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Speech recognition in the presence of highly non-stationary noise based on spatial, spectral and temporal speech/noise modeling combined with dynamic variance adaptation

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Motivation of our system

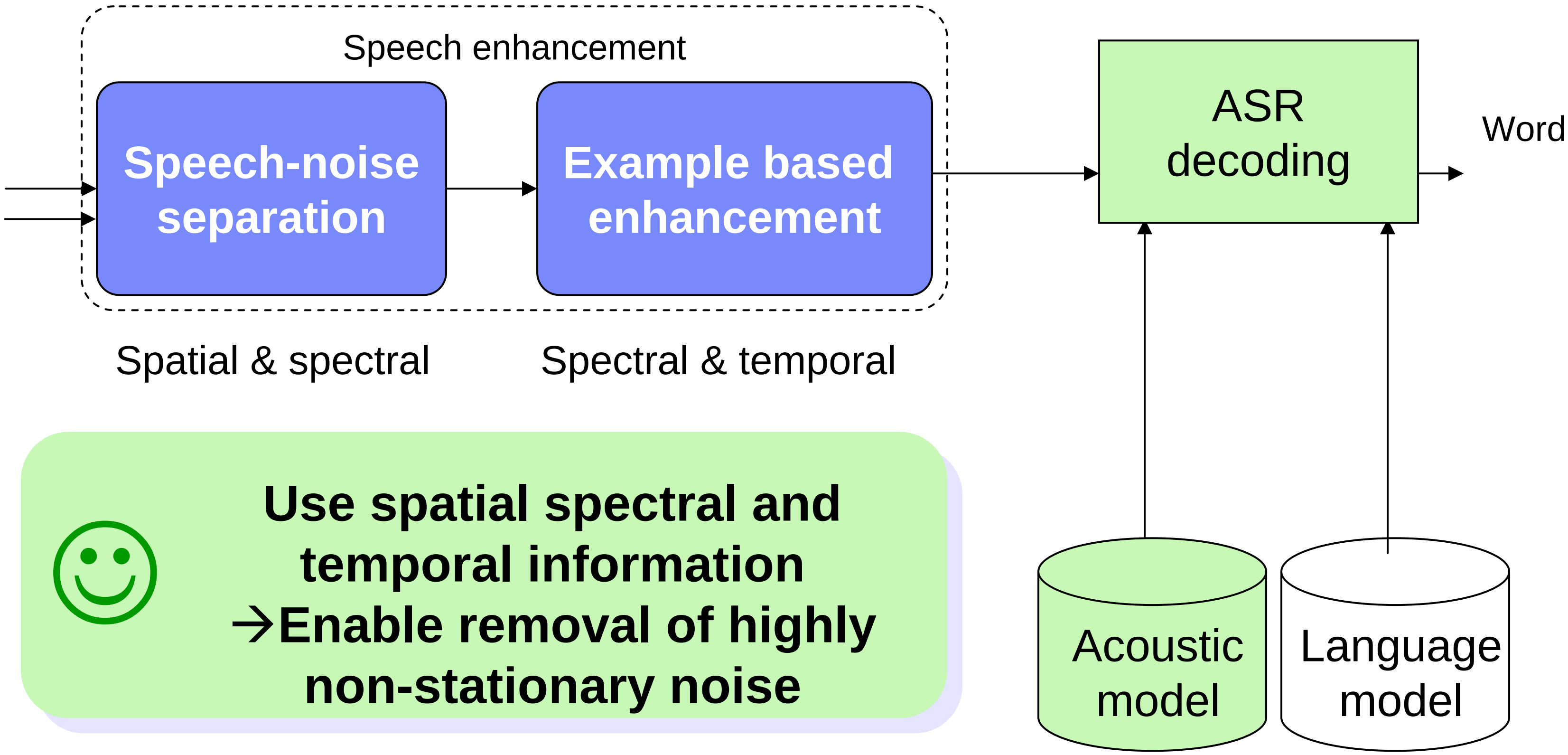
- **Speech enhancement**
  - Deal with highly non-stationary noise, using **all information** available about speech/noise
    Spatial - Spectral - Temporal
  - Realized using **two complementary** enhancement processes
- **Recognition**
  - **Interconnection** of speech enhancement and recognizer using dynamic acoustic model adaptation
  - Use of state of the art ASR technologies (**discriminative training**, **system combination**…)

Average accuracy improves 69 % → 91.7 %

Approaches for noise robust ASR

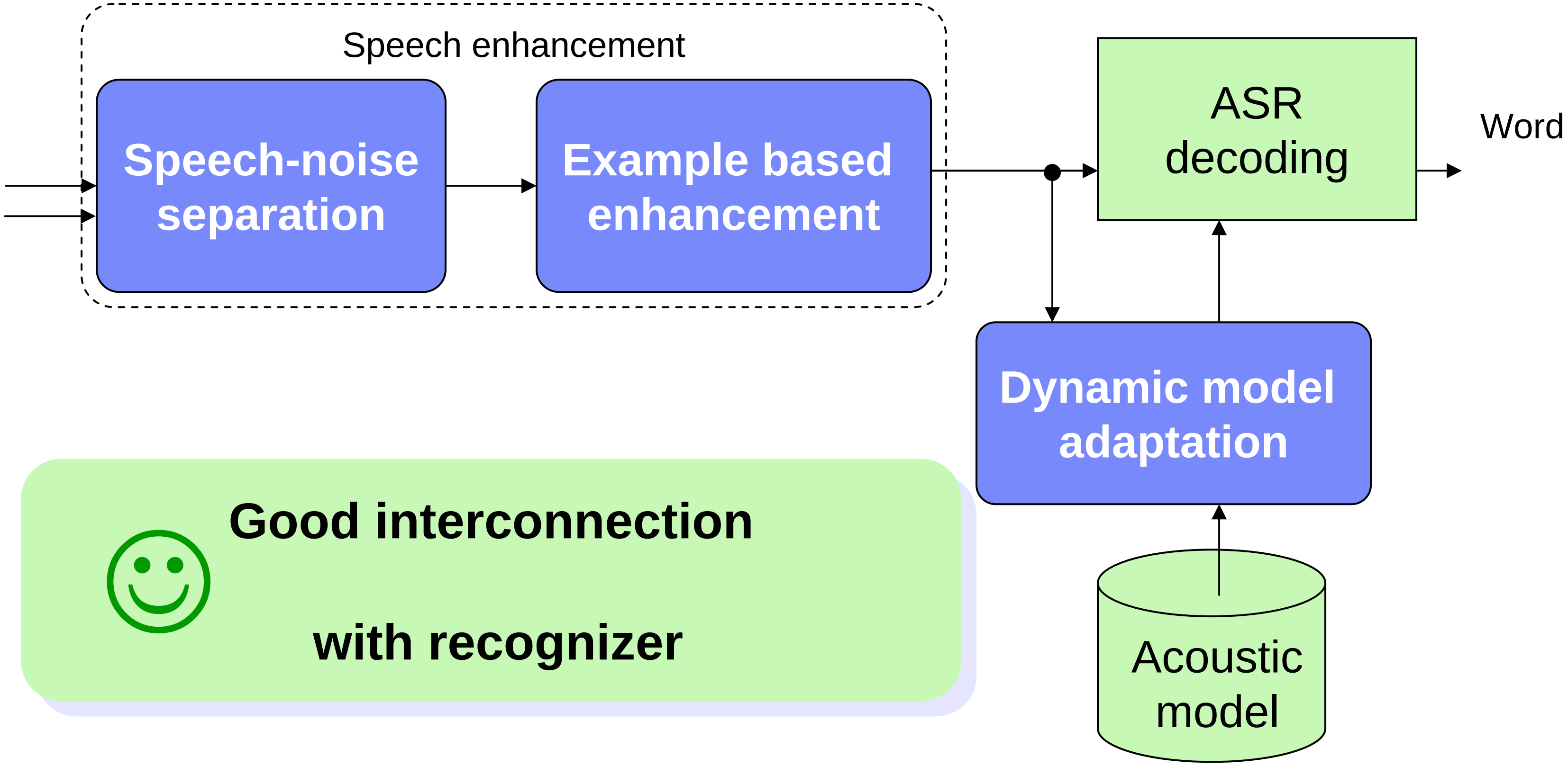
	Information used	Handling highly non-stationary noise	Interconnection w/ ASR
Acoustic model compensation, e.g. VTS	Spectral	☹	☺
Speech enhancement, e.g. BSS	Spatial/spectral/ temporal	😐	☹
Proposed			

System overview



Use spatial spectral and temporal information
→Enable removal of highly non-stationary noise

System overview

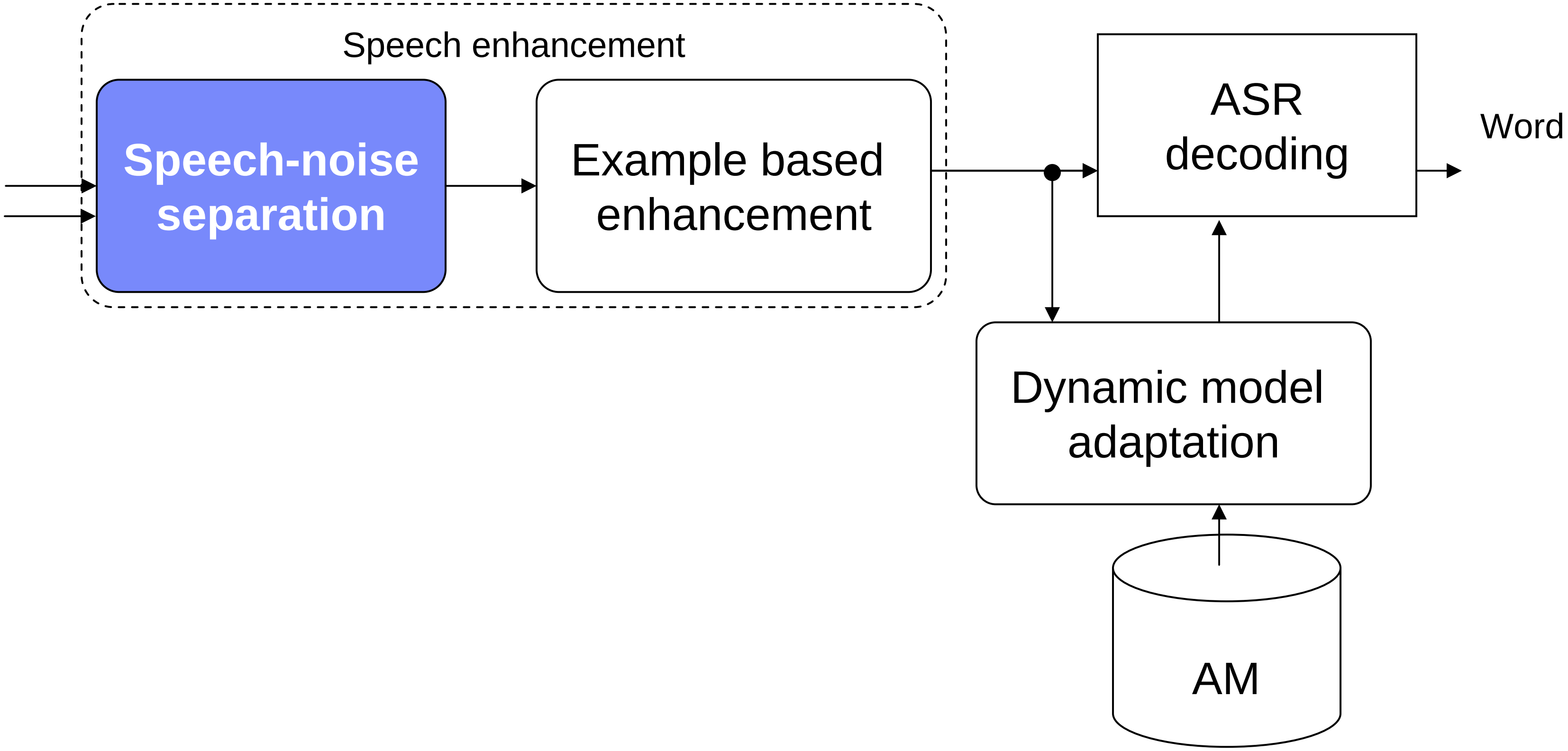


Good interconnection with recognizer

Approaches for noise robust ASR

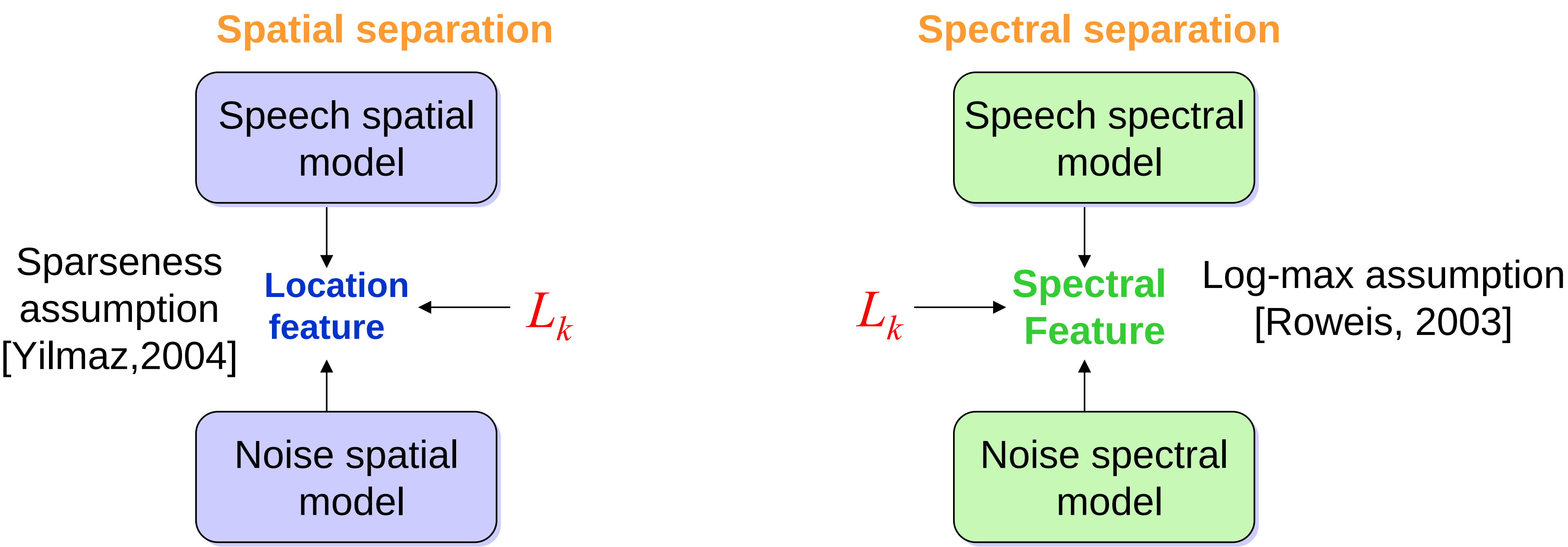
	Information used	Handling highly non-stationary noise	Interconnection w/ ASR
Acoustic model compensation, e.g. VTS	Spectral	☹	☺
Speech enhancement, e.g. BSS	Spatial/spectral/ temporal	😐	☹
Proposed	Spatial, spectral & temporal	☺	☺

System overview



Speech-noise separation [Nakatani, 2011]

- Integrate spatial-based and spectral-based separation in a single framework

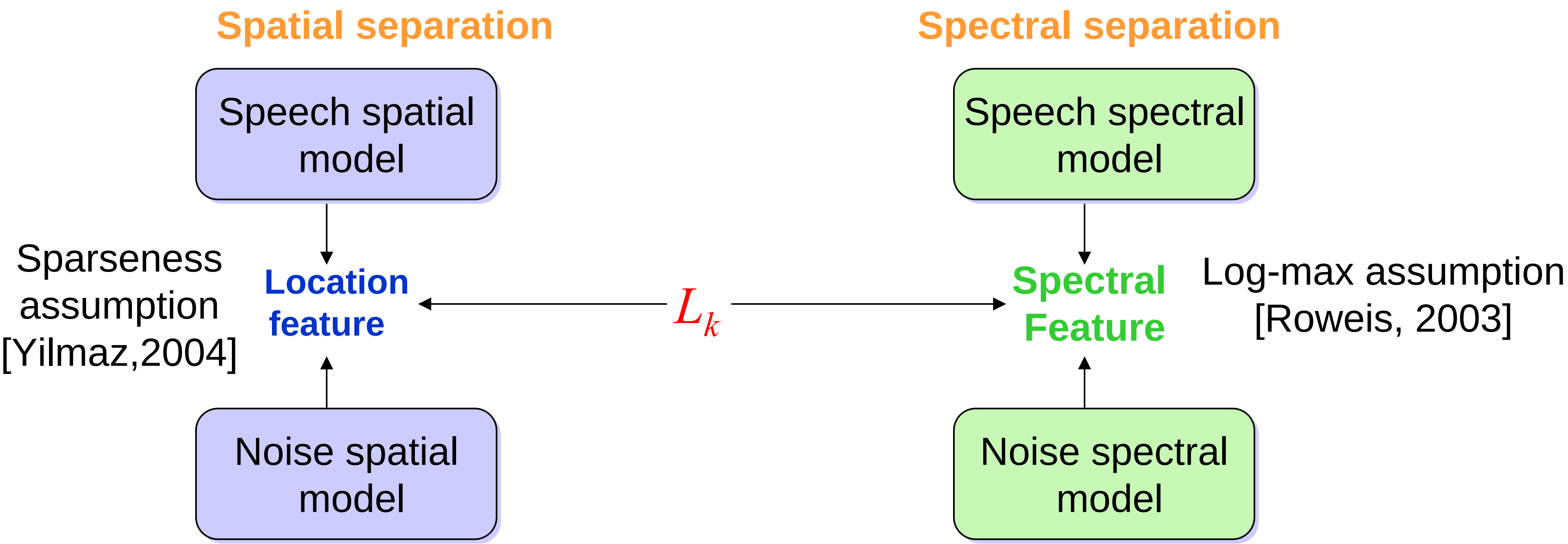


L_k **: dominant source index,**

i.e. indicates whether speech or noise is more dominant at each frequency k

Speech-noise separation [Nakatani, 2011]

- Combined using dominant source index L_k



L_k **: dominant source index,**
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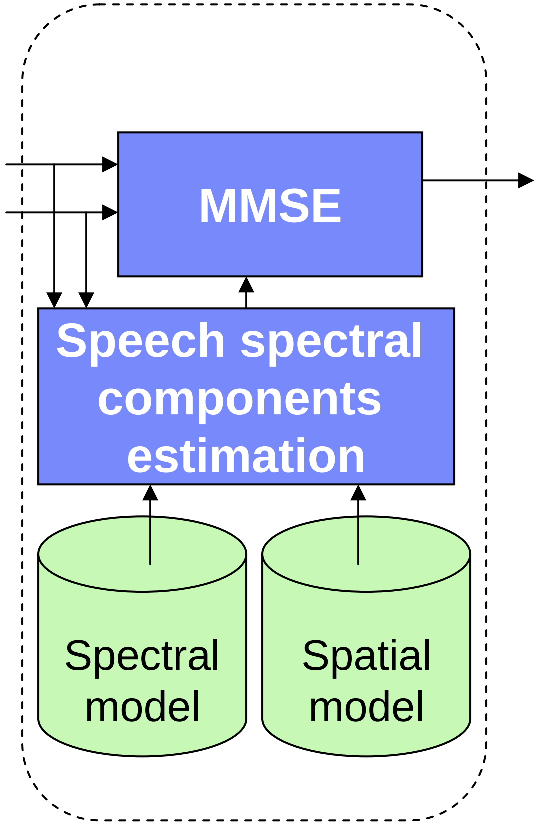
Speech-noise separation [Nakatani, 2011]

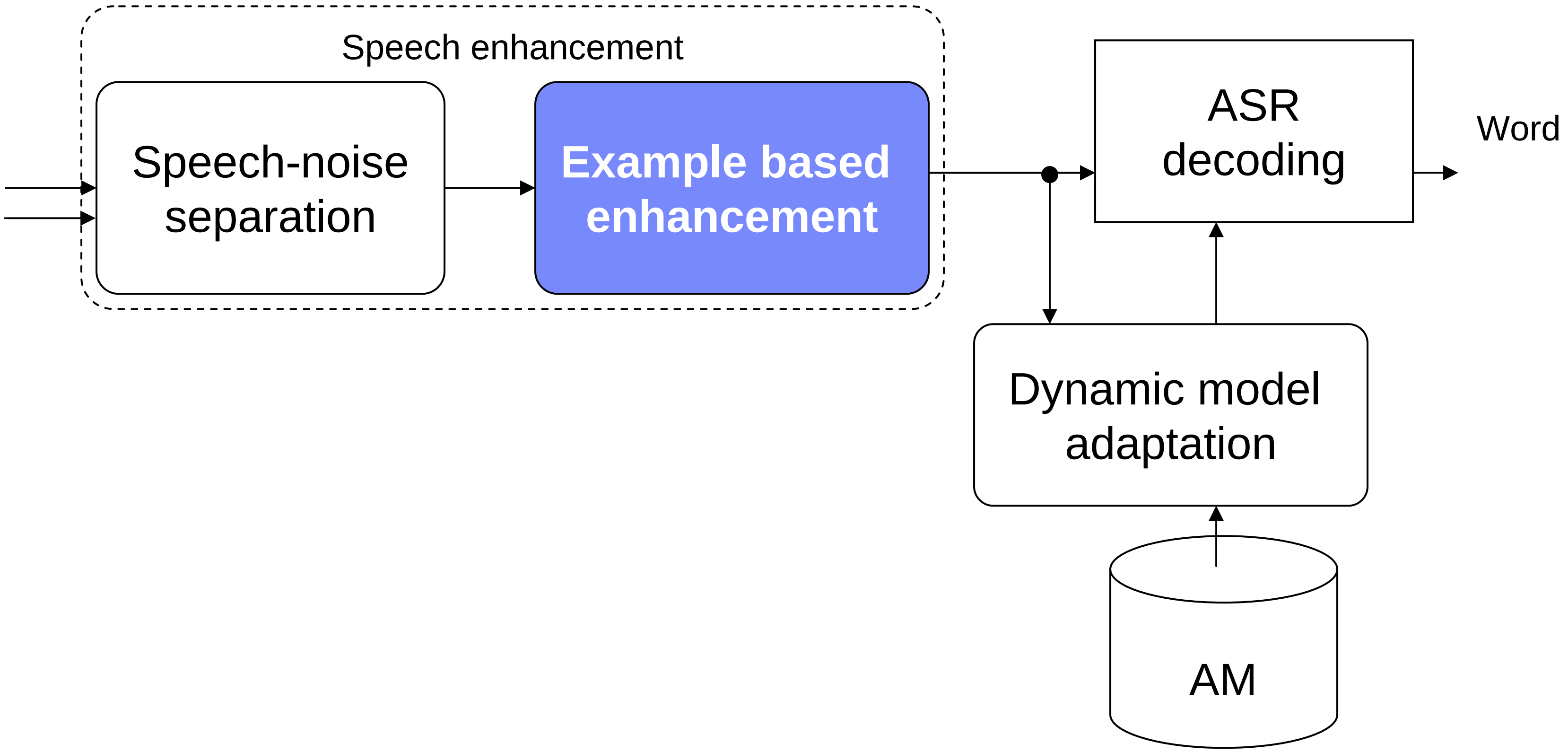
DOLPHIN *dominance based locational and power-spectral characteristics integration*



- Estimate speech spectral component sequence using EM algorithm
- Estimated speech obtained using MMSE

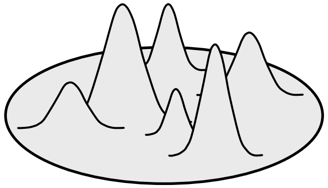
Integrate efficiently spatial and spectral information
to remove non-stationary noise

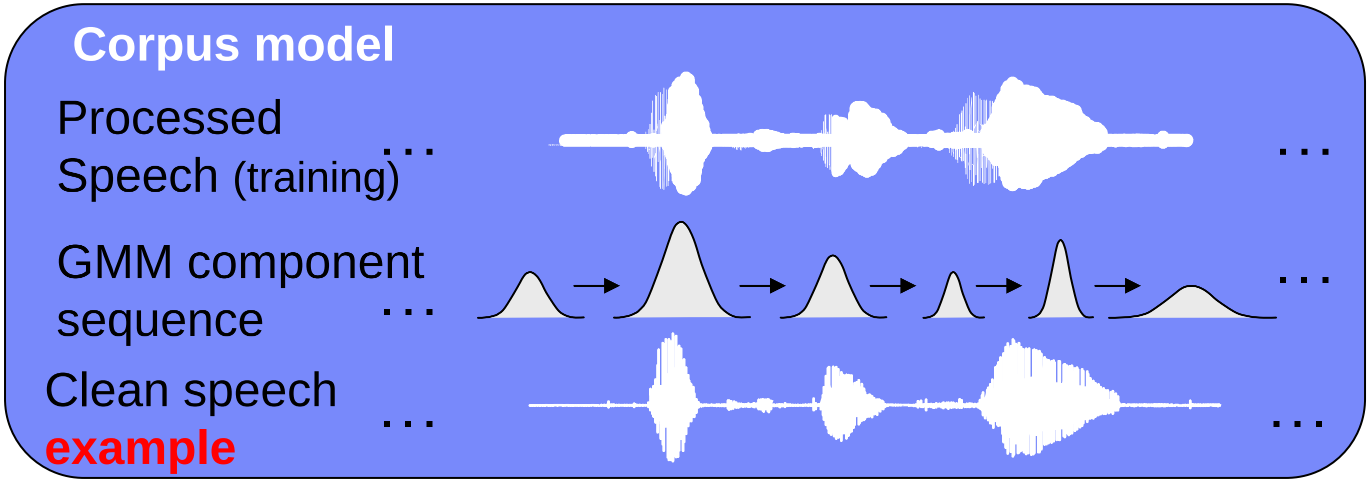
System overview



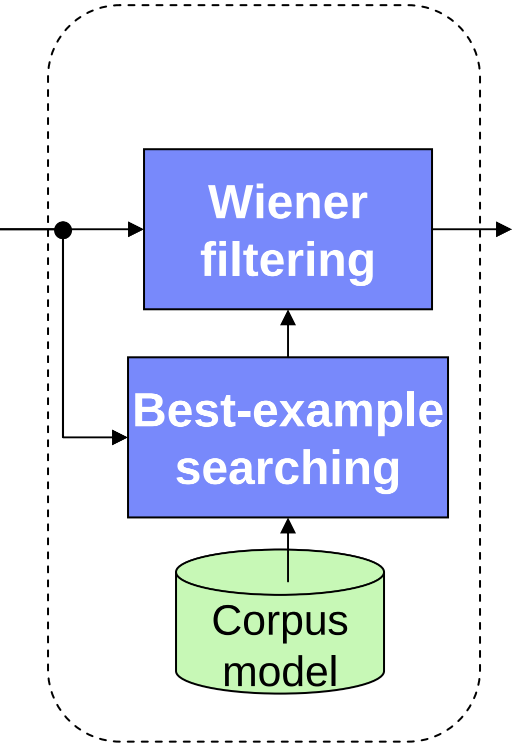
Example-based enhancement [Kinoshita,2011]

- **Use a parallel corpus model (clean and processed speech) that represents the fine spectral and temporal structure of speech**
  - Train a GMM from multi-condition training data processed with DOLPHIN
  - Generate corpus model

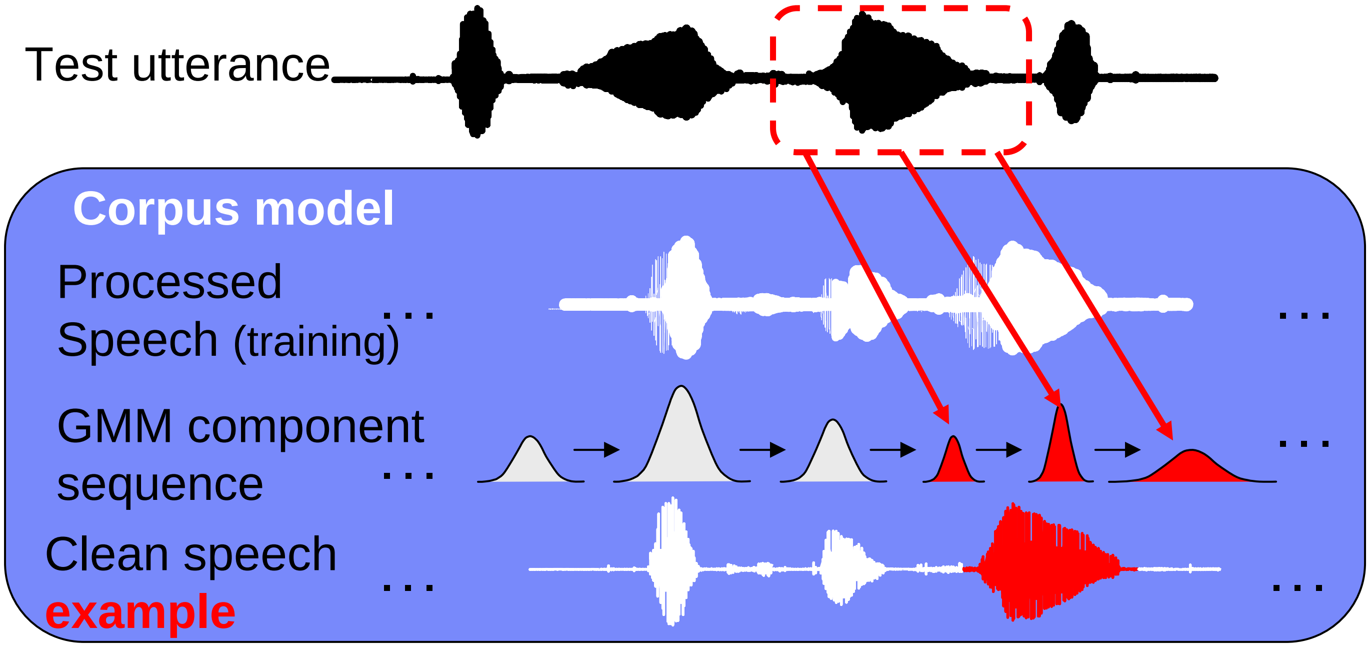




Example-based enhancement [Kinoshita,2011]



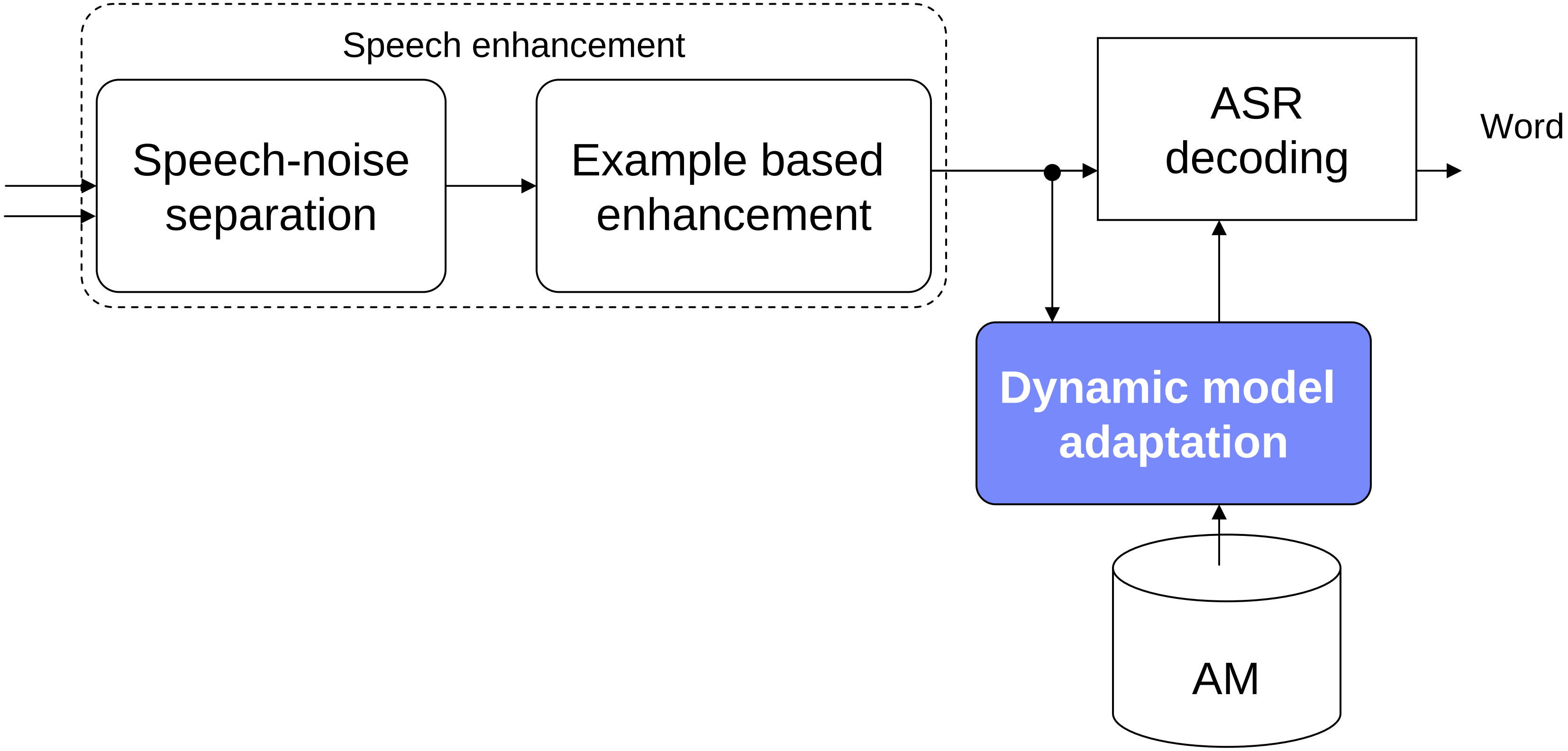
- Look for the longest example segments



- Use the corresponding clean speech example for Wiener filtering

Using precise model of temporal structure of speech
→ remove remaining highly non-stationary noise
→ recover precisely speech

System overview

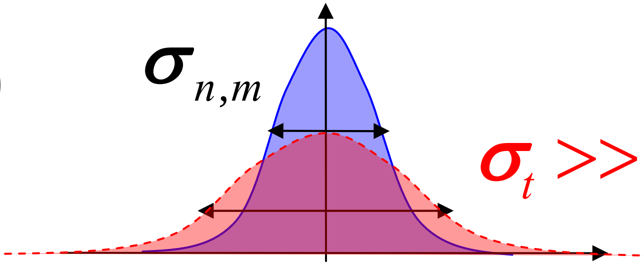


Dynamic model adaptation [Delcroix, 2009]

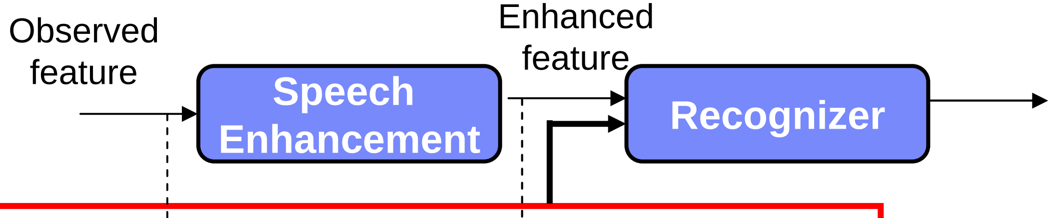
- **Compensate mismatch between enhanced speech and acoustic model**
  - Non-stationary noise & frame by frame processing
  - → Mismatch changes frame by frame (dynamic)
  - → *Conventional acoustic model compensation techniques (MLLR) not sufficient*
- **Dynamic variance compensation (Uncertainty decoding) [Deng, 2005]**
  - Mitigate the mismatch frame by frame by considering feature variance

$$p(y_t \mid n) = \sum_m p(m) N(y_t; \mu_{n,m}, \sigma_{n,m} + \boxed{\sigma_t})$$

Enhanced speech feature



Dynamic feature variance model



$$\sigma_t(\alpha) = (u_t - y_t)^2 \alpha$$

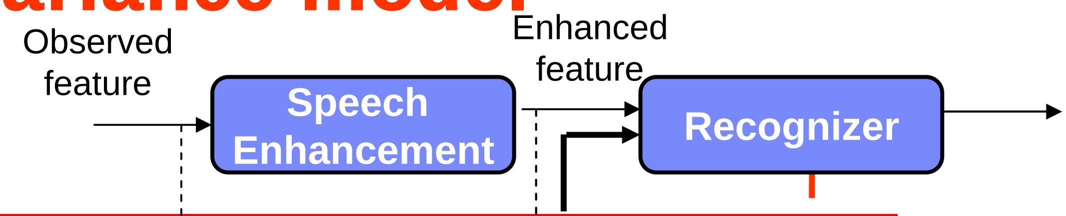
For each feature dimension

- Assumption

Feature variance (Feature uncertainty)	$\propto$	Amount of noise reduction	$\propto$	Amount of Noise

The more we process the signal, the more we introduce uncertainty

Dynamic feature variance model



$$\boxed{\sigma_t(\alpha) = (u_t - y_t)^2 \alpha}$$

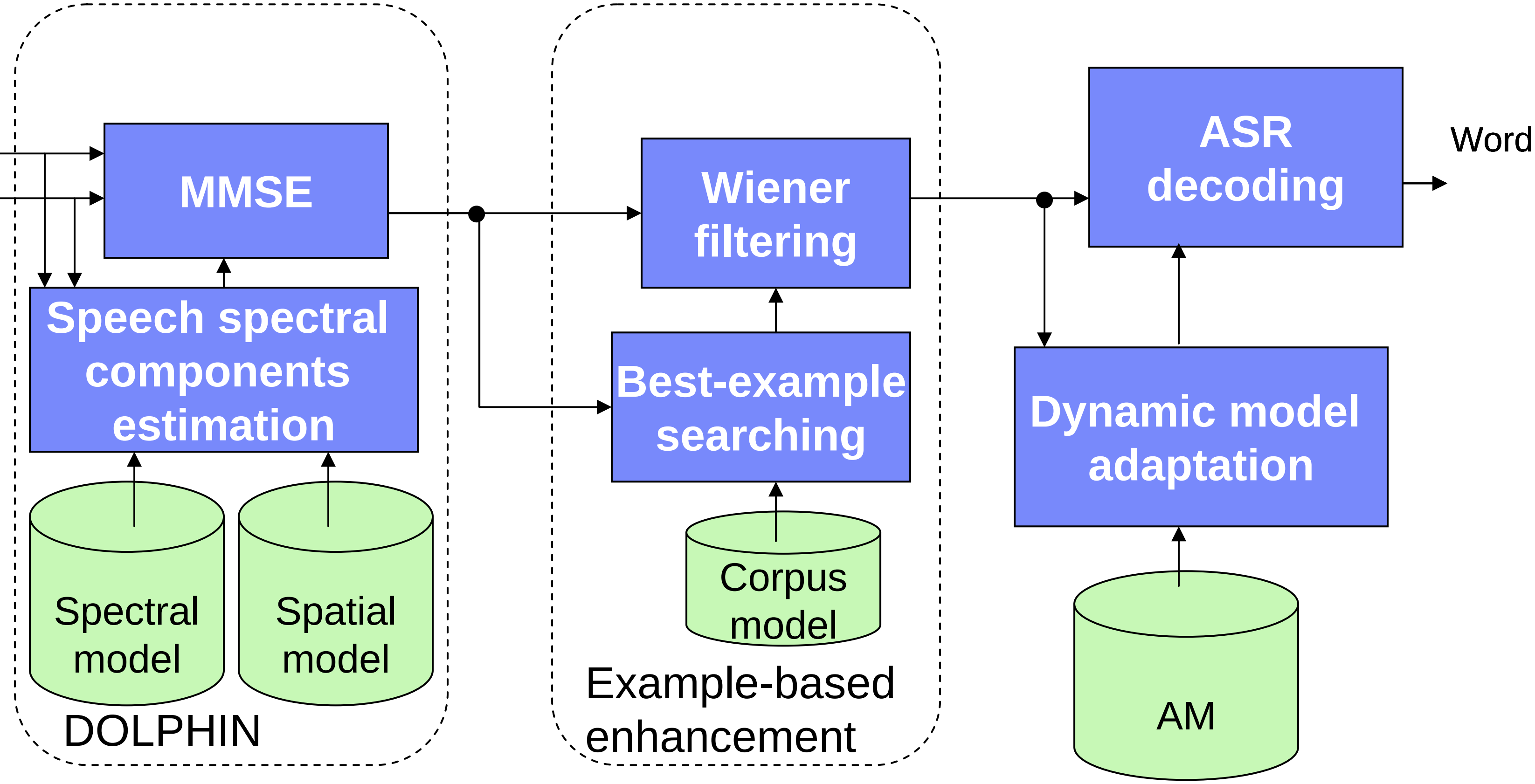
For each feature dimension

- Optimized for recognition with ML criterion using adaptation data (Dynamic variance adaptation – DVA)
- Can be combined with MLLR for static adaptation of the acoustic model mean parameters

Good interconnection

with recognizer

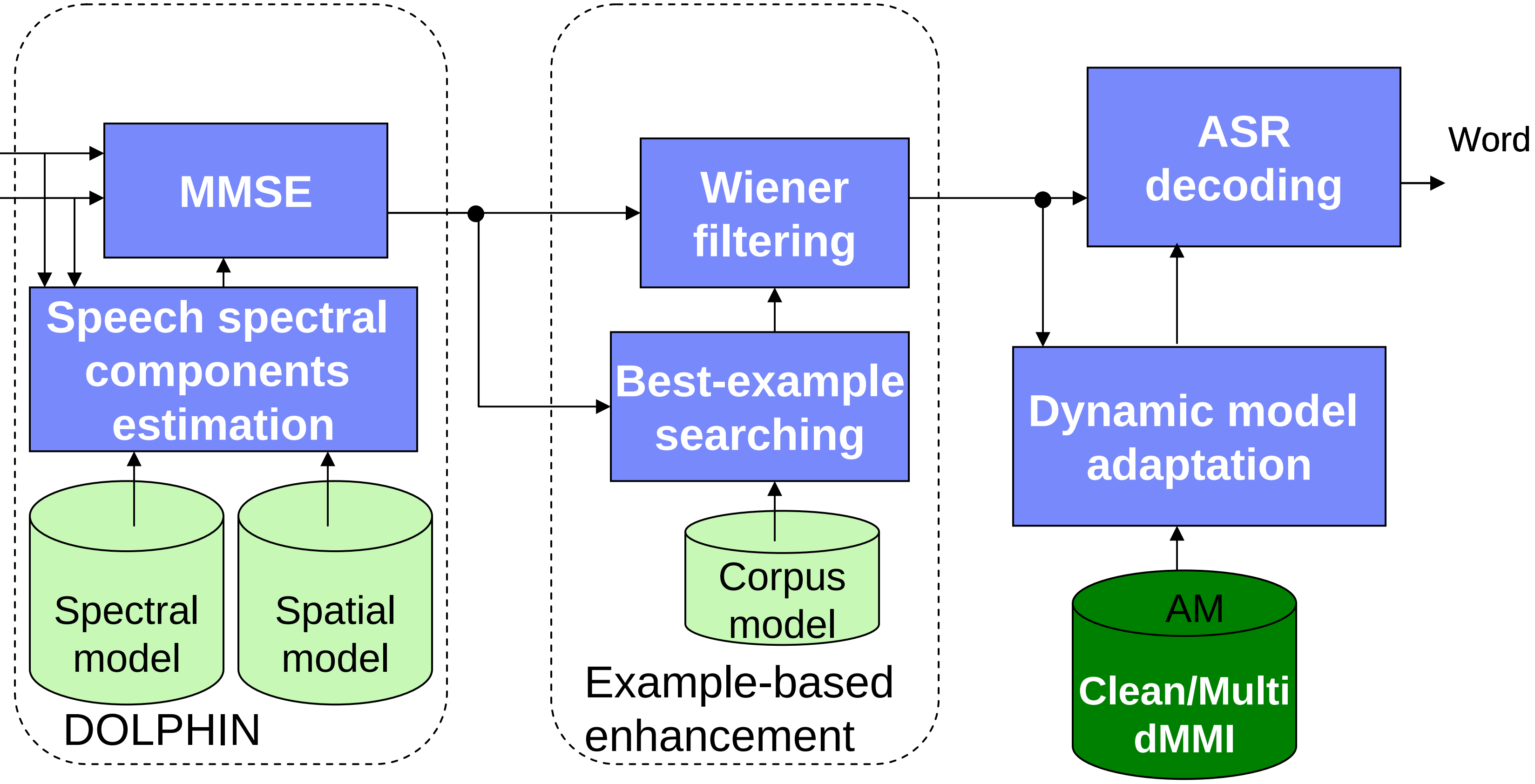
System overview



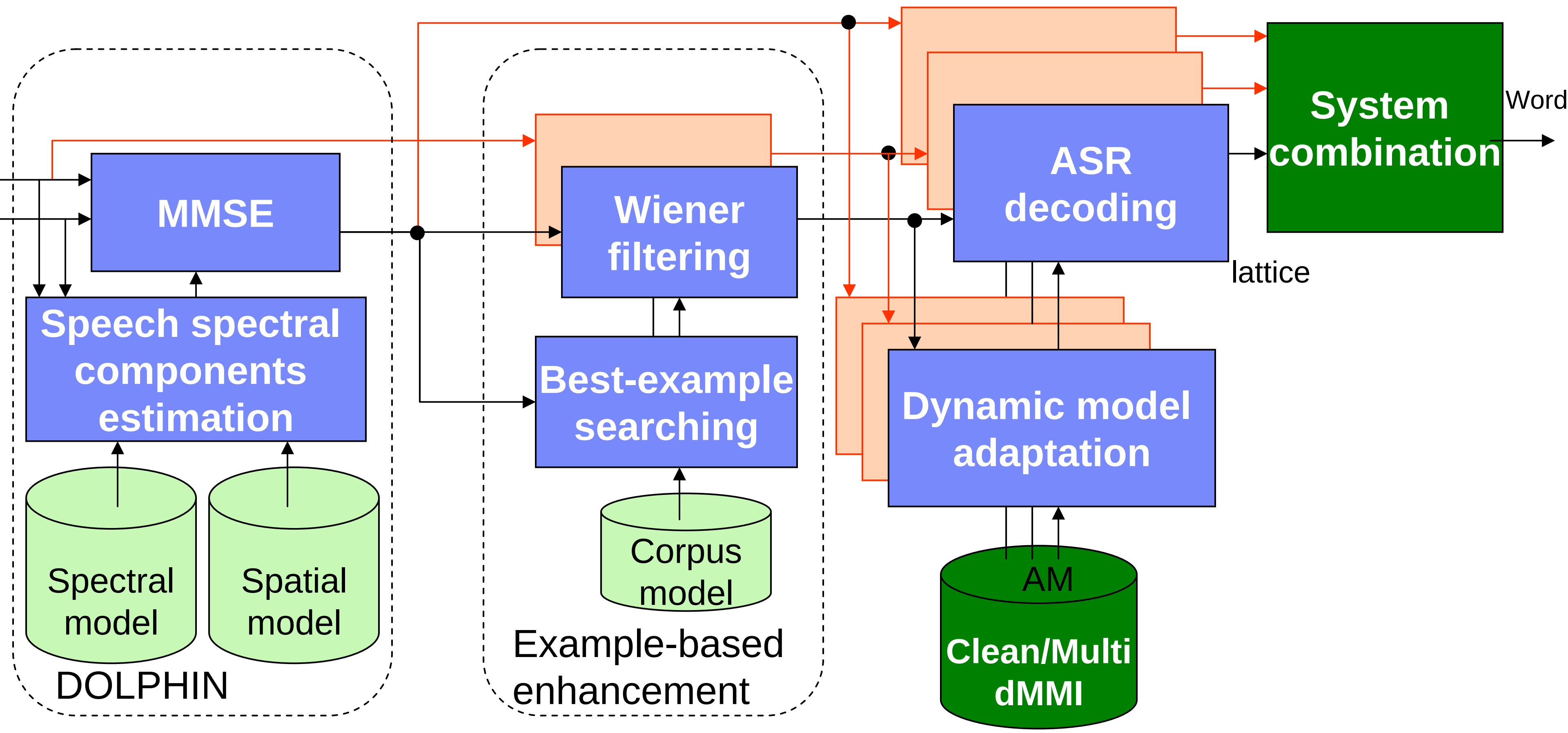
Multi-condition / discriminative training

Add background noise training samples to clean training data

dMMI : differenced maximum mutual information [McDermott, 2010]



System combination [Evermann, 2000]



Settings - Enhancement

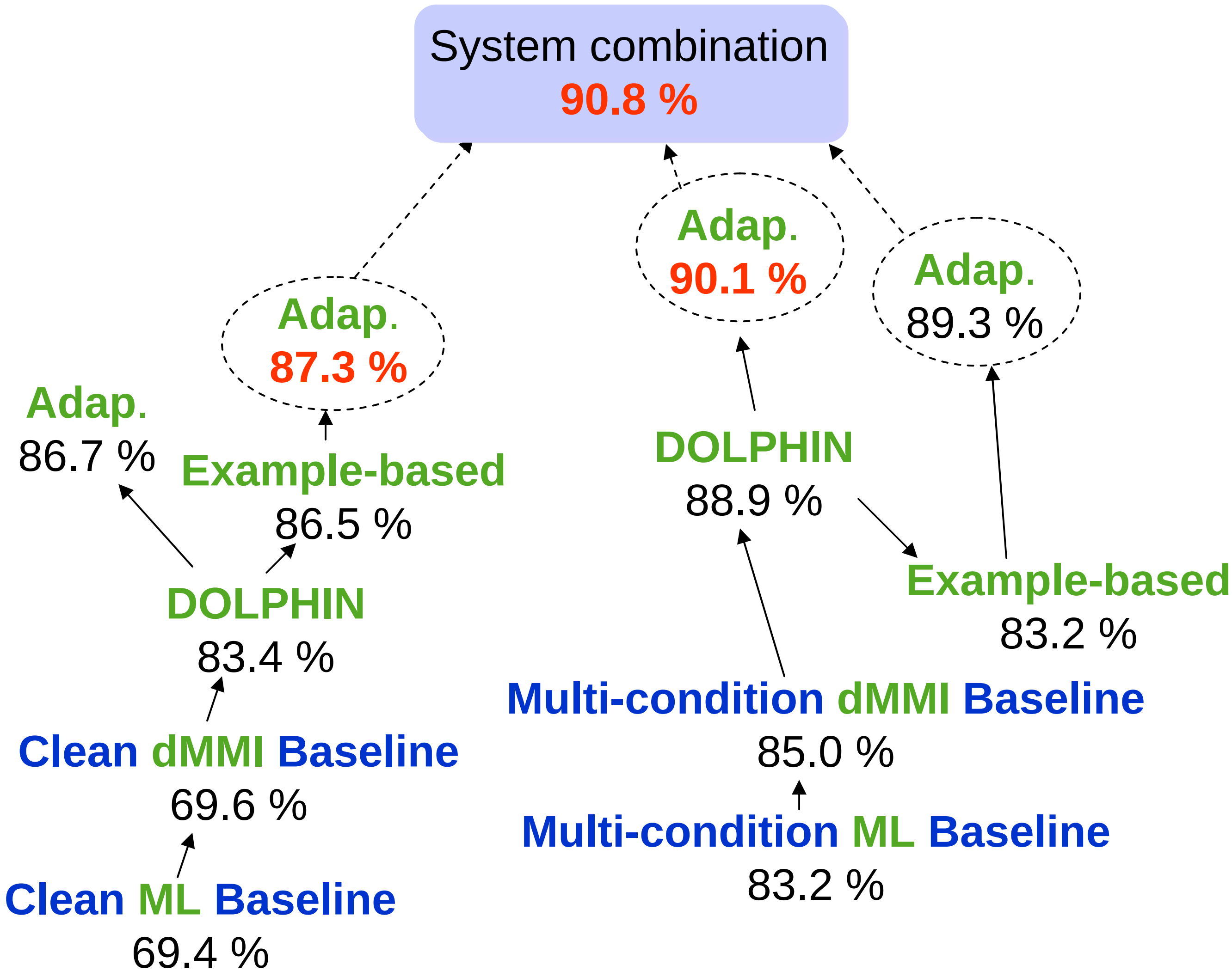
DOLPHIN	▪ Spatial model - 4 mixture components ▪ Spectral model - 256 mixture components - Speaker dependent model ▪ Models trained in advanced using the noise/speech training data ▪ Long windows (100 ms) to capture reverberation
Example-based	▪ Corpus model - GMM w/ 4096 mixture components - Trained on DOLPHIN processed speech - Features 60 order MFCC w/ log energy

Settings - Recognition

Recognizer	▪ SOLON [Hori, 2007]
Acoustic Model	▪ Trained with SOLON (ML & discriminative (dMMI)) ▪ Clean - HMM w/ 254 states (include silent state) - HMM state modeled by GMM with 7 components ▪ Multi-condition - 20 components per HMM state - No silent model
Multi-condition data	▪ Added background noise samples to clean training data ▪ 7 noise environment x 6 SNR conditions
Adaptation	▪ Unsupervised/speaker dependent ▪ use all test data for a given speaker

Development

	m6dB	m3dB	0dB	3dB	6dB	9dB	MEAN
Baseline	49.75	52.58	64.25	75.08	84.25	90.58	69.42
Proposed	84.33	88.58	90.17	92.33	94.50	95.00	90.82

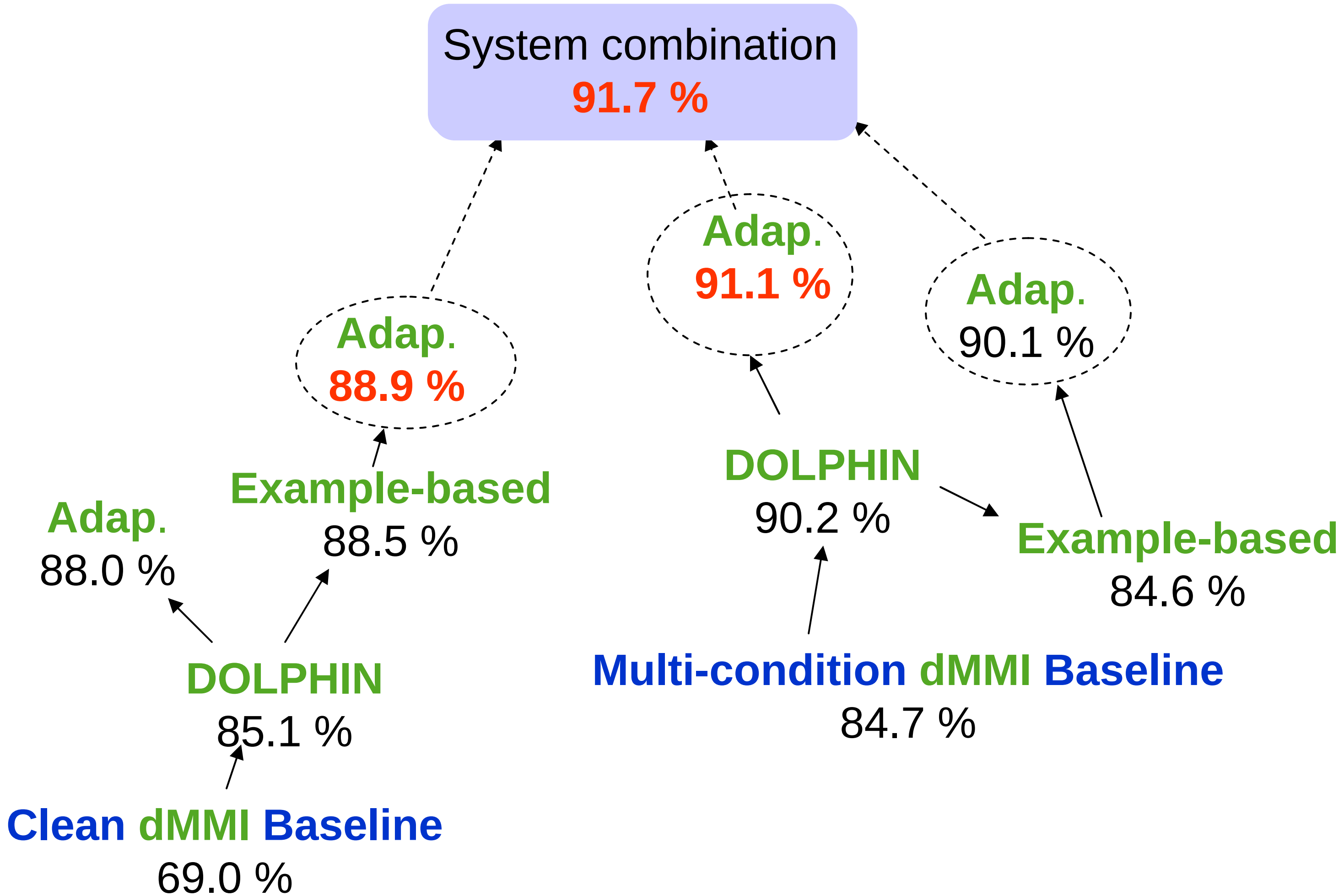


Relative improvement

Multi-cond	51%
Dolphin	**45%**
HTK baseline → SOLON	21%
Adap.	**20%**
Ex. based	**18%**
dMMI	10%
Sys comb	7%

Evaluation

	m6dB	m3dB	0dB	3dB	6dB	9dB	MEAN
Baseline	45.67	52.67	65.25	75.42	83.33	91.67	69.00
Proposed	85.58	88.33	92.33	93.67	94.17	95.83	91.65



Conclusion

- General approach
  - Fully use spatial, spectral and temporal information
  - Good interconnection with recognizer

  → Achieve great reduction of highly non-stationary noise

  → Improve ASR performance

  → Improve also audible quality

  (http://www.kecl.ntt.co.jp/icl/signal/kinoshita/publications/CHiME_demo/index.html)

- Remaining issues
  - Apply to more complex tasks
    - spontaneous speech
    - Unknown speaker location

Thank you!