ECS7006 Music Informatics

Week 8 – Musical Structure and Source Separation

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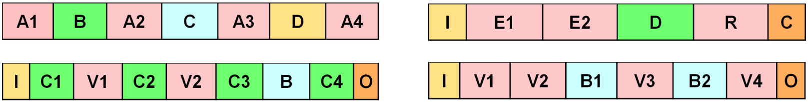
Musical Structure and Form

- The goal of structure analysis is to identify structural elements and segment music into its constituent temporal parts
- Musical structure has multiple aspects: rhythmic, harmonic, melodic, and form
- Structure can be viewed at various levels of granularity: e.g. notes phrases, sections, movements and works
- Musical form arises from repetition or similarity of the segments of a piece
- Form can be observed in the high-level aspects of music (e.g. **repetition** in rhythm, melody, harmony or timbre), or in the **similarity** of lower-level features

Common Musical Forms

- **Binary form**: two contrasting segments (A and B) with optional repetition of each segment: AB or AAB or ABB or AABB
- **Ternary form**: two contrasting segments followed by a return to the first segment: e.g. ABA or AABA
- **Rondo form**: several contrasting segments alternating with a repeating segment: e.g. ABACADA
- **Chain form**: a sequence of unrelated segments: e.g. ABCDE
- **Strophic form**: a single section is repeated several times, usually with variation (e.g. verses of a song, theme & variations): A A′ A″ A‴
- For pop music, the structure can be expressed in terms of units such as *verse*, *chorus*, *introduction* and *bridge*



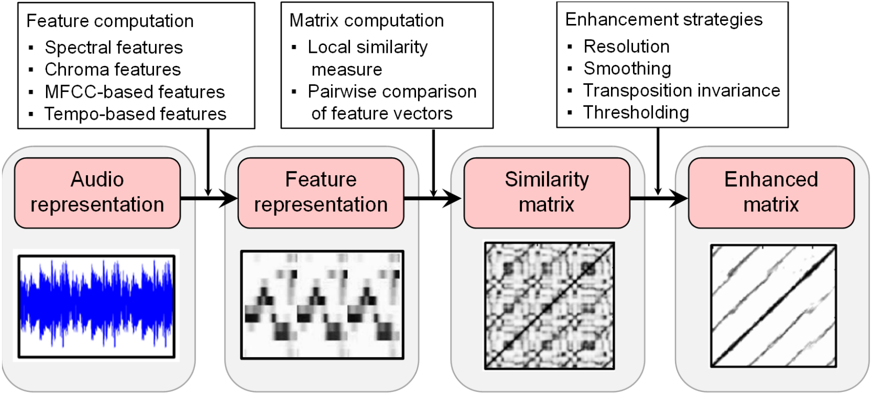
Hierarchical Form

- Form is (approximately) hierarchical: pieces contain sections which contain phrases (at multiple levels)
- e.g. **Sonata form** in Western classical music
  - Has three main sections: the *exposition*, where two contrasting themes are introduced, the *development*, based on thematic material from the exposition, and the *recapitulation*, where the two themes appear again
  - The exposition may be repeated
  - The parts may be embedded between an introduction and coda
  - A complex type of ternary form
  - Sonata form is often used for the first movement of a larger piece such as a symphony
- As in the case of metre, a precise definition of the structural level of interest is difficult

Segmentation and Structure

- **Segmentation** is the process of breaking down continuous media into discrete units
  - e.g. segmenting images into objects, video into scenes, or audio into speech, music, silence and applause
  - Involves finding boundaries between regions of high self-similarity (e.g. in texture, colour, or instrumentation)
- **Structure analysis** involves assigning meaning to segments (labelling)
  - What the segment represents (absolute, e.g. drum solo)
  - How the segment relates to other segments (relative, e.g. same as first segment)
- Can be based on repetition/similarity or homogeneity/novelty

Structure Analysis Pipeline



FMP Fig.4.9

Feature Extraction

- Audio waveforms and spectrograms are too specific for capturing repetition or similarity
- First step is to compute features
- What types of features can be used?
  - Pitch content (harmony, melody) is approximated by chroma features
  - Timbre can be appproximated by MFCCs
  - Tempo can be factored out by using *beat-synchronous* features
  - Temporal features (tempograms, Sec. 6.2.4 of text book) can also be used
- The parameters used for feature extraction (e.g. temporal resolution) greatly influence results
- Optimal parameter settings depend on the music being analysed

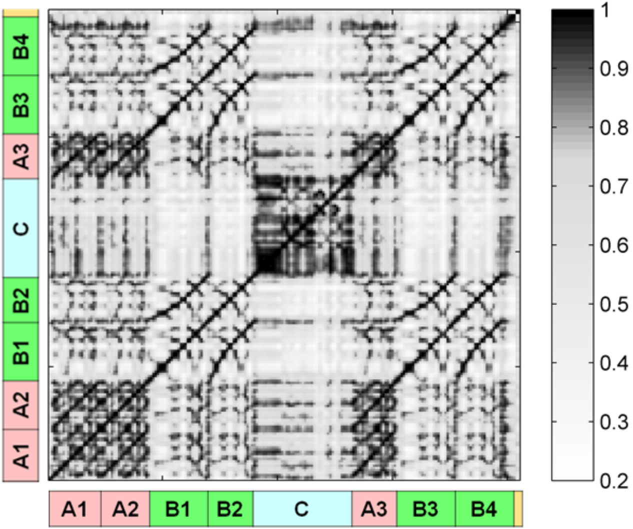
Self-Similarity Matrices

- The second step is to compute a *self-similarity matrix* (SSM), which stores the similarity of every pair of audio frames, based on the chosen features
- For the similarity function $s : \mathcal{F} \times \mathcal{F} \to \mathbb{R}$, where $\mathcal{F} = \mathbb{R}^D$ is the feature space, we use a normalised inner product:

$$s(x_n, x_m) = \frac{| < x_n, x_m > |}{(< x_n, x_n >< x_m, x_m >)^{0.5}}$$

- Results in matrix $S(n, m) = s(x_n, x_m) \in [0, 1]$
- Repetition of a segment results in a *path* of high values in S
- Homogeneous regions result in *blocks* of high values in S

Self-Similarity Matrix with Chroma Features: Paths



Processing Self-Similarity Matrices: Paths

- Given a feature sequence $X = (x_1, x_2, ..., x_N)$ and similarity matrix $S \in [0,1]^{N \times N}$, a *path* $P = ((n_1, m_1), ..., (n_L, m_L))$ with:

$$(n_l, m_l) \in [1 : N]^2$$

$$(n_{l+1}, m_{l+1}) - (n_l, m_l) \in A$$

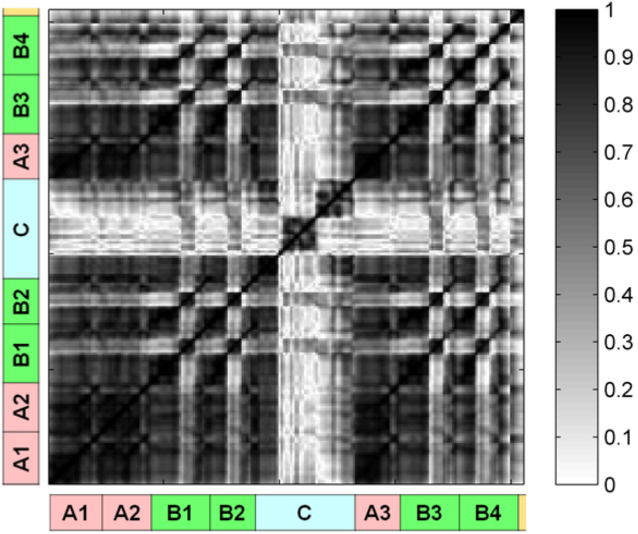
  defines a sequence of cells in S indexed by each (n_l, m_l)

- A defines the admissable step sizes, e.g. $A = \{(2,1), (1,2), (1,1)\}$
- The *score* $\sigma(P)$ of a path P is defined as:

$$\sigma(P) = \sum_{l=1}^{L} S(n_l, m_l)$$

- Repetition of segments can be discovered by finding high scoring paths

Self-Similarity Matrix with MFCC Features: Blocks



Processing Self-Similarity Matrices: Blocks

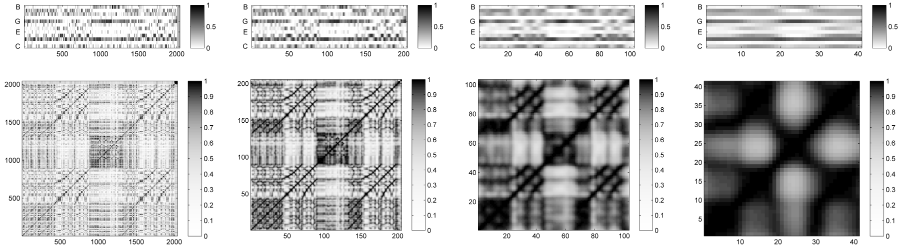
- Likewise, given two segments $\alpha_1 = [s_1 : t_1]$ and $\alpha_2 = [s_2 : t_2]$, a *block* $B = \alpha_1 \times \alpha_2$ defines a region of cells: $\{(n_l, m_l) : n_l \in \alpha_1 \text{ and } m_l \in \alpha_2\}$ in the similarity matrix S
- The score $\sigma(B)$ of a block $B = \alpha_1 \times \alpha_2$ is defined as:

$$\sigma(B) = \sum_{n \in \alpha_1, m \in \alpha_2} S(n, m)$$

- Homogeneous segments can be discovered by finding high scoring blocks

Processing Self-Similarity Matrices: Enhancement

- Path and block structures tend to be fragile due to the many types of variation that occur in music performance
- We will look at several approaches to address this problem
- Preprocessing: *feature enhancement*
  - Smoothing (e.g. median filtering) and downsampling
  - Enhance block structures at the cost of fine-grained path structures
  - Computational savings (time and space) for subsequent processing

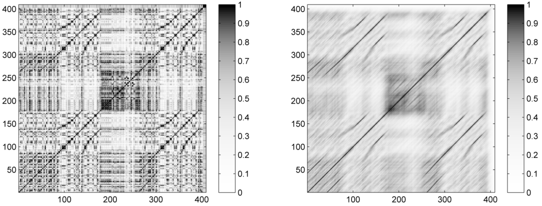


Processing Self-Similarity Matrices: Enhancement

- The second enhancement method is *path smoothing*
- The idea is to perform low-pass filtering in the direction of the diagonal

$$S_L(n,m) = \frac{1}{L}\sum_{l=1}^{L} S(n+l, m+l)$$

- Only works for fixed tempo



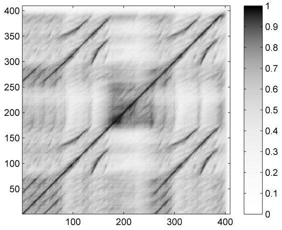
Original　　Smoothed

Processing Self-Similarity Matrices: Enhancement

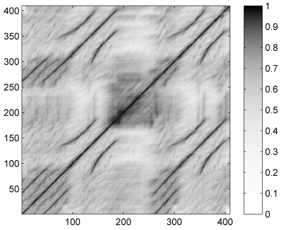
- Can add a parameter θ for tempo ratio and use:

$$S'(n,m) = \max_{\theta} \sum_{l=1}^{L} S(n+l, m+\theta l)$$

- Filter in both directions (forward and backward) for best results
- Diagonal median filtering should also work well



Tempo-invariant



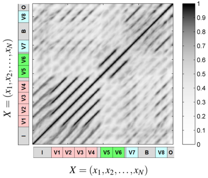
Bi-directional

- If it is desired that transposed versions should be matched, chroma features can be rotated by 0 to 11 positions, and the maximum similarity over all 12 rotations is then used:

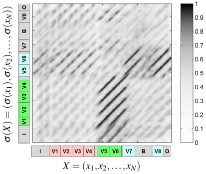
$$\rho^i(x(j)) = x((j+i) \mod 12)$$

$$\rho^i(S)(n,m) = s(\rho^i(x_n), x_m)$$

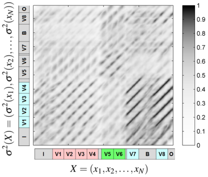
$$S^{\mathsf{TI}}(n,m) = \max_{i\in[0:11]} \rho^i(S)(n,m)$$



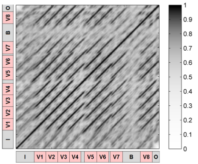
$\rho^0(S)$



$\rho^1(S)$

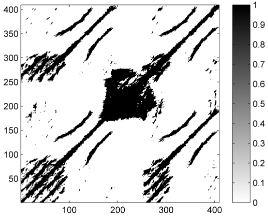


$\rho^2(S)$

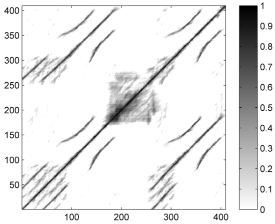


S^{TI}

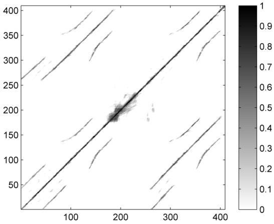
- Thesholding (with threshold τ):
  - With binarisation ($S' = (S > \tau)$) or scaling ($S' = C \times \max(S - \tau, 0)$)
  - Absolute or relative (e.g. set τ to 80th percentile)
  - Local (rowwise and columnwise) or global



Binarisation ($\tau = 0.75$)



Scaling (80th%)



Scaling (95th%)

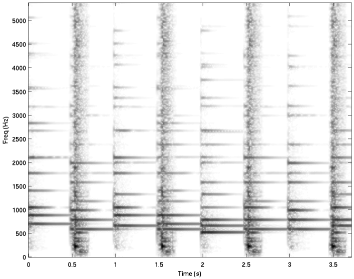
Source Separation

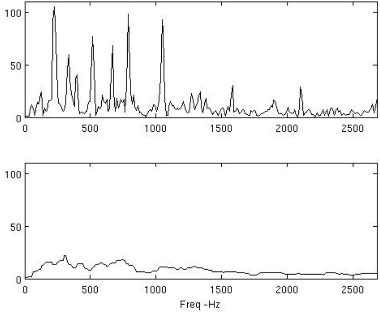
Source Separation

- Most audio signals are mixtures of several simultaneously active audio sources (voices, instruments, environmental sounds, recording noise)
- Source separation involves extracting one or several source signals in order to listen to or process them separately or remix them
- Techniques are based on properties of the sounds to be separated, or modelling and reverse engineering the mixing process
- Applications include:
  - real-time denoising for hearing aids
  - removal of vocals for karaoke
  - remixing (concerts, conferences, post-production, electronic music composition)
  - spatial enhancement (upmixing stereo to 5.1, adaptation to the listening environment)

Harmonic/Percussive Source Separation (HPSS)

- Separation of harmonic (periodic, steady-state) sounds from percussive (transient) sounds
  - Note that pitched percussive instrument sounds (e.g. piano, timpani) have both harmonic and percussive components
- Core idea: *harmonic* sounds form *horizontal structures* in a spectrogram representation (localised in frequency, spread out in time); *percussive* sounds form *vertical structures*
- Using filters to enhance one direction and suppress the other, each time-frequency point is classified as contributing either to the harmonic or percussive part of the signal
- A binary mask is used to remove time-frequency points not belonging to the desired component, and an inverse transform reconstructs the desired time-domain signal





Example: separation of piano and snare drum. Left: spectrogram; right: spectra for one time frame for the harmonic (upper) and percussive (lower) components. From: (Fitzgerald, DAFx-2010)

Filtering of Harmonic and Percussive Components

- Median filtering can be used (Fitzgerald, DAFx-2010)
- The median of a sorted list of N numbers is the middle value
  - If N is odd, it is the $\frac{N+1}{2}$-th highest value
  - If N is even, it is the average of the $\frac{N}{2}$-th and $(\frac{N}{2}+1)$-th values
- The harmonic filter F_h with width $2w+1$ is computed as:

$$F_h(X)(n,k) = \text{median}(X(n-w:n+w,k))$$

  and the percussive filter F_p of height $2h+1$ is computed as:

$$F_p(X)(n,k) = \text{median}(X(n,k-h:k+h))$$

  for a spectrogram $X(n,k)$
- Out-of-domain values are assumed to be 0

HPSS: Separation via Binary Masking

- A binary mask is a matrix containing values 0 and 1 only
- The harmonic mask M_h is given by:

$$M_h(n,k) = \begin{cases} 1, & F_h(X)(n,k) \geq F_p(X)(n,k) \\ 0, & \text{otherwise} \end{cases}$$

- The percussive mask M_p is the complement of the harmonic mask:

$$M_p(n,k) = \begin{cases} 0, & F_h(X)(n,k) \geq F_p(X)(n,k) \\ 1, & \text{otherwise} \end{cases}$$

- The masks are applied by pointwise multiplication with the original spectrogram:

$$X_h(n,k) = X(n,k)M_h(n,k)$$

$$X_p(n,k) = X(n,k)M_p(n,k)$$

- The time domain signals are computed by applying the inverse FFT, windowing and overlap-adding the frames together

Separating Instrumental Sources

- One approach to instrumental source separation is reverse engineering the mixing process
- The choice of algorithm depends firstly on the number of independent mixture channels c relative to the number of sources s:
  - If $c > s$, the system is *over-determined*
  - If $c = s$, the system is *determined*
  - If $c < s$, the system is *under-determined*
- The type of mixture also has an impact:
  - Instantaneous: trivial mixing filters (gains, no delays)
  - Anechoic: trivial mixing filters (gain and delay pairs)
  - Convolutive (or echoic): non-trivial mixing filters
  - Reverberant: mixing filters exhibit a realistic reverberation time
- The final factor is whether the mixing filters change over time

Identification and Filtering

- Source separation is often addressed as a two-part problem:
  - *identification* of the source properties (spatial directions, short-term power spectra)
  - *filtering* of the mixture channels based on the identified properties
- Identification algorithms include:
  - direction-based algorithms (ICA, DUET, ADRess)
  - transcription-based algorithms
  - hybrid algorithms
- Filtering techniques include:
  - beamforming
  - time-frequency masking

Degenerate Unmixing Estimation Technique (DUET)

- The Degenerate Unmixing Estimation Technique (DUET) is an identification algorithm for (under)-determined instantaneous stereo mixtures
- The model assumes that the sources have different spatial directions and that no more than one source is present at any given time-frequency point
- If source j only is active at (n, f), then the inter-channel intensity difference (IID):

$$\text{IID}(n, f) = 20 \log_{10} \left(\frac{|X_2(n, f)|}{|X_1(n, f)|} \right)$$

approximates the relative mixing gain, indicating the source direction

DUET

- DUET separates the sources as follows:
  - Compute IID for each time-frequency point
  - Find source positions corresponding to peaks in the IID histogram
  - Associate each time-frequency point with the closest source and perform binary masking
- The gains can be better estimated at time-frequency points with a high inter-channel coherence (correlation), which probably contain a single active source
- For convolutive mixtures, the inter-channel phase difference (IPD) also provides relevant information:

$$\text{IPD}(n, f) = \angle X_2(n, f) - \angle X_1(n, f)$$

- For a far-field microphone pair recording, where source j only is active at (n, f), then $\text{IPD}(n, f) = 2\pi f \tau_j \mod 2\pi$, where τ_j is the time delay of arrival between the two microphones

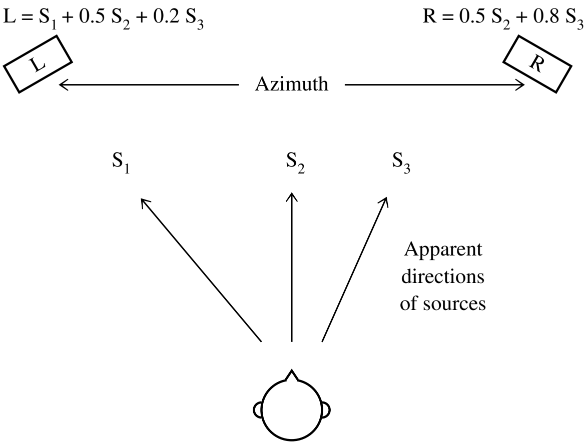
ADRess

- Azimuth Discrimination and Resynthesis (Barry et al., 2004) is a source separation method for under-determined stereo mixtures
- ADRess has a simple and efficient real-time implementation
- Assumes stereo images created with a pan-pot (phase coherence between channels)

$$x_L(t) = \sum_{j=1}^{J} P_{L,j} S_j(t) \qquad\qquad x_R(t) = \sum_{j=1}^{J} P_{R,j} S_j(t)$$

  where x_L, x_R are the mixture signals, $P_{i,j}$ the panning coefficient (gain) for channel i and source j, and S_j the unmixed source signals
- Assumes each source has a different fixed spatial location (pan setting)

ADRess Example



- ADRess uses the relative levels of a source in the two channels to locate spectral energy belonging to the source position

ADRess Algorithm

- The idea is to find the gain factor $g_j = \frac{P_{L,j}}{P_{R,j}}$ which equalises the intensity of source j in the left and right channels
- Then source j can be removed by subtraction: $x_L(t) - g_j x_R(t)$
- To avoid numerical problems, the left and right channels are interchanged if $P_{L,j} > P_{R,j}$, ensuring $g_j \leq 1$
- Apply this idea to each time-frequency bin
- To recover the sources, left and right frequency-azimuth planes A_L and A_R are computed, sampled at $2\beta + 1$ points in the azimuth dimension, representing the possible positions of instruments

$$A_L(n, k, i) = |X_L(n, k) - \frac{i}{\beta} X_R(n, k)|$$

$$A_R(n, k, i) = |X_R(n, k) - \frac{i}{\beta} X_L(n, k)|$$

where X_L and X_R are STFTs of the two channels

ADRess Algorithm (continued)

- (To simplify notation, we omit the time argument n here)
- The azimuth points corresponding to minima in A_L and A_R are singled out as sources at that position

$$A'_L(k,i) = \begin{cases} \max_i A_L(k,i) - \min_i A_L(k,i) & \text{if } i = \text{argmin}_i A_L(k,i) \\ 0 & \text{otherwise} \end{cases}$$

$$A'_R(k,i) = \begin{cases} \max_i A_R(k,i) - \min_i A_R(k,i) & \text{if } i = \text{argmin}_i A_R(k,i) \\ 0 & \text{otherwise} \end{cases}$$

- Harmonic overlap between sources causes “azimuth smearing”, i.e. the minima appear between the source positions
- To compensate, a window of width $h < \beta$ is constructed around the apparent source position d to capture harmonics that have drifted from their source

ADRess Algorithm (continued)

- Resynthesis of a single source is achieved by:
  - summing across the window:

$$Y_L(k) = \sum_{i=d-h/2}^{d+h/2} A'_L(k,i) \qquad\qquad Y_R(k) = \sum_{i=d-h/2}^{d+h/2} A'_R(k,i)$$

  - combining with the original phase values $\phi_L(k)$ and $\phi_R(k)$ and taking the IFFT
  - combining frames with a standard overlap-add scheme

Summary and Resources

- Direction-based source separation algorithms are simple and fast, but only work for multi-channel mixtures where the time-frequency overlap between sources and the reverberation are minimal
- *Informed* source separation algorithms take advantage of knowledge of the score or source instruments to achieve better separation (e.g. Open Unmix by Sony 2019; Spleeter by Deezer, 2019)
- For further reading:
  - S. Rickard, *The DUET Blind Source Separation Algorithm*, in S. Makino et al. (eds.), Blind Speech Separation, pp 217–241, 2007
  - D. Barry, B. Lawlor and E. Coyle, *Sound Source Separation: Azimuth Discrimination and Resynthesis*, 7th International Conference on Digital Audio Effects, 2004
  - F.-R. Stöter, S. Uhlich, A. Liutkus and Y. Mitsufuji, *Open-Unmix – A Reference Implementation for Music Source Separation*, Journal of Open Source Software, 2019