Musical Instruments Signal Analysis and Recognition Using Fractal Features

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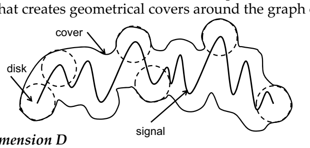
1. Outline - Contributions

- Analyze musical signals using the theory of fractals: model the geometrical complexity of the waveform via the fractal dimension
- Novel approach for the analysis of the structure of musical instruments signals at multiple levels
- Timbre analysis for the distinction of different instrument classes and exploration of the differences between the attack and steady state of the tones
- Goal: Feature configurations focusing at multiple scales and the statistical self-similarity of the signals that offer a modest improvement to the performance of a recognition task

2. Multiscale Fractal Dimension(MFD)

- *Short-time fractal dimension* D: approximately quantifies the degree of turbulence.
- *Multiscale fractal dimension profile* MFD[s]: quantifies the multiscale complexity of the waveform, thus the degree of fragmentation.
- Algorithm: based on multiscale nonlinear operators of morphological filtering that creates geometrical covers around the graph of the signal

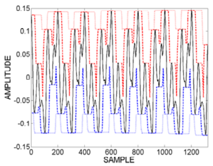


Fractal Dimension D

$$D = \lim_{s \to 0} \frac{\log[(\text{Area of dilated graph by disks of radius s}) / s^2]}{\log(1/s)} \quad (1)$$

Algorithm

- Measure the area of the difference between dilations and erosions
  - Structuring Element: symmetric 3-sample flat line segment
- Least-squares fit a straight line to the log-log data of (1) over a small scale window $\{s, s+1, \ldots s+w-1\}$ of w scales
- Move along the s axis and create a profile of local multiscale fractal dimensions $D(s,t)$ at each time location t of the short time analysis frame.
- D ∈ [1,2] for 1-D signals
- The larger D, the larger the amount of geometrical fragmentation.

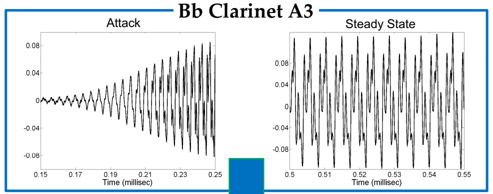


Bb Clarinet A3 Steady state (solid line) and its dilation (red lines) & erosions (blue lines) at scales s = 25, 75, with D = 1.1.

3. MFD on attack & steady state

1st Step: Processing of the input signal

Bb Clarinet A3

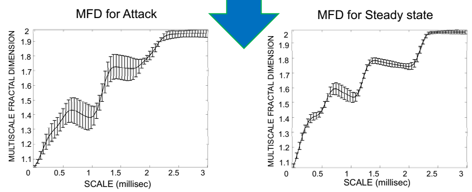


2nd Step: Analysis Using Multiscale Fractal Exponents

MFD

Calculate the short time MFDs of the tones, 30-ms segments, updated every 15-ms

- Sampling Frequency: 44.1KHz
- MFD[s] are analyzed for discrete scales $s = 1, \ldots, 133$
- Time scales s_t from 1/44.1 to 3 ms

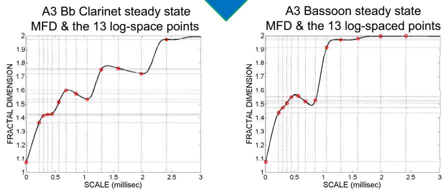


3rd Step: Feature set configuration

Feature sets

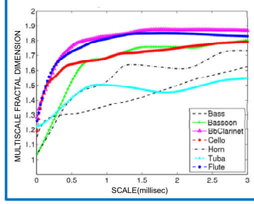
- 13 MFD[log-spaced] features (MFDLG)
- 6 PCA components (MFDPC)

examples



4. Analysis cases

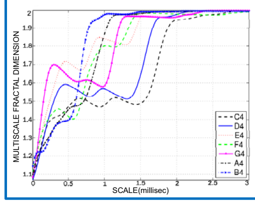
Average MFDs on Attack



Estimated for 7 instruments

- Similar as for the steady state
- Higher D for small scales s_t and more fragmentation.
- Increased value of $D(s = 1)$.
- Clear distinction of D among some of the analyzed instruments.

Bb Clarinet (C4-B4) Steady State MFD Variability



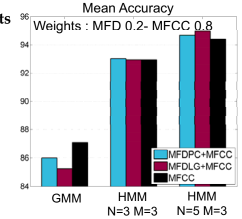
- Dependence on the acoustical frequency and the MFD profile that increases rapidly for higher frequency sounds.
- The instruments' specific MFDs beholds the shape observed for the specific octave.

5. Experimental Evaluation

4th Step: Recognition Experiments

Experimental Setup

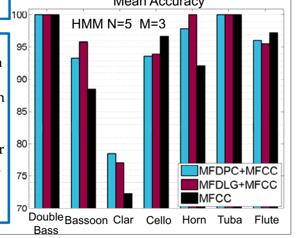
- 1333 notes, 7 instruments
- 5 feature sets
  - 6 MFDPC
  - 13 MFDLG
  - 13 MFCC
  - 6 MFDPC + 13 MFCC
  - 13 MFDLG + 13 MFCC
- 2 classification methods
  - GMM M[1-3] mixtures
  - Multi-stream HMM N[3-9] states and M[1-3] mixtures



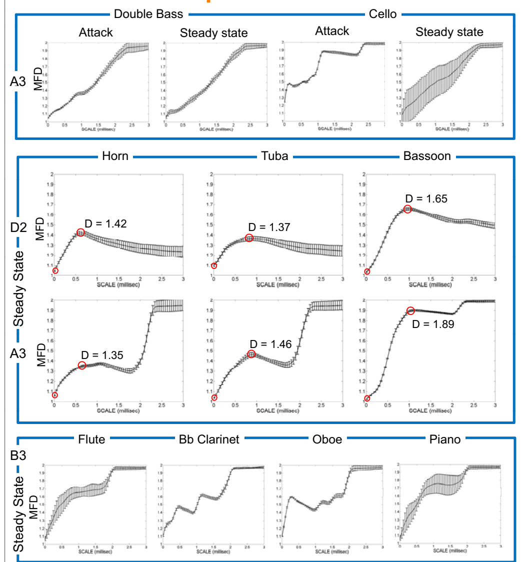
Results

MFD+MFCC — MFD

- Double Bass, Bassoon & Tuba best recognized
- Low discriminability between Bb Clarinet & Flute
- Enhanced discriminability for Bassoon, Bb Clarinet and Horn
- Decreased for Cello & Flute



6. More examples



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Acknowledgments

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