Feature Extraction Combining Spectral Noise Reduction and Cepstral Histogram Equalization For Robust ASR

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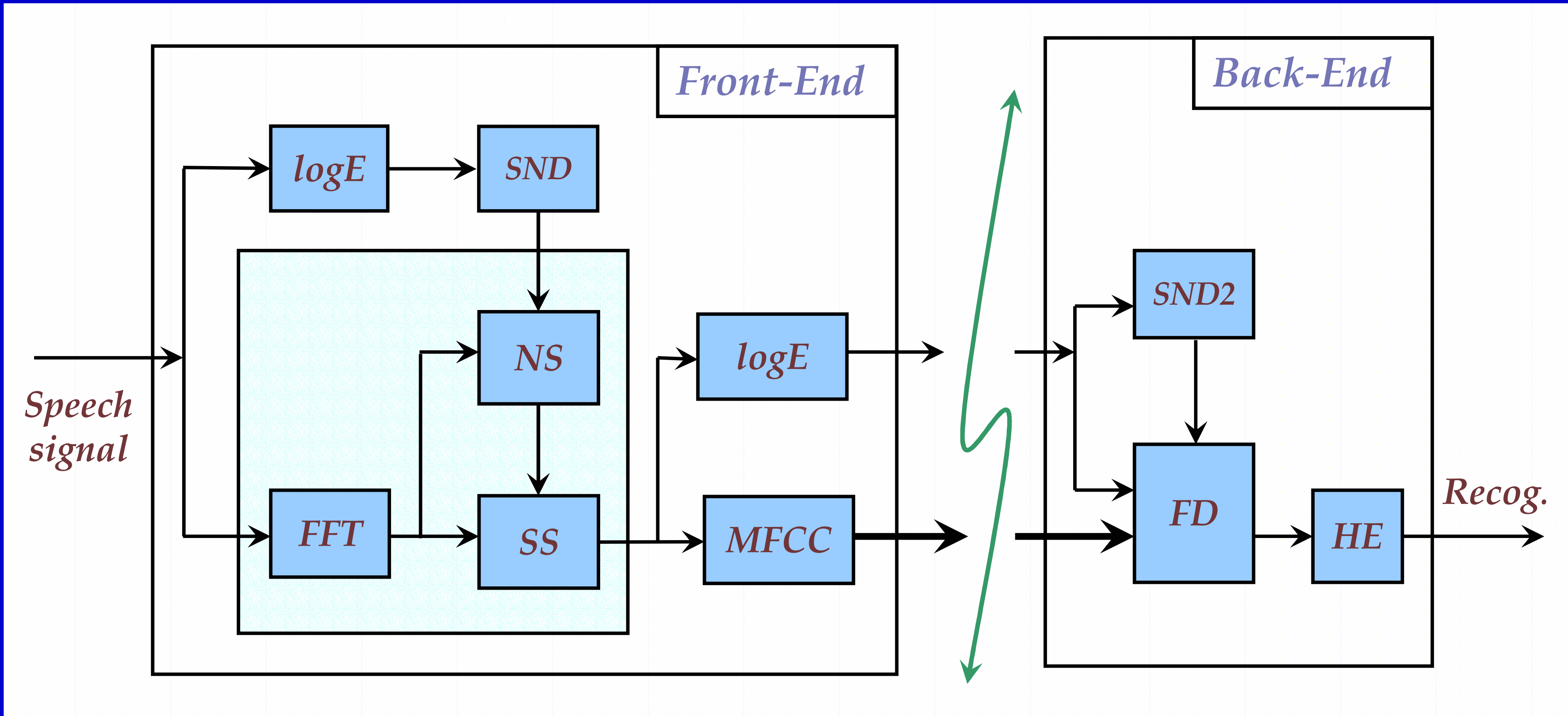
Introduction

- Results for Noisy TI-Digits at ICASSP'02
  - Histogram Equalization (HE) can reduce the mismatch of noisy speech better than CMS and CMVN
  - Its performance is increased when applied over partially compensated speech features
- In this work we explore HE performance in combination with Spectral Subtraction

Outline

- System description
- Front-End Spectral Noise Reduction
  - Speech/Non-Speech Detection
  - Spectral Subtraction
- Back-End Processing
  - Frame-Dropping
  - Feature Normalization
- Experimental set-up
- Results and discussion

System Description



Spectral Subtraction

- Standard implementation on the magnitude spectrum

$$\left|\hat{X}_t(w)\right| = \max\left\{ \left(\left|Y_t(w)\right| - \alpha \left|\hat{N}_t(w)\right| \right), \beta \left|Y_t(w)\right| \right\}$$

$$\left|\hat{N}_t(w)\right| = \begin{cases} \lambda \left|\hat{N}_{t-1}(w)\right| + (1-\lambda)\left|Y_t(w)\right| & \textit{Non-Speech} \\ \left|\hat{N}_{t-1}(w)\right| & \textit{Speech} \end{cases}$$

Over-subtraction	$\alpha = 1.1$	$\hat{N}(w)$:	*Noise estimate*
Maximum attenuation	$\beta = 0.3$	$Y(w)$:	*Noisy speech*
Forgetting factor	$\lambda = 0.95$	$\hat{X}(w)$:	*Clean speech estimate*

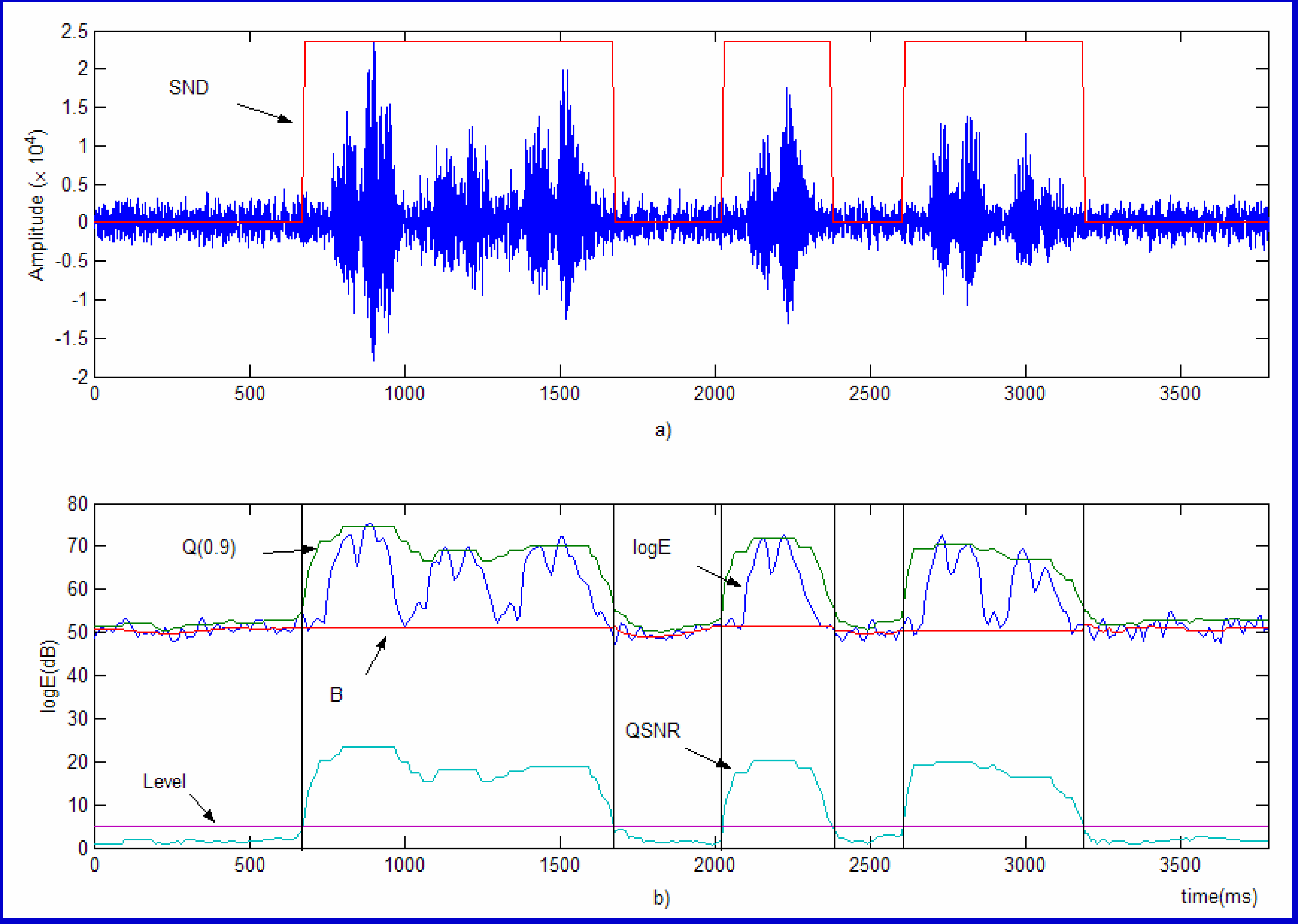
Speech/Non-Speech Detection (I)

- Based on log-Energy quantile difference
- Quantiles are estimated over a sliding window of 21 frames (at a frame rate of 100Hz)
  - $Q_{0.5}$ (median) is used to track the noise level B
  - $Q_{0.9}$ is used to track the speech level
- $Q_{SNR} = Q_{0.9} - B$ is thresholded to detect speech
- Noise level B is updated with $Q_{0.5}$ whenever non-speech is detected

Speech/Non-Speech Detection (II)

- Characteristics of the SND algorithm
  - Easy and fast implementation
  - Fast tracking of noise level
  - Q_{SNR} is smooth enough to prevent false speech detections
  - Implicit symmetric hang-over

Speech/Non-Speech Detection (III)



Frame-Dropping

- The objective is to remove long speech pauses
- Based on same SND algorithm
  - It works over the noise reduced speech
- One frame is removed only if in the middle of a non-speech segment of predefined length
  - This prevents over-dropping
  - 11 frames are used in this work

Feature Normalization (I)

- CDF-matching for non-linear distortion compensation
  - Given a zero-memory one-to-one general transformation $y=T[x]$

$$x \rightarrow p_X(x) \qquad\qquad y = T[x] \rightarrow p_Y(T[x]) = p_Y(y)$$

$$C_X(x) = \int_{-\infty}^{x} p_X(u)\,du \qquad\qquad C_Y(y) = \int_{-\infty}^{y} p_Y(u)\,du$$

$$C_X(x) = C_Y(y) \qquad \Rightarrow \qquad x = T^{-1}[y] = C_X^{-1}(C_Y(y))$$

Feature Normalization (II)

- Two ways of using CDF-matching for mismatch reduction

- CDF-matching for feature compensation
  - $C_X(x)$ is estimated during training
  - During test, $C_Y(y)$ estimate is used to compensate for the mismatch

$$\hat{x} = \hat{T}^{-1}[y] = C_X^{-1}(\hat{C}_Y(y))$$

- CDF-matching for feature normalization
  - A predefined $C_X(x)$ is selected (usually Gaussian)
  - For both training and test, features are transformed to match the reference distribution using an estimate of $C_Y(y)$
  - Can be viewed as an extension of CMVN

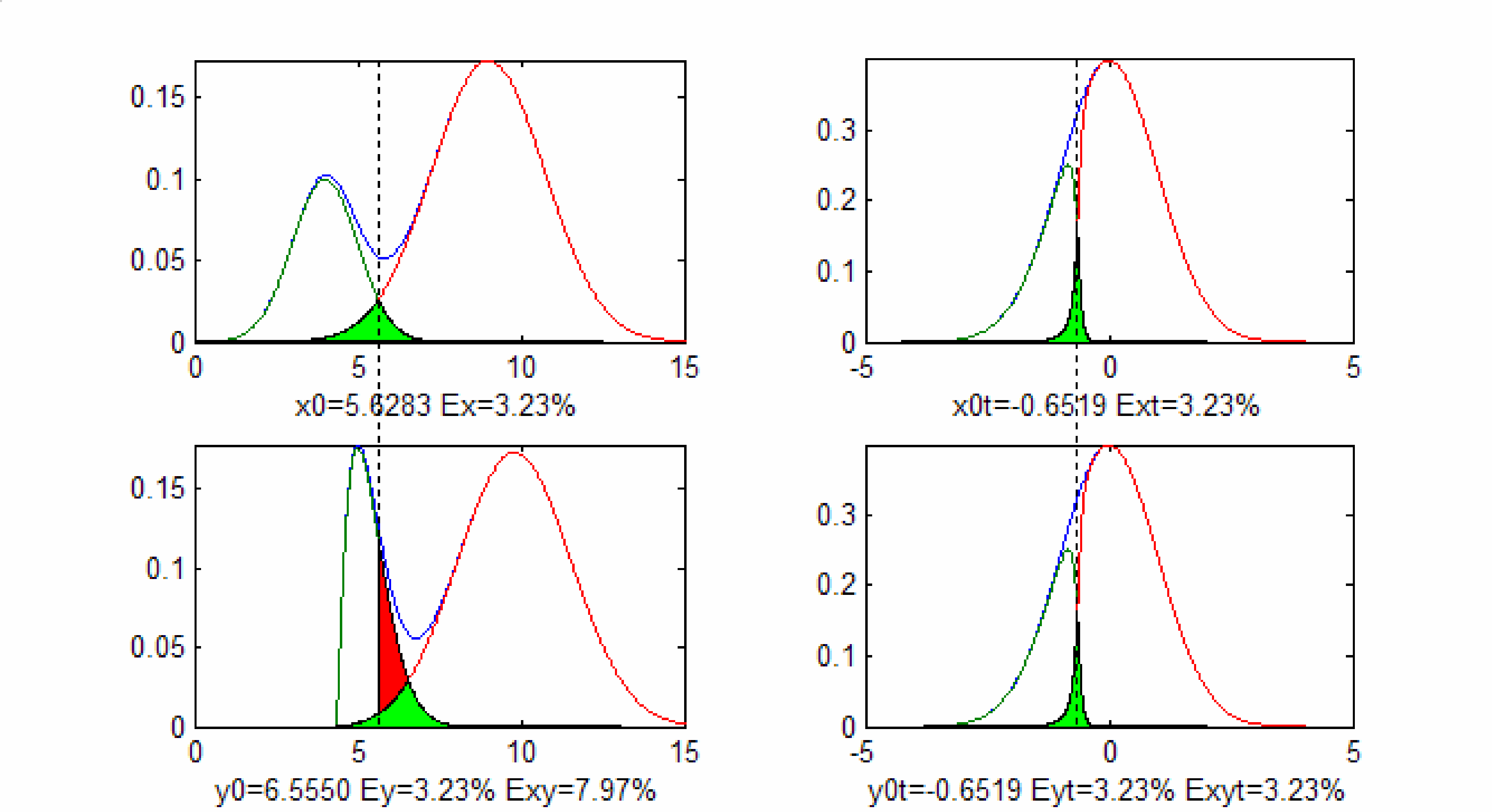
Feature Normalization (III)

- Previous works: Feature compensation
  - R. Balchandran, R. Mammone. ***Non-parametric estimation and correction of non-linear distortion in speech systems*** [ICASSP'98]
    - Domain: Speech samples
    - Task: Speaker ID / Sigmoid and cubic distortions
  - S. Dharanipragada, M. Padmanabhan. ***A nonlinear unsupervised adaptation technique for speech recognition*** [ICSLP'00]
    - Domain: Cepstrum
    - Task: Speech Recognition / Handset / Speaker-phone mismatch
  - F. Hilger, H. Ney. ***Quantile based histogram equalization for noise robust speech recognition*** [EUROSPEECH'01]
    - Domain: Filter-bank Energy
    - Task: Speech Recognition / AURORA task

Feature Normalization (IV)

- Previous works: Feature normalization
  - J. Pelecanos, S. Sridharan. ***Feature warping for robust speaker verification*** [Speaker Odyssey'01]
    - Domain: Cepstrum
    - Task: NIST 1999 Speaker Recognition Evaluation database
  - B. Xiang, U.V. Chaudhari,… ***Short-time gaussianization for robust speaker verification*** [ICASSP'02]
    - Domain: Cepstrum / Short-time
    - Task: Speaker Verification
  - J.C. Segura, A. de la Torre, M.C. Benítez,… ***Non-linear transformations of the feature space for robust speech recognition*** [ICASSP'02]
    - Domain: Cepstrum
    - Task: Speech Recognition / AURORA

Feature Normalization (V)

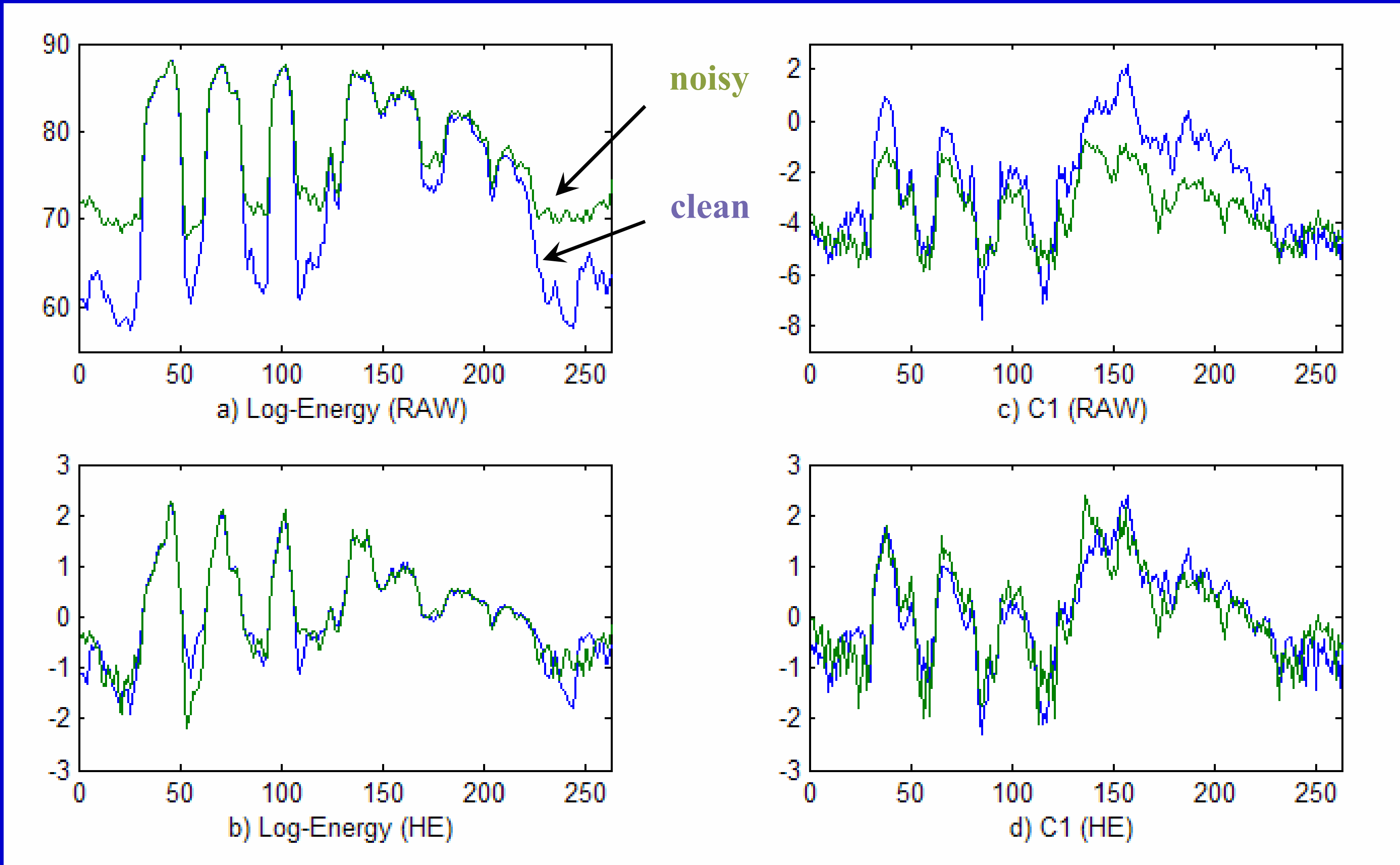


$$y = \log(\exp(x+h)+\exp(n)) \qquad h = 0.8 \qquad n = 3.5$$

Feature Normalization (VI)

- Implementation details
  - CDF-matching is applied in the cepstrum domain in a feature transformation scheme
  - Each cepstral coefficient is transformed independently to match a Gaussian reference distribution
  - Algorithm
    - $C_Y(y)$ is estimated for each feature of each utterance using cumulative histograms
    - The bins centers are transformed and a piecewise linear transformation is constructed
    - The transformation is applied to the input features to get the transformed ones

Feature Normalization (VII)



Experimental set-up

- Database end-pointing
  - Noisy TI-digits and SpeechDat Car databases have been automatically end-pointed
  - SND algorithm is used on clean speech (channel 0) utterances
  - 200ms of silence have been added at the end-points
- Acoustic features
  - Standard front-end: 12 MFCC + logE
  - Delta and acceleration coefficients are appended at the recognizer with regression lengths of 7 and 11 frames respectively
- Acoustic modeling
  - One 16 emitting states left-to-right continuous HMM per digit
  - 3 Gaussian mixture per state

Aurora 2 results

TI-Digits Multi-condition Training					
	A	B	C	Average	Rel.Imp.
Baseline	88.07	87.22	84.56	87.03	----
SS	90.94	88.69	86.29	89.11	9.43%
SS+HE	90.72	89.74	90.03	90.19	15.42%
SS+FD+HE	90.89	89.80	90.11	90.30	17.99%

TI-Digits Clean-condition Training					
	A	B	C	Average	Rel.Imp.
Baseline	58.74	53,40	66.00	58.06	----
SS	73.71	69.35	75.63	72.35	37.71%
SS+HE	82.08	82.61	81.73	82.22	55.59%
SS+FD+HE	82.51	82.78	81.87	82.49	56.45%

23.57%
35.51%
37.22%

Aurora 3 results

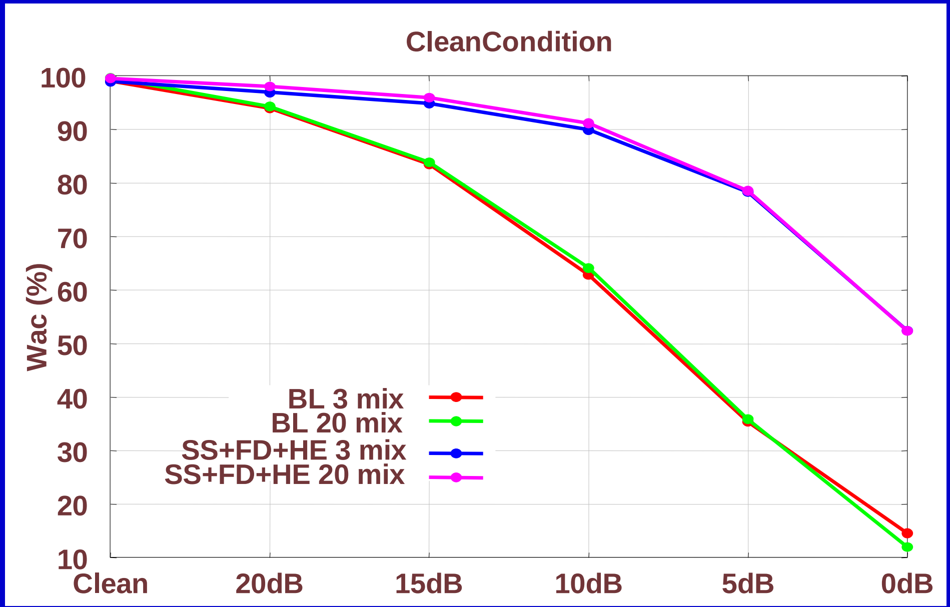
Finnish					
	WM	MM	HM	Average	Rel.Imp.
Baseline	92.74	80.51	40.53	75.41	-----
SS	95.09	78.80	69.19	82.91	21.92%
SS+HE	94.58	86.53	74.20	86.67	35.10%
SS+FD+HE	94.58	86.73	73.11	86.46	35.00%

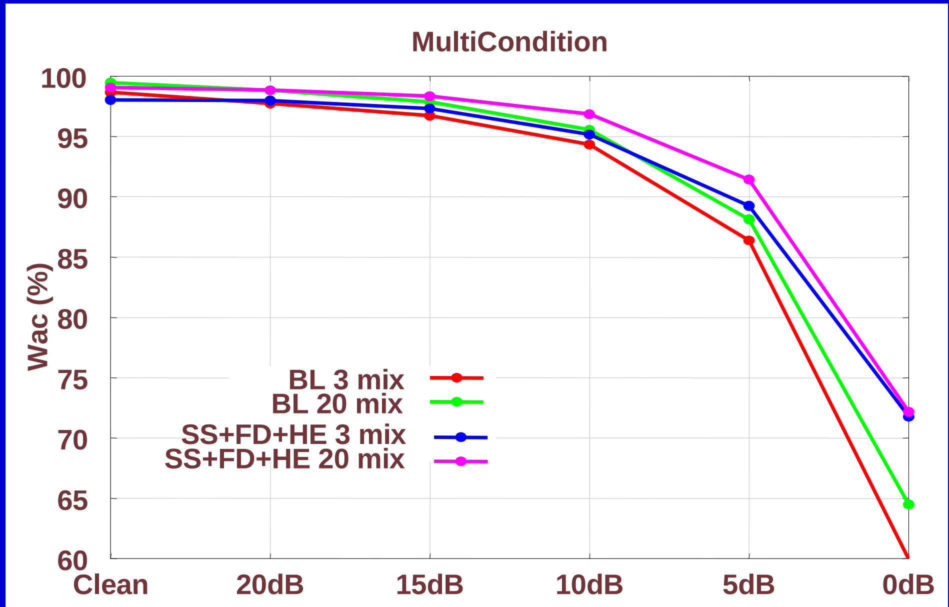
Spanish					
	WM	MM	HM	Average	Rel.Imp.
Baseline	92.94	83.31	51.55	79.22	-----
SS	95.58	89.76	71.94	87.63	39.00%
SS+HE	96.15	93.15	86.77	93.00	57.00%
SS+FD+HE	96.65	94.10	87.03	93.35	61.95%

German					
	WM	MM	HM	Average	Rel.Imp.
Baseline	91.20	81.04	73.17	83.14	-----
SS	93.41	86.60	84.32	88.75	30.70%
SS+HE	94.79	88.58	89.32	91.25	45.29%
SS+FD+HE	94.57	88.07	88.95	90.89	43.00%

30.54%
45.79%
46.65%

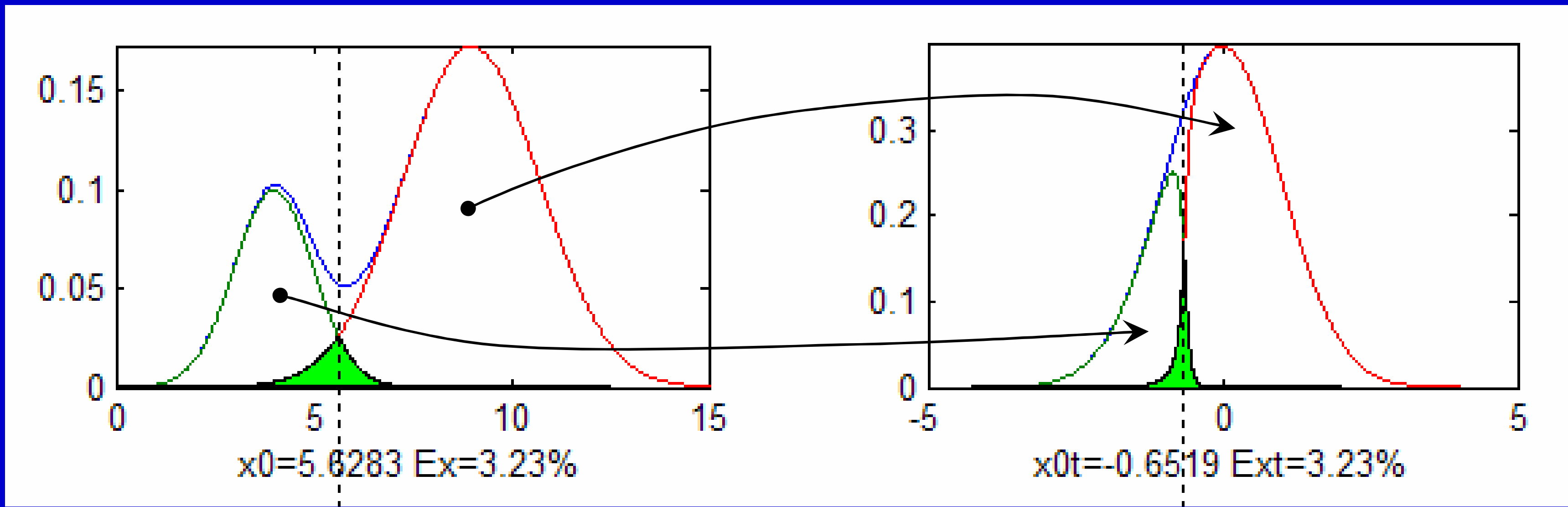
20 mixtures Aurora 2 results





Features	Clean Condition		Multi Condition	
	Absolute	Relative	Absolute	Relative
BL 3mix	58.06	--.--	87.03	--.--
BL 20mix	58.04	4.51%	88.98	26.39%
SS+FD+HE 3mix	82.49	56.45%	90.30	17.99%
SS+FD+HE 20mix	83.22	62.67%	91.53	41.38%

Gaussian class distortion



- Gaussian class densities are transformed into non-Gaussian ones

Conclusions

- A simple and effective SND algorithm based on logarithmic energy quantile difference is presented
- HE is evaluated in combination with classical spectral subtraction with mean relative improvements of 37.22% and 46.65% for AURORA 2 and 3 tasks
- Performance for the 20 mixtures system suggest the need of a higher number of Gaussians after HE

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This slides are available at

http://sirio.ugr.es/segura/pdfdocs/icslp02_sl.pdf