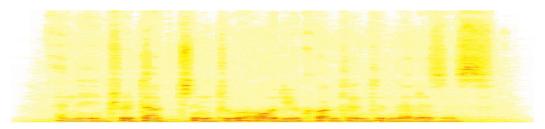
Introduction to Audio Content Analysis

Module 6.1: Onset Detection

alexander lerch





introduction

overview

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corresponding textbook section

Chapter 5 — Temporal Analysis: pp. 135–139

lecture content

- detection of the start of musical events
- fundamental methods for generating a novelty function
- fundamental methods for peak picking

learning objectives

- describe the term onset
- implement an automatic onset detection system



introduction

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Chapter 5 — Temporal Analysis: pp. 135–139

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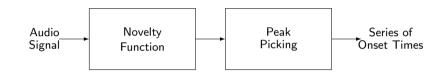
onset detection problem statement

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- onset: begin of musical event
- polyphonic audio signals:
 - unknown number of voices and events
 - multiple onsets occur at "the same" time
 - onset might be obfuscated by other musical content

onset detection overview

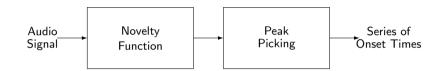




- novelty function
 - measure of probability for new events/signal change over time
- peak picking
 - identify the most likely locations for onsets

overview

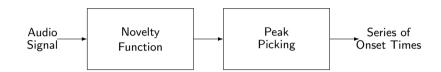
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overview

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terms

- detection function
- difference function

- extract features
- compute derivative
- smooth result
- apply Half-Wave-Rectification HWR

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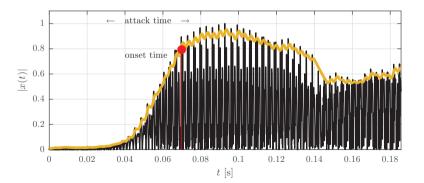
- extract features
- Occupation of the compute derivative
- smooth result
- apply Half-Wave-Rectification HWR

novelty function examples 1/3

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time domain

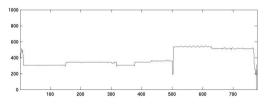
- extract time domain envelope
- calculate slope



novelty function examples 1/3

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- time domain
 - extract time domain envelope
 - calculate slope
- pitch-based: evaluate pitch changes¹



¹N. Collins, "Using a pitch detector for onset detection," in *ISMIR*, 2005, pp. 100–106.

novelty function examples 2/3

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- STFT-based: compute block difference
 - flux

$$\begin{aligned} & \boldsymbol{d}_{\mathrm{hai}}(\boldsymbol{n}) = \sum_{k=0}^{\mathcal{K}/2-1} \log_2 \left(\frac{|X(k,n)|}{|X(k,n-1)|} \right) \\ & \boldsymbol{e} \ \ \boldsymbol{d}_{\mathrm{lar}}(\boldsymbol{n}) = \sum_{k=k(f_{\mathrm{min}})}^{k(f_{\mathrm{max}})} \sqrt{|X(k,n)|} - \sqrt{|X(k,n-1)|} \end{aligned}$$

- cosine distance
- complex

novelty function examples 2/3

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- STFT-based: compute block difference
 - flux

$$\begin{array}{l} \bullet \ \, d_{\mathrm{hai}}(n) = \sum\limits_{k=0}^{\mathcal{K}/2-1} \log_2 \left(\frac{|X(k,n)|}{|X(k,n-1)|} \right) \\ \bullet \ \, d_{\mathrm{lar}}(n) = \sum\limits_{k=k(f_{\mathrm{min}})}^{k(f_{\mathrm{max}})} \sqrt{|X(k,n)|} - \sqrt{|X(k,n-1)|} \end{array}$$

cosine distance

•
$$d_{\text{foo}}(n) = 1 - rac{\sum\limits_{k=0}^{\mathcal{K}/2-1} |X(k,n)| \cdot |X(k,n-1)|}{\sqrt{\left(\sum\limits_{k=0}^{\mathcal{K}/2-1} |X(k,n)|^2\right) \cdot \left(\sum\limits_{k=0}^{\mathcal{K}/2-1} |X(k,n-1)|^2\right)}}$$

complex

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novelty function examples 2/3

STFT-based: compute block difference

flux

$$\bullet \ d_{\mathrm{hai}}(n) = \sum_{k=0}^{K/2-1} \log_2 \left(\frac{|X(k,n)|}{|X(k,n-1)|} \right)$$

•
$$d_{\text{lar}}(n) = \sum_{k=k(f_{\text{min}})}^{\kappa=0} \sqrt{|X(k,n)|} - \sqrt{|X(k,n-1)|}$$

cosine distance

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complex

$$d_{\text{dux}}(n) = \sum_{k=0}^{K/2-1} |X(k,n) - X(k,n-1)|$$

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novelty function examples 3/3

- STFT-based cont'd
 - Goto-distance²
 - higher power than closest preceding and following bins

 $\begin{array}{c|c} & p(t+1,f) \\ & p(t,f) \\ & p(t,f) \\ & p(t+1,f) \\ & p(t+1,f) \\ & p(t+1,f) \\ & f \\ &$

²M. Goto and Y. Muraoka, "Music Understanding At The Beat Level Real-time Beat Tracking For Audio Signals," in *Proceedings of the Workshop on Computational Auditory Scene Analysis (IJCAI)*, Aug. 1995.

novelty function: variants



number of frequency bands

- varies: 1, 3, 6, 21, 960, FFT length, ...
- larger number of bands not necessarily better
 - ightarrow adjust number of bands adaptively?

combination of bands

- (weight and) add novelty functions per band
- onset detection per band and combine results

novelty function: variants



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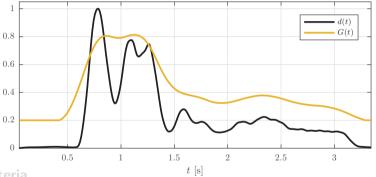
combination of bands

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peak picking: introduction

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detect onsets in the smoothed novelty function



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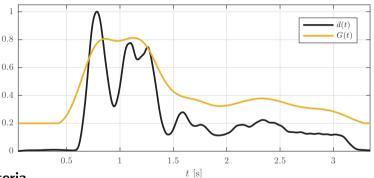
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onset detection

peak picking: introduction

detect onsets in the smoothed novelty function



- typical criteria
 - local maximum & salient peak
 - higher than minimum likelihood
 - not too close to maxima with higher likelihood
 - other options: high attack slope, distance to prev. min, ...

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- peak picking: thresholding
 - options for thresholding
 - fixed threshold

$$G_{d, ext{c}}=\lambda_1$$

smoothed threshold

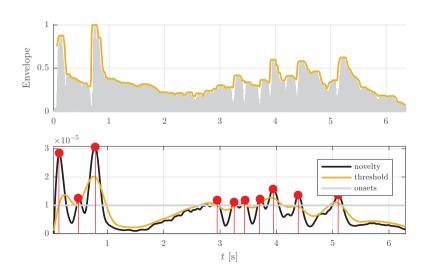
$$G_{d, ext{ma}} = \lambda_2 + \sum_{j=0}^{\mathcal{O}-1} b(j) \cdot d(i-j)$$

median threshold

$$G_{d,\mathrm{me}} = \lambda_2 + \hat{Q}_d(0.5)$$

peak picking: thresholding





summary

lecture content



novelty function

- measure of unexpectedness likelihood of an event
 - often a measure similar to flux

peak picking

- detecting peaks (onsets) in the novelty function
- usually done by smoothing and adaptive thresholding

