Low-level features and timbre

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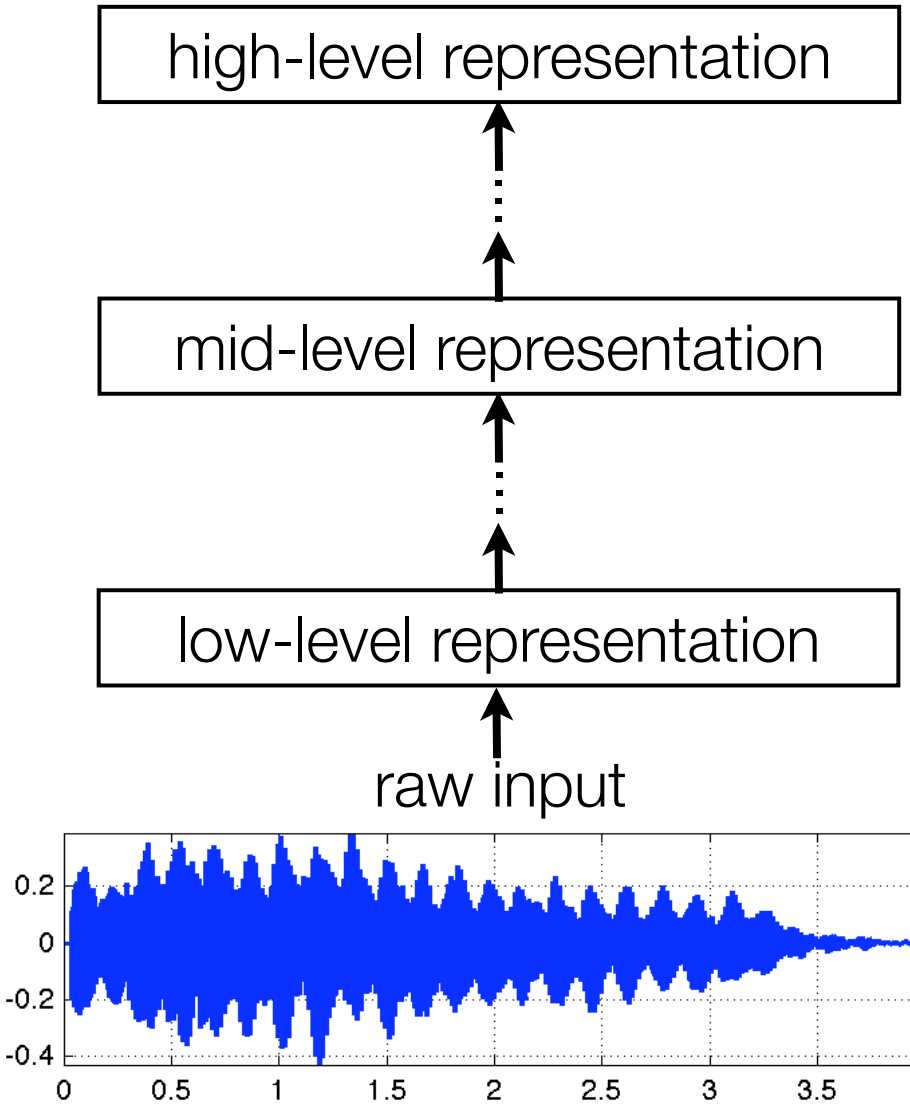
Music signal analysis



e.g: style, artist, mood, form

e.g: pitch, onsets, beats

e.g: spectral flux, ACF, cepstrum

[... 0.2 0.1 0.05 -0.05 -0.1 ...]

Low-level features

- The raw input data is often too large, noisy and redundant for analysis.
- Feature extraction: input signal is transformed into a new (smaller) space of variables that simplify analysis.
- Features: measurable properties of the observed phenomenon, usually containing information relevant for pattern recognition.
- They result from neighborhood operations on the input signal. If the operation produces a local decision -> feature detection.
- Usually one feature is not enough: combine several features into feature vectors, describing a multi-dimensional space.

Timbre

- Timbre: tonal qualities that define a particular sound/source. It can refer to, e.g., class (e.g. violin or piano), or quality (e.g. bright, rough)

- Oftentimes defined comparatively: attribute that allows us to differentiate sounds of the same pitch, loudness, duration and spatial location (Grey, 75)

- Timbre spaces: empirically measure the perceived (dis)similarity between sounds and project to a low-dimensional space where dimensions are assigned a semantic interpretation (brightness, temporal variation, synchronicity, etc).

- Audio-based: recreate timbre spaces by extracting low-level features with similar interpretations (centroid, spectral flux, attack time, etc). Most of them describe the steady-state spectral envelope.

Temporal features

- The root-mean-square (RMS) level coarsely approximates loudness:

$$\mathrm{RMS}(m) = \sqrt{\frac{1}{N} \sum_{n=-N/2}^{N/2} \left(x(n+mh)\right)^2 w(n)}$$

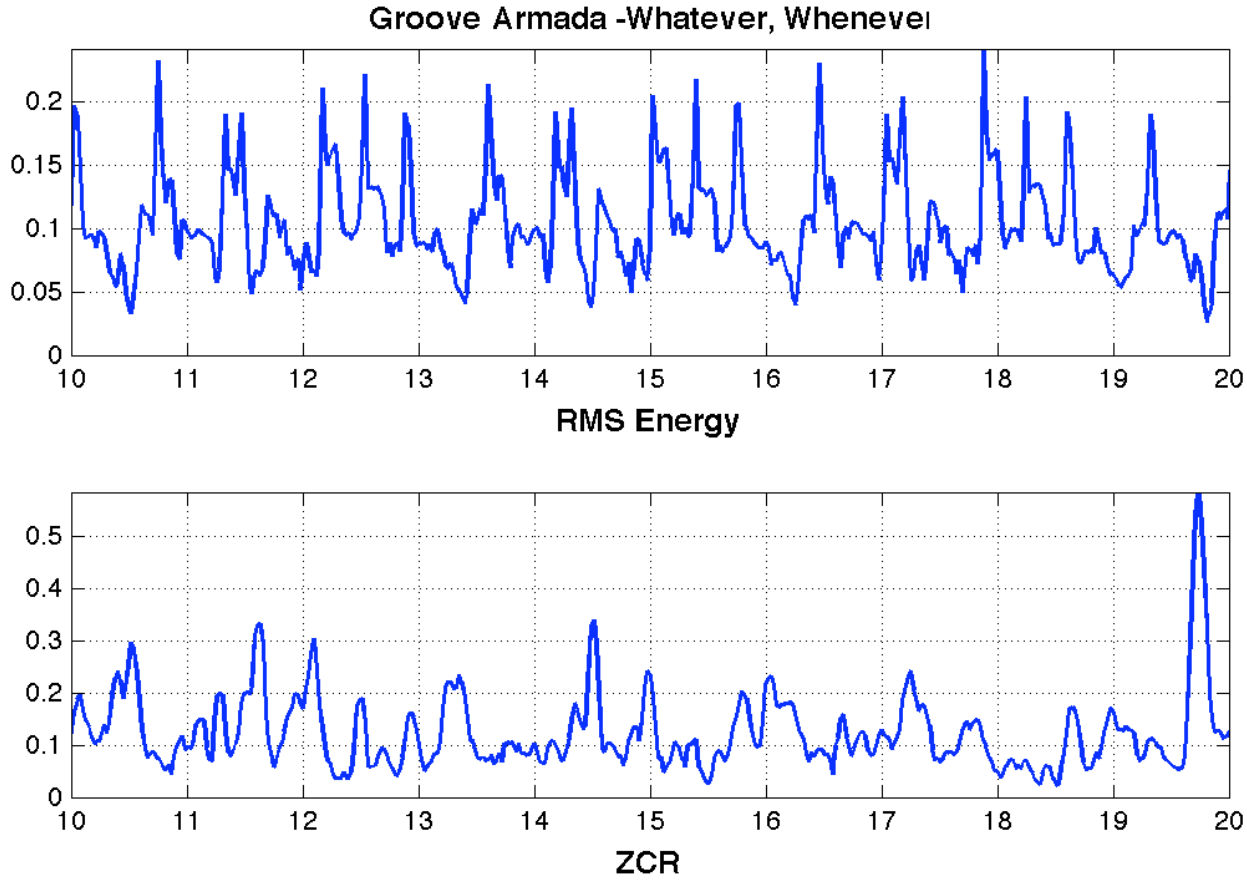
- Zero-crossing rate (ZCR) is a weighted measure of the number of times the signal changes sign in a frame:

$$\mathrm{ZCR}(m) = \frac{1}{2N} \sum_{n=-N/2}^{N/2} |sgn(x(n+mh)) - sgn(x(n+mh-1))|$$

$$sgn(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases}$$

Temporal features

- ZCR is high for noisy (unvoiced) sounds and low for tonal (voiced) sounds
- For simple periodic signals, it is roughly related to the fundamental frequency



Spectral features

- The most common is the spectral centroid (SC):

$$\mathrm{SC}(m) = \frac{\sum_k f_k |X(m,k)|}{\sum_k |X(m,k)|}$$

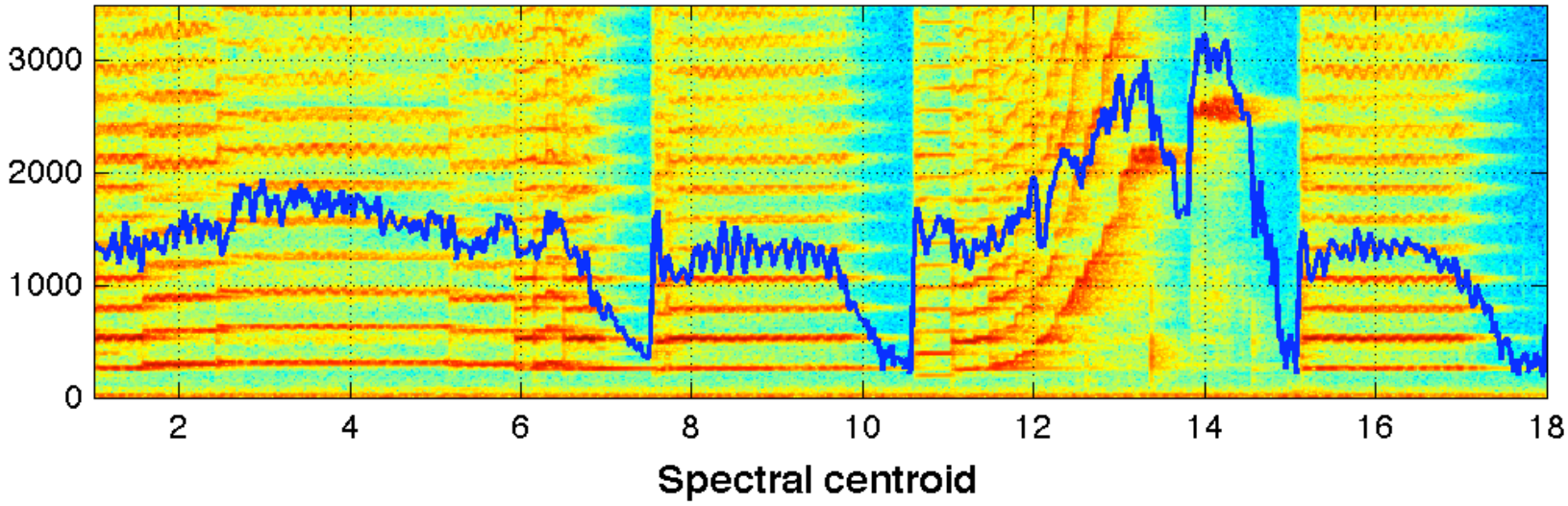
- It is usually associated with the sound's "brightness"

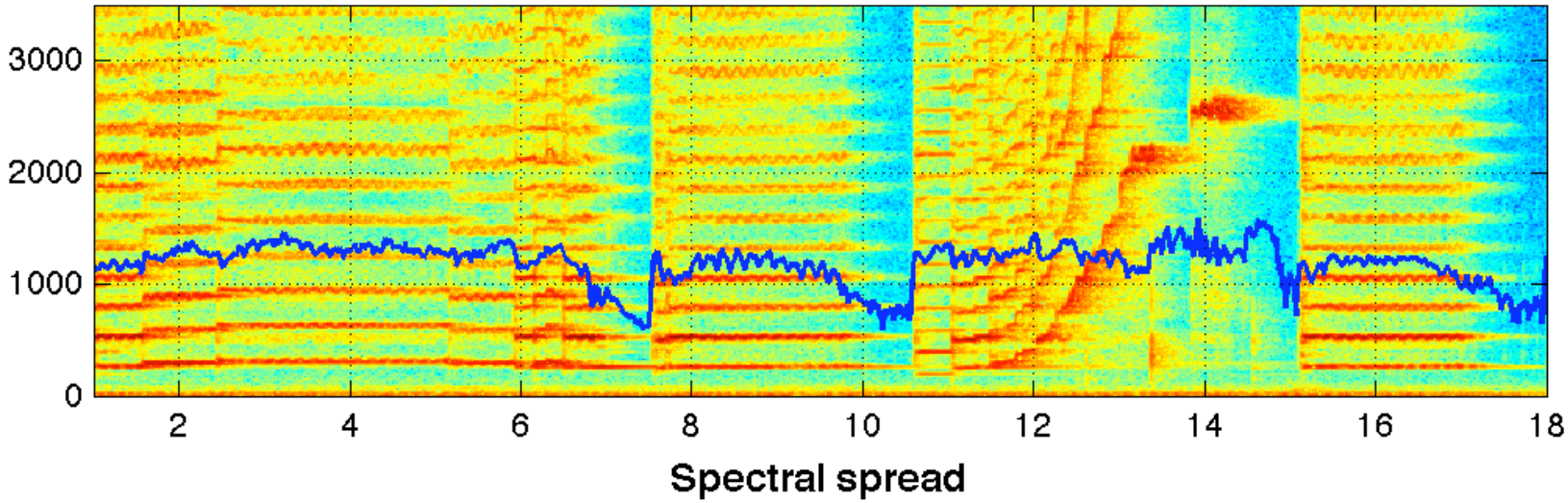
- Spectral spread (SS) is a measure of the bandwidth of the spectrum:

$$\mathrm{SS}(m) = \frac{\sum_k (f_k - SC(m))^2 |X(m,k)|}{\sum_k |X(m,k)|}$$

- Higher-order moments can be used to characterize the asymmetry and peakedness of the distribution

Spectral features





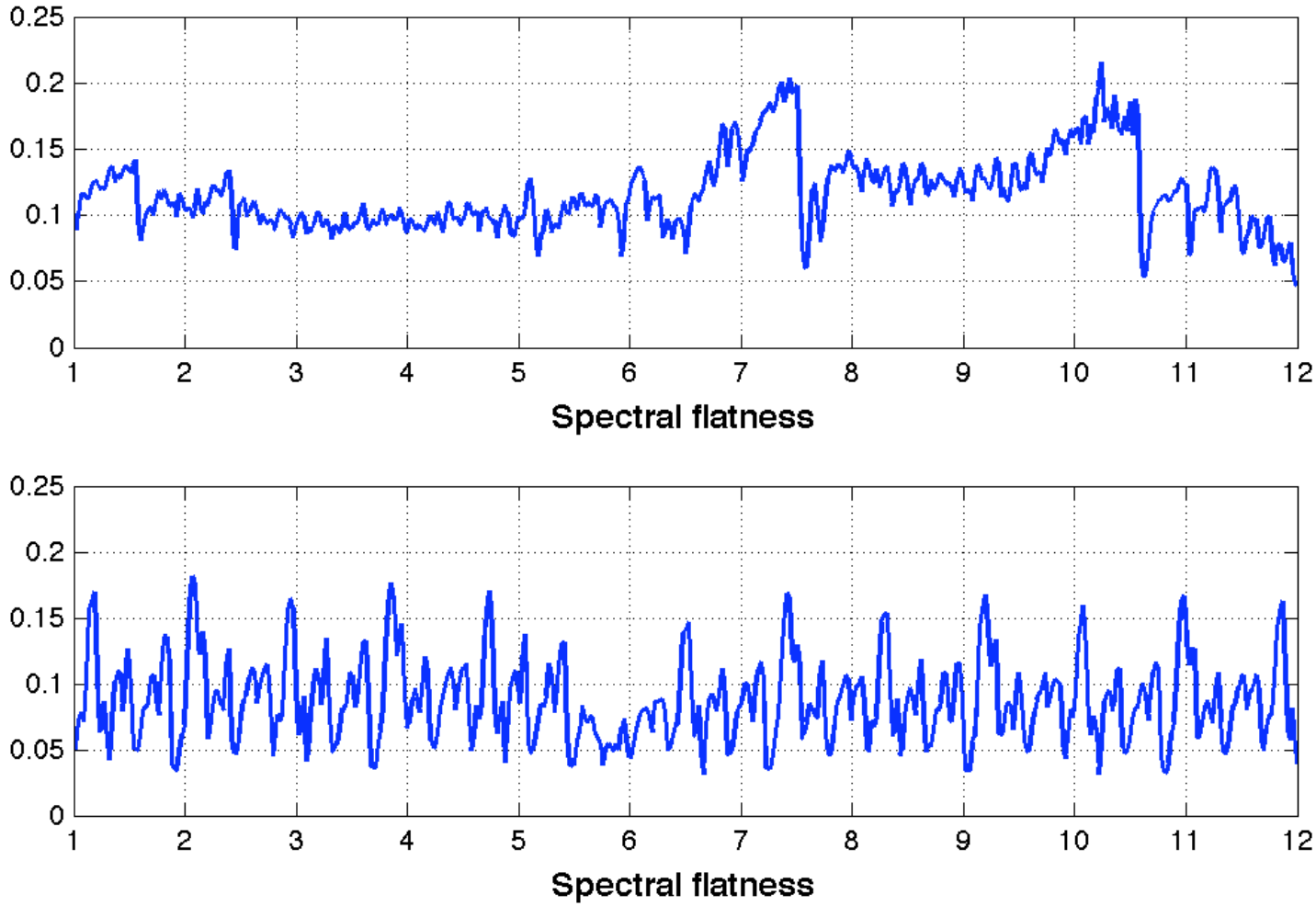
Spectral flatness

- Spectral flatness is a measure of the noisyness of the magnitude spectrum.
- It is the ratio between the geometric and arithmetic means:

$$\mathrm{SF}(m) = \frac{\left(\prod_k |X(m,k)|\right)^{\frac{1}{K}}}{\frac{1}{K}\sum_k |X(m,k)|}$$

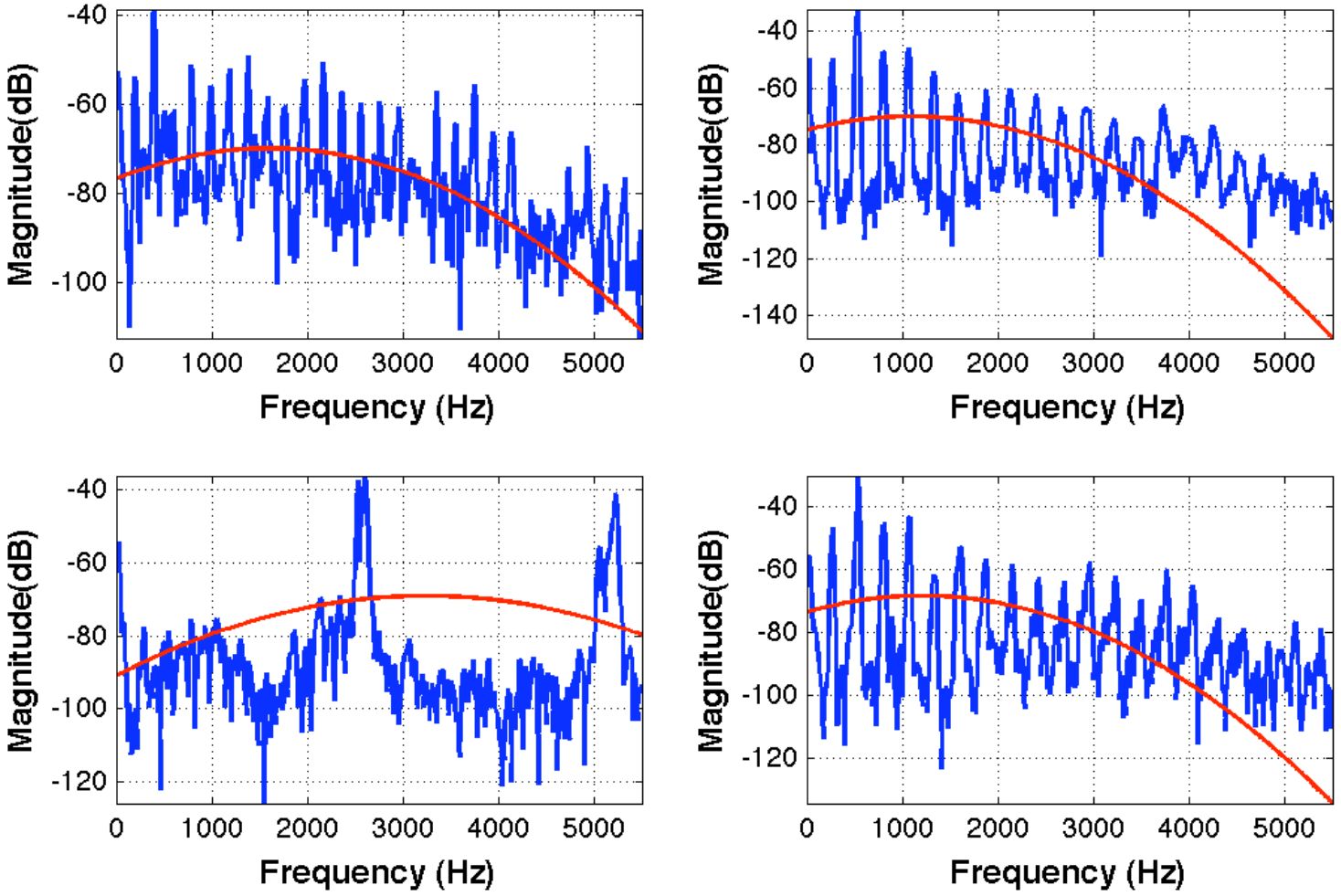
- Different filterbanks can be used for pre-processing, s.t. k refers to band number and K to total number of bands.
- It is often used as a “tonality” coefficient (in dB)

Spectral flatness



Spectral envelope

- SC and SS define a coarse (unimodal) model of the spectral envelope



Channel Vocoder

- Decomposes the sound using a bank of bandpass filters + sums magnitude for each bandpass signal

- For a set of L-long filters w overlapped by L-1 bins:

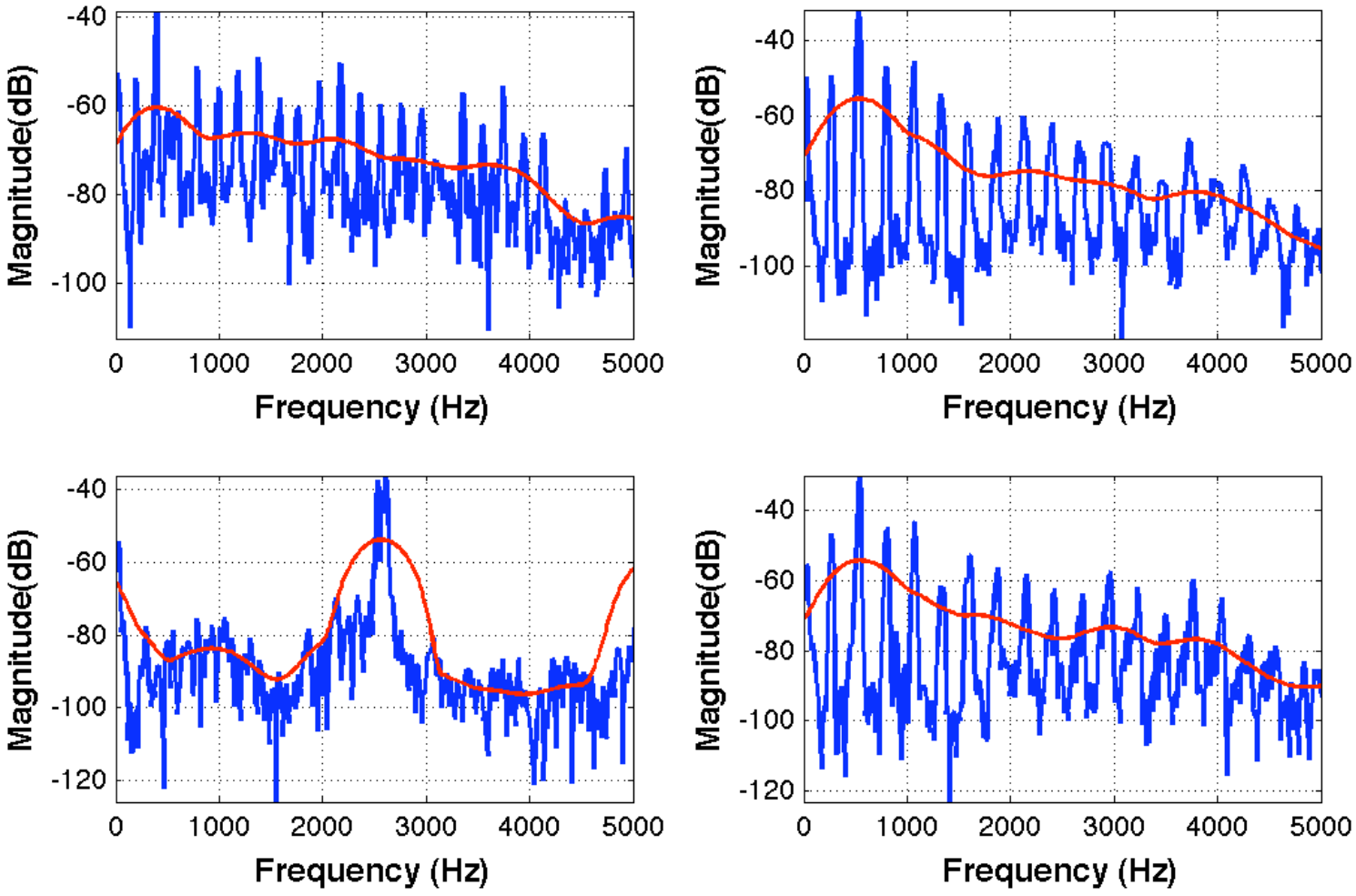
$$\mathrm{CV}(m) = |X(m,k)| * w(k)$$

$$\mathrm{CV}(m) = \mathbb{R}\left(\mathrm{IFFT}\left[\mathrm{FFT}(|X(m,k)|) \times \mathrm{FFT}(w(k))\right]\right)$$

- w(k) is normalized to unit sum, zero-padded to the length of X, and circularly shifted s.t. its center coincides with the first bin.

Channel Vocoder

- The spectral envelope approximation is coarser/finer depending on L



Remember Cepstrum?

- Treat the log magnitude spectrum as if it were a signal -> take its (I)DFT
- Measures rate of change across frequency bands (Bogert et al., 1963)
- For a real-valued signal it's defined as:

$$c_x(l) = real(IFFT(log(|FFT(x)|)))$$

- Followed by low-pass "liftering" in the cepstral domain

Cepstrum

- The real cepstrum can be weighted using a low-pass window of the form:

$$w_{LP}(l) = \begin{cases} 1 & \text{if } l = 0, L_1 \\ 2 & \text{if } 1 \leq l < L_1 \\ 0 & \text{if } L_1 < l \leq L - 1 \end{cases}$$

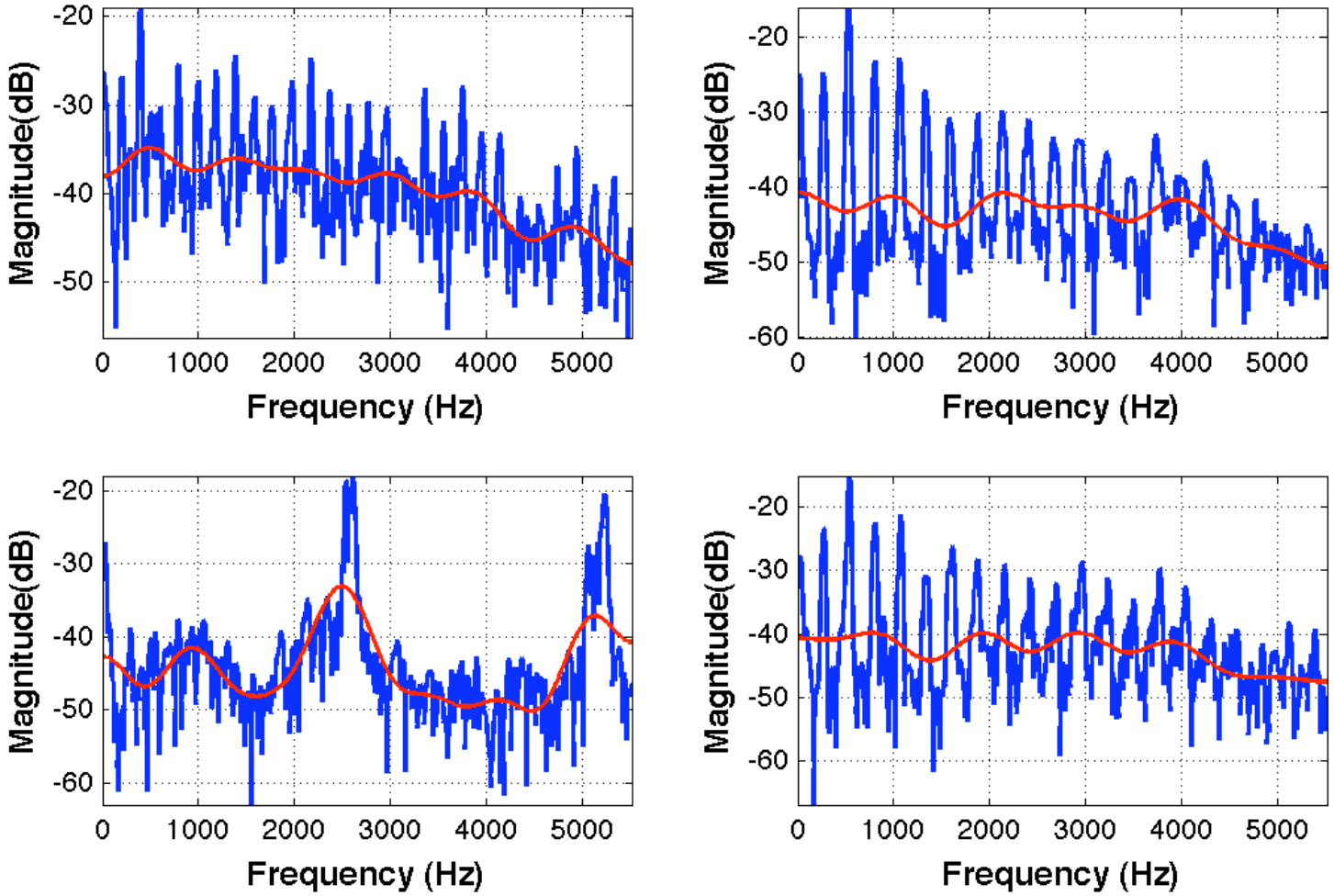
$$c_{LP}(l) = c_x(l) \times w_{LP}(l)$$

$$C_{LP}(k) = e^{\mathbb{R}[\mathrm{FFT}(c_{LP}(l))]}$$

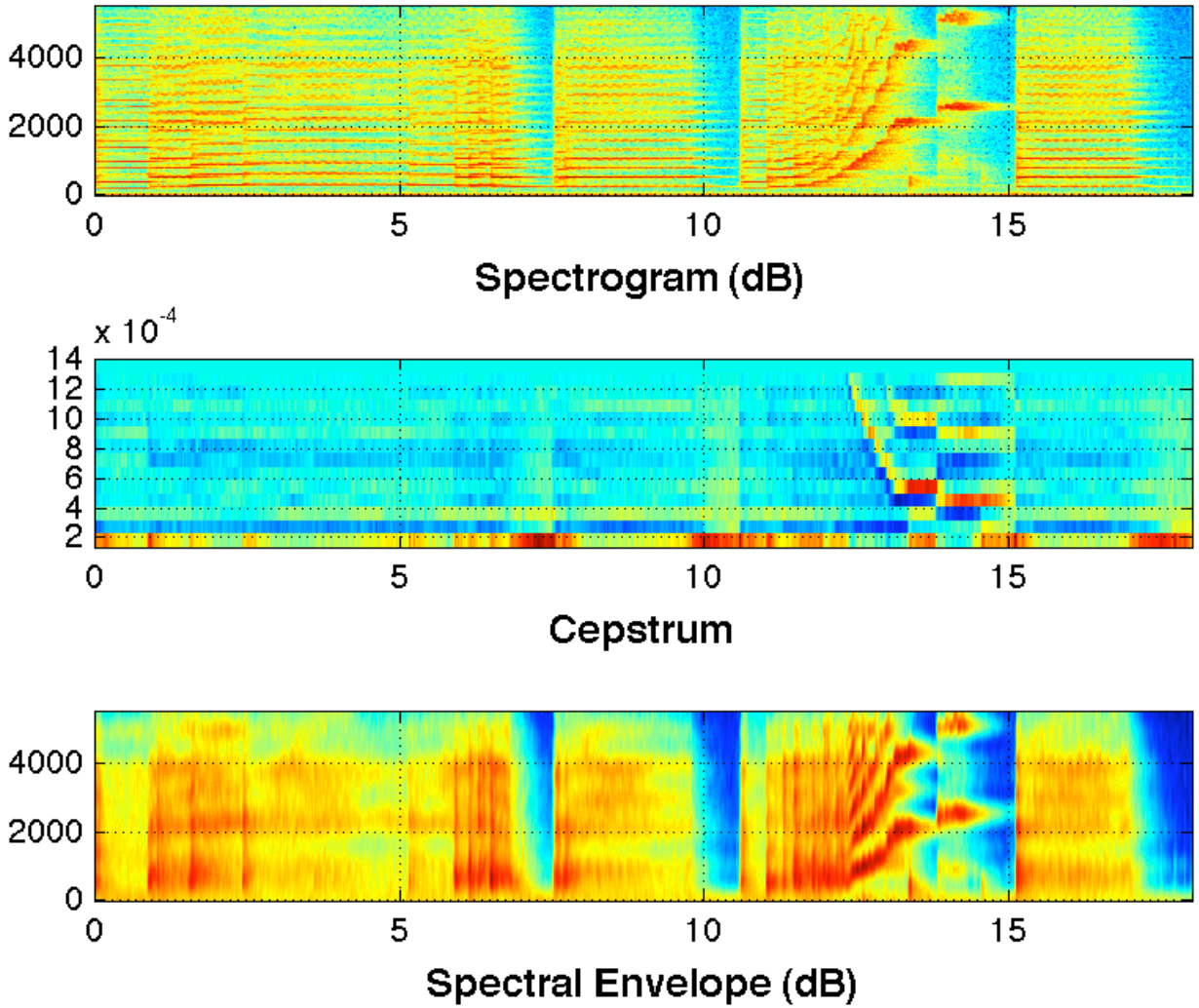
- Such that $L_1 \leq L/2$, and C_{LP} is the spectral envelope.

Cepstrum

- The spectral envelope approximation is coarser/finer depending on L_1



Cepstrum

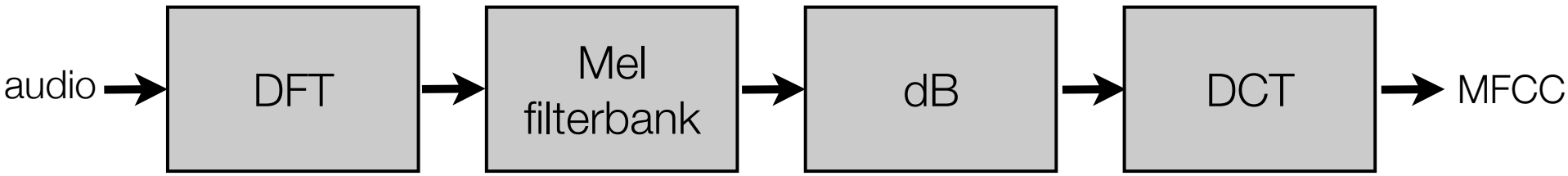

4000
2000
0
0
5
10
15
Spectrogram (dB)
x 10^-4
14
12
10
8
6
4
2
0
5
10
15
Cepstrum
4000
2000
0
0
5
10
15
Spectral Envelope (dB)

MFCC

- Mel-frequency Cepstral Coefficients (MFCC): variation of the linear cepstrum, widely used in audio analysis.

- Most popular features in speech: due to their ability to compactly represent the audio spectrum

- Introduced to music DSP by Logan (ISMIR, 2000).



MFCC

- The Mel scale is a non-linear perceptual scale of pitches judged to be equidistant:

$$\text{mel} = 1127.01028 \times \log\left(1 + \frac{f}{700}\right)$$

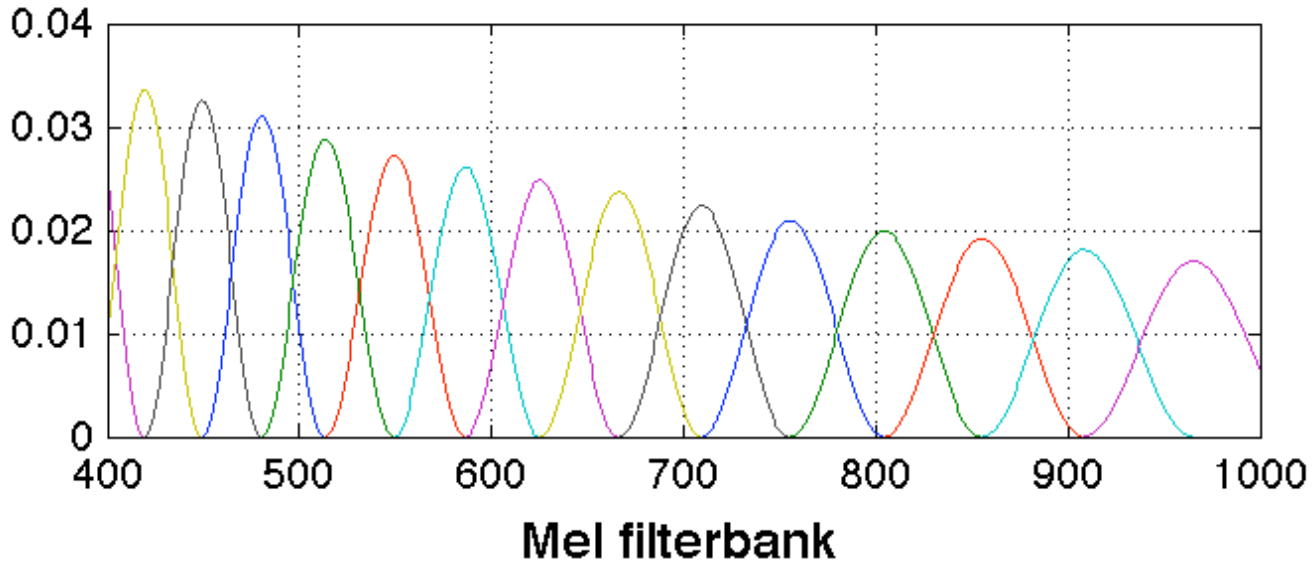
$$f = 700 \times (e^{\frac{\text{mel}}{1127.01028}} - 1)$$

- Approx. linear f < 1kHz; logarithmic above that.

- Reference point is at f = 1kHz, which corresponds to 1000 Mel: a tone perceived to be half as high is 500 Mel, twice as high is 2000 Mel, etc.

MFCC

- Filterbank of overlapping windows
- Center frequencies uniformly distributed in mel scale, s.t. the center frequency of one window: starting point of next window and end point of previous window.



- All windows are normalized to unity sum.

MFCC

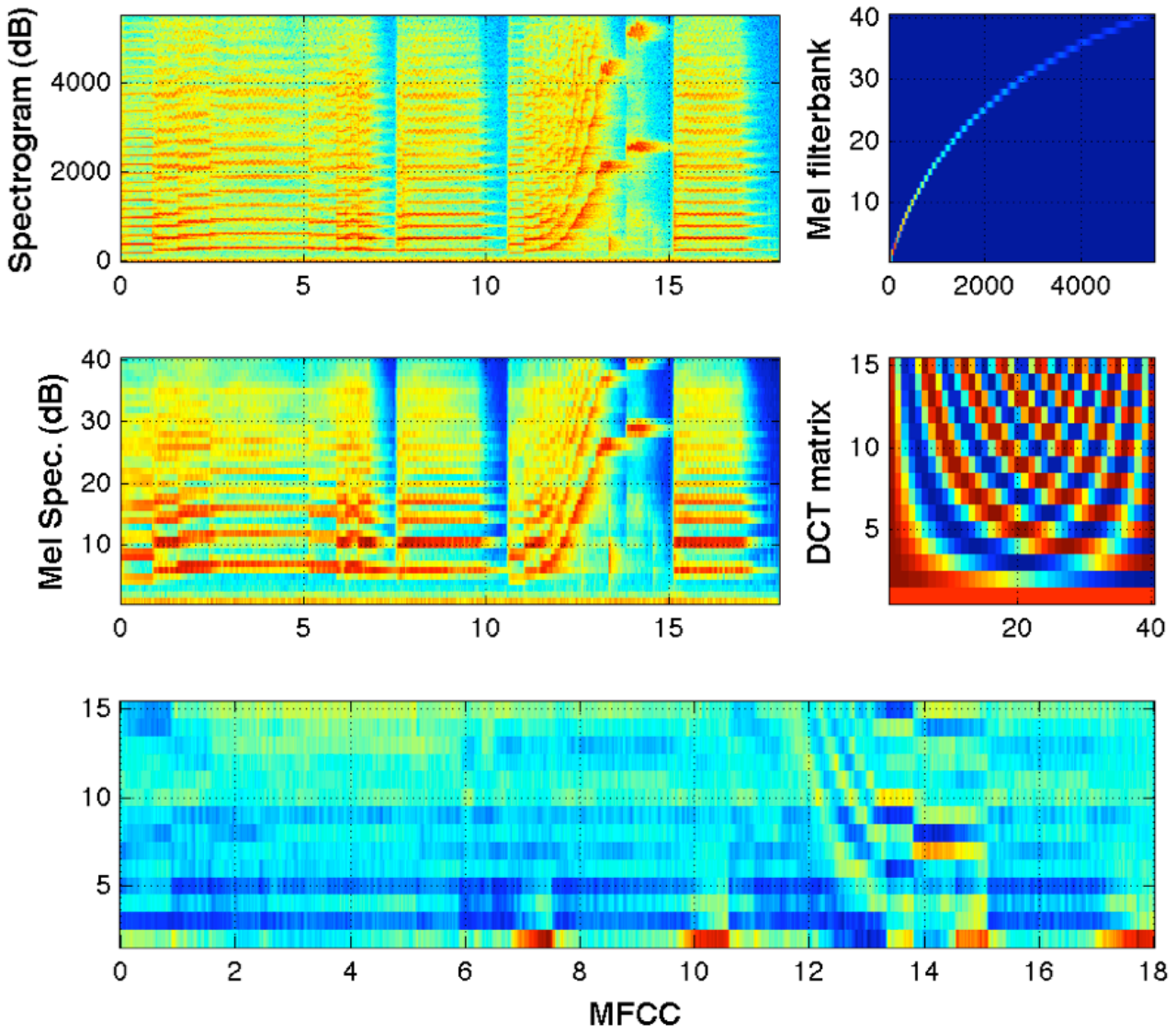
- An efficient representation of the log-spectrum can be obtained by applying a transform that decorrelates the Mel dB spectrum (see Rabiner and Juang, 93).

- This decorrelation is commonly approximated by means of the Discrete Cosine Transform (DCT)

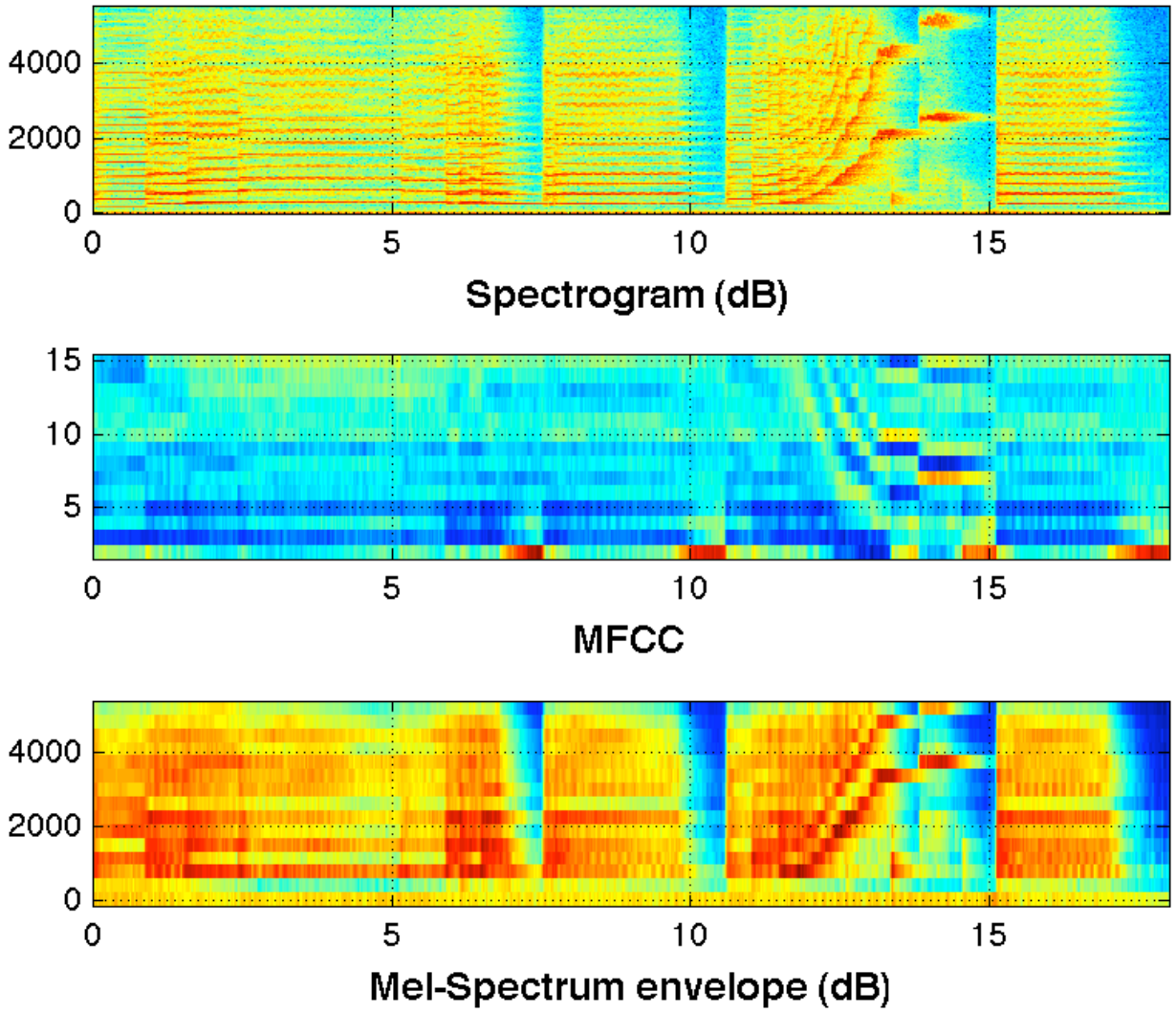
- DCT: real-valued transform, similar to the DFT. Most of its energy is concentrated on a few low coefficients (effectively compressing the spectrum)

$$X_{DCT}(k) = \sqrt{\frac{2}{N}} \sum_{n=0}^{N-1} x(n) \cos\left[\frac{\pi k}{N}\left(n - \frac{1}{2}\right)\right]$$

MFCC

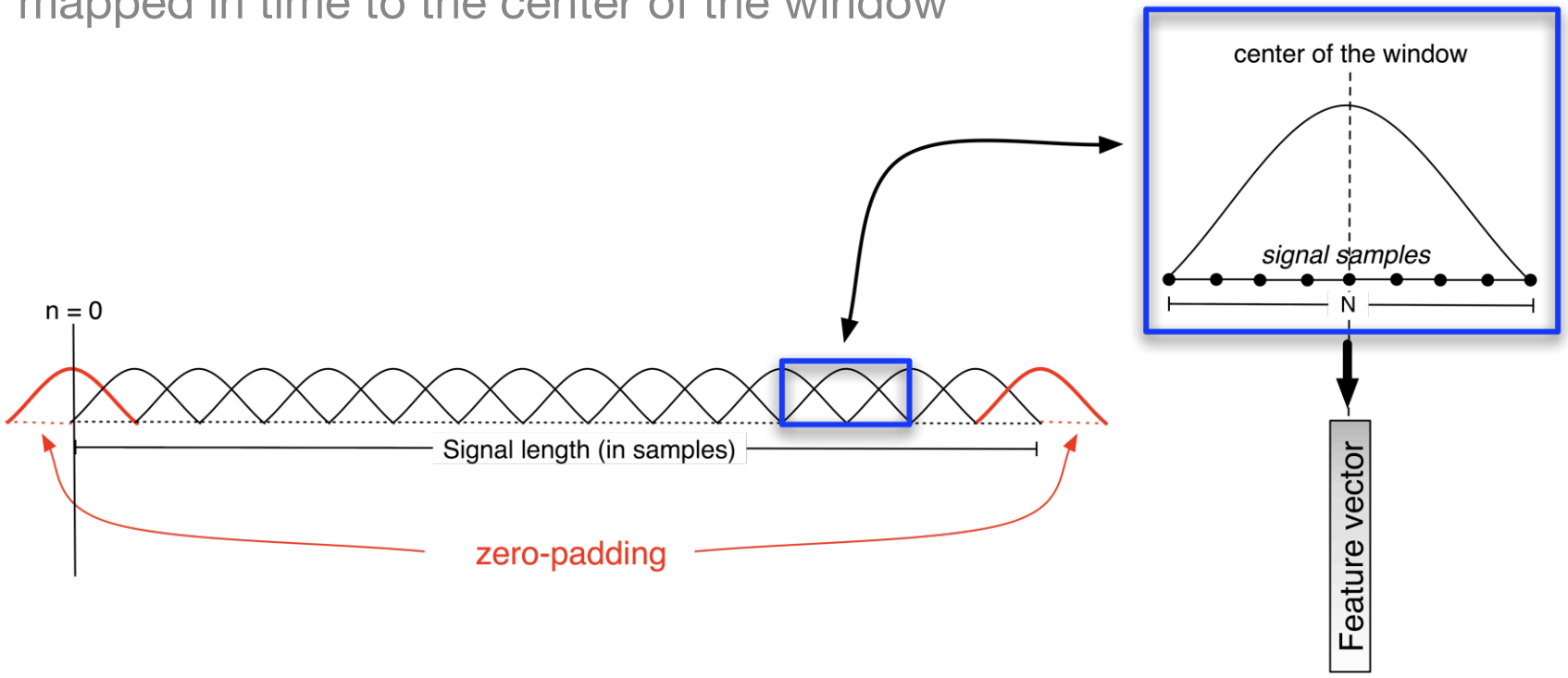

Spectrogram (dB)
4000
2000
0
0
5
10
15
Mel filterbank
40
30
20
10
0
2000
4000
Mel Spec. (dB)
40
30
20
10
0
5
10
15
DCT matrix
15
10
5
20
40
15
10
5
0
2
4
6
8
10
12
14
16
18
MFCC

MFCC


4000
2000
0
0
5
10
15
Spectrogram (dB)
15
10
5
0
5
10
15
MFCC
4000
2000
0
0
5
10
15
Mel-Spectrum envelope (dB)

A reminder

- The feature vector is representing an N-long time segment, and is best mapped in time to the center of the window



- Zero-padding can be used to map the first vector to n = 0, and ensure all the signal is analyzed

Post-processing

- We can characterize the short-term temporal dynamics of feature coefficients by using delta and acceleration coefficients:

$$\Delta y = \frac{y(n) - y(n-h)}{h}$$

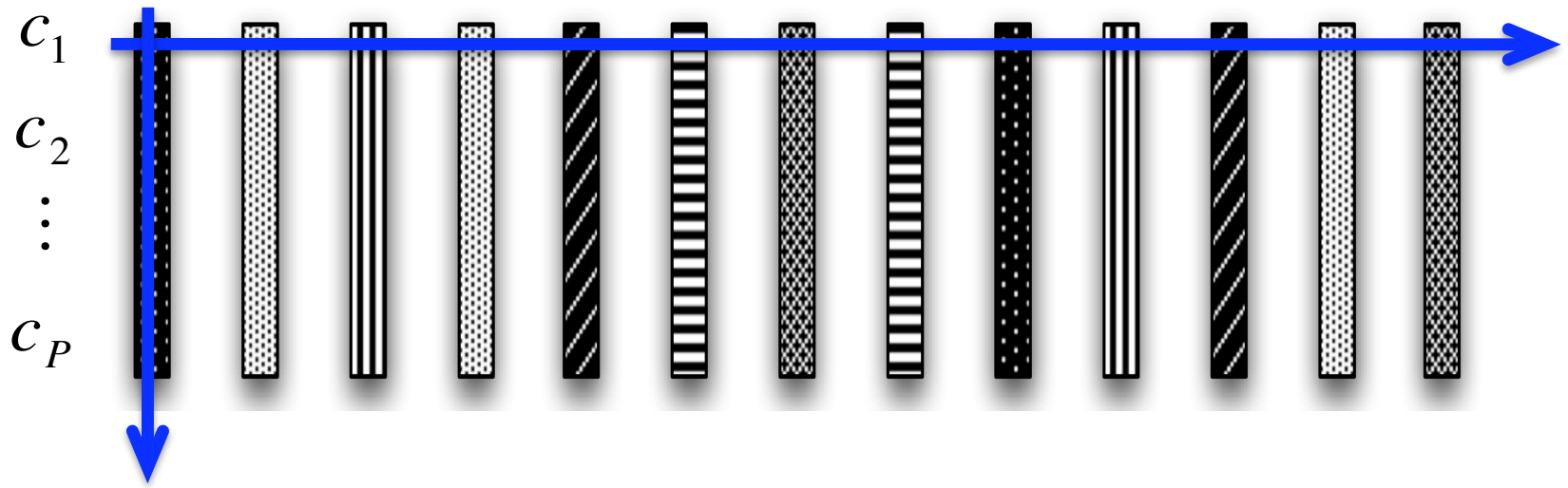
$$\Delta\Delta y = \frac{y(n) - 2y(n-h) + y(n-2h)}{h^2}$$

- Normalization is often necessary/beneficial:

$$\hat{y} = \frac{y - \min(y)}{\max(y - \min(y))} \qquad \hat{y} = \frac{y - \mu_y}{\sigma_y}$$

Post-processing

- Normalizing features across time avoids bias towards high-range features

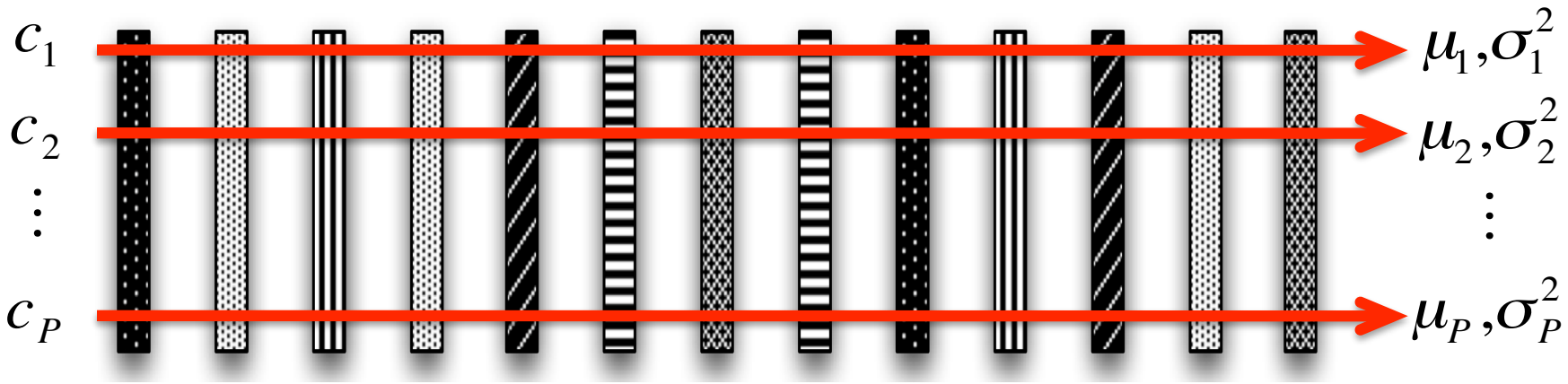


- Normalizing feature vectors make them more comparable to each other

- Looses dynamic change information

Summarization

- Global (song/sound) features can be obtained by summarizing frame-level features:

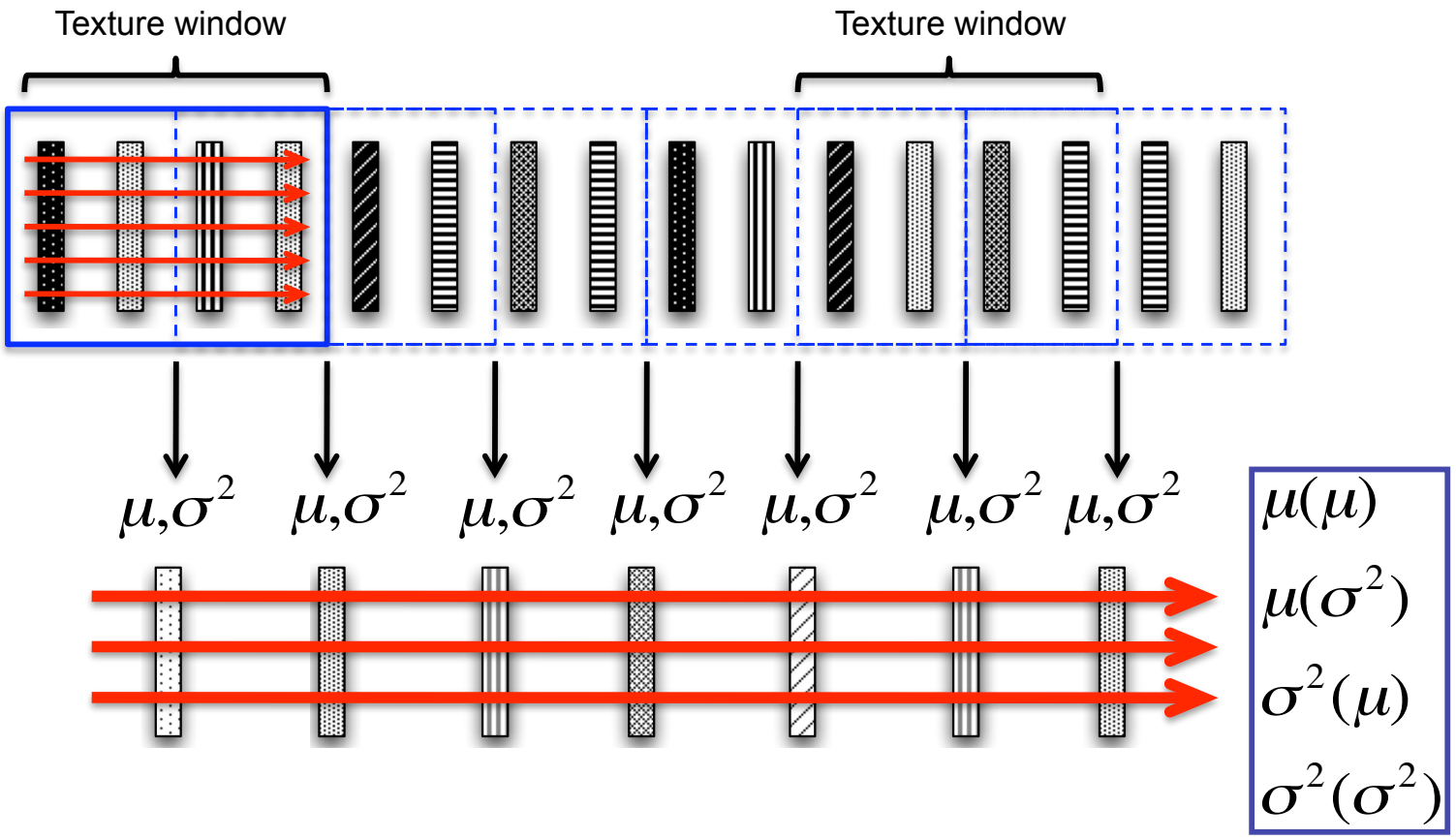


- Resulting on a single 2xP-long feature vector of means and variances.
- If not independent we measure the covariance:

$$\text{cov} = \sum_m (y - \mu_y)(y - \mu_y)^T / M$$

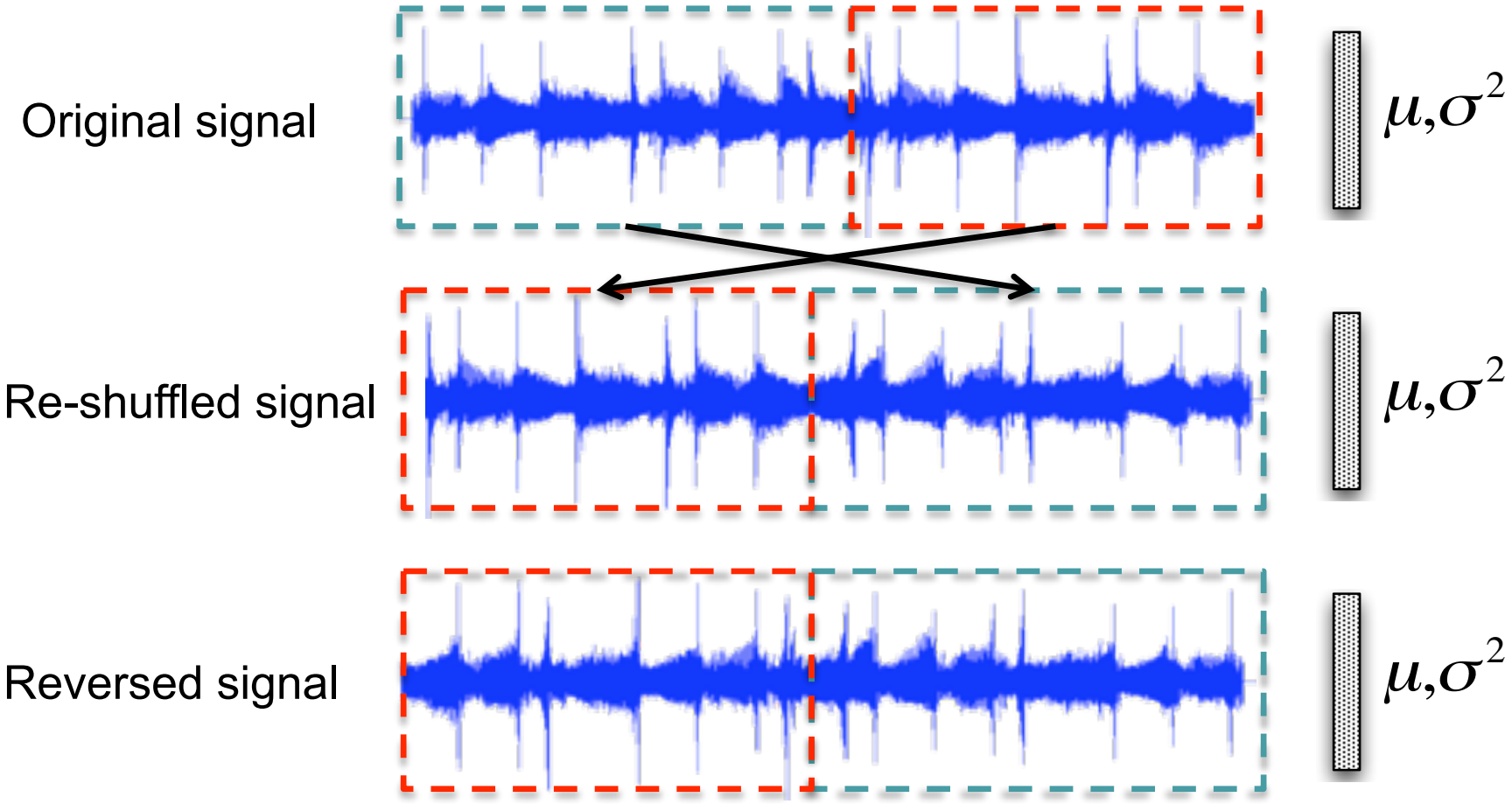
Summarization

- Texture windows can be used to capture local behavior:



Summarization

- Computing simple statistics across time ignores temporal ordering. Same global features for:



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