



Introduction to **Audio Content Analysis**

module 12.2: musical genre classification

alexander lerch

introduction

overview

corresponding textbook section

section 12.2

■ lecture content

- musical genre
- processing steps in basic genre classifiers
- example: genre classification with a kNN

■ learning objectives

- discuss ambiguities in the definition of musical genre and the possible impact on automatic systems
- describe the processing steps for traditional musical genre classifiers
- implement your own music genre classifier with Matlab



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musical genre classification

introduction

- one of the early/**seminal research topics** in MIR
- classic *machine learning* task
 - features → classification
- related tasks:
 - speech-music classification
 - instrument recognition
 - artist identification
 - music emotion recognition

musical genre classification

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musical genre classification

applications

- large music databases:
 - annotation
 - sorting, browsing, retrieving
- recommendation and music discovery systems
- automatic playlist generation
- improving downstream MIR tasks by using side information/conditioning

musical genre classification

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musical genre classification

genre: definition

what is musical genre



musical genre classification

genre: definition

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- clusters of musical similarity?

→ hard to answer in general, there are many **systematic problems**

musical genre classification

genre: definition



what is musical genre

- clusters of musical similarity?

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1 non-agreement on taxonomies

- ▶ e.g., AllMusic vs. Pandora

2 genre label scope

- ▶ e.g., song, album, artist, piece of a song

3 ill-defined genre labels

- ▶ e.g., geographic (*indian music*), historic (*baroque*), technical (*barbershop*), instrumentation (*symphonic music*), usage (*christmas songs*)

4 taxonomy scalability

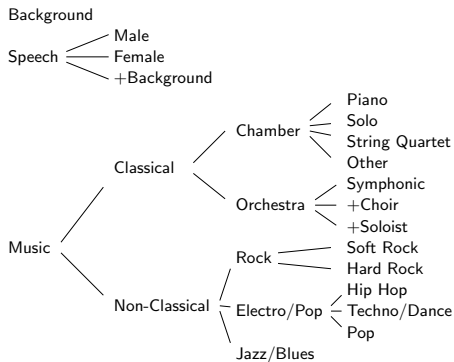
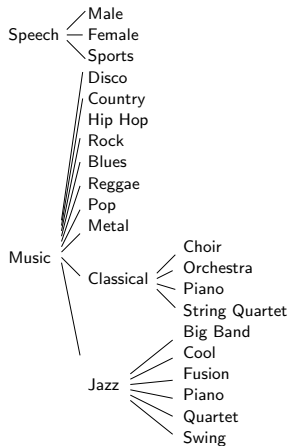
- ▶ e.g., genres and subgenres evolve over time

5 non-orthogonality

- ▶ e.g., several genres for one piece of music

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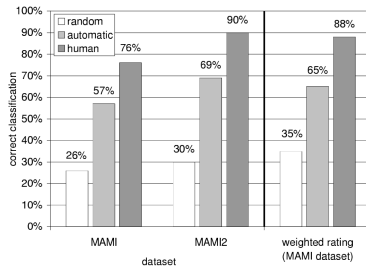
genre: taxonomy examples



musical genre classification

observations with humans

- 1 human classification far from perfect:
75–90 % for limited set of classes
 - 2 for many genres, humans need only a
fraction of a second to classify
- ⇒ short time timbre features sufficient?



plots from^{1,2}

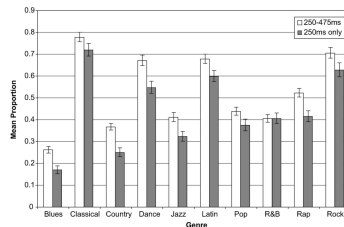
¹S. Lippens, J.-P. Martens, T. D. Mulder, *et al.*, "A Comparison of Human and Automatic Musical Genre Classification," in *Proceedings of the International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, Montreal, 2004.

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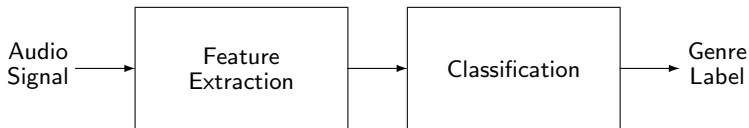
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musical genre classification

overview



1 feature extraction

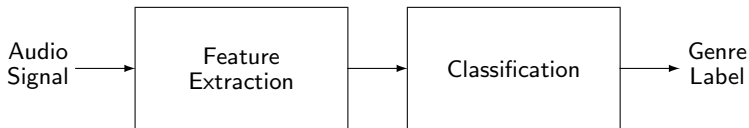
- compressed, meaningful representation

2 classification

- map or convert feature to comprehensible domain

musical genre classification

overview



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musical genre classification

feature categories

■ high level similarities?

- melody, hook lines, bass lines, harmony progression
- rhythm & tempo
- structure
- instrumentation & timbre

■ technical feature categories

- tonal
- technical
- timbral
- temporal
- intensity

■ extracted features should be

- extractable (not: time envelope in polyphonic signals)
- relevant (not: pitch chroma for instrument ID)
- non-redundant
- have discriminative power

musical genre classification

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musical genre classification

instantaneous features

- spectral features (**timbre**):
Spectral Centroid, MFCCs, Spectral Flux, ...
- pitch features (**tonal**):
pitch chroma distribution/change, ...
- rhythm features (**temporal**):
onset density, beat histogram features, ...
- statistical features (**technical**):
standard deviation, skewness, zero crossings, ...
- **intensity** features:
level variation, number of “pauses”, ...

musical genre classification

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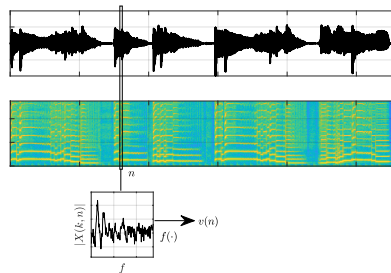
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musical genre classification

feature extraction process

1 extract **instantaneous** features



- 2 compute **derived** features (derivatives etc.)
- 3 compute **long term** features & subfeatures per texture window or file
- 4 **normalize** subfeatures
- 5 (select or) **transform** subfeatures
- 6 feature vector → **classifier** input

musical genre classification

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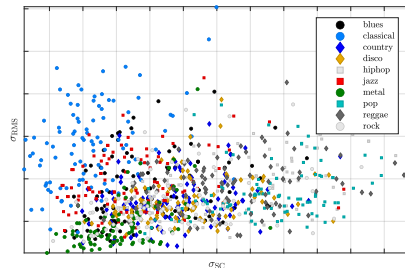
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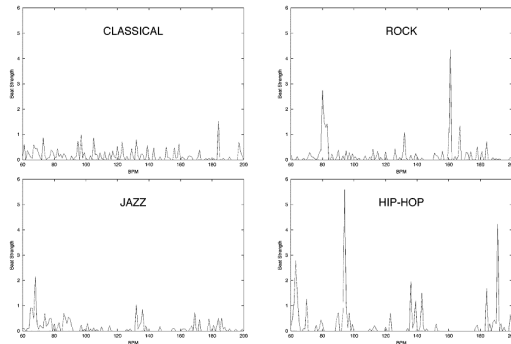


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long term features 1/2

derived from beat histogram³

- statistical histogram features
- number and values of top maxima
- location (relation) of top maxima
- . . .



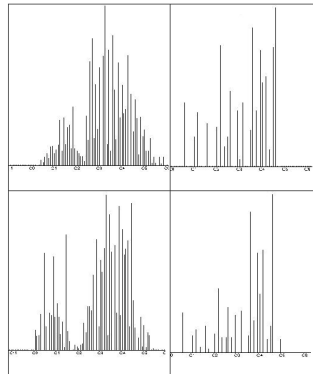
³G. Tzanetakis and P. Cook, "Musical genre classification of audio signals," *Transactions on Speech and Audio Processing*, vol. 10, no. 5, pp. 293–302, Jul. 2002, ISSN: 1063-6676. DOI: [10.1109/TSA.2002.800560](https://doi.org/10.1109/TSA.2002.800560).

musical genre classification

long term features 2/2

derived from pitch histogram or pitch chroma⁴

- statistical histogram features
- number and values of top maxima
- location (relation) of top maxima
- ...



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musical genre classification

additional possible features

■ stereo features

- mid channel energy vs. side channel energy
- spectral channel differences

■ features at higher semantic levels:

- tempo, structure, harmonic complexity, instrumentation

musical genre classification

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musical genre classification

results

- classification results depend on training set, test set, and number of classes
- typical range: ≈ 10 classes \Rightarrow 50–80%
- main challenges
 - ill-defined genre boundaries
 - non-uniformly distributed classes
 - overfitting through songs from same album or artist
 - ...

musical genre classification

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musical genre classification

speech/music classification baseline example

binary classification task

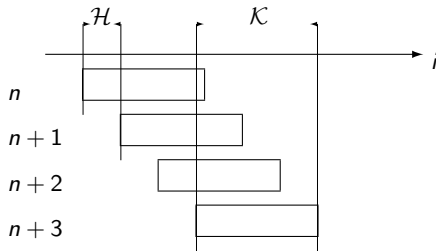
- 1 extract features
- 2 represent each file with its 2-dimensional feature vector
- 3 kNN to classify unknown audio files
- 4 evaluate classification performance

musical genre classification

speech/music classification example: features 1/2

for each audio file

1 split input signal into (overlapping) blocks



2 compute 2 feature series (spectral centroid, RMS)

3 aggregate feature series to one value per file

- *mean* of Spectral Centroid μ_{SC}
- *standard deviation* of RMS σ_{RMS}

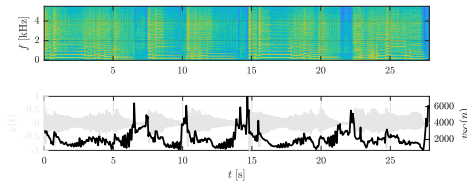
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musical genre classification

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- 2 compute 2 feature series (spectral centroid, RMS)
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 - *mean* of Spectral Centroid μ_{SC}

$$\mu_{SC} = \frac{1}{N} \sum_{\forall n} v_{SC}(n)$$

- *standard deviation* of RMS σ_{RMS}

$$\sigma_{RMS} = \sqrt{\frac{1}{N} \sum_{\forall n} (v_{RMS}(n) - \mu_{RMS})^2}$$

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musical genre classification

speech/music classification example: features 1/2

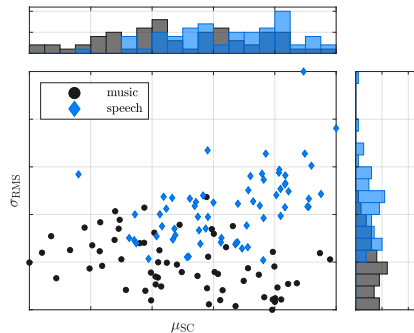
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$$(\mu_{SC}, \sigma_{RMS})^T$$

musical genre classification

speech/music classification example: features 2/2



musical genre classification

speech/music classification example: training set

- use **dataset** annotated as speech and music:
 - requirements
 - ▶ large compared to number of features
 - ▶ representative for use case (diverse)
 - here (toy example):
 - ▶ 64 speech files
 - ▶ 64 music files
- extract the features for the dataset
 - centroid mean
 - rms std
- use 3NN classifier
- procedure: Leave-One-Out-Cross-Validation

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speech/music classification example: results (kNN)

■ confusion matrix:

	speech	music	# files
gt speech	51	13	64
gt music	11	53	64

■ ⇒ classification rate:

$$\frac{53 + 54}{64 + 64} = 81.25\%$$

■ single feature classification results

- Spectral Centroid: 63.28%
- RMS: 73.44%

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summary

lecture content

■ musical genre

- ill-defined, subjective, no general agreement
- some human agreement

■ MGC: features

- from all possible categories as all categories might depend on genre
- timbre seems most meaningful feature

■ MGC: classifier

- any classifier works, and most have been used

■ MGC: standard baseline

- 1 MFCCs
- 2 SVM

