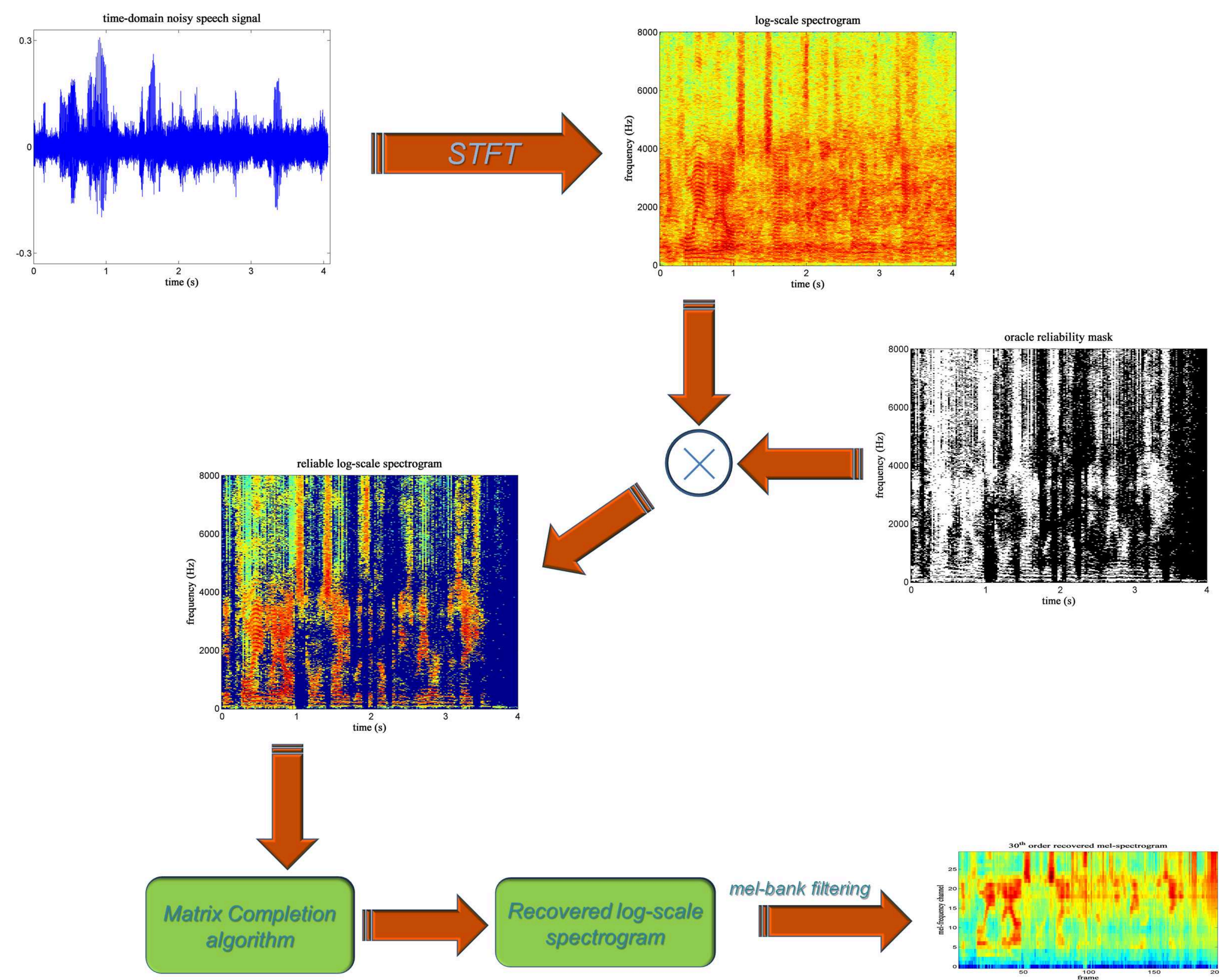
- recover incomplete matrix by computing the tractable *nuclear norm minimization problem*

$$\min_{\mathrm{X}} \|\mathrm{X}\|_*\,, \ \text{s.t.} \quad \| \mathcal{A}_\Omega(\mathrm{X}) - \mathcal{A}_\Omega(\mathrm{M}) \|_F^2 \leq \epsilon$$

where $\sigma_1,\dots,\sigma_{\min\{p,q\}} \geq 0$ are the singular values of X, the nuclear norm is defined as $\|\mathrm{X}\|_* = \sum_{k=1}^{\min\{p,q\}} \sigma_k$, and the Frobenius norm of X is $\|\mathrm{X}\|_F^2 = \sum_{k=1}^{\min\{p,q\}} \sigma_k^2$

Missing data imputation using matrix completion

- Reduce noise effects after feature extraction
- Distinguish reliable from unreliable (missing) spectrographic speech data by applying an oracle *reliability mask*
- Observed spectrographic speech data $\mathrm{M}(l,t) = \mathrm{S}(l,t) + \mathrm{N}(l,t)$, where $l = 1,\dots,L$ and $t = 1,\dots,T$
  - L: FFT size
  - T: number of frames
    - $\mathrm{M}(l,t) \in \mathbb{C}^{L\times T}$: short-time Fourier transform (STFT) of the *noisy* speech signal
    - $\mathrm{S}(l,t) \in \mathbb{C}^{L\times T}$: STFT of the *clean* speech signal
    - $\mathrm{N}(l,t) \in \mathbb{C}^{L\times T}$: STFT of the *noise* signal



- The oracle binary mask is computed as

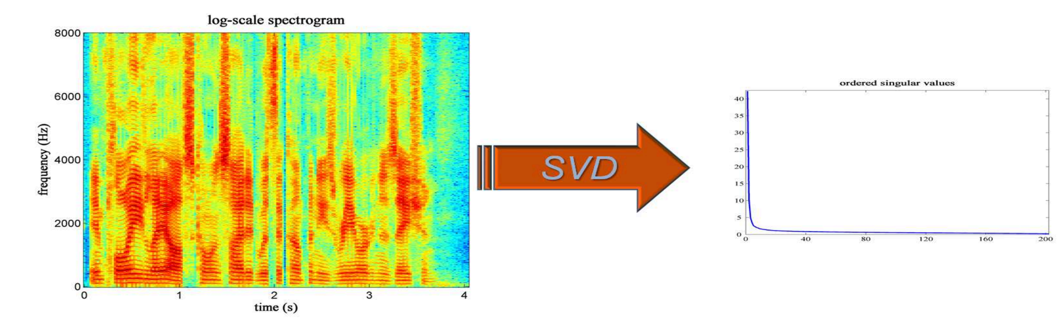
$$\mathbb{R}^{L\times T} \ni \mathrm{W}(l,t) = \begin{cases} 1 := \text{reliable}, & \frac{|\mathrm{S}(l,t)|^2}{|\mathrm{N}(l,t)|^2} > \lambda \\ 0 := \text{unreliable, otherwise} \end{cases}$$

  - λ: SNR-threshold (during the simulations $\lambda = -3$ dB)
- Recover the missing spectrographic data by solving the optimization problem

$$\hat{\mathrm{X}} = \min_{\mathrm{X}} \|\mathrm{X}\|_*\,, \ \text{s.t.} \quad \| \mathcal{A}_\Omega(\mathrm{X}) - \mathcal{A}_\Omega(10\log_{10}(|\mathrm{W} \odot \mathrm{M}|)) \|_F^2 \leq \epsilon$$

  - $\odot$: element-wise product of two matrices

- The *ordered singular values* of the clean spectrographic speech data are depicted in the figure below



  - *low-rankness assumption* is satisfied $\Longrightarrow$ the majority of the singular values tend to approach zero
- Singular Value Thresholding (SVT) algorithm used to recover the low-rank log-scale spectrographic speech data matrix

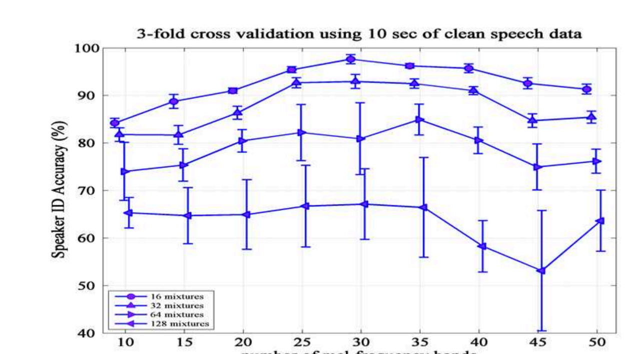
Experimental results

- VOICES corpus: 12 speakers
  - sampling rate @ 22 kHz $\longrightarrow$ downsampling @ 16 kHz
  - analysis window: 640 samples with 50% overlapping
  - number of mel-frequency bands: 30
  - training data per speaker: 10 sec
    - Universal Background Model (UBM)-GMM training model: 16 Gaussian mixtures were used using diagonal covariance matrix
  - test segment length: 400 frames (~ 8 sec)

$$\underbrace{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \dots, \mathbf{x}_Q}_{1^{\text{st}}\ \text{segment}}, \mathbf{x}_{Q+1}, \mathbf{x}_{Q+2}, \dots$$

$$\mathbf{x}_1, \underbrace{\mathbf{x}_2, \mathbf{x}_3, \dots, \mathbf{x}_Q, \mathbf{x}_{Q+1}}_{2^{\text{nd}}\ \text{segment}}, \mathbf{x}_{Q+2}, \dots$$

$$\boxed{\text{correct ident. rate} = \frac{\#\ \text{correctly identified segments}}{\text{total}\ \#\ \text{of segments}} \cdot 100\%}$$



MEAN CORRECT IDENTIFICATION RATES (%) USING UBM-GMM COMPARING MC AND BASELINE SYSTEM AFTER 10 MONTE CARLO RUNS

noise	SNR (dB)	speech babble	car engine	factory floor	train passing
baseline	5	76.15	94.01	96.71	93.80
	0	54.72	92.51	85.28	58.89
	-5	27.29	90.21	46.50	36.13
MC	5	98.45	99.58	95.98	97.33
	0	90.68	99.57	89.20	88.02
	-5	78.80	98.21	73.71	74.16

Future work

- Training-data based matrix completion
- Comparisons with other missing data techniques
- Use practical binary masks during the simulations
- Extend the experiments to moderate-size speech databases