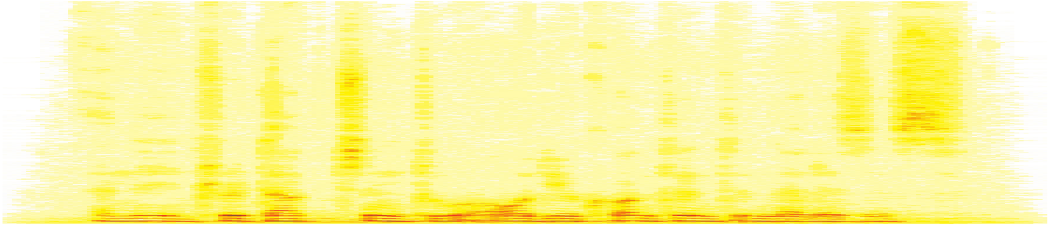
Introduction to Audio Content Analysis

Module 9.0: Audio Fingerprinting

alexander lerch



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introduction

overview

corresponding textbook section

Chapter 9: Audio Fingerprinting (pp. 163–167)

- **lecture content**
  - introduction to audio fingerprinting
  - in-depth example for fingerprint extraction and retrieval
- **learning objectives**
  - discuss goals and limitations of audio fingerprinting systems as compared to watermarking or cover song detection systems
  - describe the processing steps of the Philips fingerprinting system

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audio fingerprinting

introduction

- **objective**:
    - represent a recording with a compact and unique digest ($\rightarrow$ *fingerprint*, *perceptual hash*)
    - allow quick matching between previously stored fingerprints and an extracted fingerprint
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    - *broadcast monitoring*: automate verification for royalties/infringement claims
    - *value-added services*: offer information and meta data

audio fingerprinting
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audio fingerprinting

fingerprinting vs. watermarking

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- **fingerprinting**:
  - identifies *recording*
- **watermarking**:
  - embeds perceptually “unnoticeable” data block in the audio
  - identifies *instance* of recording

Property	Fingerprinting	Watermarking
Allows Legacy Content Indexing	+	−
Allows Embedded (Meta) Data	−	+
Leaves Signal Unchanged	+	−
Identification of	Recording	User or Interaction

audio fingerprinting

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audio fingerprinting

fingerprint requirements

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- **accuracy & reliability**:
  minimize false negatives/positives
- **robustness & security**:
  robust against distortions and attacks
- **granularity**:
  quick identification in a real-time context
- **versatility**:
  independent of file format, etc.
- **scalability**:
  good database performance
- **complexity**:
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audio fingerprinting

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audio fingerprinting

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audio fingerprinting

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audio fingerprinting

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audio fingerprinting
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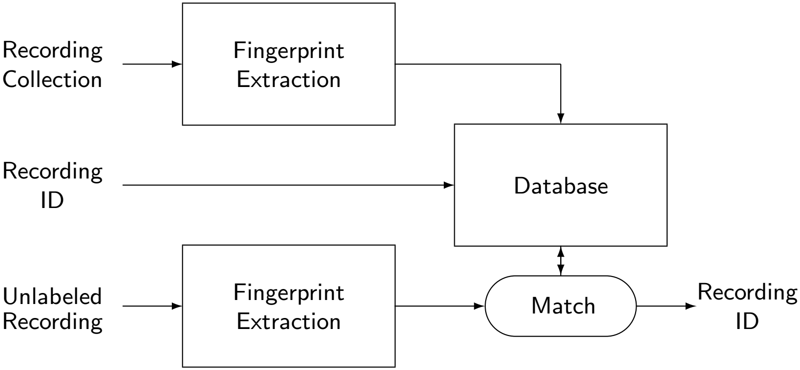
audio fingerprinting

general fingerprinting system



audio fingerprinting
brainstorm

How does it work? MD5?

audio fingerprinting
brainstorm

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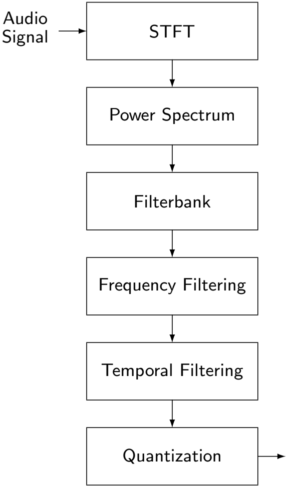
audio fingerprinting

system example: philips extraction 1/3

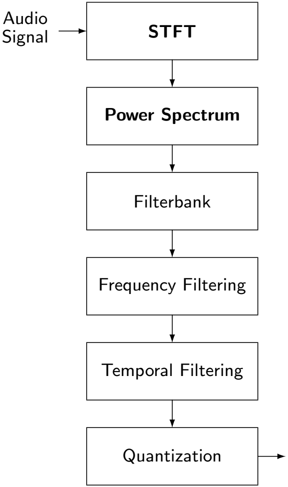


1. **pre-processing**:
   downmixing & downsampling (5 kHz)
2. **STFT**: $\mathcal{K} = 2048$, overlap $\frac{31}{32}$
3. **log frequency bands**:
   33 bands from 300–2000Hz
4. **freq derivative**: 33 bands
5. **time derivative**: 32 bands
6. **quantization**:

$$v_{\mathrm{FP}}(k,n) = \begin{cases} 1 & \text{if } (\Delta E(k,n) - \Delta E(k,n-1)) > 0 \\ 0 & \text{otherwise} \end{cases}$$

⇒ **32 bit** *subfingerprint*

audio fingerprinting
system example: philips extraction 1/3



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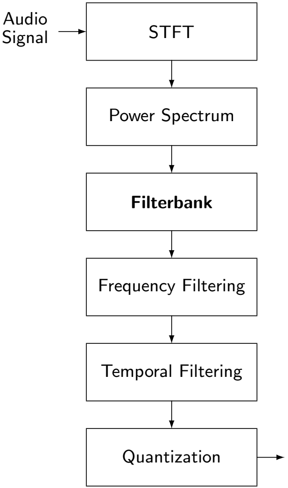

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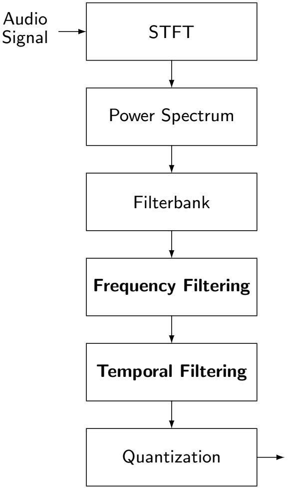

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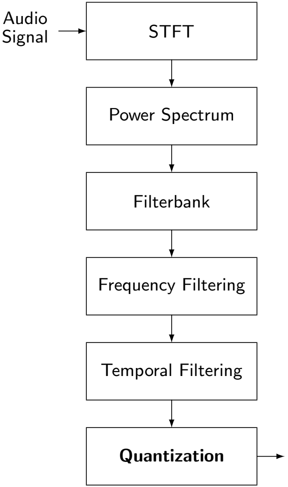

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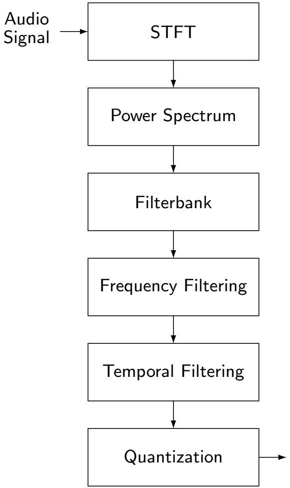

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audio fingerprinting

system example: philips extraction 2/3

fingerprint

- 256 subsequent subfingerprints

$\Rightarrow$

- *length*: 3 s
- *size*: $256 \cdot 4\,\mathrm{Byte} = 1\,\mathrm{kByte}$

example:

- 5 min song

$$1\,\mathrm{kByte} \cdot \frac{5 \cdot 60\mathrm{s}}{3\,\mathrm{s}} = 100\,\mathrm{kByte}$$

- database with 1 million songs (avg. length 5 min)

$$10^6 \cdot 256 \cdot \frac{5 \cdot 60\mathrm{s}}{3\,\mathrm{s}} = 25.6 \cdot 10^9\ \mathrm{subfingerprints}$$

$\Rightarrow$ 100 GByte storage

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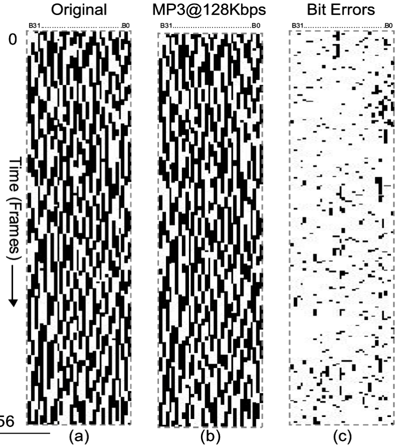

plot from[1]

[1] J. Haitsma and T. Kalker, "A Highly Robust Audio Fingerprinting System," in *Proceedings of the International Conference on Music Information Retrieval (ISMIR)*, Paris, 2002.

audio fingerprinting

system example: philips identification 1/3

- **database**
  - contains all subfingerprints for all songs
  - previous example database: 25 billion subfingerprints
- **problem**
  - how to identify fingerprint efficiently?

audio fingerprinting

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- **simple system**:
  1. create lookup table with all possible subfingerprints (2^{32}) pointing to occurrences
  2. assume at least one of the extracted 256 subfingerprints is error-free
     $\Rightarrow$ only entries listed at 256 positions of the table have to be checked
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audio fingerprinting

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audio fingerprinting

system example: philips identification 3/3

- **variant 1**:
  - allow *one* bit error
  - ⇒ workload increase by factor 33

- **variant 2**:
  - introduce concept of bit error probability into fingerprint extraction
    - small energy difference → high error probability
    - large energy difference → low error probability
  - rank bits per subfingerprint by error probability and check only for bit errors at likely positions

audio fingerprinting

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audio fingerprinting

other systems: shazam

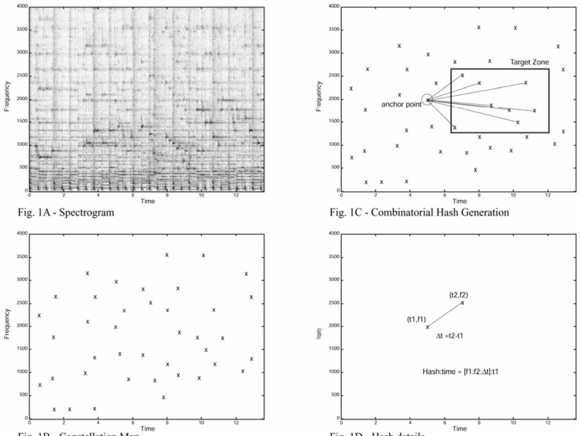

Fig. 1A - Spectrogram
Fig. 1C - Combinatorial Hash Generation
Fig. 1B - Constellation Map
Fig. 1D - Hash details

plot from[2]

[2] A. Wang, "An Industrial Strength Audio Search Algorithm," in *Proceedings of the 4th International Conference on Music Information Retrieval (ISMIR)*, Washington, 2003.

summary
lecture content

- **audio fingerprinting**
  - represent recording with compact, robust, and unique fingerprint
  - allow efficient matching of this fingerprint with database

- **often confused with other tasks**
  1. audio watermarking
  2. cover song detection