Onset Detection

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MUMT501: Digital Signal Processing

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April 20, 2022

What is an Onset?

Attack: Temporal interval in which the amplitude envelope increases

Transient: Interval when the signal changes unpredictably before stabilizing (steady-state)

Onset: Instant in which the transient begins

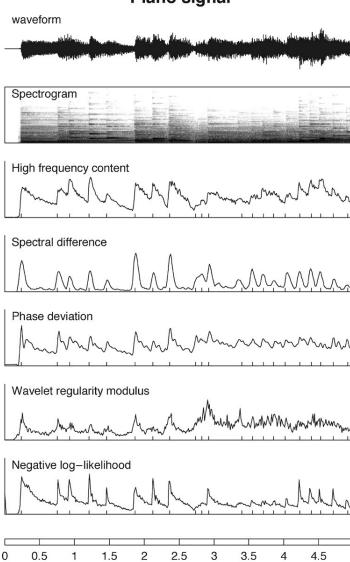
Elements of an Onset Detection Algorithm

- 1. Preprocessing
 - Optional, but yields better results (separate signal into multiple frequency bands, isolate the transient)
- 2. Reduction (Detection Function)
- 3. Postprocessing
- 4. Peak-picking

Reduction

- Subsample the signal and pass it through detection functions to find the onset
- Signal Features
 - Temporal characteristics (amplitude increase)
 - Spectral features (STFT)
 - Phase deviation
- Probabilistic Model
 - Sequential probability
 - "Surprises"
- Some work better for certain sounds

Piano signal



time (s)

Postprocessing and Peak-Picking

Postprocessing

- Improve detection function values for more accuracy in peak-picking
- Smooth through filtering, normalization

Peak-Picking

- Select peaks above threshold, use parabolic interpolation
- Can be further refined and pruned (ex.: adaptive thresholding)

Scherrer and Depalle: "Onset Time Estimation for the Exponentially Damped Sinusoids Analysis of Percussive Sounds"

- Goal: create an algorithm to detect onsets in pitched percussive sounds (ex.: piano, marimba)
- Detection Algorithms:
 - Frequency-domain detection function (rough estimate)
 - ► Start with STFT $X[l, b] = \sum_{n=0}^{N-1} w[n] x[n + lH] e^{\frac{j2\pi nb}{N}}$ with $b \in [0; N-1]$
 - ▶ Compare each STFT frame $d_f[l] = \sqrt{\sum_{b=0}^{\frac{N}{2}} (|X[l,b]| |X[l-1,b]|)^2}$
 - ▶ Time-domain detection function (refined estimate)
 - Make up for delay by performing detection a few hop sizes before each rough estimate

Scherrer and Depalle: "Onset Time Estimation for the Exponentially Damped Sinusoids Analysis of Percussive Sounds"

- Post-processing through zero-mean, normalizing, and smoothed with a normalized derivative filter
- \triangleright Peak-picking above threshold α dB
- Adaptive thresholding and pruning applied to peaks
 - Adaptive thresholding to set a minimum value for a threshold at a given index
 - Prune "repeated" onsets (i.e. onsets within a given number of samples)
- Algorithm tested on synthetic and real sounds

Variables for Rough and Refined Onsets

- ► N: FFT size
- ► *H*: Hop size
- ▶ *J*: Number of samples for Eq. 3
- \triangleright v: Regularization factor for Eq. 3
- γ : Coefficient for the normalized derivative filter at the post-processing stage
- τ : Absolute threshold for the adaptive threshold
- p: Order for the median filter
- ▶ l: Control for how much the median filtered function impacts the absolute threshold
- \triangleright α : Threshold for peak-finding using parabolic interpolation (in dB)
- ▶ *I*: Number of samples used for pruning repeated onsets

Defining the Parameters

Synthetic Sounds

Rough onsets	Refined onsets
N: 2048	J:200
H: 1024	$v: 10^{-4}$
$\gamma:0.3$	$\gamma:0.1$
$\tau : 0.1$	$\tau : 0.5$
p:5	p:5
$\ell: 0.5$	$\ell: 0.5$
α : 6dB	α : 6dB
I:900	I:900

Real Sounds (Guitar)

Rough onsets	Refined onsets
N: 1024	J:400
H:512	$v: 10^{-4}$
$\gamma:0.3$	$\gamma:0.1$
$\tau : 0.15$	$\tau : 0.5$
p:5	p: 5
$\ell: 0.5$	$\ell:0.5$
α : 6dB	α: 6dB
I: 2205	I:900

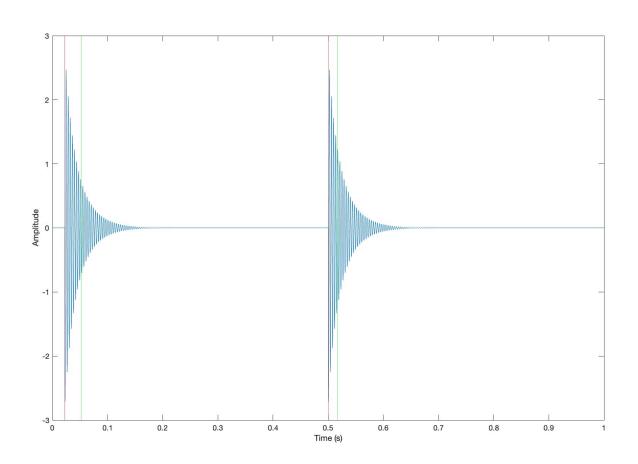
My Implementation: The Algorithm

- Recreated Scherrer and Depalle's algorithm in MATLAB
 - Equations detailed and each step outlined clearly
- ► Hanning window size for STFT → FFT size
- Pruning algorithm tricky to implement
 - Needed nested while loops for dynamic algorithm that adjusted as array changed size
- Sound files linked in the paper
 - Unfortunately, the music.mcgill.ca link is out of commission

My Implementation: Synthetic Sounds

- Used a combination of different exponentially damped sinusoids to create a signal with multiple partials and transients
- Created a signal with 5 partials
 - ▶ Frequencies chosen to recreate C4 piano note
 - ► Each partial: two EDS with slightly different values of A, a, f, and phi
 - Two transients
 - Make it easy to visually determine the onsets by the waveform (no noise added, no overlapping transients)

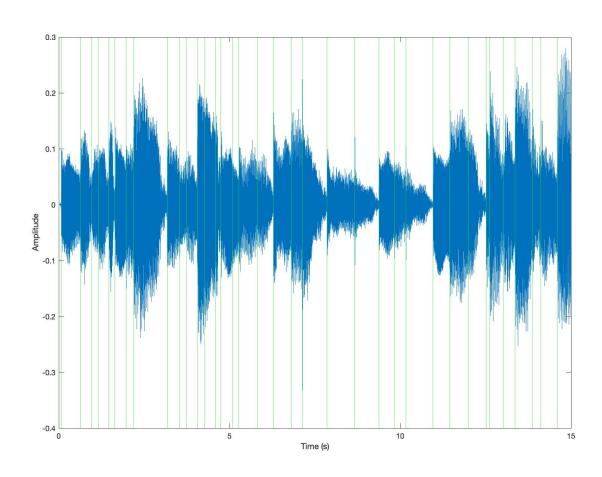
My Implementation: Synthetic Sound Results



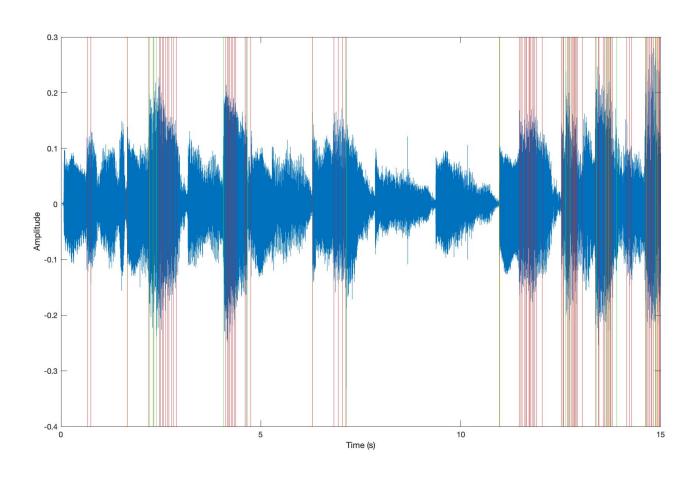
My Implementation: Real Sounds

- Used the sound file "guitar2.wav" from the Leveau dataset
 - External link mentioned briefly in the paper still worked!
 - Includes files with the correct onset annotations for easy answer-checking
- Paper didn't specify which sound file was used when tuning parameters
 - ► Expecting inaccuracies in results

My Implementation: Real Sounds Expectation



My Implementation: Real Sound Results



In Summary...

- Onset detection algorithms are built from a similar foundation and adjusted based on the type of sound
- We looked at a specific implementation designed for percussive sounds
- Paper was very helpful in recreating the algorithm structure and design
 - ► Couldn't access the specific synthetic sound files used
- Using paper parameters...
 - Accurate and reliable for synthetic sounds
 - Real sounds require extensive parameter tuning

References

- J.P. Bello, L. Daudet, S. Abdallah, C. Duxbury, M. Davies, and M.B. Sandler, "A Tutorial on Onset Detection in Music Signals," *IEEE Transactions on Speech and Audio Processing*, vol. 13, no. 5, Sep., pp. 1035-1047, 2005.
- B. Scherrer and P. Depalle, "Onset Time Estimation for the Exponentially Damped Sinusoids Analysis of Percussive Sounds," In Proc. of the 17th International Conference on Digital Audio Effects, 2014, pp. 1-7.
- S. Dixon, "Onset Detection Revisited," In Proc. of the 9th International Conference on Digital Audio Effects 2006, pp. 1-6.

Thank you!

Any questions?