



music genre recognition

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systems in motion

- ▷ music genre recognition by analysis of texture
- ▷ kyrah's masters thesis at fh hagenberg
- ▷ system for the automatic recognition of music genres, based only on the sound signal
- ▷ no meta-data, no DB lookup, . . . only based on sound properties
- ▷ question: how do you do it?

two steps:

- ▷ feature extraction
calculate numerical representation of audio data
choosing the right features is crucial!
- ▷ classification
use output of feature extraction as basis for classification

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- ▷ use information available in sound signal

music files cannot be compared directly
instead: calculate feature representation, i.e.
essential information needed to differentiate classes

“feature vector” – point in n-dimensional space
classification based on distance

features used in mugrat:

- ▷ music texture features (short-time spectral change)
- ▷ beat-related features (rhythm and beatedness)

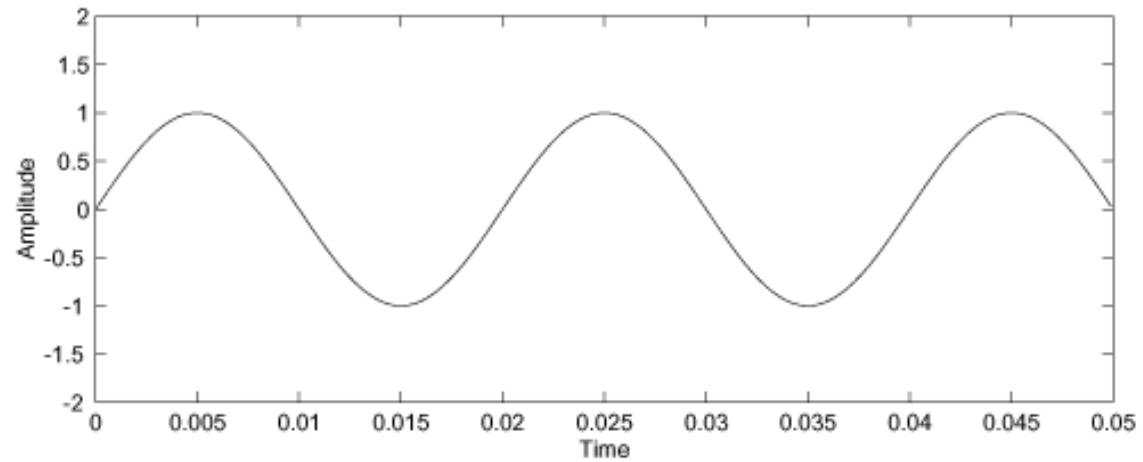
spectral attributes;
mean and variance to capture short-time spectral change

- ▷ spectral centroid
- ▷ rolloff
- ▷ flux
- ▷ zero-crossing rate

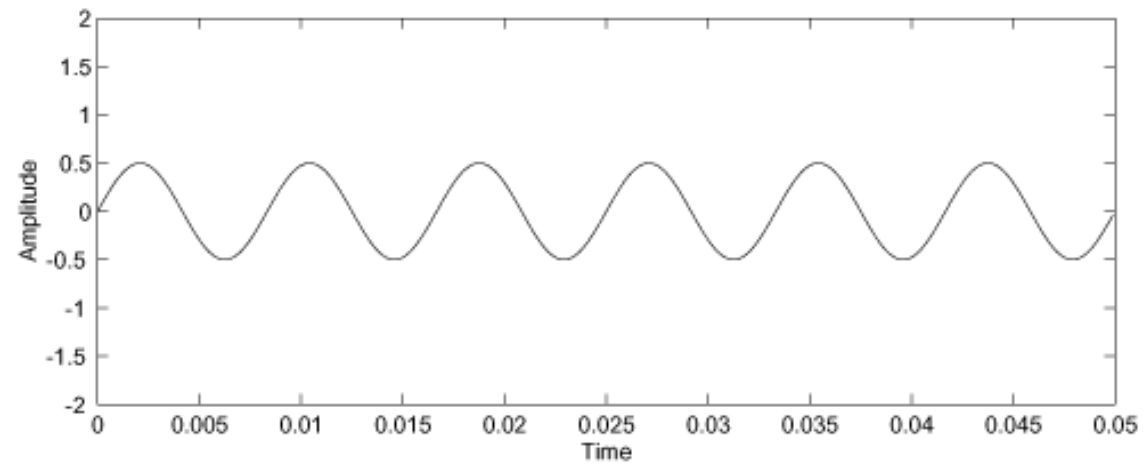
feature set based on:

George Tzanetakis, Georg Essl, and Perry Cook. Automatic Musical Genre Classification of Audio Signals. In: Proceedings International Symposium for Audio Information Retrieval (ISMIR), Princeton, N.J., October 2001.

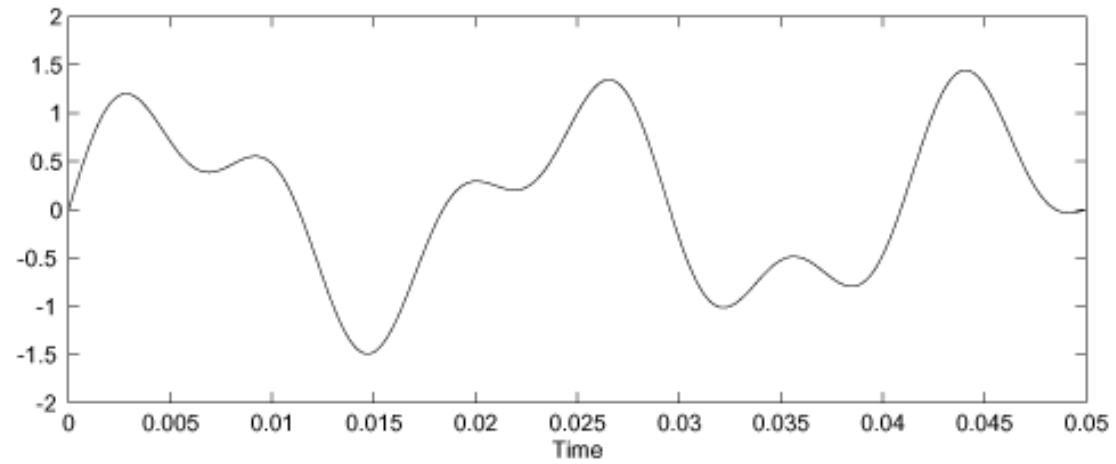
[background :: sine superposition :: $a = \sin(2\pi 50t)$]



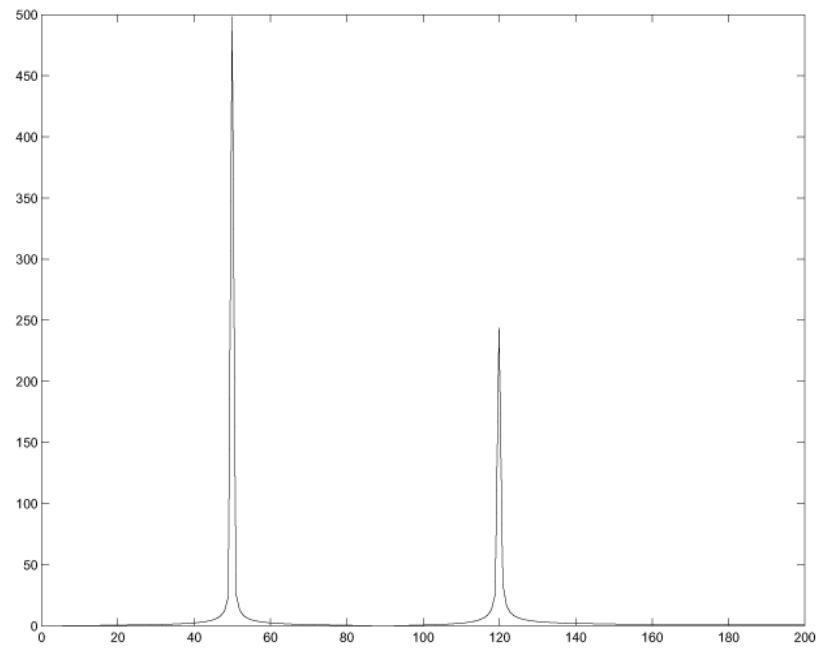
[background :: sine superposition :: $b = 0.5 \sin(2\pi 120t)$]



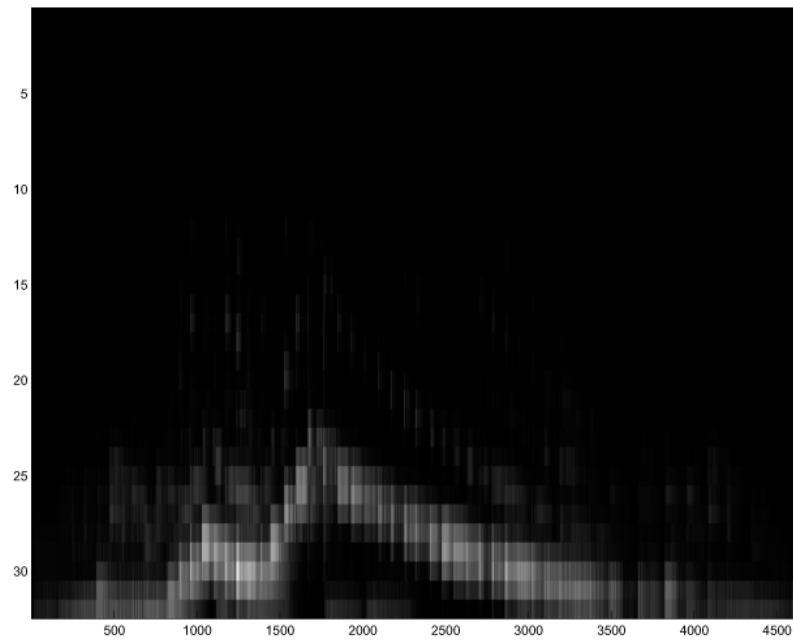
[background :: sine superposition :: $c = a + b$]



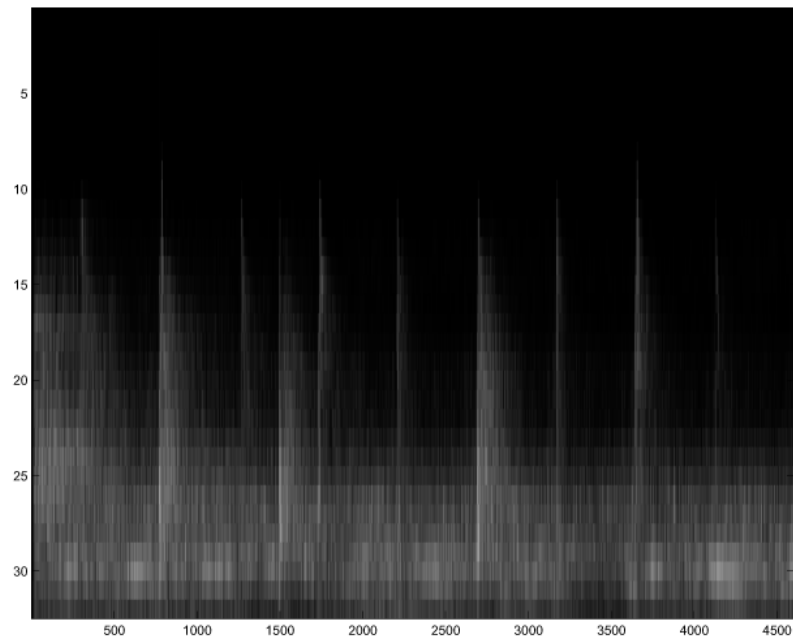
[background :: fourier analysis]



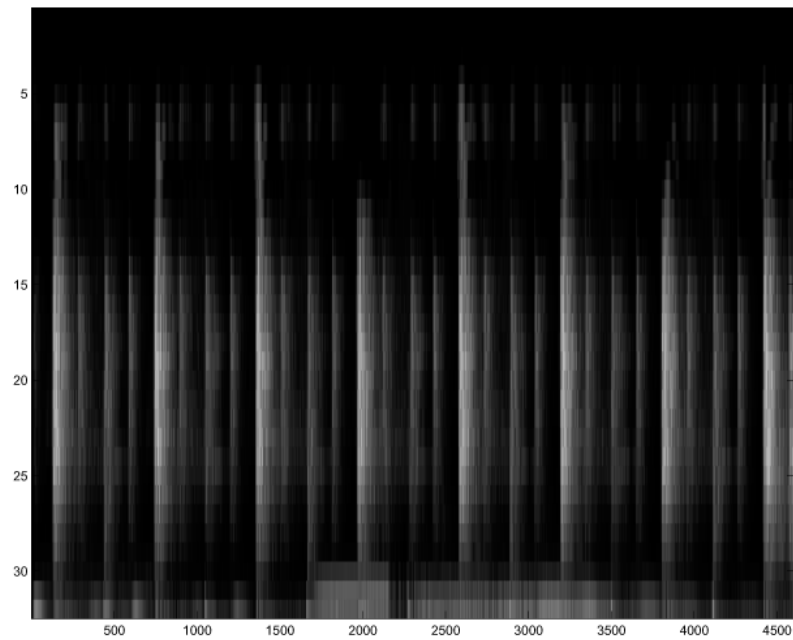
[classical spectrogram]



[metal spectrogram]



[dance spectrogram]



▷ spectral centroid

balancing point of spectrum
measure of spectral shape
associated with spectral brightness

$$C = \frac{\sum_{n=1}^N M_t[n] \cdot n}{\sum_{n=1}^N M_t[n]}$$

▷ rolloff

measure of spectral shape
frequency R corresponding to
 $r\%$ of the magnitude distribution, so that

$$\sum_{n=1}^R M_t[n] = r \cdot \sum_{n=1}^N M_t[n]$$

in mugrat prototype $r = 80\%$

▷ flux

measure of local spectral change

$$F = \sum_{n=1}^N (N_t[n] - N_{t-1}[n])^2$$

▷ zero-crossing rate

zero-crossing:

successive samples in a digital signal have different signs

measure of the noisiness of a signal

time domain feature!

$$Z = \sum_{n=1}^N |s(x[n]) - s(x[n - 1])|$$

DWT, envelope extraction, autocorrelation, beat histogram generation:
main beat (strength and BPM), second-strongest beat, relationship of these two, general beatedness

- ▷ relative amplitude
of first and second beat histogram peak
- ▷ ratio of amplitude second peak / first peak
- ▷ period of the first and second peak in BPM
- ▷ sum of the histogram
(indication of beat strength)

genres defined in terms of typical members
do i know songs that sound like this one?

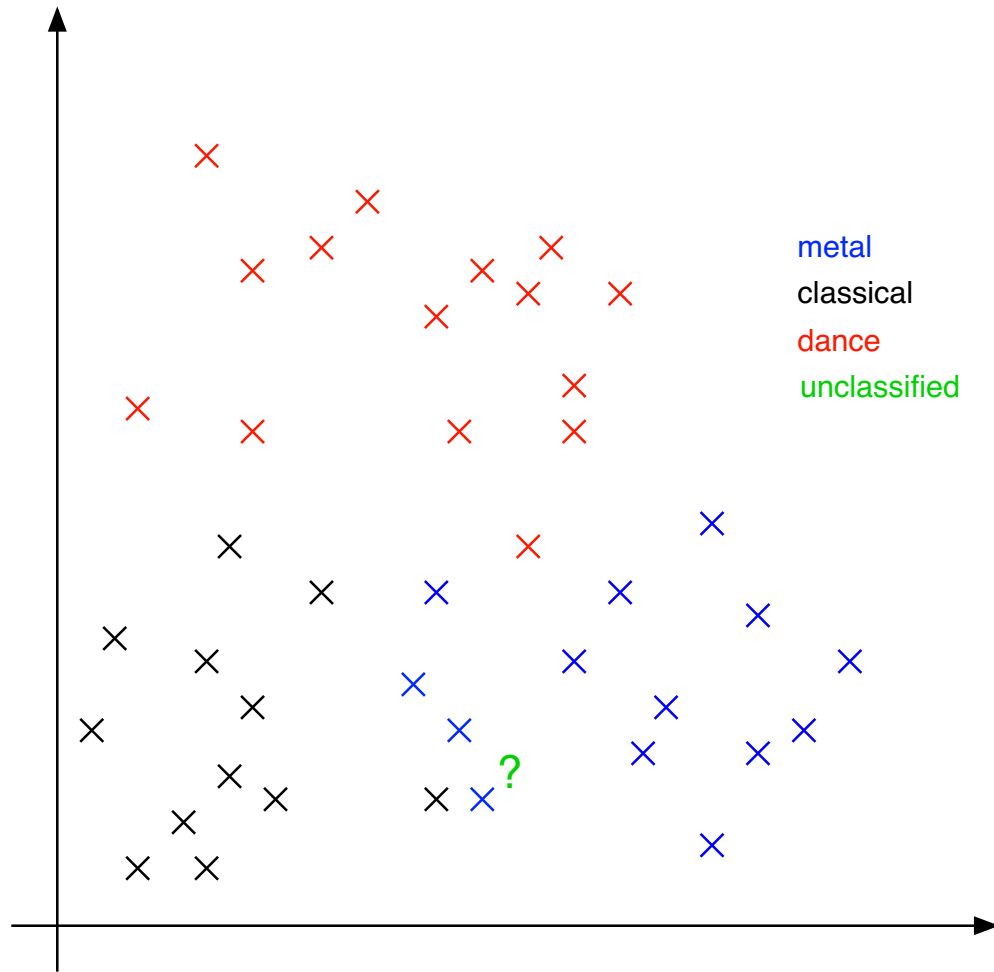
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k-nearest-neighbour classification:
data items == points in feature space
labels of songs that are close to test instance,
weighted by distance



3 genres:

- ▷ metal
- ▷ dance
- ▷ classical

189 test songs (63, 65, 61)

88.36% accuracy

remember:

information is not knowledge; knowledge is not wisdom;
wisdom is not truth; truth is not beauty; beauty is not love;
love is not music; music is the best

(frank zappa)

