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An Evaluation of Noise Power Spectral Density Estimation Algorithms in Adverse Acoustic Environments

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AUDIS
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Outline

- Motivation
- Overview of algorithms
- Evaluation measures
  - Mean estimation error
  - Estimation error variance
- Experimental results
- Conclusions

Motivation

- Noise power estimation, a crucial part of speech enhancement
- Effective on quality and intelligibility of enhanced speech
- Many new noise power estimators available
- Framework aims:
  - Presenting performance of some recent and some well-known noise estimators
  - New measure for more comprehensive evaluation of performance

Overview of algorithms

- Minimum statistics (**MS**) [Martin, 2001]
- Minima-controlled recursive averaging (**MCRA**) [Cohen, 2002]
- 3 other algorithms belonging to MCRA category
  - Improved minima-controlled recursive averaging (**IMCRA**) [Cohen, 2003]
  - **EMCRA** [Fan et al., 2007]
  - **MCRA-MAP** [Kum et al., 2009]
- Subspace noise tracking (**SNT**) [Hendriks et al., 2008]
- 2 algorithms based on minimum mean-squared error (MMSE) estimation
  - **MMSE-Yu** [Yu, 2009]
  - **MMSE-Hendriks** [Hendriks et al., 2010]

Evaluation measures

- Two issues taken into account:
  - Evaluation shall be independent of speech enhancement system
    - To separate effects of any specific speech enhancement system
  - Having a suitable reference noise is necessary, since
    - During speech activity instantaneous noise power is not available
    - Most noise reduction approaches require a smoothed noise estimate
    - To reduce impact of random fluctuations in original noise periodogram

Evaluation measures ...

- Mean estimation error: averaged log distance $LogErr_{mean}$ between the estimated noise PSD $\hat{\delta}_D^2$ and reference noise PSD δ_D^2

$$LogErr_{mean} = \frac{1}{IK}\sum_{i=1}^{I}\sum_{k=1}^{K}\left|10\log_{10}\left[\frac{\delta_D^2(k,i)}{\hat{\delta}_D^2(k,i)}\right]\right|$$

$I \rightarrow$ **Number of frames**

$K \rightarrow$ **Number of frequency bins**

- Estimation error variance

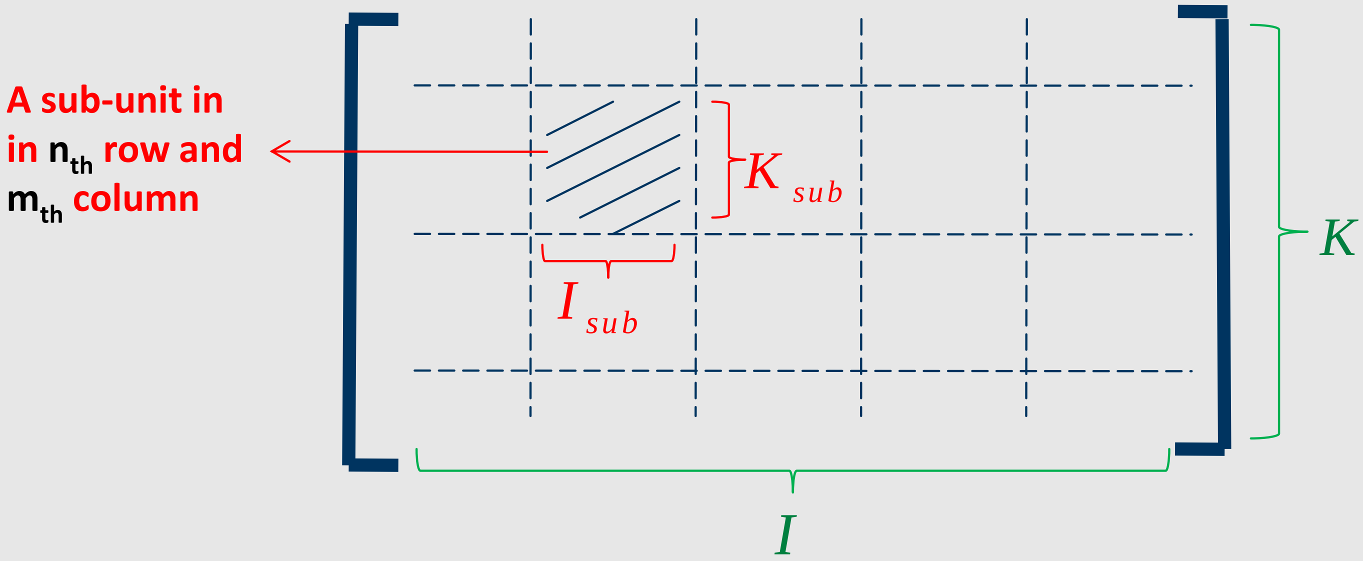
$$LogErr_{var} = \frac{1}{N\,M}\sum_{n=1}^{N}\sum_{m=1}^{M} Variance\left(\left|10\log_{10}\left[\frac{\delta_D^2}{\hat{\delta}_D^2}\right]\right|\right)^{n,m}$$

$M \rightarrow$ **Number of sub-units in the column**

$Variance(.)^{n,m} \rightarrow$ **The variance computed for the sub-unit in the n_{th} row and m_{th} column**

$N \rightarrow$ **Number of sub-units in the row**

Variance computation



$$Variance\left(\left|10\log_{10}\left[\frac{\delta_D^2}{\hat{\delta}_D^2}\right]\right|\right)^{n,m} = \frac{1}{I_{sub}\,K_{sub}} \sum_{i=(m-1)I_{sub}+1}^{m\,I_{sub}} \left[\sum_{k=(n-1)K_{sub}+1}^{n\,K_{sub}} \left(\left|10\log_{10}\left[\frac{\delta_D^2(k,i)}{\hat{\delta}_D^2(k,i)}\right]\right| - \mu_i^n \right)^2 \right],$$

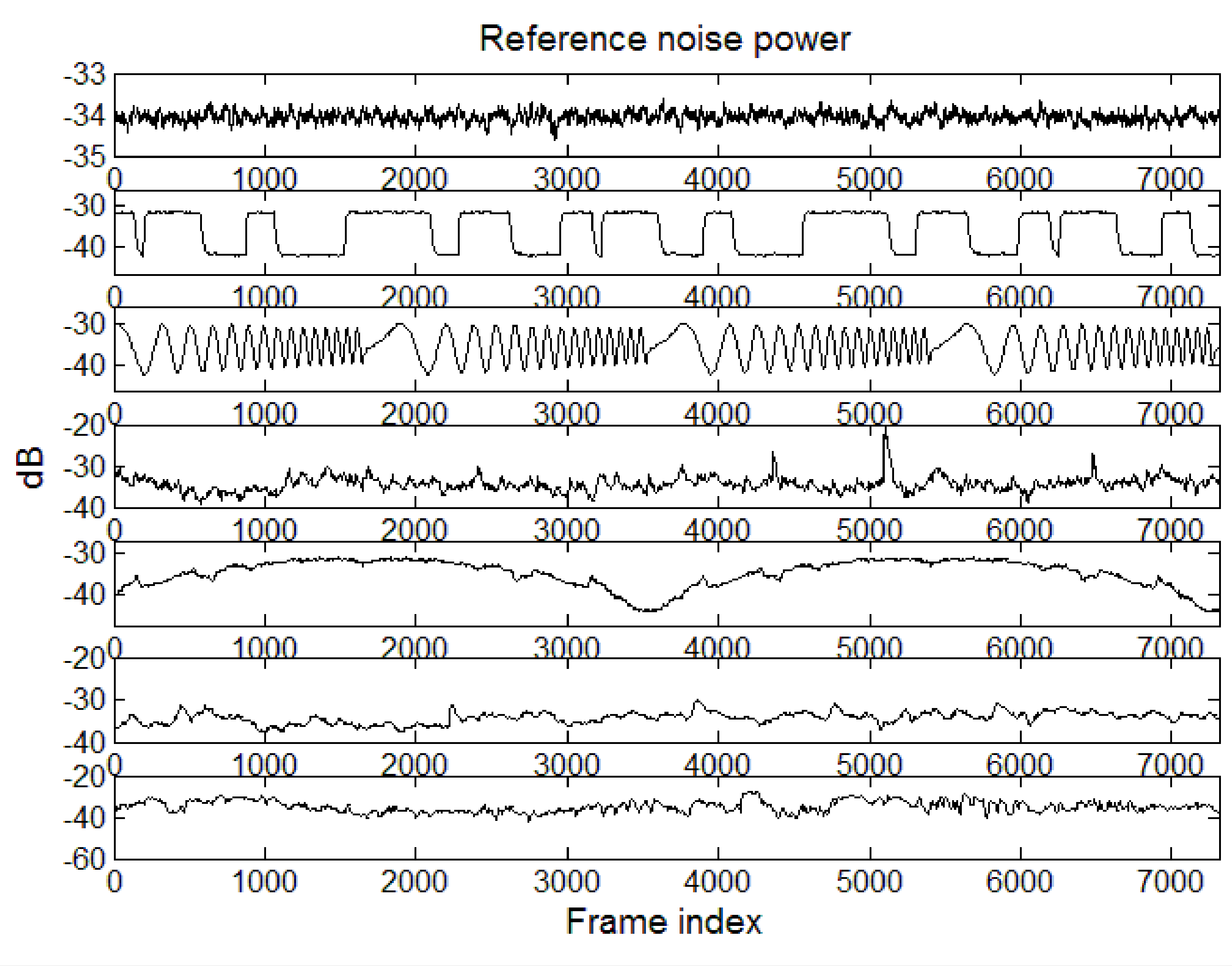
$$\mu_i^n = \frac{1}{K_{sub}} \sum_{k=(n-1)K_{sub}+1}^{n\,K_{sub}} \left(\left|10\log_{10}\left[\frac{\delta_D^2(k,i)}{\hat{\delta}_D^2(k,i)}\right]\right| \right)$$

In our experiments: $I_{sub} = 15$ and $K_{sub} = 10$

Experimental results

- 8 algorithms are considered
- Sampling frequency of all signals is 8 KHz
- Window length as well as the DFT length 256 samples
- Clean speech signals from TIMIT database
  - One female speech and one male speech; each one with 2 minutes length
- 7 different types of noise signals (taken from SOUND-IDEAS)
  - WGN, VaryingStep WGN, Sinusoidally modulated WGN, Babble, Car, Traffic1, Traffic2
  - The range of input SNR is from -5 dB to 20 dB
- Reference noise:
  - Several methods for smoothing were tested
  - Finally, a recursive temporal smoothing of noise periodograms was found to be more appropriate (smoothing factor 0.9)

Experimental results …



WGN

Varying-Step WGN

Sinusoidal WGN

Babble noise

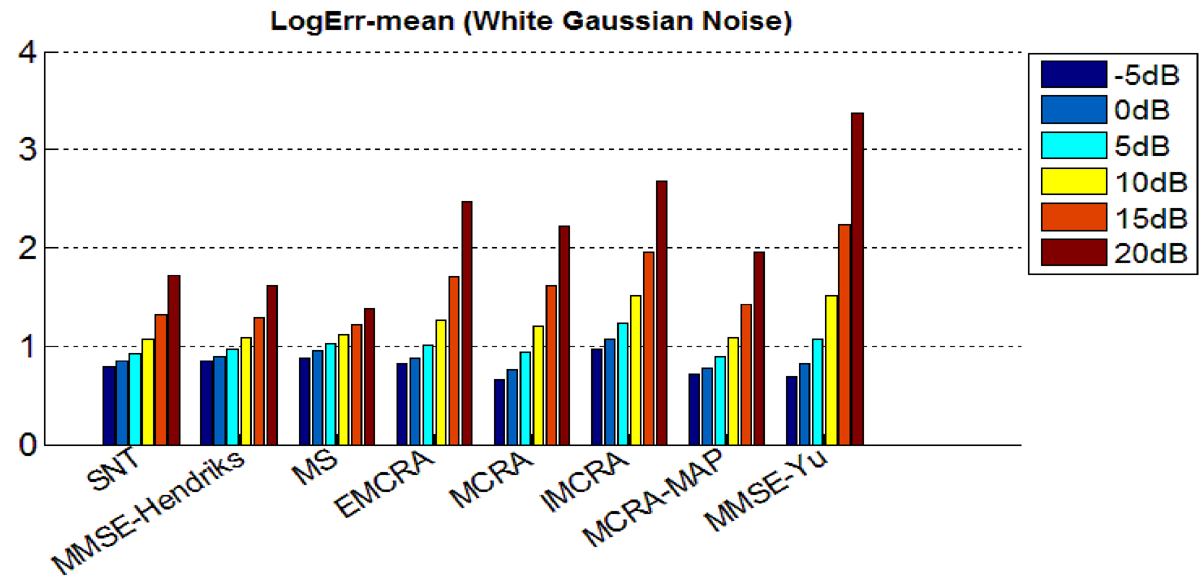
Car noise

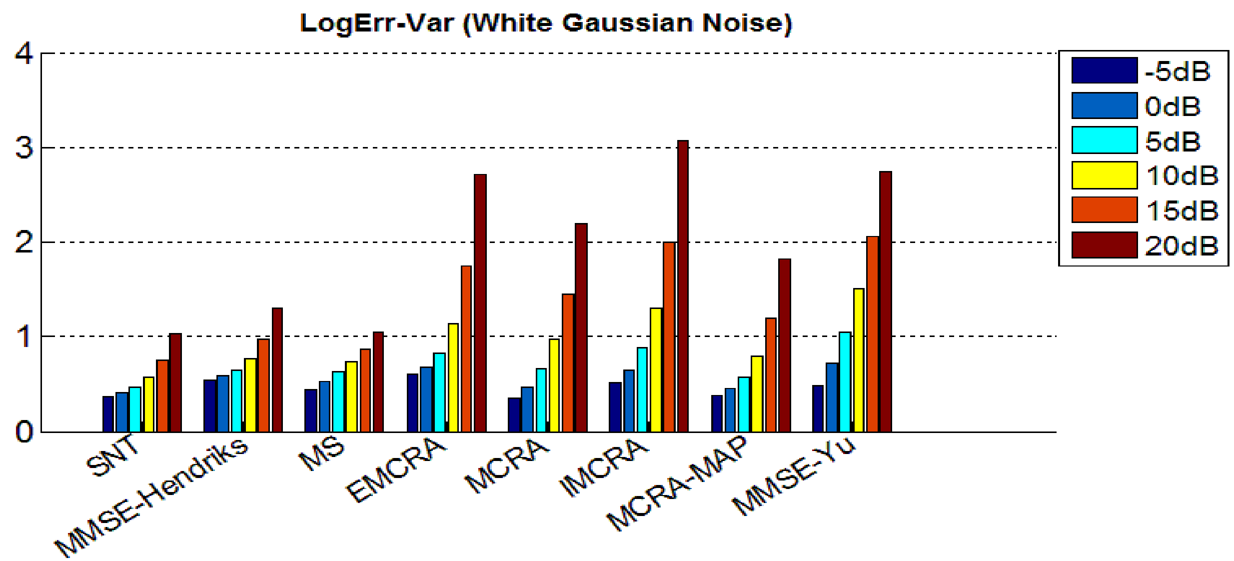
Traffic1 noise

Traffic2 noise

Experimental results …

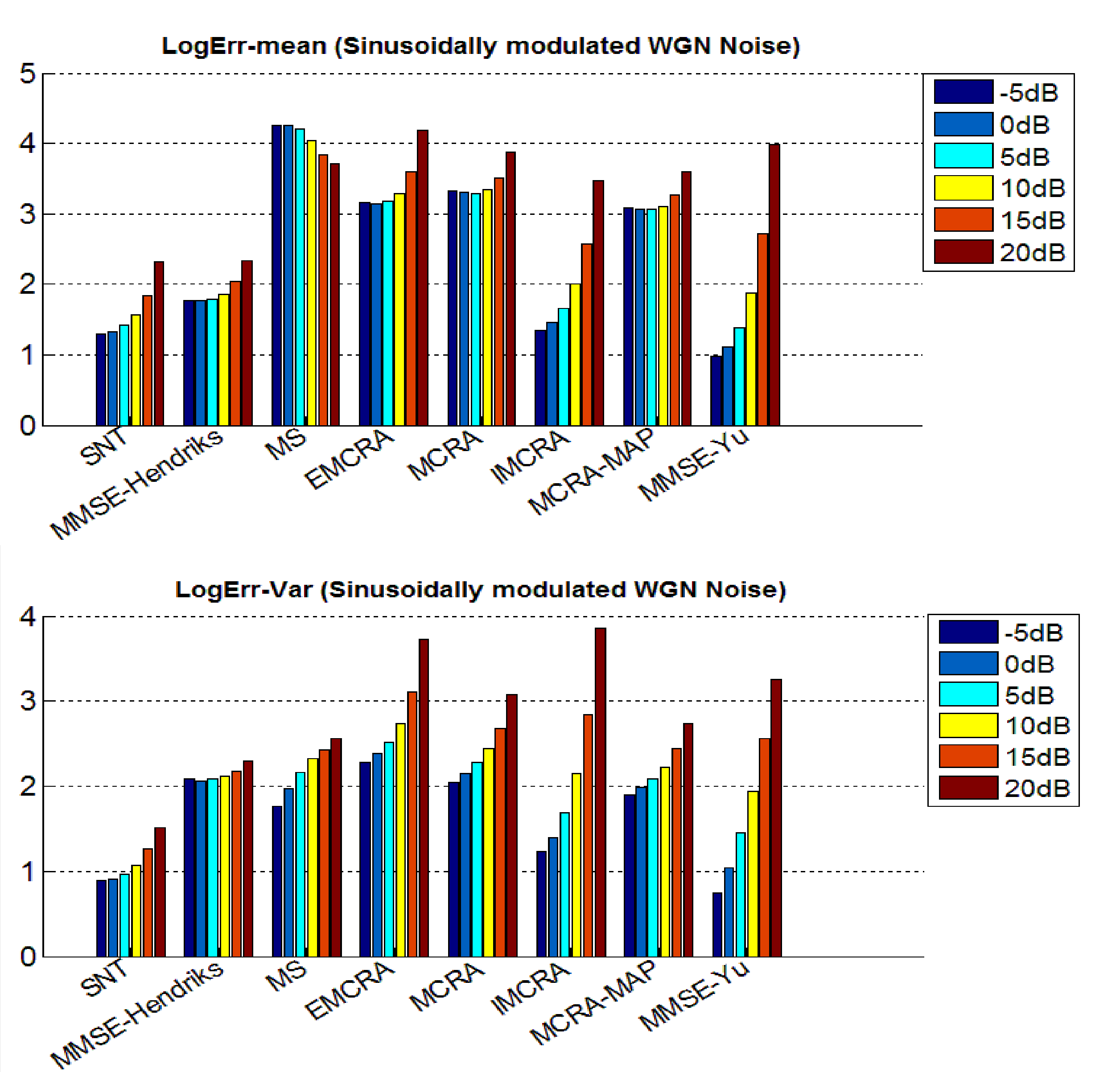
Performance results of 8 algorithms in the case of WGN in terms of LogErr-mean and LogErr-Var





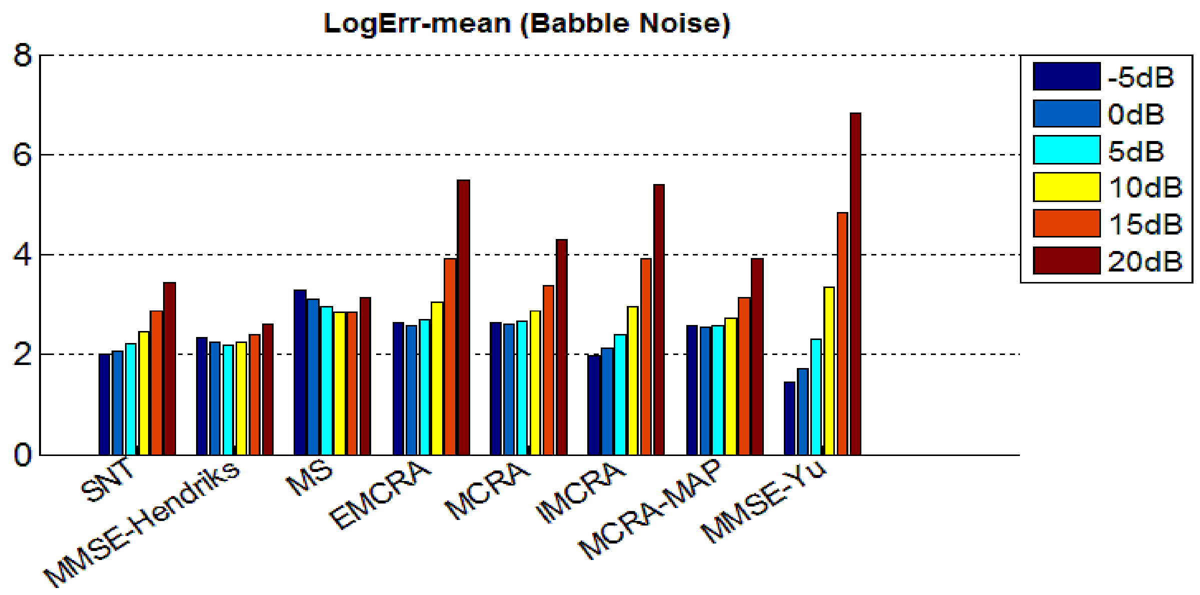
Experimental results …

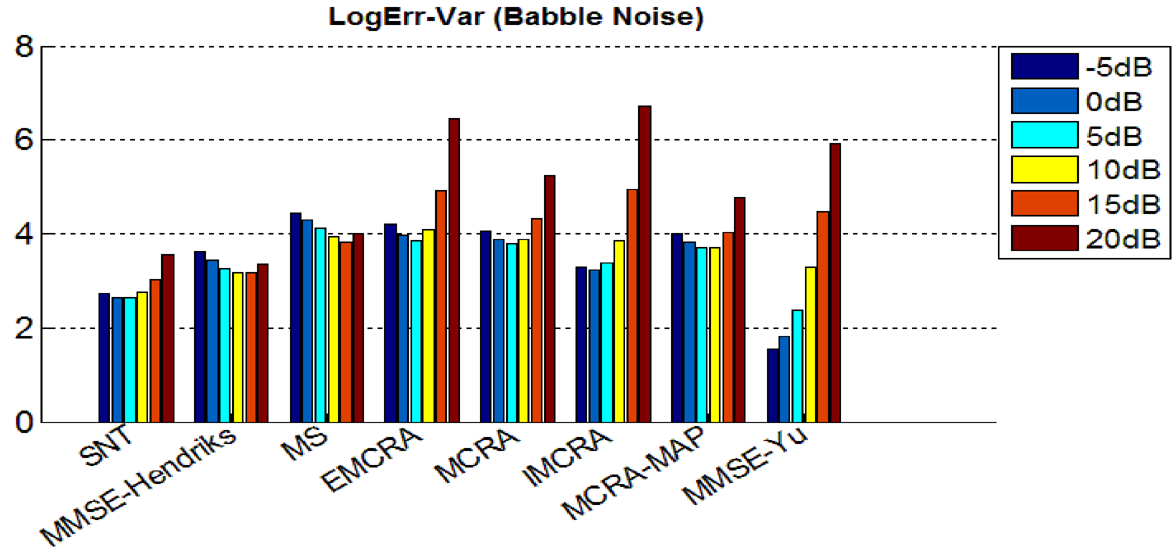
Performance results of 8 algorithms in the case of Sinusoidally modulated noise in terms of LogErr-mean and LogErr-Var



Experimental results …

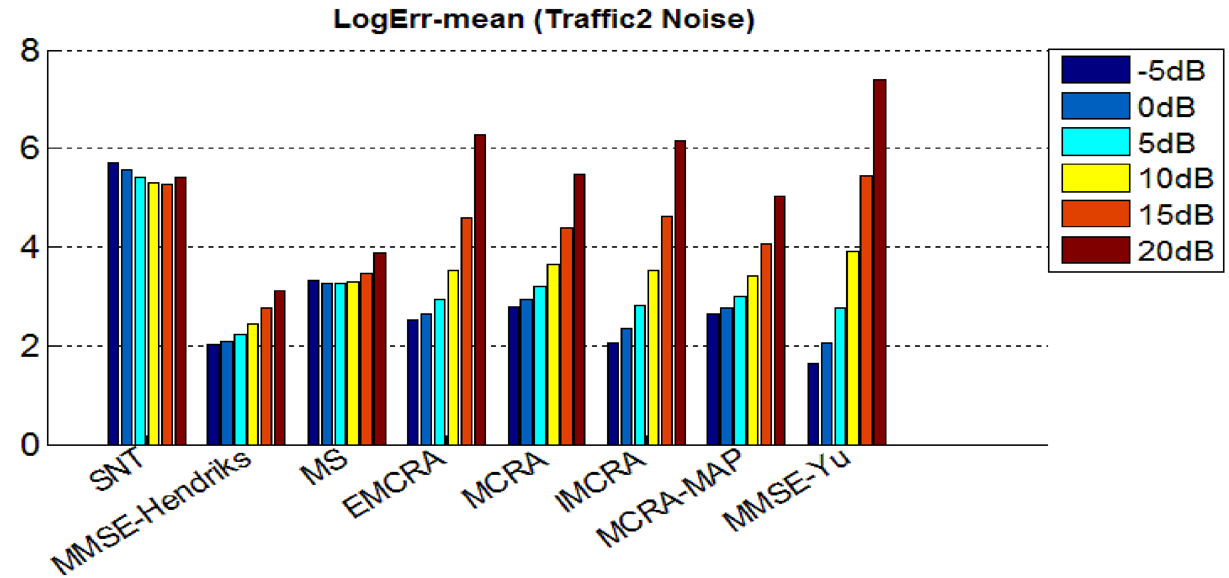
Performance results of 8 algorithms in the case of Babble noise in terms of LogErr-mean and LogErr-Var

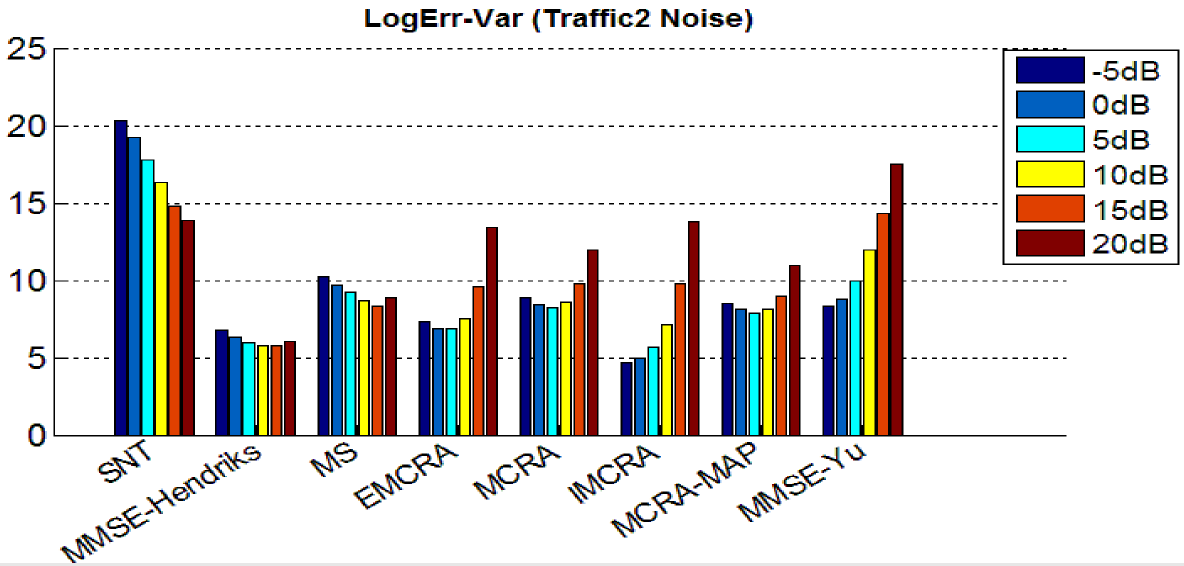




Experimental results …

Performance results of 8 algorithms in the case of Traffic2 noise in terms of LogErr-mean and LogErr-Var

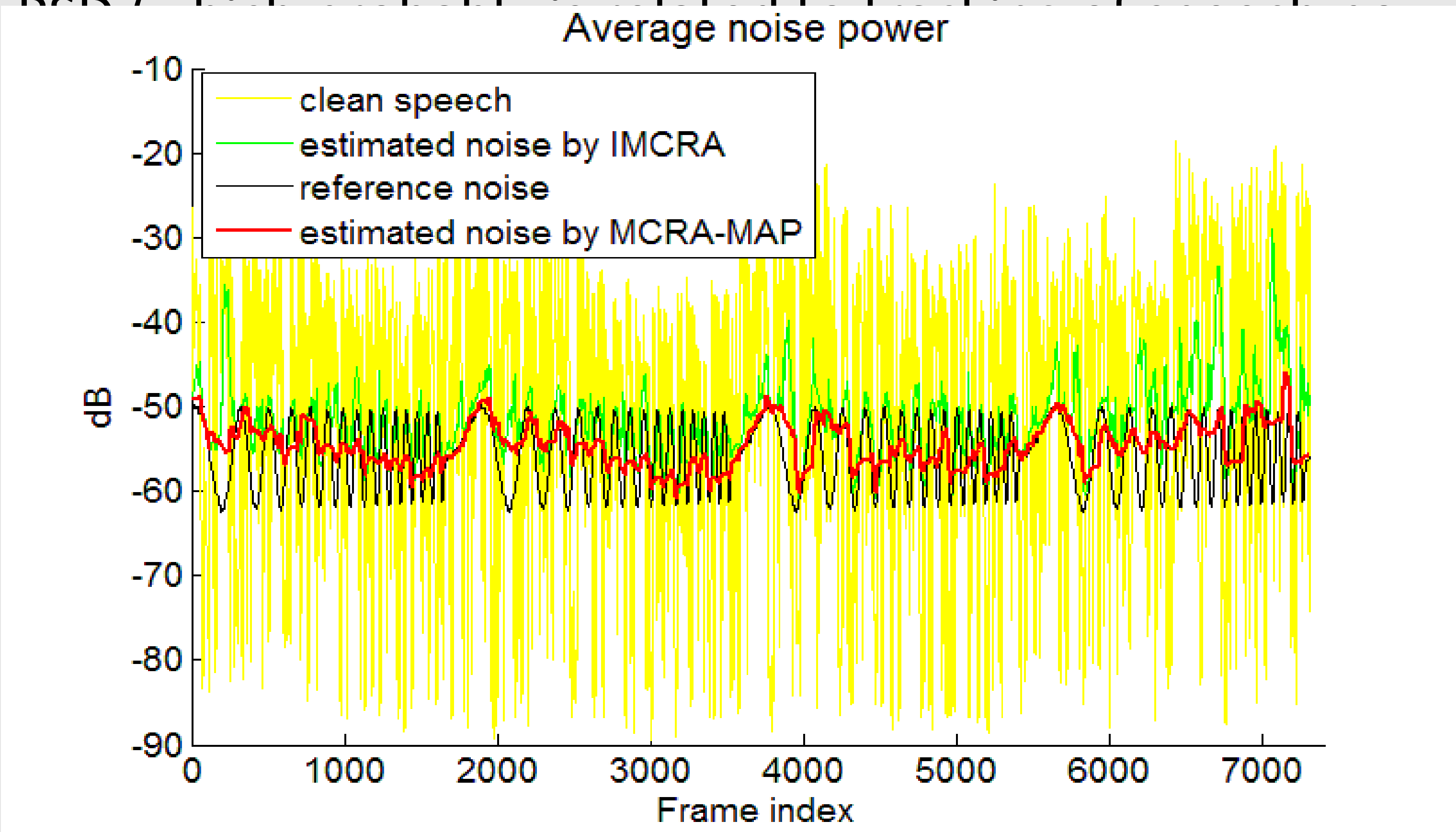




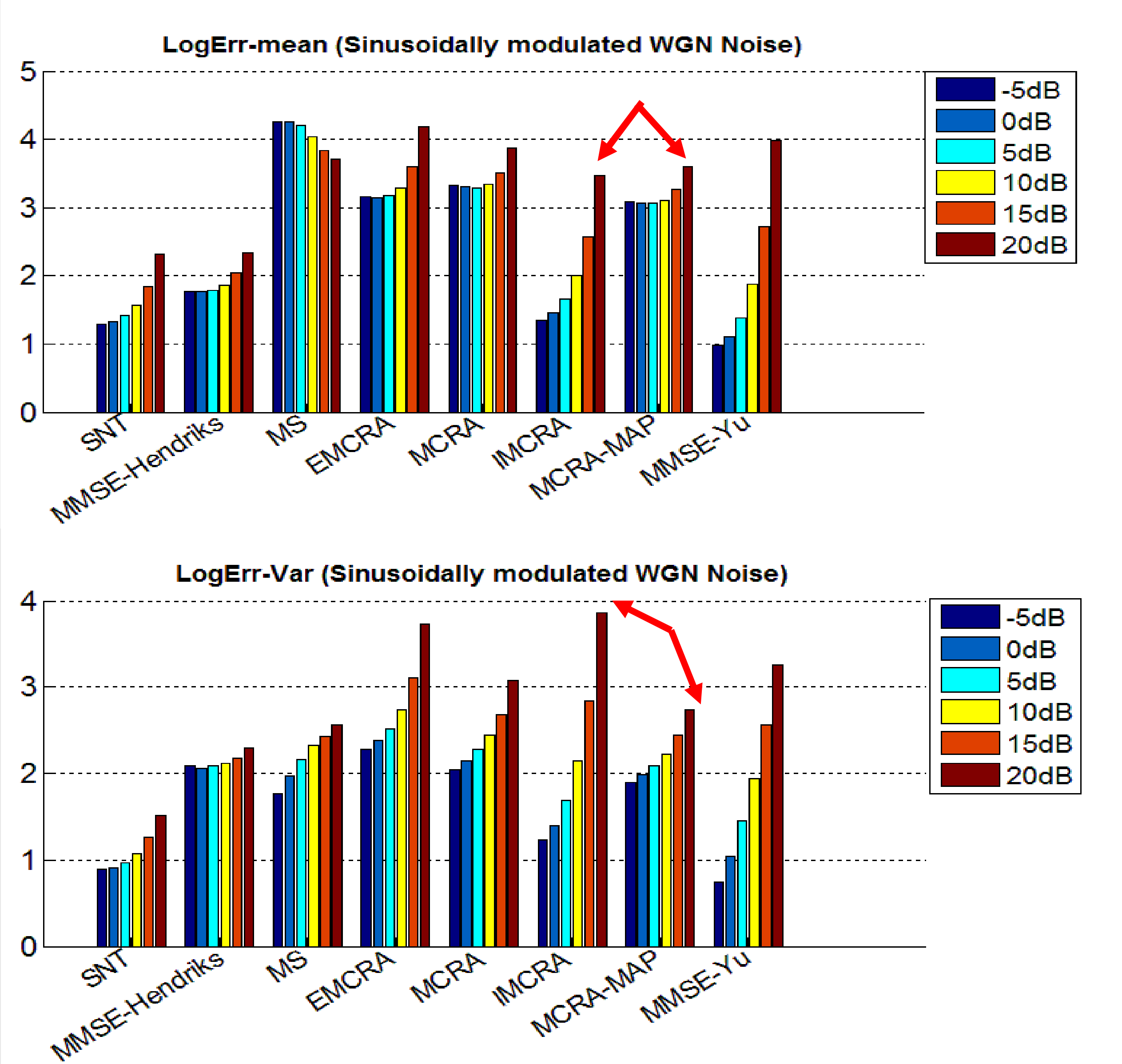
Experimental results …

- Estimation error variance gives additional insight
  - It measures the amount of fluctuations in the estimated noise PSD (… er)
  - … ance in

Female speech degraded by Sinusoidally modulated WGN with 20dB input SNR



Experimental results …



Conclusions

- Some of noise power estimators are very susceptible to the level of input SNR
- **Estimation error variance** allows us to measure *amount of fluctuations* in tracking noise power, and perhaps producing *musical noise*
- For non-stationary noise a few methods show to be robust
  - MMSE-Hendriks → the most robust noise power estimator according to our experiments

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