# Beat detection and BPM tempo estimation

In this tutorial, we will show how to perform automatic beat detection (https://en.wikipedia.org/wiki/Beat\_detection) (beat tracking) and tempo (BPM) (https://en.wikipedia.org/wiki/Tempo) estimation using different algorithms in Essentia.

## RhythmExtractor2013 & &

We generally recommend using RhythmExtractor2013

(https://essentia.upf.edu/reference/std\_RhythmExtractor2013.html) for beat and tempo estimation. This a wrapper algorithm providing two approaches, slower and more accurate multifeature vs. faster degara, using the auxiliary BeatTrackerMultiFeature

(https://essentia.upf.edu/reference/std\_BeatTrackerMultiFeature.html) and BeatTrackerDegara (https://essentia.upf.edu/reference/std\_BeatTrackerDegara.html) for beat position estimation, respectively.

The RhythmExtractor2013 algorithm outputs the estimated tempo (BPM), time positions of each beat, and confidence of their detection (in the case of using multifeature). In addition, it outputs the list of BPM estimates and periods between consecutive beats throughout the entire input audio signal. The algorithm relies on statistics gathered over the whole music track, and therefore it is not suited for real-time detection.

Similarly to our *onset detection tutorial*, to sonify the results, we mark the estimated beat positions in the audio, using AudioOnsetsMarker

(http://essentia.upf.edu/documentation/reference/std\_AudioOnsetsMarker.html). To save the audio to a file, we use MonoWriter (https://essentia.upf.edu/reference/std\_MonoWriter.html). Consult that tutorial for more details.

```
import essentia.standard as es
from tempfile import TemporaryDirectory
# Loading an audio file.
audio = es.MonoLoader(filename='../../test/audio/recorded/dubstep.flac')()
# Compute beat positions and BPM.
rhythm extractor = es.RhythmExtractor2013(method="multifeature")
bpm, beats, beats confidence, , beats intervals = rhythm extractor(audio)
print("BPM:", bpm)
print("Beat positions (sec.):", beats)
print("Beat estimation confidence:", beats confidence)
# Mark beat positions in the audio and write it to a file.
# Use beeps instead of white noise to mark them, as it is more distinctive.
marker = es.AudioOnsetsMarker(onsets=beats, type='beep')
marked audio = marker(audio)
# Write to an audio file in a temporary directory.
temp dir = TemporaryDirectory()
es.MonoWriter(filename=temp_dir.name + '/dubstep_beats.flac')(marked_audio)
```

```
BPM: 139.98114013671875

Beat positions (sec.): [0.42956915 0.8591383 1.3003174 1.7182766 2.1478457 2.577415 2.9953742 3.4249432 3.8661225 4.2956915 4.7252607 5.15483 5.584399 6.013968 6.431927 ]

Beat estimation confidence: 3.9443612098693848
```

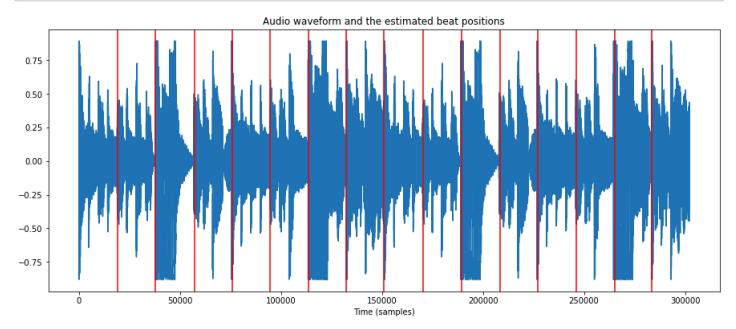
We can now listen to the resulting audio with the beats marked by beeps. We can also visualize beat estimations.

```
import IPython
IPython.display.Audio(temp_dir.name + '/dubstep_beats.flac')
```

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```
from pylab import plot, show, figure, imshow
%matplotlib inline
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (15, 6)

plot(audio)
for beat in beats:
    plt.axvline(x=beat*44100, color='red')
plt.xlabel('Time (samples)')
plt.title("Audio waveform and the estimated beat positions")
show()
```



#### **BPM** histogram

The BPM value output by RhythmExtactor2013 is the average of all BPM estimates done for each interval between two consecutive beats. Alternatively, we can analyze the distribution of all those intervals using BpmHistogramDescriptors

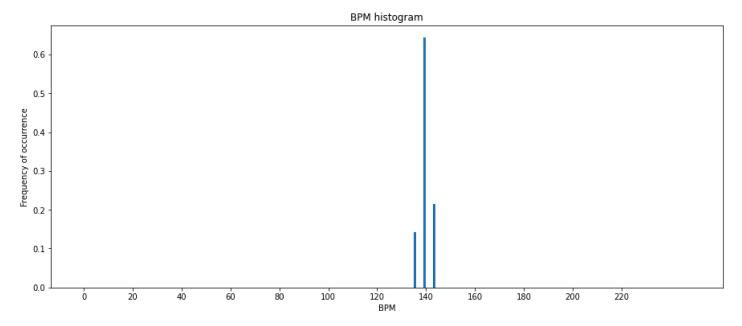
(http://essentia.upf.edu/documentation/reference/std\_BpmHistogramDescriptors.html). This is especially useful for music with a varying tempo (which is not the case in our example).

```
peak1_bpm, peak1_weight, peak1_spread, peak2_bpm, peak2_weight, peak2_spread, histogram = \
    es.BpmHistogramDescriptors()(beats_intervals)

print("Overall BPM (estimated before): %0.1f" % bpm)
print("First histogram peak: %0.1f bpm" % peak1_bpm)
print("Second histogram peak: %0.1f bpm" % peak2_bpm)

fig, ax = plt.subplots()
ax.bar(range(len(histogram)), histogram, width=1)
ax.set_xlabel('BPM')
ax.set_ylabel('Frequency of occurrence')
plt.title("BPM histogram")
ax.set_xticks([20 * x + 0.5 for x in range(int(len(histogram) / 20))])
ax.set_xticklabels([str(20 * x) for x in range(int(len(histogram) / 20))])
plt.show()
```

```
Overall BPM (estimated before): 140.0
First histogram peak: 140.0 bpm
Second histogram peak: 0.0 bpm
```



## BPM estimation with PercivalBpmEstimator

PercivalBpmEstimator (https://essentia.upf.edu/reference/std\_PercivalBpmEstimator.html) is another algorithm for tempo estimation.

```
# Loading an audio file.
audio = es.MonoLoader(filename='../../test/audio/recorded/dubstep.flac')()
# Compute BPM.
bpm = es.PercivalBpmEstimator()(audio)
print("BPM:", bpm)
```

BPM: 140.14830017089844

#### BPM estimation for audio loops

The BPM detection algorithms we considered so far won't necessarily produce the best estimation on short audio inputs, such as audio loops used in music production. Still, it is possible to apply some post-processing heuristics under the assumption that the analyzed audio loop is expected to be well-cut.

We have developed the LoopBpmEstimator

(https://essentia.upf.edu/reference/std\_LoopBpmEstimator.html) algorithm specifically for the case of short audio loops. Based on PercivalBpmEstimator, it computes the likelihood of the correctness of BPM predictions using the duration of the audio loop as a reference.

```
# Our input audio is indeed a well-cut loop. Let's compute the BPM.
bpm = es.LoopBpmEstimator()(audio)
print("Loop BPM:", bpm)
```

Loop BPM: 140.0

#### **BPM** estimation with TempoCNN

Essentia supports inference with TensorFlow models for a variety of MIR tasks, in particular tempo estimation, for which we provide the TempoCNN models.

The TempoCNN (https://essentia.upf.edu/reference/std\_TempoCNN.html) algorithm outputs a global BPM estimation on the entire audio input as well as local estimations on short audio segments (patches) throughout the track. For local estimations, it provides their probabilities that can be used as

a confidence measure.

To use this algorithm in Python, follow our instructions for using TensorFlow models (https://essentia.upf.edu/machine\_learning.html#using-pre-trained-tensorflow-models).

To download the model:

song BPM: 125.0

```
!curl -SLO https://essentia.upf.edu/models/tempo/tempocnn/deeptemp-k16-3.pb
 % Total
            % Received % Xferd Average Speed
                                               Time
                                                      Time
                                                               Time Current
                               Dload Upload
                                              Total
                                                      Spent
                                                               Left Speed
                                          0 --:--:- 8829k
100 1289k 100 1289k
                            0 8829k
import essentia.standard as es
sr = 11025
audio 11khz = es.MonoLoader(filename='../../test/audio/recorded/techno loop.wav', sampleRate=sr)(
global bpm, local bpm, local probs = es.TempoCNN(graphFilename='deeptemp-k16-3.pb')(audio 11khz)
print('song BPM: {}'.format(global bpm))
```

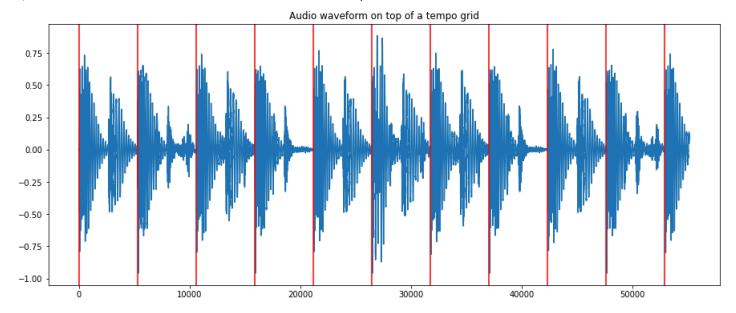
We can plot a slice of the waveform on top of a grid with the estimated tempo to get visual verification

```
import numpy as np

duration = 5 # seconds
audio_slice = audio_11khz[:sr * duration]

plt.plot(audio_slice)
markers = np.arange(0, len(audio_slice), sr / (global_bpm / 60))
for marker in markers:
    plt.axvline(x=marker, color='red')

plt.title("Audio waveform on top of a tempo grid")
show()
```



TempoCNN operates on audio slices of 12 seconds with an overlap of 6 seconds by default. Additionally, the algorithm outputs the local estimations along with their probabilities. The global value is computed by majority voting by default. However, this method is only recommended when a constant tempo can be assumed.

```
print('local BPM: {}'.format(local_bpm))
print('local probabilities: {}'.format(local_probs))
```

local BPM: [125. 125. 125.] local probabilities: [0.9679363 0.9600502 0.9681525 0.9627014]

#### Contact

Contact MTG (https://www.upf.edu/web/mtg/contact)
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