PADERBORN UNIVERSITY
The University for the Information Society

Communications Engineering

A generalized log-spectral amplitude estimator for single-channel speech enhancement

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- Clean speech $s(n)$ contaminated by an additive noise $d(n)$

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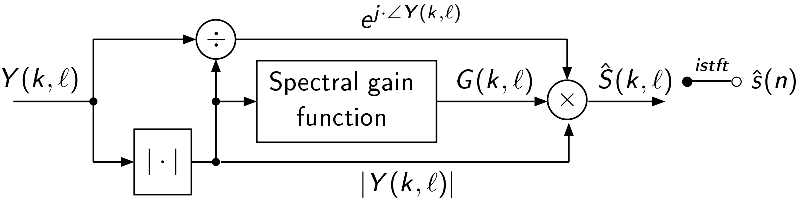

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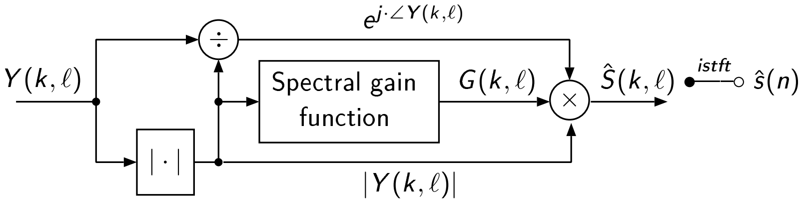

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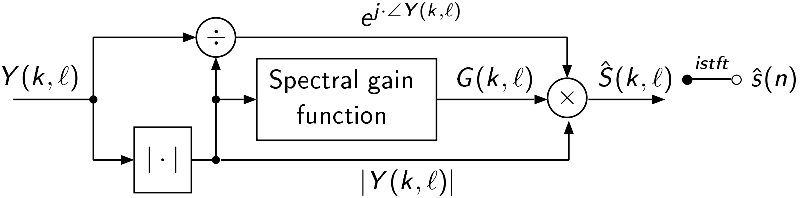

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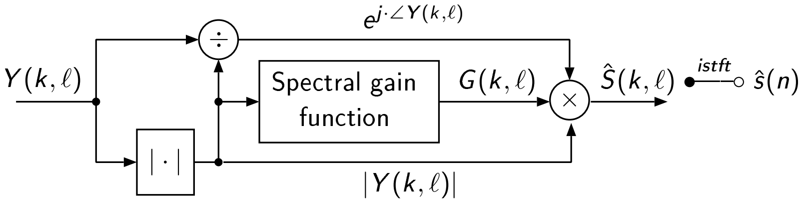

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  a) Generalized spectral amplitude (GSA) $|S(k,\ell)|^{\alpha}$ for $\alpha \in \mathbb{R}_{>0}$
  b) Generalized probability density function (PDF) $p_S(s)$ for $\alpha = 1$

Generalized model-based gain functions

	a) GSA $\|S\|^\alpha$	b) Gen. PDF	Gen. Gamma	Gamma	Chi	Weibull	MMSE	MAP	log-estimator
1. [Sim, 1998]	(✓)						(✓)		
2. [You, 2003]	✓						✓		
3. [Dat, 2005]		✓	✓					✓	
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5. [Andrianakis, 2006]		✓		✓	✓		✓	✓	
6. [Erkelens, 2007]		✓	✓	✓	✓		✓		
7. [Breithaupt, 2008]	(✓)	(✓)			✓		✓		
8. [Borgstrom, 2011]		(✓)		✓	✓		✓		(✓)
9. [Zhao, 2012]		✓		✓			✓		✓

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8. [Borgstrom, 2011]		(✓)		✓	✓		✓		(✓)
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10. Proposed	(✓)	(✓)				(✓)		(✓)	(✓)

A novel nonlinearity in a MAP-based estimator

- Merging two nonlinearities $f(\cdot)$ of MMSE spectral estimators

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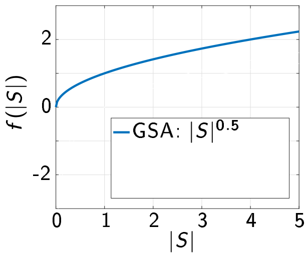

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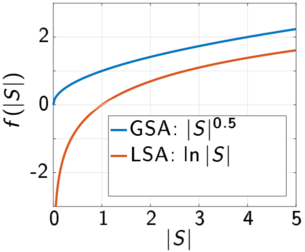
- $f_2(|S|) = \ln |S|$ from perceptually motivated log-spectral amplitude (LSA) estimator [Ephraim, 1985]



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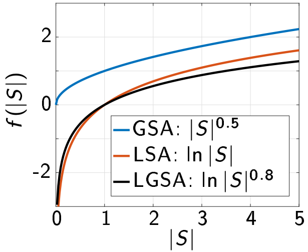
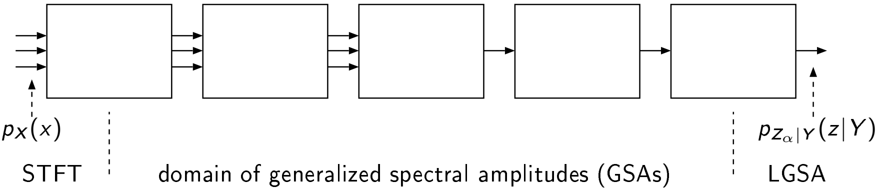


- A novel nonlinearity $\boxed{Z_\alpha = f_3(|S|) = \ln|S|^\alpha}$ resulting in a logarithmic GSA (LGSA) e.g. with $\alpha = 0.8$ for a MAP estimator

$$f_3(|\hat{S}|) = \arg\max_z \; p_{Z_\alpha|Y}(z|y)$$

② Logarithmic generalized spectral amplitude (LGSA) estimator

- 5 steps from PDFs $p_X(x)$ for $X \in \{S, D, Y\}$ to PDF $p_{Z_\alpha|Y}(z|y)$



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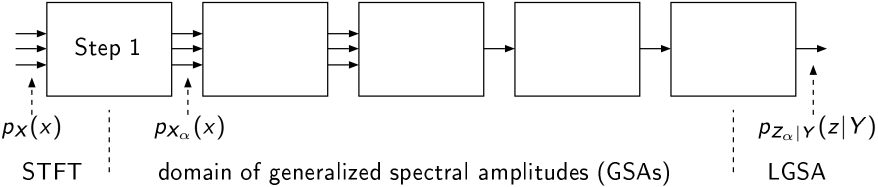

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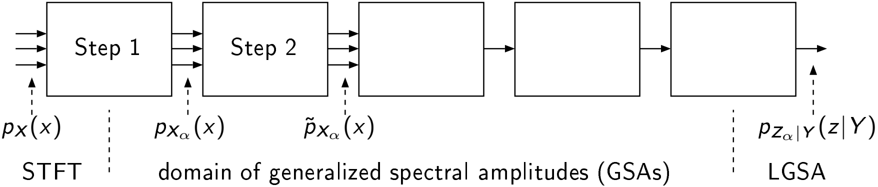

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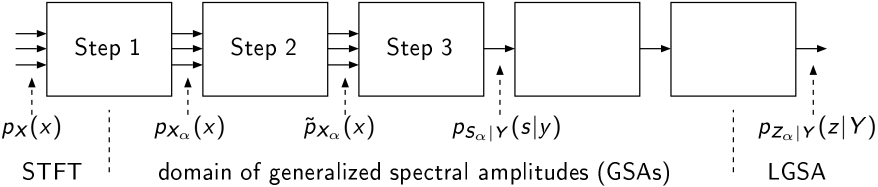

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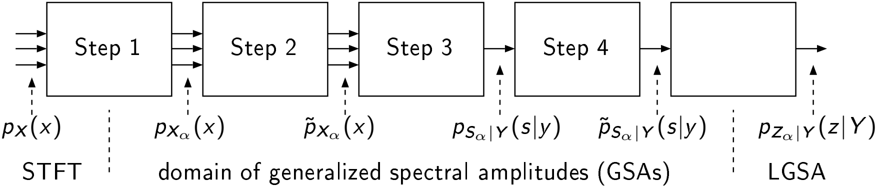

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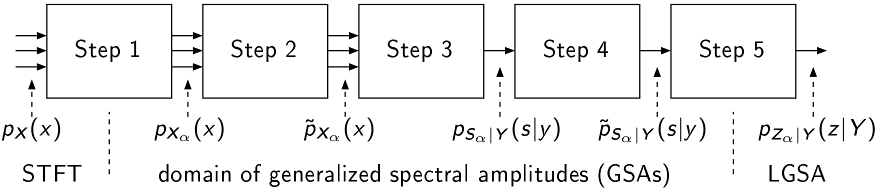

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- Step 5: Transformation to logarithmic GSA $Z_\alpha = \ln S_\alpha$

Statistical modelling of generalized spectral amplitudes

- Step 1: Transformation to GSAs $X_\alpha = |X|^\alpha$ for $X \in \{S, D, Y\}$

$$p_X(x) = \mathcal{N}_C\,(x; 0,\, \lambda_X) \quad \Rightarrow \quad p_{X_\alpha}(x) = \mathrm{Weib}(x;\, \lambda_X,\, \alpha)$$

with power spectral densities $\lambda_X(k, \ell) = \mathbb{E}[|X(k, \ell)|^2]$.

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$$\text{Weib}(x; \lambda_X, \alpha) \approx \mathcal{N}\left(x; \mu_X, \sigma_X^2\right)$$

with μ_X and $\sigma_X^2 = g(\alpha) \cdot \mu_X^2$ using statistical moment matching.

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$$p_{S_\alpha|Y}(s|y) = \mathcal{N}(s; \mu_{S|Y},\ \sigma^2_{S|Y})$$

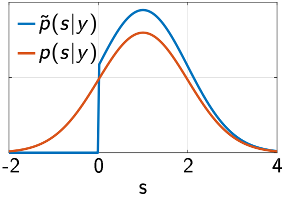
with MMSE-GSS estimator $\hat{S}_\alpha^{\text{GSS}} = \mu_{S|Y} = G_\alpha^{\text{GSS}} \cdot Y_\alpha$ [Sim, 1998].

Zero-truncation and logarithmic transformation

- Step 4: Zero-truncation of $p_{S_\alpha|Y}(s|y)$ for log-transformation

$$p_{S_\alpha|Y}(s|y) \approx \tilde{p}_{S_\alpha|Y}(s|y)$$

to get a conditional PDF only for positive GSA values $S_\alpha > 0$.



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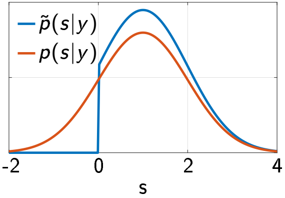

- Step 5: Transformation to logarithmic GSA $Z_\alpha = \ln S_\alpha$

$$p_{Z_\alpha|Y}(z|y) = \frac{e^z}{Q\left(-\frac{\mu_{S|Y}}{\sigma_{S|Y}}\right)} \cdot \mathcal{N}(e^z; \mu_{S|Y}, \sigma^2_{S|Y})$$

with the complementary cumulative distribution of the standard normal density $Q(x)$.

MAP-based LGSA estimator

- Computationally efficient MAP-based LGSA estimator

$$\hat{S}_{\alpha}^{\mathrm{LGSA}} = \frac{\mu_{S|Y}}{2} + \sqrt{\left(\frac{\mu_{S|Y}}{2}\right)^2 + \sigma_{S|Y}^2} = G_{\alpha}^{\mathrm{LGSA}} \cdot Y_{\alpha}$$

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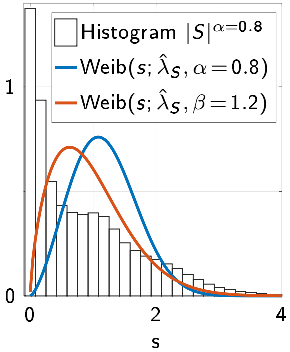
- Additional modeling freedom
  - Decouple compression factor α from a Weibull shape parameter β

$$p_{X_\alpha(k,\ell)}(x) = \text{Weib}(x;\ \lambda_X(k,\ell),\ \beta)$$



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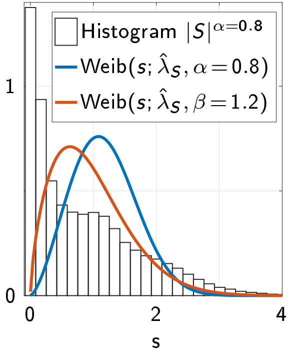
$$p_{X_\alpha(k,\ell)}(x) = \mathrm{Weib}(x;\ \lambda_X(k,\ell),\ \beta)$$

  - Resulting in a spectral gain dependent only on β

$$\boxed{\hat{S}_\alpha^{\mathrm{LGSA}} = G_\beta^{\mathrm{LGSA}} \cdot Y_\alpha}$$



③ Parameter optimization of GSS and LGSA gain functions

- A loosely coupled version of the MMSE-based generalized spectral subtraction (GSS) estimator $\hat{S}_{\alpha}^{\mathsf{GSS}} = G_{\beta}^{\mathsf{GSS}} \cdot Y_{\alpha}$ [Sim, 1998]

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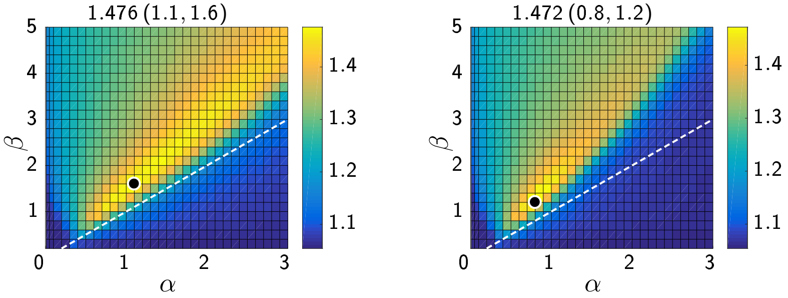

(a) MMSE-GSS (b) MAP-LGSA

- Quality of denoised speech titled by $\text{MOS-LQO}_{\text{opt}}(\alpha_{\text{opt}}, \beta_{\text{opt}})$
  - $\text{SNR}_{\text{IN}} = 5\,\text{dB}$: The same quality in operating point $\beta_{\text{opt}} > \alpha_{\text{opt}}$

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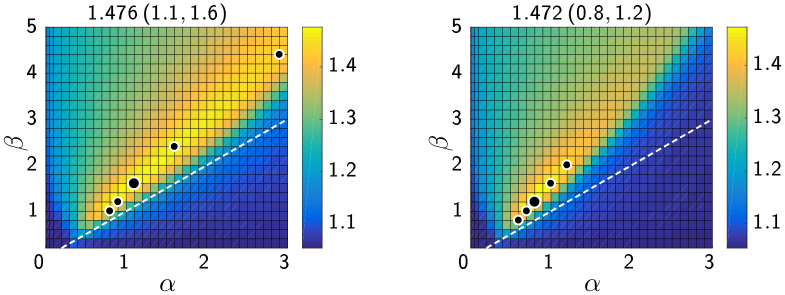

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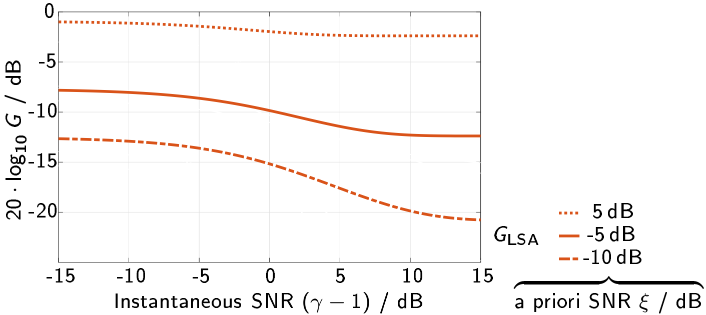
  - $\text{SNR}_{\text{IN}} = \{\text{-5} : 5 : 15\}\text{dB}$: GSS optima scatter more than of LGSA

Discussion of resulting gain curves after optimization



- Reducing musical tones: decreasing of curves with growing γ
  - LSA: Price to pay for high quality - weak noise suppression

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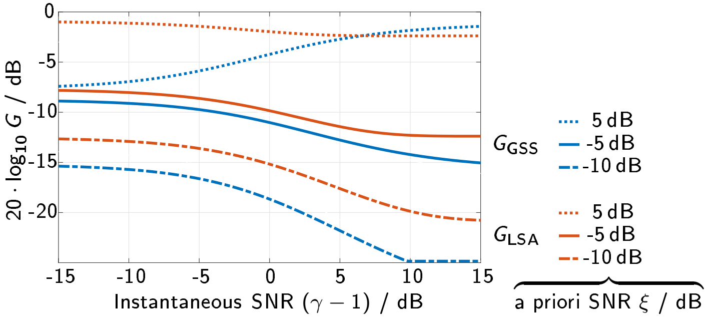

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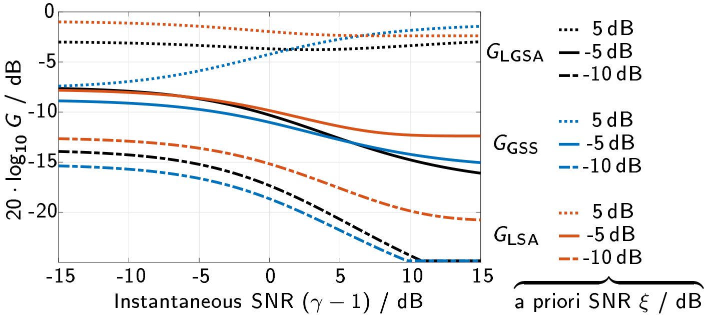

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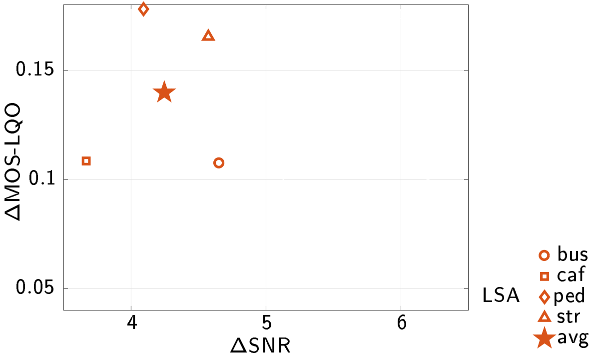
④ Experimental results on CHiME-3 database



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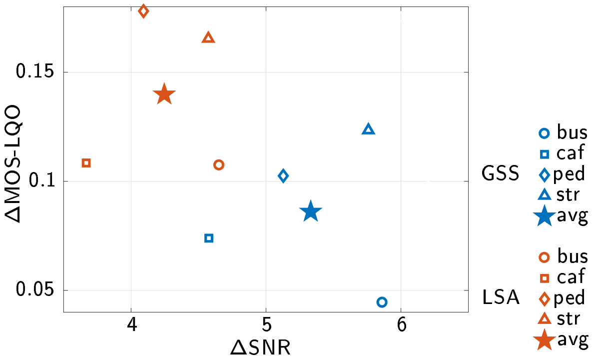

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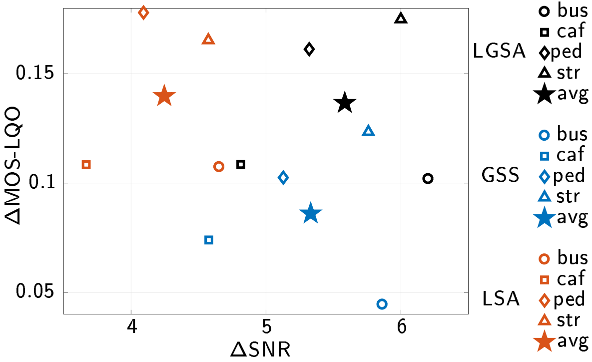

- Speech quality improvement over noise suppression gain
  - LSA: Good overall speech quality and poor noise suppression
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  - LGSA: The best noise suppression w.o. loss of speech quality

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Thank you very much for your attention!

Sound examples

Example 227

	clean	noisy	MMSE-LSA	MMSE-GSS	MAP-LGSA
MOS-LQO		1.208	**1.377**	1.318	**1.372**
SNR/dB		2.29	9.84	**12.16**	**12.18**

Example 649

	clean	noisy	MMSE-LSA	MMSE-GSS	MAP-LGSA
MOS-LQO		1.346	**1.454**	1.417	**1.468**
SNR/dB		9.40	12.62	**13.42**	**13.64**

Example 1280

	clean	noisy	MMSE-LSA	MMSE-GSS	MAP-LGSA
MOS-LQO		1.219	1.611	1.605	**1.664**
SNR/dB		4.40	11.70	**13.89**	**13.83**

Subfamilies of Generalized Gamma distribution

- Generalized Gamma distribution with three parameters

$$\mathrm{GenGam}(x;\, \alpha, \tau, \lambda) = \frac{2}{\alpha \cdot \lambda \cdot \Gamma(\tau)} \cdot x^{\frac{2\tau}{\alpha} - 1} \cdot \exp\left(-\frac{x^{2/\alpha}}{\lambda^{1/\tau}}\right)$$

- Subfamilies of GenGam(x): Gamma, Chi and Weibull distributions

Probability distribution	Degree of freedom 1	Degree of freedom 2	Scale parameter
Generalized Gamma	τ	α	λ
Gamma	τ	2	λ
Chi	τ	1	λ
Weibull	1	α	λ