Improved feature extraction based on spectral noise reduction and nonlinear feature normalization

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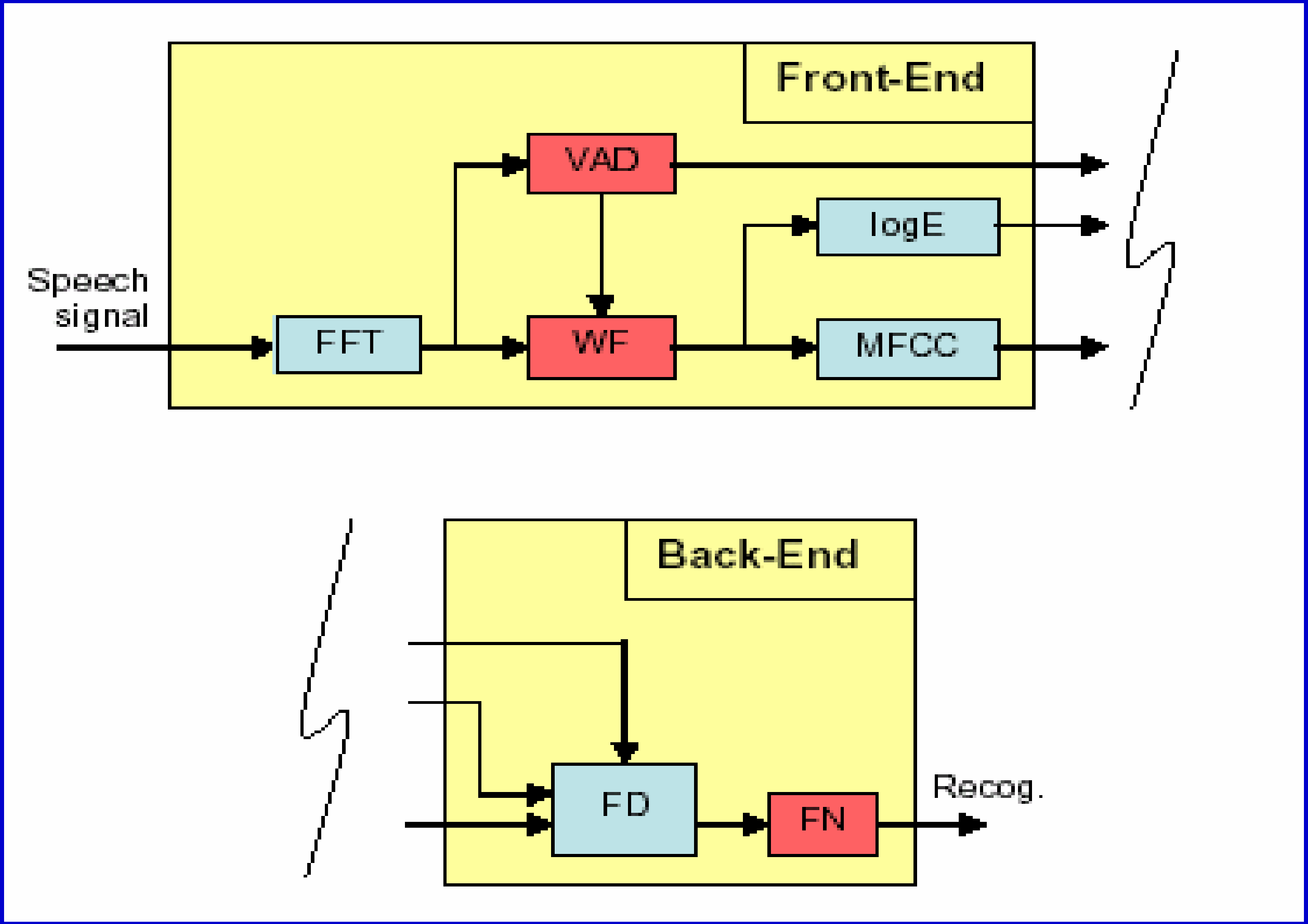
Introduction

- 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
- Results for AURORA 2 and 3 at ICSLP'2002
  - Feature extraction combining spectral noise reduction and cepstral histogram equalization for robust ASR
- In this work we explore CDF-matching performance in combination with Wiener filtering

Outline

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

System Description



Speech/Non-Speech Detection (I)

- Long Term Spectral Estimation VAD algorithm

- LTSE estimation using a sliding window of 3 frames

$$LTSE(k) = \max\left\{X(k, n+l)\right\}_{l=-N}^{l=+N}$$

- Decision rule

$$LTSD = 10\log_{10}\left(\frac{1}{NFFT}\sum_{k=0}^{NFFT-1}\frac{LTSE^2(k)}{Ne^2(k)}\right)$$

- LTSD is compared with an adaptive threshold γ

Speech/Non-Speech Detection (II)

- Threshold γ function of the noise energy

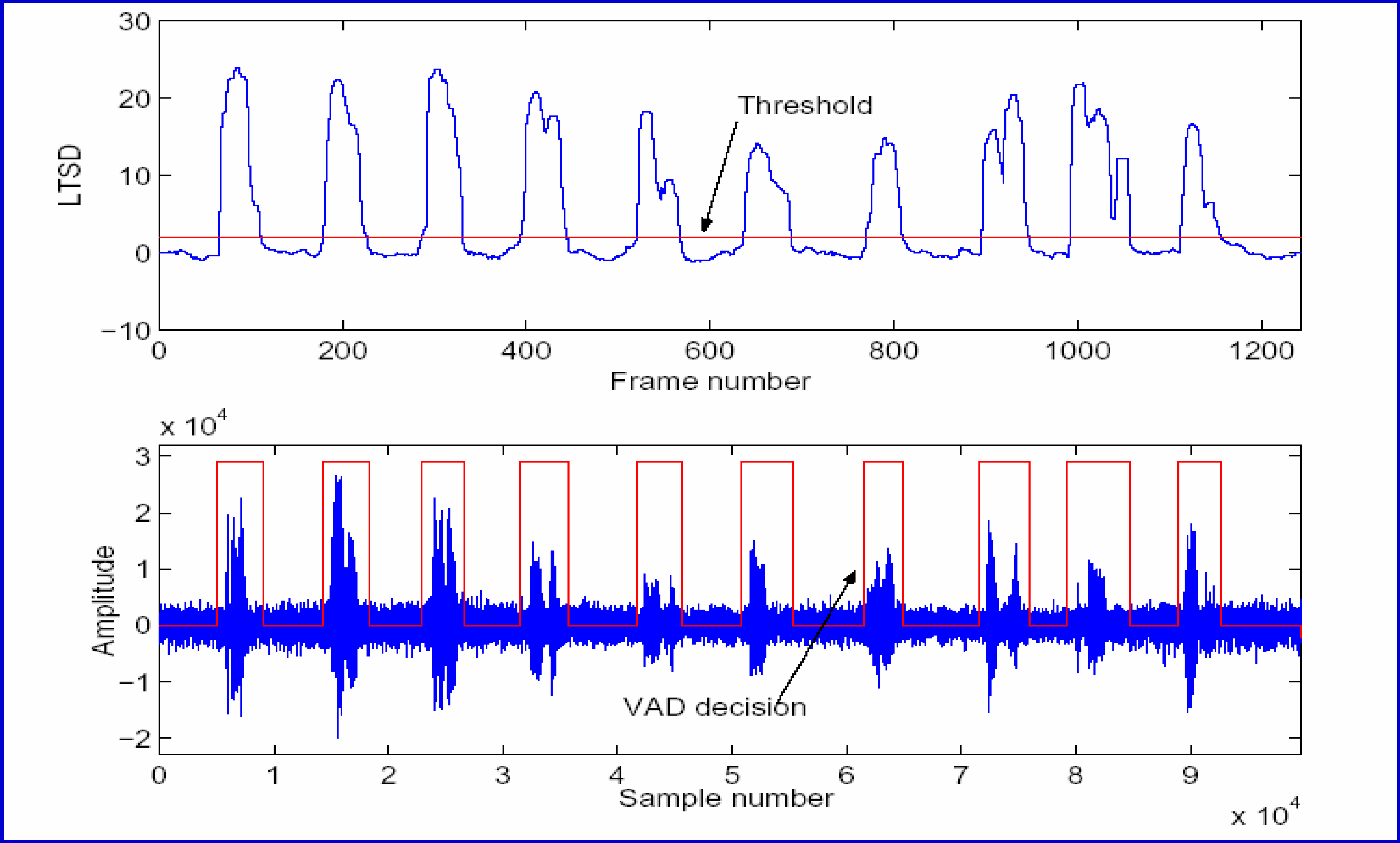
$$\gamma = \begin{cases} \gamma_0 & E \le E_0 \\ \dfrac{\gamma_0 - \gamma_1}{E_0 - E_1}(E - E_0) + \gamma_0 & E_0 < E < E_1 \\ \gamma_1 & E \ge E_1 \end{cases}$$

- VAD parameters

$$N = 3 \qquad NFFT = 256$$
$$\gamma_0 = 5dB \qquad E_0 = 30dB \qquad (low \quad noise \quad energy)$$
$$\gamma_1 = 1.5dB \qquad E_1 = 50dB \qquad (high \quad noise \quad energy)$$

- Adaptive VAD to time varying noise environments
- Details of the algorithm
  - A New Adaptive Long-Term Spectral Estimation Voice Activity Detector (EUROSPEECH'03)

Speech/Non-Speech Detection (III)

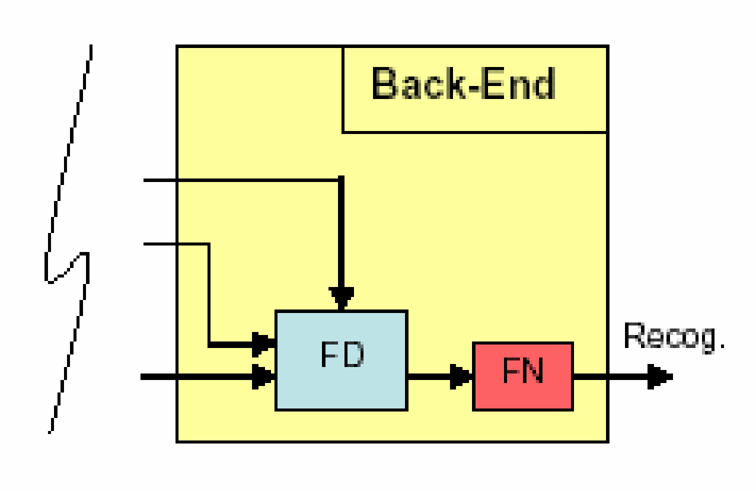


Spectral noise reduction

- Noise reduction implementation as in the first stage of the ETSI ES 202 050 without mel-scale warping.
- Temporal and frequency smoothing of the magnitude spectrum of the noisy frames is applied.
- Maximum attenuation is fixed at 22dB.
- FIR filter with 17 taps is obtained.
- Noise of spectrum estimation as (with $\lambda = 0.99$)

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

Back-end processing



- Frame Dropping
  - Remove all the frames labeled as non-speech
- Feature Normalization
  - ECDF-matching

Feature Normalization (I)

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

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

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

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

Feature Normalization (II)

- 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
- 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

Feature Normalization (III)

- Ecdf Algorithm:
  - Temporal buffer for a given distorted features

$$Y_t = \{ y_{-T}, \cdots, y_t, \cdots, y_T \}$$

  - Order statistics of data

$$y_{(1)} \leq y_{(2)} \leq \cdots \leq y_{(r)} \cdots \leq y_{(2T+1)}$$

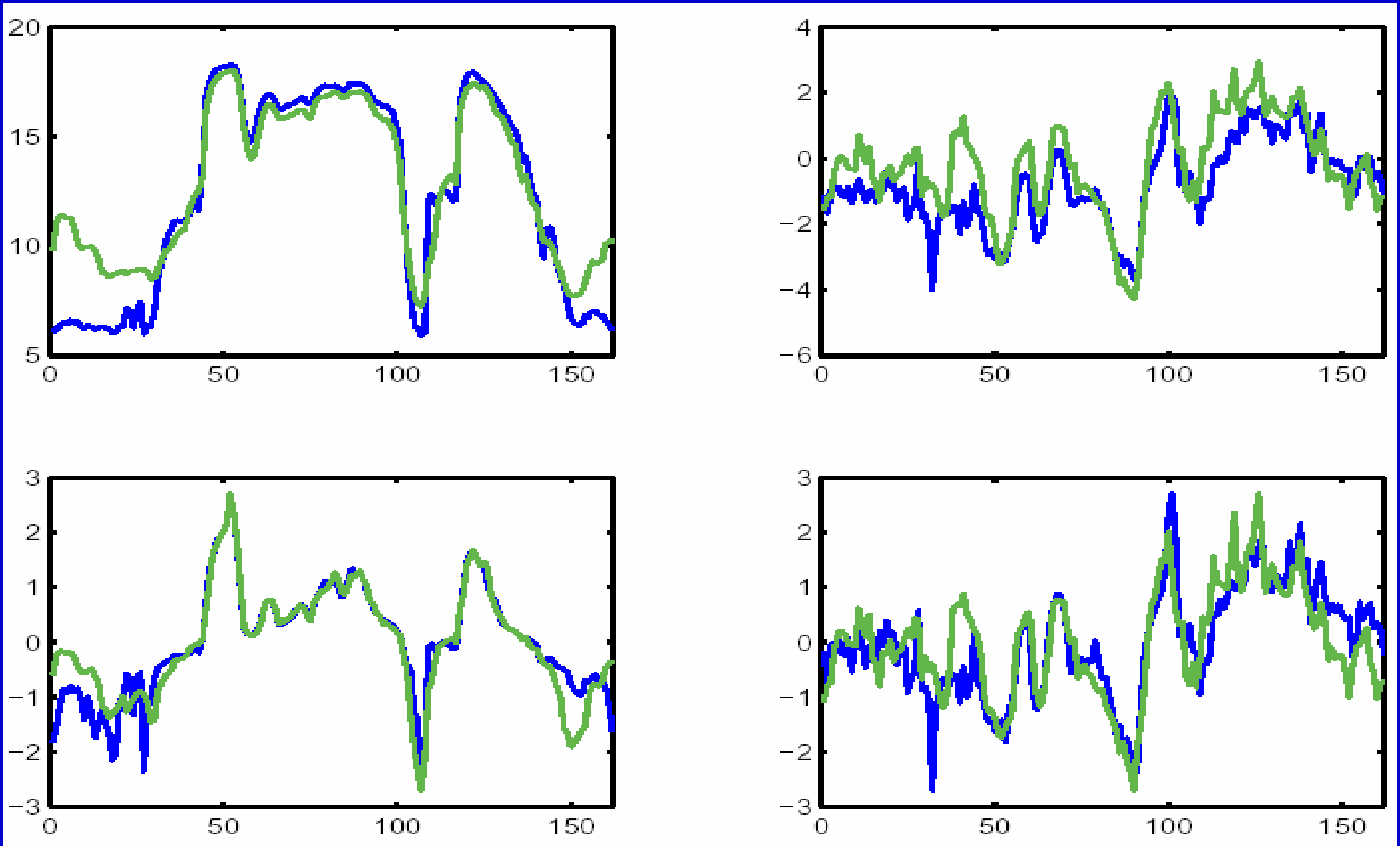
  - Asymptotically unbiased point estimation of the CDF

$$\hat{x}_t = C_x^{-1}\left(\hat{C}(y_t)\right) = C_x^{-1}\left(\frac{r(y_t) - 0.5}{2T+1}\right)$$

  - Estimation of the transformed value of the distorted feature

$$\hat{C}(y_{(r)}) = \frac{r - 0.5}{2T+1} \qquad r = 1, \cdots, 2T+1$$

Feature Normalization (IV)



Experimental set-up (I)

- 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 for AURORA 3
  - 20 Gaussian mixture per state for AURORA 2

Experimental set-up (II)

- Batch implementation
  - Using all the features of a given input utterance to perform the normalization
- Segmental implementation
  - Non-stationary noise
  - Using a short temporal window around the frame to be normalized
  - 121 frames of temporal window

Experimental Results (I)

- Results with *Batch* implementation
  - Comparative results over the previous system (ICSLP'02)

Aurora 2 Relative Improvement				
	Set A	Set B	Set C	Overall
Multi	16,47%	21,79%	20,70%	19,44%
Clean	30,46%	30,59%	28,78%	30,18%
Average	23,46%	26,19%	24,74%	24,81%

Aurora 3 Relative Improvement					
	Finnish	Spanish	German	Danish	Average
Well (x40%)	23,62%	6,57%	19,52%		16,57%
Mid (x35%)	20,12%	-8,98%	15,34%		8,83%
High (x25%)	52,81%	21,36%	19,19%		31,12%
Overall	29,69%	4,82%	17,97%		17,50%

- Spectral Subtraction ----- Wiener filtering
- Quantile based VAD ----- LTSD VAD
- Histogram Equalization ----- ECDF

★ Comparative results over AFE

Aurora 2 Word Error Rate				
	Set A	Set B	Set C	Overall
Multi	6,16%	6,50%	7,27%	6,52%
Clean	12,83%	12,07%	13,63%	12,69%
Average	9,49%	9,28%	10,45%	9,60%

Aurora 2 Relative Improvement				
	Set A	Set B	Set C	Overall
Multi	-8,59%	-4,21%	-3,86%	-5,89%
Clean	-21,13%	-10,50%	-4,46%	-13,54%
Average	-14,86%	-7,35%	-4,16%	-9,72%

Aurora 3 Word Error Rate					
	Finnish	Spanish	German	Danish	Average
Well (x40%)	4,14%	3,13%	4,37%	6,01%	4,41%
Mid (x35%)	10,60%	6,43%	10,10%	14,31%	10,36%
High (x25%)	12,69%	10,20%	8,93%	21,07%	13,22%
Overall	8,54%	6,05%	7,52%	12,68%	8,70%

Aurora 3 Relative Improvement					
	Finnish	Spanish	German	Danish	Average
Well (x40%)	-5,88%	6,85%	10,63%	9,35%	5,24%
Mid (x35%)	44,44%	-5,76%	-10,26%	22,69%	12,78%
High (x25%)	5,23%	-20,71%	-2,06%	-3,23%	-5,19%
Overall	14,51%	-4,45%	0,15%	10,87%	5,27%

❖ Segmental Implementation

Aurora 2 Word Error Rate				
	Set A	Set B	Set C	Overall
Multi	6,33%	6,55%	7,51%	**6,65%**
Clean	13,16%	12,04%	13,64%	**12,81%**
Average	**9,74%**	**9,29%**	**10,57%**	**9,73%**

Aurora 2 Relative Improvement				
	Set A	Set B	Set C	Overall
Multi	-12,68%	-7,21%	-8,87%	**-9,73%**
Clean	-28,78%	-14,51%	-9,10%	**-19,14%**
Average	**-20,73%**	**-10,86%**	**-8,99%**	**-14,43%**

Aurora 3 Word Error Rate					
	Finnish	Spanish	German	Danish	Average
Well (x40%)	4,14%	3,31%	5,09%	6,68%	**4,80%**
Mid (x35%)	10,60%	6,61%	11,27%	16,86%	**11,34%**
High (x25%)	13,25%	8,99%	10,78%	20,44%	**13,37%**
Overall	**8,68%**	**5,89%**	**8,68%**	**13,68%**	**9,23%**

Aurora 3 Relative Improvement					
	Finnish	Spanish	German	Danish	Average
Well (x40%)	-5,88%	1,49%	-4,09%	-0,75%	**-2,31%**
Mid (x35%)	44,44%	-8,72%	-23,03%	8,91%	**5,40%**
High (x25%)	1,05%	-6,39%	-23,20%	-0,15%	**-7,17%**
Overall	**13,46%**	**-4,05%**	**-15,50%**	**2,78%**	**-0,83%**

Conclusions

- Feature extraction algorithm based on the combination of spectral noise reduction and nonlinear features normalization
- New VAD based on Long Term spectral envelope
  - Improve the noise estimation
  - Frame dropping
  - Better discrimination speech/noise
- More computational efficiency of the feature normalization algorithm
- Segmental version of the feature normalization algorithm
  - Performance is only slightly worse
- Results presented for AURORA 2 and AURORA 3

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These slides are available at

http://sirio.ugr.es/segura/pdfdocs/eurospeech'03_sl.pdf