

Introduction to Audio Content Analysis

Module 9.3: Onset Detection

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introduction overview

corresponding textbook section

Section 9.3

■ 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



Module 9.3: Onset Detection

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Module 9.3: Onset Detection

onset detection problem statement

- onset: begin of musical event
- **goal**: detect the point in time of an onset
- challenges:
 - which time stamp of the initial attack time actually marks the onset time?
 - 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 onset time

■ note onset time:

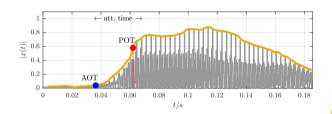
• time the instrument is triggered

■ acoustic onset time:

• time of first *measurable* instrument output

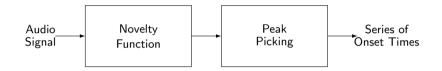
perceptual onset time:

• time the event is *perceived* by listener



onset detection overview

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novelty function

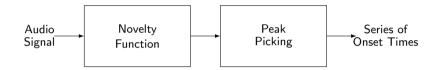
measure of probability for new events/signal change over time

2 peak picking

identify the most likely locations for onsets

onset detection overview





1 novelty function

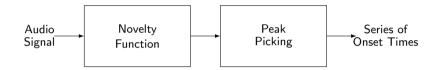
measure of probability for new events/signal change over time

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identify the most likely locations for onsets

onset detection overview





novelty function

measure of probability for new events/signal change over time

2 peak picking

• identify the most likely locations for onsets

- alternative **terms** for *novelty function*
 - detection function
 - difference function

processing steps

- 1 extract features
- 2 compute derivative
- 3 smooth result
- 4 apply Half-Wave-Rectification (HWR)

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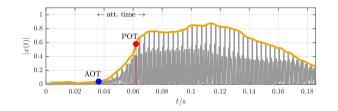
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1 time domain example

- feature: time domain envelope
- derivative: slope of envelope
 - HWR: only interested in onsets, not offsets



2 pitch domain:

- feature: pitch contour
- derivative: changes in pitch

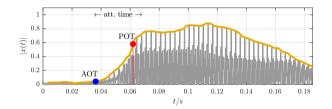
onset detection novelty function examples 1/3

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matlab source: plotOnset.m

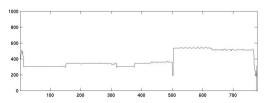
1 time domain example

- *feature*: time domain envelope
- derivative: slope of envelope
- *HWR*: only interested in onsets, not offsets



2 pitch domain:

- feature: pitch contour
- derivative: changes in pitch



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

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onset detection novelty function examples 2/3

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3 STFT-based: compute block difference

flux

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

- cosine distance
- complex

onset detection novelty function examples 2/3

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cosine distance

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onset detection novelty function examples 2/3

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

cosine distance

• complex

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

onset detection novelty function examples 3/3

3 STFT-based cont'd

- Goto-distance²
 - higher power than closest preceding and following bins

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

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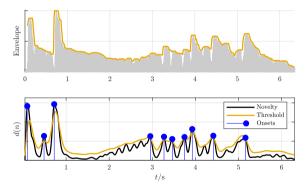
²M. Goto and Y. Muraoka, "Music Understanding At The Beat Level – Real-time Beat Tracking For Audio Signals," in *Proceedings of the Workshop on Computational Auditory Scene Analysis (IJCAI)*, Aug. 1995.

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.

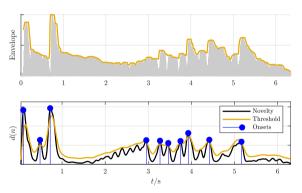


onset detection peak picking: introduction

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- other options: high attack slope, distance to prev. min, . . .



- options for thresholding
 - fixed threshold

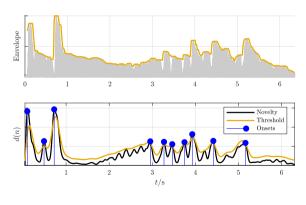
$$G_{d,c} = \lambda_1$$

smoothed threshold

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

median threshold

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



onset detection

■ goal

• compare a series of ground truth onset time stamps with a series of predicted time stamps

■ ground truth annotation problems

- deviations between annotators
- how to annotate quasi-synchronous onsets

metrics

- measure TP with tolerance range ⇒ TP, FN, FP (TN only implicitly)
- Precision, Recall, F-Measure
- other metrics
 - ► mean (absolute) deviation
 - standard deviation
 - max deviation

onset detection evaluation

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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

