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WaveBeat: End-to-end beat and downbeat tracking in the time domain



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Beat and downbeat tracking



Estimating a sequence of time instants that reflect how a human listener may tap along with a musical piece.

Deep learning-based beat tracking systems



Böck, Sebastian, Florian Krebs, and Gerhard Widmer. "Joint Beat and Downbeat Tracking with Recurrent Neural Networks." ISMIR. 2016. Matthew E. P. Davies and Sebastian Böck. "Temporal convolutional networks for musical audio beat tracking." EUSIPCO. 2019.

Spectral vs. Time domain



- Considers only spectral magnitude (and ignores phase)
- Subsampling (pooling) spectral frames discards temporal information

Time domain approaches (phase information) was used in traditional beat tracking systems, so why not have an **end-to-end time domain beat tracking** model?

Time domain architecture for beat (downbeat) tracking



- Often requires receptive field of over 30 seconds
- Equates to over **1/2 million time steps** at 22.05 kHz
- Most time domain models have a receptive field of around a few seconds at most

We use a TCN (feedforward WaveNet) with **rapidly** growing dilation factors for a large receptive field.

WaveBeat Architecture



Architecture

Convolutional block

- Residual 1D convolutional layers (kernel=15)
- Use stride=2 to downsample in time
- Batch normalization for stability
- PReLU (learnable activation function)





Architecture

TCN Stack

- Each TCN stack is composed of 4 blocks
- Convolutional channels increases by 32 at each block (more parameters, deeper)
- Dilation increases by factor of 8ⁿ (1, 8, 64, 512)
- This pattern repeats at each stack





Architecture

Complete WaveBeat

- Complete architecture is composed of -2 stacks (total of 8 layers)
- Final 1x1 convolution downmixes channels to 2 outputs (beat and downbeat activations)
- Sigmoid forces outputs between 0 and 1 -

001000100010001



Use BCE loss where target is 1 at beat location and 0 elsewhere.





Training & Experiments

- WaveBeat with 8 layers and 2.9 M parameters
- Receptive field of over **1 million time steps** (~47 sec)
- Train for 100 epochs (1 epoch = 1000 segments 1.6 min long)
- Use Adam optimizer and learning rate 1e-3
- Decrease learning rate on plateau after 10 epochs (F-Measure)
- Model operates on waveforms with 22.05 kHz sample rate

Training datasets

- .5 11010
- Beatles
- Hainsworth
- Ballroom
- RWC Popular

Held-out test sets

- GTZAN
- SMC

Data augmentation

- additive white noise (p = 0.05)
- tanh nonlinearity (p = 0.2)
- random phase inversion (*p* = 0.5)
- highpass and lowpass filters with random cutoff frequencies (*p* = 0.25)
- random pitch shifting between -8 and 8 semitones (p = 0.5)
- shifting the beat locations by a random amount between \pm 70 ms (p = 0.3)
- dropping block of audio and beats no more than 10% of the input (p = 0.05)

Time domain beat tracking is competitive

			Beat			Downbeat		
Dataset	Size	Model	F-measure	CMLt	AMLt	F-measure	CMLt	AMLt
		Spectral TCN [15]	0.962	0.947	0.961	0.916	0.913	0.960
Ballroom	5 h 57 m	WaveBeat (Peak)	0.961	0.929	0.929	0.904	0.762	0.803
		WaveBeat (DBN)	0.925	0.829	0.937	0.953	0.916	0.941
		Spectral TCN [15]	0.902	0.848	0.930	0.722	0.696	0.872
Hainsworth	3 h 19 m	WaveBeat (Peak)	0.965	0.937	0.937	0.912	0.748	0.843
		WaveBeat (DBN)	0.973	0.976	0.976	0.954	0.886	0.970
		Spectral TCN [15]	-	-	-	0.837	0.742	0.862
Beatles	8 h 09 m	WaveBeat (Peak)	0.887	0.733	0.790	0.689	0.327	0.585
		WaveBeat (DBN)	0.929	0.894	0.894	0.732	0.509	0.724
GTZAN	8 h 20 m	Spectral TCN [15]	0.885	0.813	0.931	0.672	0.640	0.832
		WaveBeat (Peak)	0.825	0.682	0.767	0.563	0.279	0.515
		WaveBeat (DBN)	0.828	0.719	0.860	0.598	0.503	0.764
SMC	2 h 25 m	Spectral TCN [15]	0.544	0.443	0.635	-	-	-
		WaveBeat (Peak)	0.403	0.163	0.255	-	-	-
		WaveBeat (DBN)	0.418	0.280	0.419	-	-	-

- WaveBeat sometimes outperforms Spectral TCN but other times doesn't
- The benefit of the DBN is clear, sometimes it helps, sometimes not.

Improving time domain beat tracking

Time domain models are data hungry



- More data augmentations

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- Which augmentations change the audio without hurting performance?
- Semi/Self-supervised learning
 - Can we create "noisy" beat annotations from large music corpora
 - Pre-train a large time domain model with this data
 - Then fine-tune the model on our human labeled beat tracking datasts

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https://github.com/csteinmetz1/wavebeat



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