Metrical Analysis of Music Signals

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What's the song?

- rhythm is essential to music

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What's the song?

- rhythm is essential to music
- *pulse* and *meter* characteristics are very robust to signal transformation
  - transformed
  - original

Objective of this presentation

- Give a general overview about the metrical analysis of music signals as well as some research axis of my PhD work

Presentation content

- Introduction
- Beat-tracking model
- Performance analysis
- Conclusions

Introduction

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- metrical analysis is an essential part of this field
  - important for many audio applications
    - rhythm alignement of musical instruments
    - cut and paste operations in audio editing
    - MIR
    - music transcription
    - special effects

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- metrical analysis is an essential part of this field
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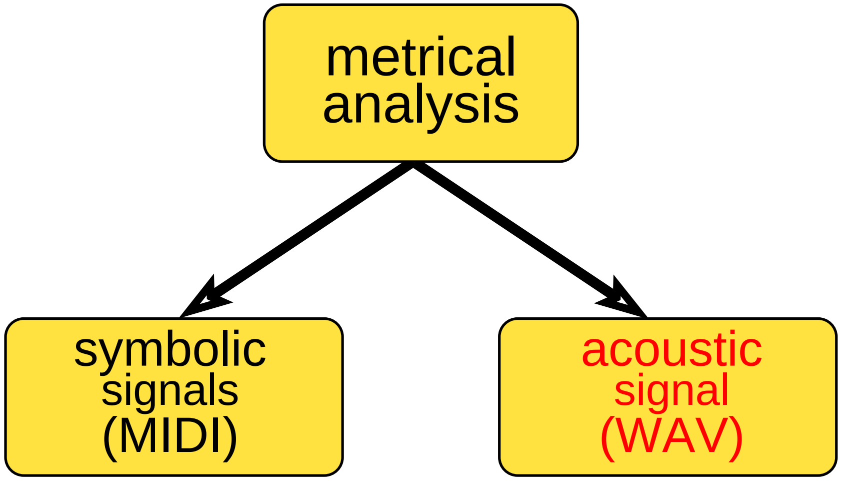
  - our approach deals with music recordings



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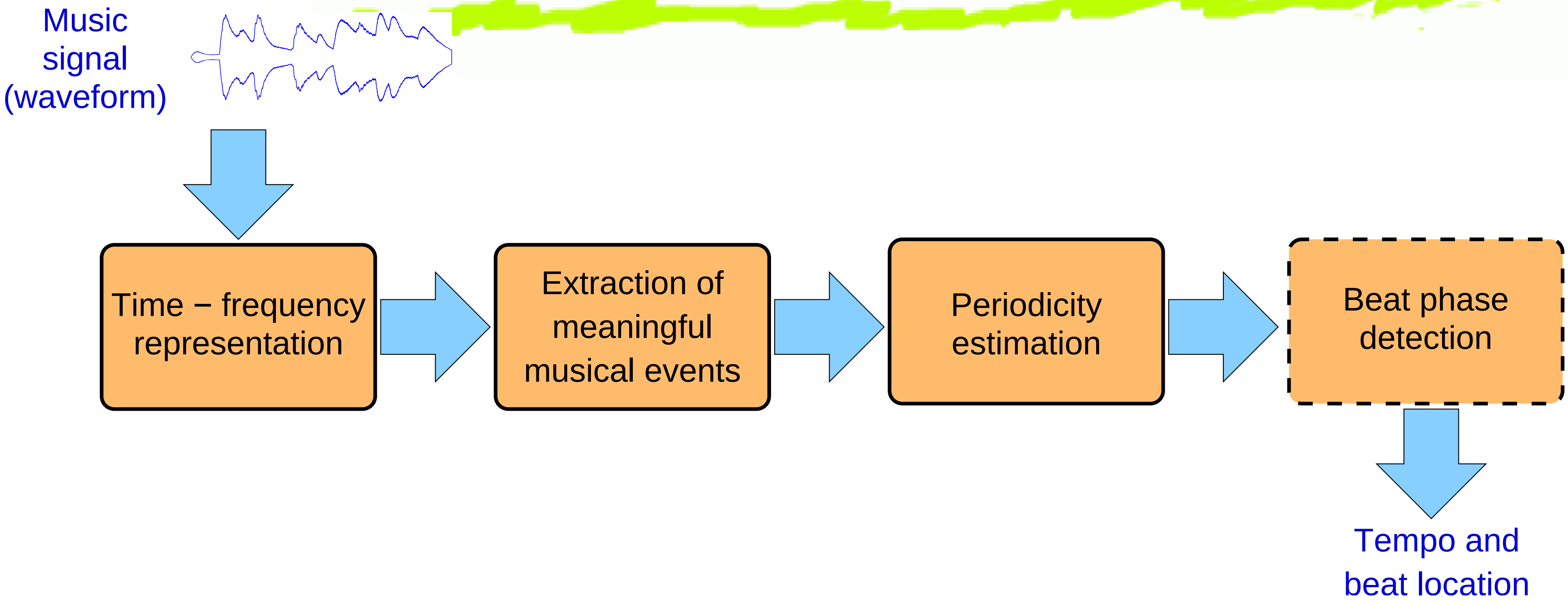
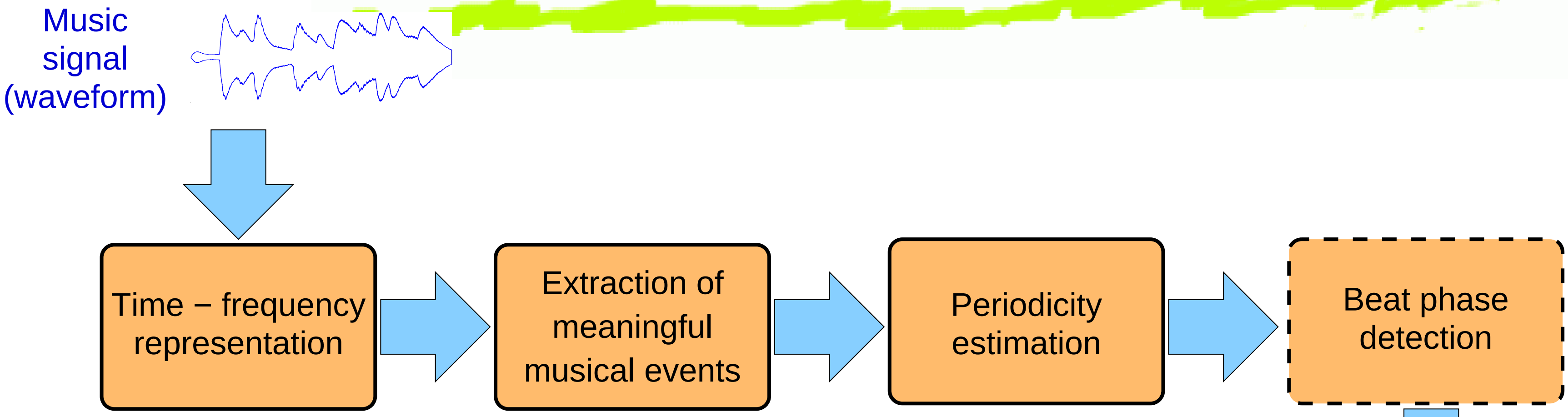
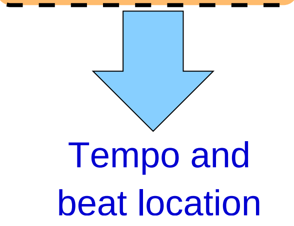
- the proposed system aims at various musical genres
- most algorithms are based on the same general architecture

General architecture



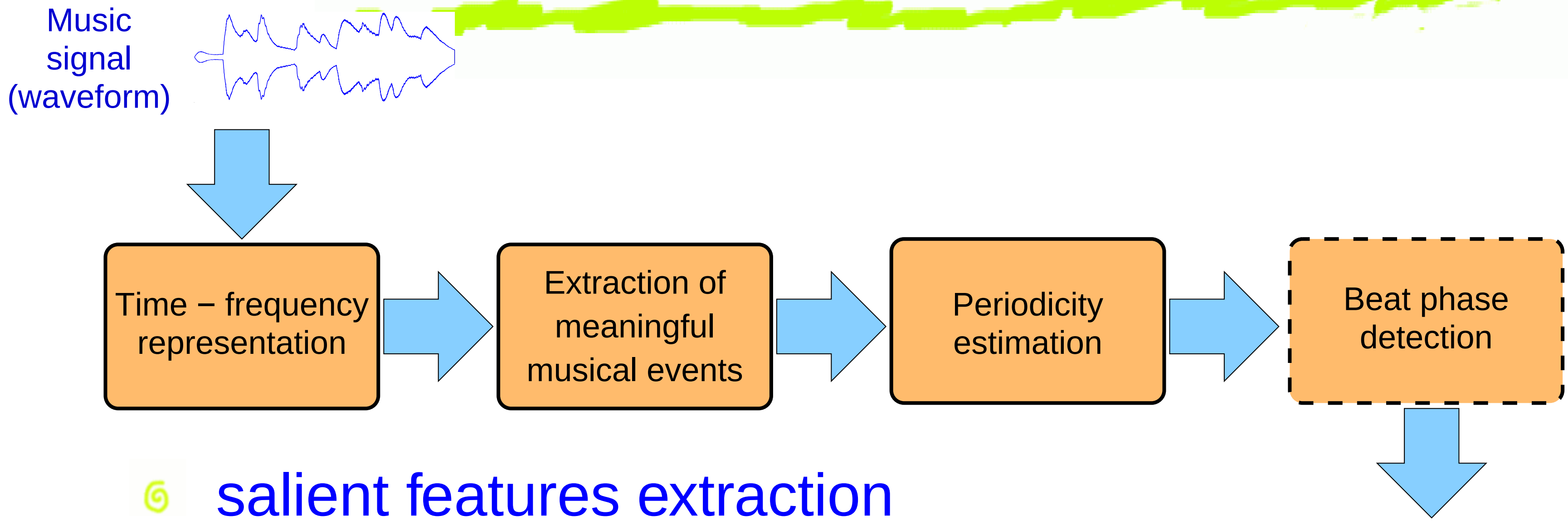
General architecture





- time-frequency representation
  - filter banks
  - STFT
  - wavelets
  - matching pursuit
  - parametric models
  - Wigner-Ville

General architecture



- salient features extraction
  - energy content
  - high-frequency content
  - spectral difference
  - phase stability
  - probabilistic models
  - SVM
  - ICA

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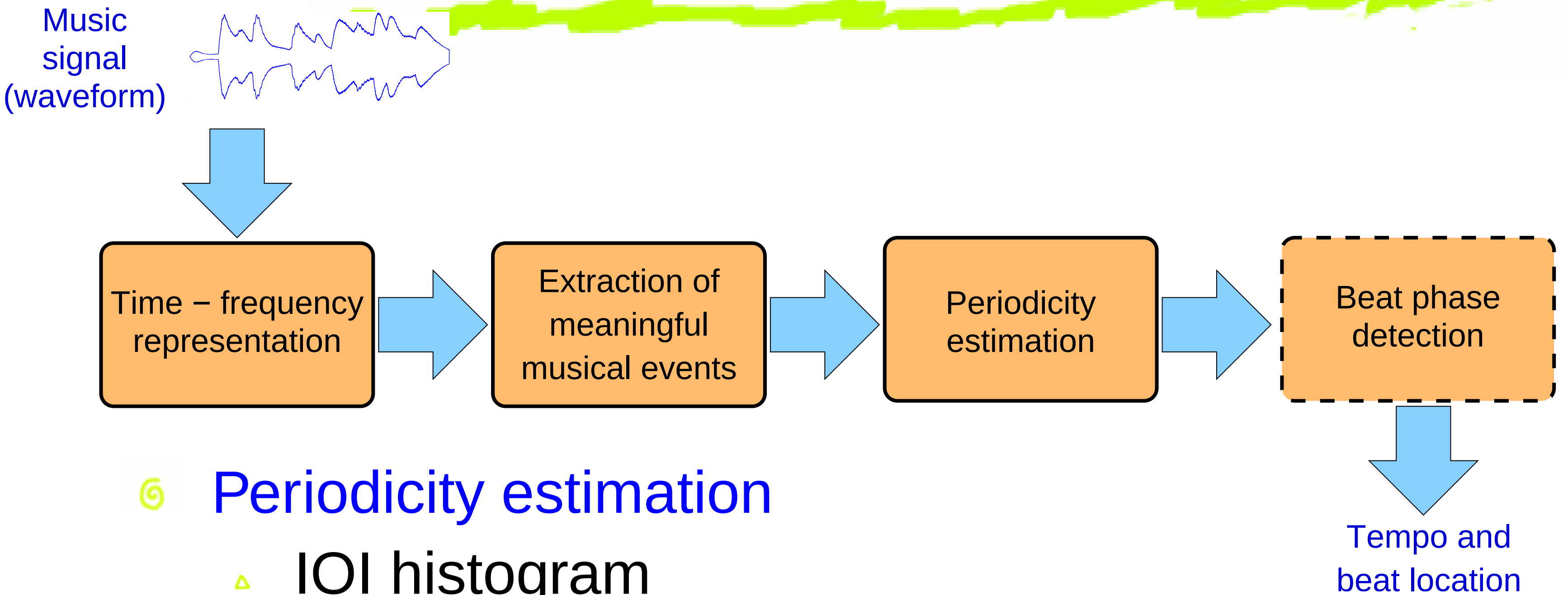
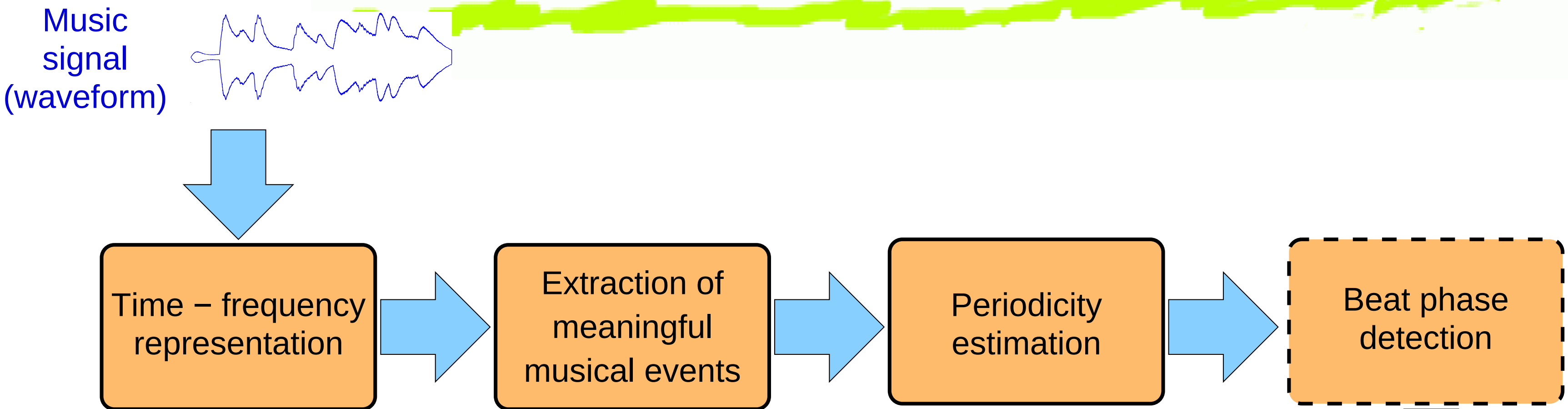


Periodicity estimation

- IOI histogram
- pitch estimation methods (ACF, spectral product, YIN, etc.)
- bank of *comb filter resonators*
- probabilistic models (GMM, bayesian neworks)
- resonators based on neural networks
- periodicity transform

General architecture



- Beat phase detection
  - cross-correlation with a pulse-train
  - pick-picking

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  - the residual part was computed using a *noise subspace projection* approach
  - the audio signal is modeled as:

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  - if cannot be modeled as a complex exponential (i.e., onsets, attacks) it is considered as the *residual*

Harmonic plus noise decomposition

- piano example original and residual
- french horn example original and residual
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  - much more precise than Fourier analysis
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  - very robust to high noise levels
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  - not required to subtract the sinusoids
  - very computationally demanding
  - the *model order* must be well estimated

detection of salient features

- what is a *salient feature*?

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  - those timepoints where there is a marked change in any of the perceived psychoacoustical properties of sound, i.e., *loudness, timbre and pitch*
- robust detection for polyphonic music is a difficult task
- motivated by previous work, we define the *Spectral Energy Flux (SEF)* $E(f, k)$ of an audio signal

Spectral energy flux (1/2)

- Piano example

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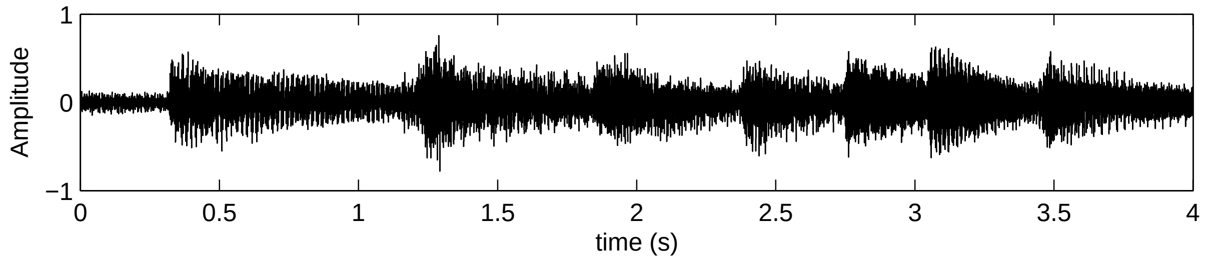

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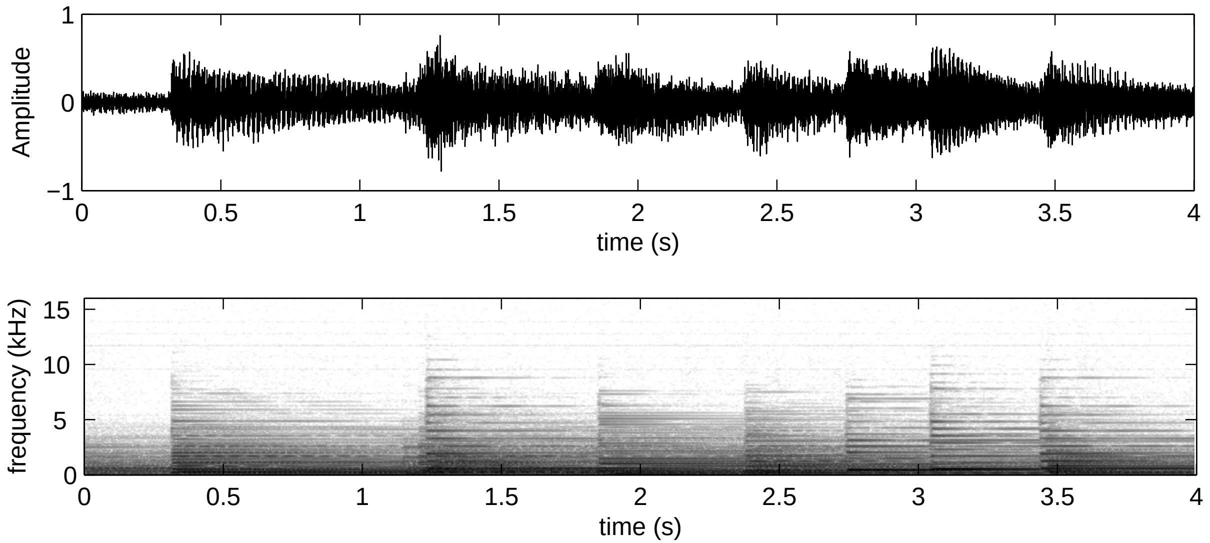

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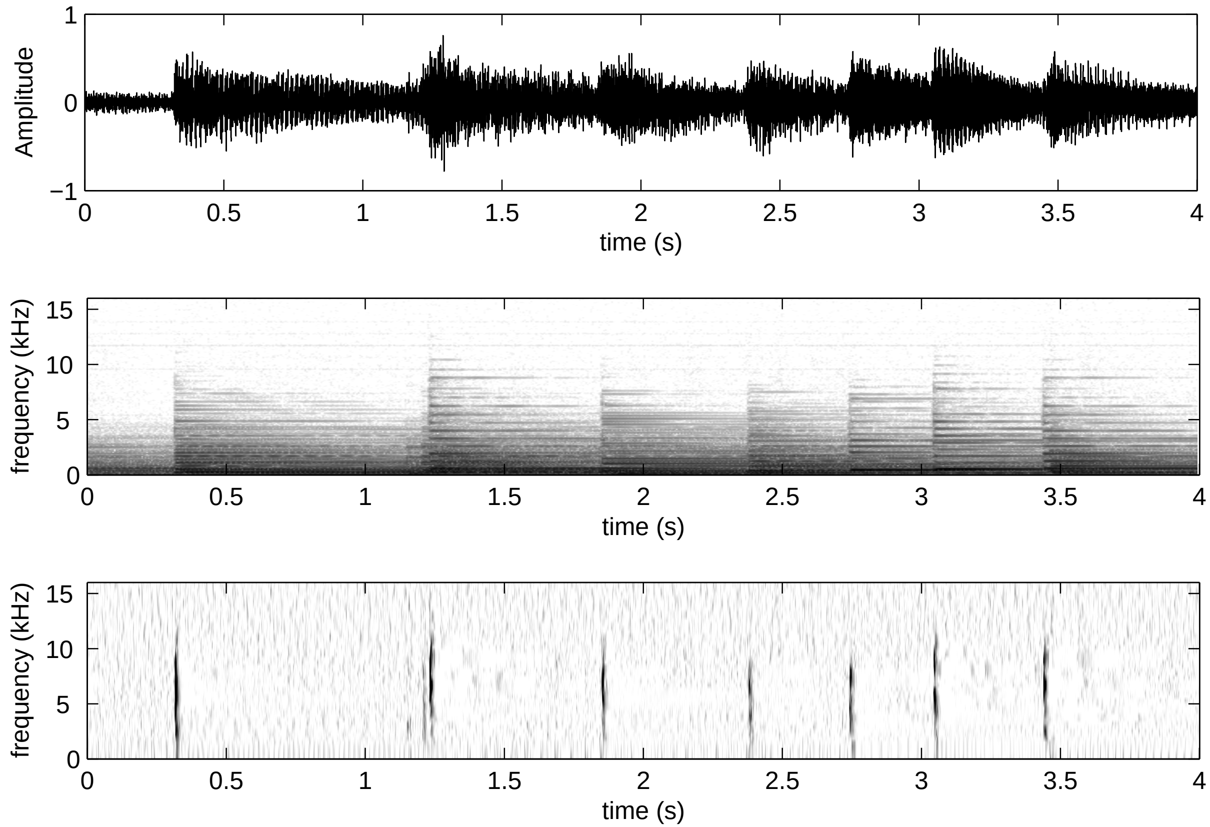

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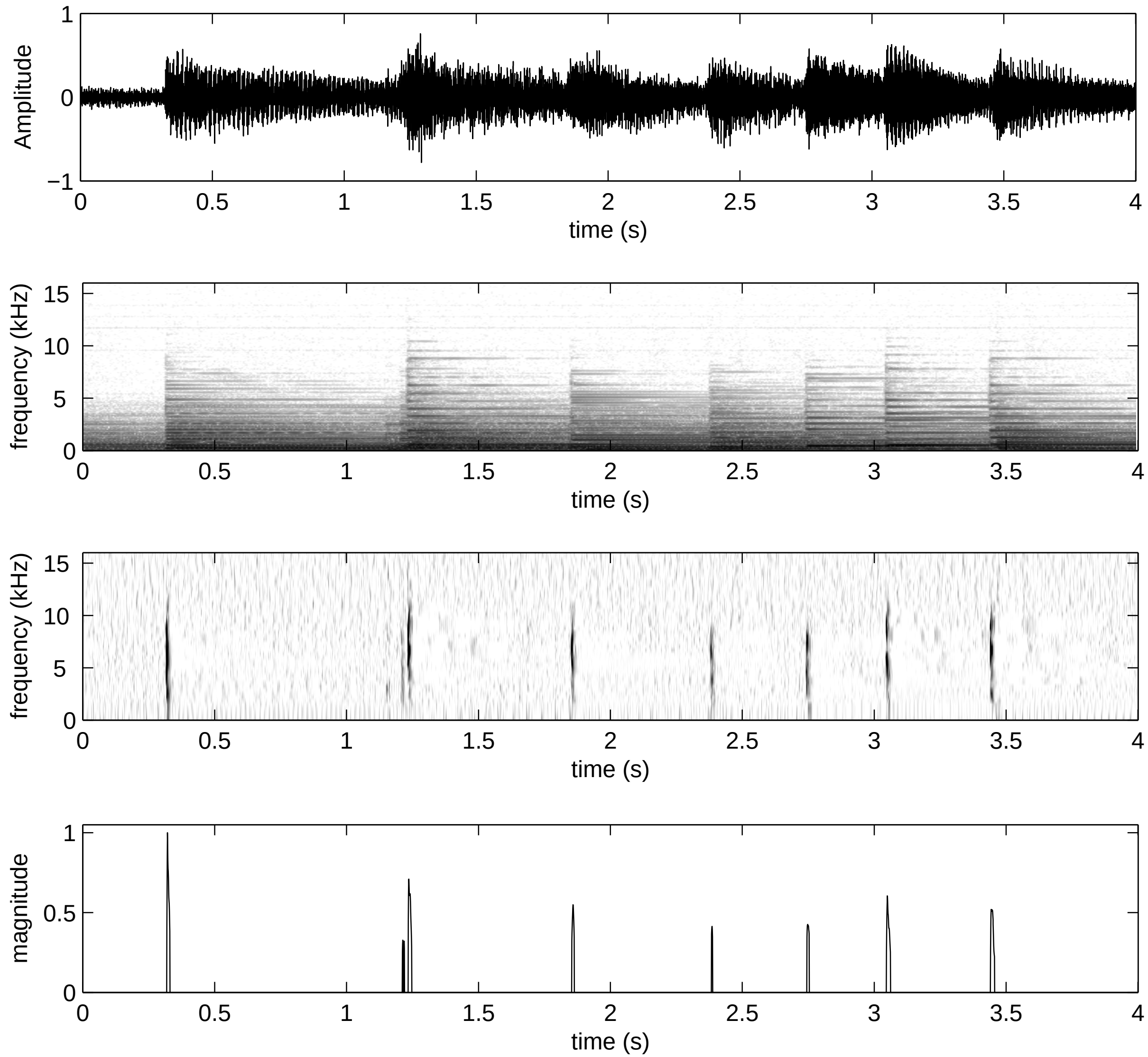

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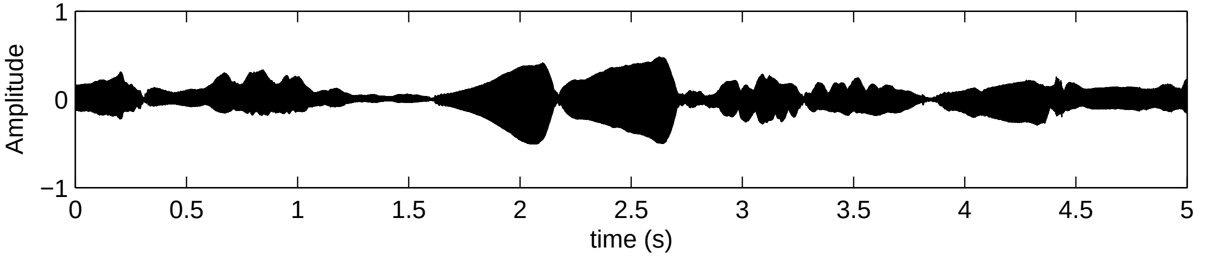

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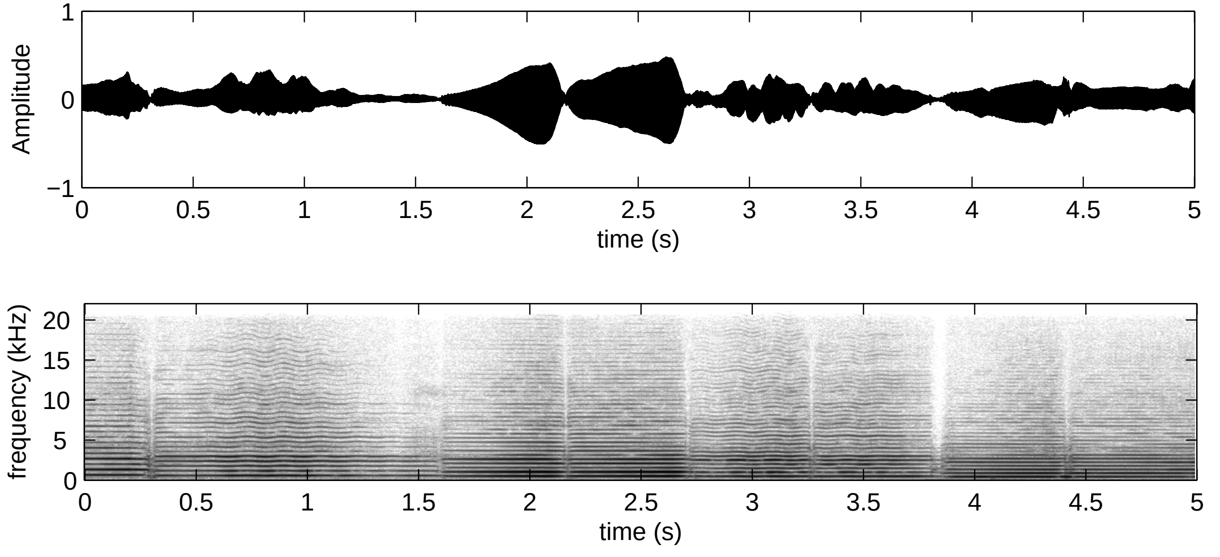

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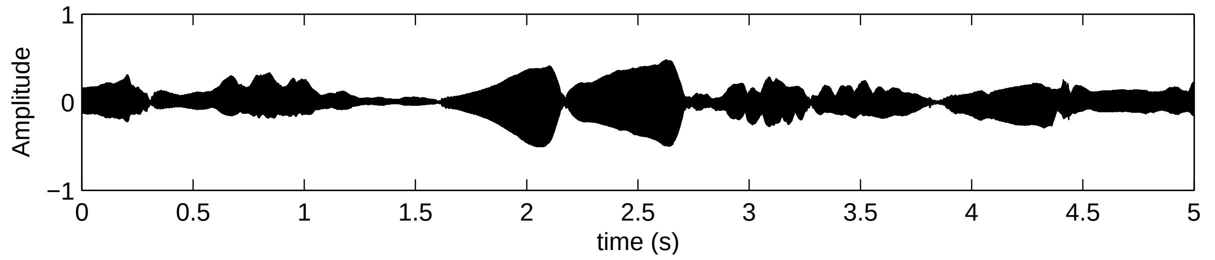

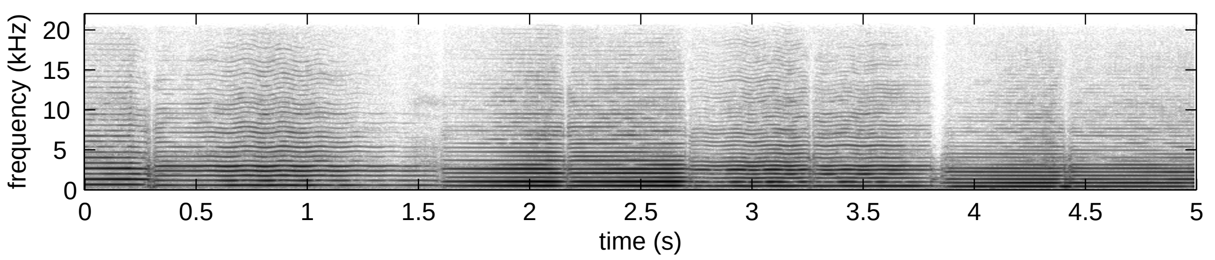

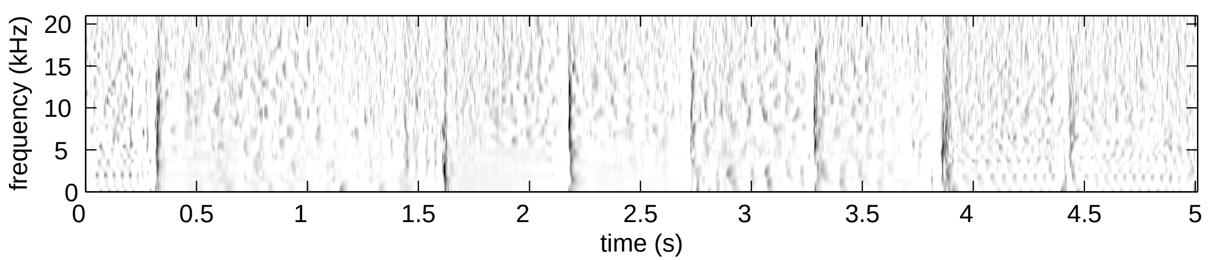

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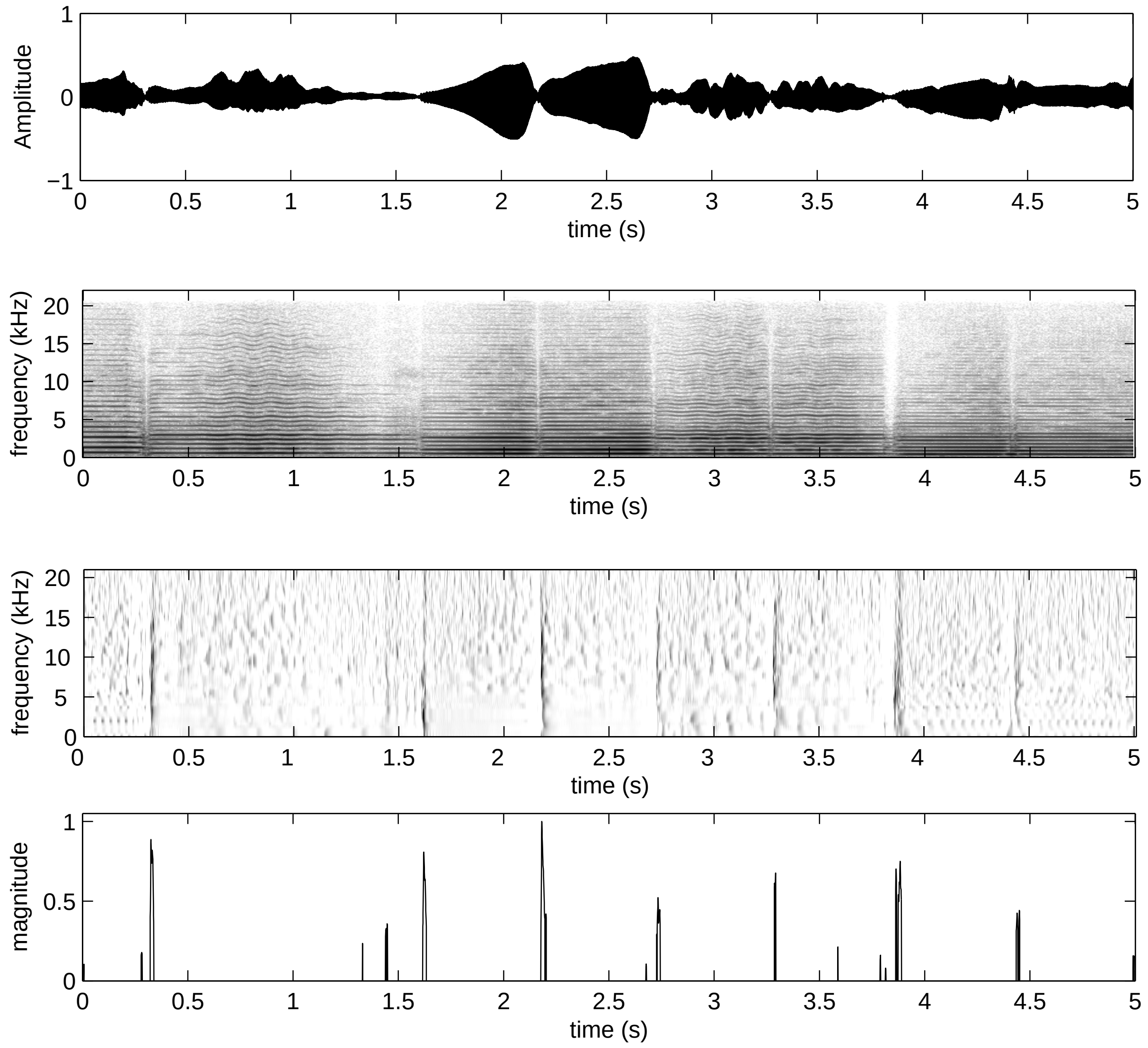

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- detection function periodicity is found using two different methods
  - *spectral product*
  - *autocorrelation function*
- beat location is found via a cross-correlation with an artificial pulse-train

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Genre	Pieces	Percentage
classical	137	28.0 %
jazz	79	16.2 %
latin	37	7.6 %
pop	40	8.2 %
rock	44	9.0 %
reggae	30	6.1 %
soul	24	4.9 %
rap, hip-hop	20	4.1 %
techno	23	4.7 %
other	55	11.2 %
total	**489**	**100 %**

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- wide variety of instruments, dynamic range, etc.
- tempi in the 50 to 200 BPM range
- the tempo of each musical piece was manually annotated and cross-validated by at least two musicians

Results

- the algorithm was compared to our previous work
- it was also compared to our own implementation of the methods proposed by Paulus[1] and Scheirer[2]
- overall recognition rate for the evaluated systems

Method	Recognition rate
Paulus	56.3 %
Scheirer	67.4 %
SP .	63.2 %
AC .	73.6 %
SP using SEF.	84.0 %
AC using SEF	89.7 %

[1] Paulus J. and Klapuri A.,"*Measuring the similarity of rhythmic patterns*", Proc. ISMIR 2002.

[2] Scheirer, E.D., "*Tempo and beat analysis of acoustic music signals*", JASA, January 1998.

Sound examples

- example rock
- example country music
- example soul
- example salsa
- example guitarre
- example jazz 1
- example jazz 2
- example musique classique 1
- example musique classique 2

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- global success rate of 89.7%
- the system works off-line