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Motivation

- Speech dereverberation fundamental for enabling far-field humancomputer interaction, particularly with the recent advent of smart loudspeaker devices (e.g., Sonos One ©).
- Blind methods based on multi-channel linear prediction (MCLP) applied in the STFT-domain particularly effective for the task:
 - no prior knowledge of the room acoustics,
 - relatively easy and cheap to implement.
- Popular MCLP-based methods look for a sparse desired speech signal, assuming reverberation as a convolutive process (approximated by the predicted speech) on a STFT bin-by-bin basis. This is done by applying nonconvex algorithms [1, 2].
- We propose alternative formulations for sparse approximation based on convex optimization [3].

MCLP-based Dereverberation

- Focus on utterance-based batch processing
- Reverberant speech signal model at m-th mic $m \in \{1, ..., M\}$:

$$x_m(k,n) = \underbrace{\sum_{l=0}^{\tau-1} h_m(k,l) s(k,n-l)}_{d_m(k,n)} + \underbrace{\sum_{l=\tau}^{L_g-1} h_m(k,l) s(k,n-l)}_{r_m(k,n)} + \underbrace{\sum_{l=\tau}^{L_g-1} h_m(k,l) s(k,n-l)$$

- ▶ $n \in \{1, ..., N\}$ frame index, $k \in \{1, ..., K\}$ frequency bin index
- \blacktriangleright s(k, n): clean speech
- \blacktriangleright $d_m(k, n)$: desired speech
- \blacktriangleright $r_m(k, n)$: reverberation term
- \blacktriangleright $h_m(k, I)$ ATF between the speech source and the *m*-th microphone
- \blacktriangleright τ : delay to model direct speech and early reflections
- \blacktriangleright L_q: prediction order
- \blacktriangleright Desired speech signal using M predictors (order $(L_a 1)$):

$$d_m(k,n) = x_m(k,n) - \sum_{i=1}^{M} \sum_{l=0}^{L_g-1} x_i(k,n-\tau-l)g_{m,i}$$

 \blacktriangleright $g_{m,i}(k, l)$: *l*-th prediction coefficient between the *i*-th and the *m*-th channel

References

[1]	T. Nakatani, T. Yoshioka, K. Kinoshita, M. Miyoshi, and BH. Juang, "Speech dereverberation based on va
[2]	A. Jukić, T. van Waterschoot, T. Gerkmann, and S. Doclo, "Group sparsity for MIMO speech dereverberation
[3]	T. L. Jensen, D. Giacobello, T. van Waterschoot, and M. G. Christensen, "Fast algorithms for high-order sp

Speech Dereverberation based on Convex Optimization Algorithms for Group Sparse Linear Prediction

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Group Sparse Linear Prediction ► The model in (2) in matrix form becomes [2]: $\mathbf{D}(k) = \mathbf{X}(k) - \mathbf{X}_{\tau}(k)\mathbf{G}(k)$ with $\mathbf{D}(k) = [\mathbf{d}_1(k), \cdots, \mathbf{d}_M(k)] \in \mathbb{C}^{N \times M}$ $\mathbf{d}_m(k) = \left[d_m(k, 1), \cdots, d_m(k, N)\right]^T \in \mathbb{C}^{N \times 1}$ $\mathbf{X}(k) = [\mathbf{X}_1(k), \cdots, \mathbf{X}_M(k)] \in \mathbb{C}^{N \times M}$ $\mathbf{X}_m(k) = \left[x_m(k, 1), \cdots, x_m(k, N) \right]^T \in \mathbb{C}^{N \times 1}$ $\mathbf{X}_{\tau}(k) = [\mathbf{X}_{\tau,1}(k), \cdots, \mathbf{X}_{\tau,M}(k)] \in \mathbb{C}^{N imes ML_g}$ $\mathbf{G}(k) = [\mathbf{g}_1(k), \cdots, \mathbf{g}_M(k)] \in \mathbb{C}^{ML_g imes M}$ $\mathbf{g}_{m}(k) = [g_{m,1}(k,0), \cdots, g_{m,1}(k, L_{g}-1), \dots]$ $g_{m,M}(k,0),\cdots,g_{m,M}(k,L_g-1)]^T\in\mathbb{C}^{ML_g\times 1}$ \blacktriangleright G in (3) is then found by solving the optimization problem: $\hat{\mathbf{G}} = \operatorname{argmin} \| \mathbf{X} - \mathbf{X}_{\tau} \mathbf{G} \|_{\rho,1}^{1} + \alpha \| \mathbf{G} \|_{1,1}^{1}$ $|| \cdot ||_{p,1}^{1} : \mathbf{V} \in \mathbb{C}^{n \times m}, \, ||\mathbf{V}||_{p,1} = \left(\sum_{i=1}^{n} ||\mathbf{V}_{i,:}||_{p} \right)$ $||\mathbf{V}_{i,:}||_{p}$ is the ℓ_{p} norm of the i-th row-vector $\mathbf{V}_{i,:}$ For p = 1, (4) is a element-wise regularized least-sum-of-absolute (1) n - lFor p = 2, (4) is a group LASSO problem $\triangleright \alpha \|\mathbf{G}\|_{1,1}^1$ regularization term meaning: * ill-conditioning when closed-spaced microphones: $\mathbf{X}_{\tau}^{H}\mathbf{X}_{\tau} \rightarrow \text{singular}$ \star model order selection penalization if L_q is not chosen appropriately **Experimental Setup** 6-microphone circular array of 72 mm diameter Performance evaluated by simulating artificial utterances that mimic real use cases specific for voice enabled smart speakers: Room size: w ∈ [3, 8] m, l ∈ [3, 10] m h ∈ [2, 4] m Position: d ∈ [1, 7] m, azimuth θ ∈ [-180, 180], elevation φ ∈ [45, 135] Tuned reflection coefficients of cuboid to obtain T₆₀ ∈ [300, 700] ms COMSOL[®] used to solving the scalar wave equation using the finite element method • diffuse HVAC noise, SNR \in [10, 30] dB (focus on dereverberation) i(k, l)(2) ASR engine trained using the Librispeech 100hrs corpus: 100 hours of *clean* speech, 125 male, 125 female speakers), audiobooks data STFT 50% overlap 32ms Hamming ($f_s = 16$ kHz). $L_q = 10$, $\tau = 2$ 100 iterations of ADMM, 5-7 iterations IRLS

ariance-normalized delayed linear prediction," IEEE Transactions on Audio, Speech, and Language Processing, vol. 18, no. 7, pp. 1717–1731, 2010. ion," in IEEE Workshop on Applications of Signal Processing to Audio and Acoustics (WASPAA), 2015. parse linear prediction with applications to speech processing," Speech Communication, vol. 76, pp. 143–156, 2016.

(4)

(3)

Convex Formulations

Least Absolute Devation (LAD) \blacktriangleright *p* = 1 in (4), problem is separable: Group LASSO (GL) 1. $\hat{\mathbf{G}}^{i} = (\mathbf{X}_{\tau}^{H}\mathbf{X}_{\tau} + \alpha \mathbf{I})^{-1} \begin{bmatrix} \alpha \mathbf{I} & \mathbf{X}_{\tau}^{H} \end{bmatrix} (\mathbf{Z}^{i} + \begin{vmatrix} \mathbf{0} \\ \mathbf{X} \end{vmatrix} - \mathbf{L}^{i})$ 2. $\mathbf{R}^{i} = \begin{bmatrix} \alpha \hat{\mathbf{G}}^{i} \\ \mathbf{X}_{\tau} \hat{\mathbf{G}}^{i} - \mathbf{X} \end{bmatrix}$ 3. $\mathbf{Z}^{i+1} = S_t(\mathbf{R}^i + \mathbf{L}^i)$ 4. $\mathbf{L}^{i+1} = \mathbf{L}^{i} + \mathbf{R}^{i} - \mathbf{Z}^{i+1}$



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- Non-convex formulation (Iteratively Reweighted Least-Squares) ▶ ℓ_q norm (0 < $q \le 1$) approximated using IRLS. *i*-th step:
 - $\hat{\mathbf{G}}^{i} = \operatorname{argmin} \|\mathbf{W}_{i}^{1/2} \left(\mathbf{X} \mathbf{X}_{\tau} \mathbf{G}\right)\|_{2}^{2}$ • with $\mathbf{W}^i = \text{diag}(\mathbf{w}^i)$, $\mathbf{w}^i = (\|\mathbf{d}_n\|_2^2 + \epsilon)^{q/2-1}$, $\forall n$, updated from $\hat{\mathbf{D}}^i$ $\hat{\mathbf{g}}_m = \operatorname{argmin} \|\mathbf{x}_m - \mathbf{X}_{\tau} \mathbf{g}_m\|_1 + \alpha \|\mathbf{g}_m\|_1, \quad m = 1, \dots, M$ known ADMM formulation [3] for $\hat{\mathbf{g}}_m = \operatorname{argmin}_{\mathbf{g}_m} \left\| \begin{bmatrix} \mathbf{x}_m \\ \mathbf{0} \end{bmatrix} - \begin{bmatrix} \mathbf{x}_\tau \\ \alpha \end{bmatrix} \mathbf{g}_m \right\|_{\mathbf{x}_m}$
 - > p = 2 in (4), problem is non separable, *i*-th ADMM steps are:
- where the proximity operator $S_t(\cdot)$ subproblem is separable • Complexity: IRLS $\mathcal{O}((ML_g)^3 + N(ML_g)^2)$, ADMM $\mathcal{O}(M^3L_g^2)$ Code available at: https://github.com/giacobello/