Audio Mining with emphasis on Music Genre Classification

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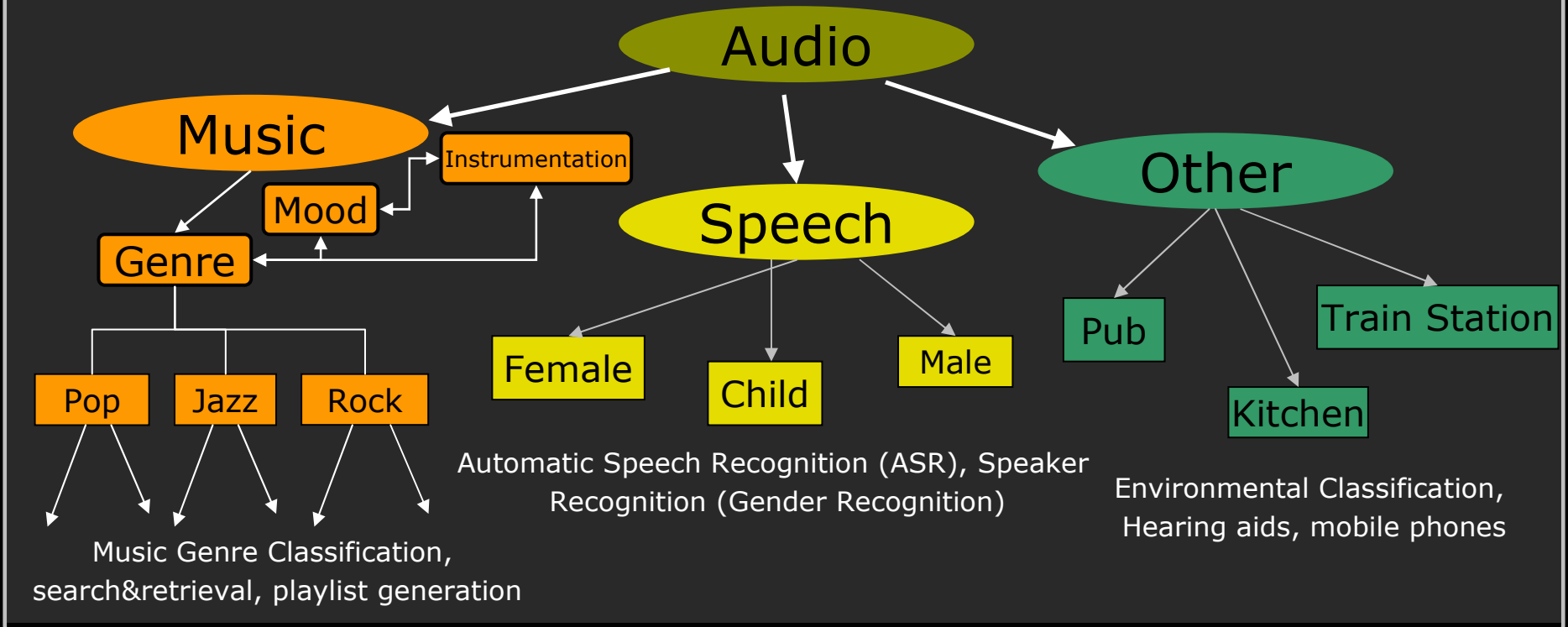
Agenda

- Introduction
- Feature Extraction
- Classification
- Feature integration project *[Meng04]*
- Summary

Example of Audio Hierarchy

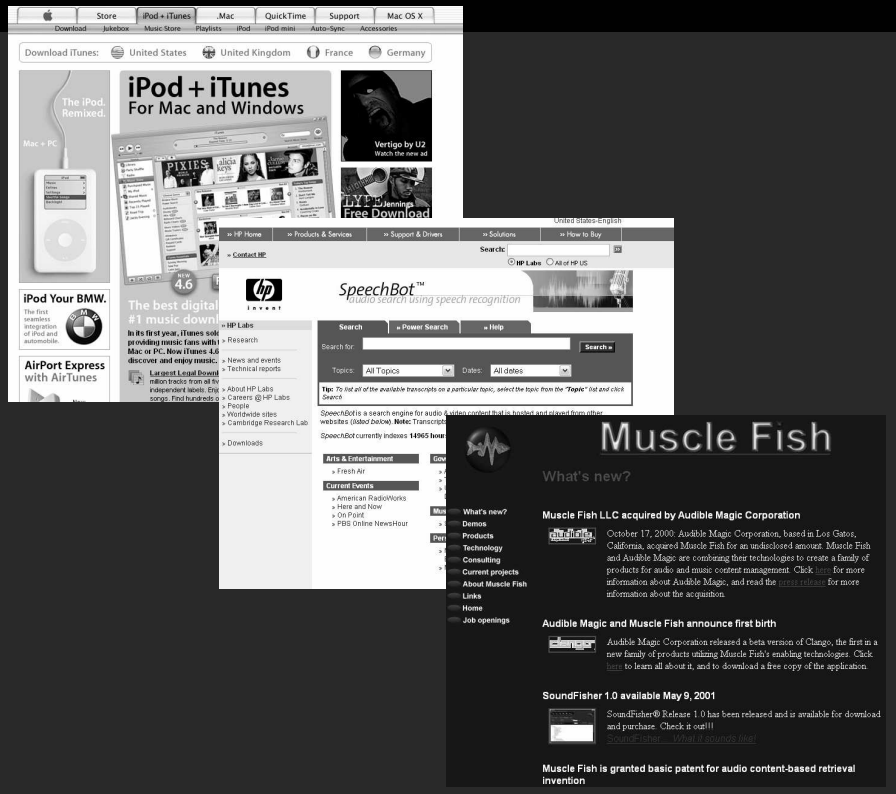


What's the idea ?

- Music is everywhere – and often described by genre
- Want to be able to automatically annotate music with genre, see e.g. *[tzanetakis02]*
- Sound features which are interesting in genre classification, may also be interesting in related fields of research – like music search and retrieval, segmentation, playlist generation.

Applications

- Large on-line music stores
  - like Apple's iTunes (1,000,000+ songs), Sony, Amazon, etc.
- Next generations of media management products
  - query-by-humming, search and retrieval, MPEG-7 Format
- Some existing products
  - MuscleFish (now soundfisher at http://www.soundfisher.com/)
  - SpeechBot (http://speechbot.research.compaq.com/)
  - Findsounds (http://www.findsounds.com/).



FindSounds

Search the Web for Sounds

Search for train Search Help

Need Examples?

File Formats	Number of Channels	Minimum Resolution	Minimum Sample Rate	Maximum File Size
☑ AIFF	☑ mono	8-bit	8000 Hz	2 MB
☑ AU	☑ stereo			
☑ WAVE				

Sounds 1-10 of 200 labelled "train"

1.

http://sep800.mine.nu/files/sounds/toytrainhorn.wav
toy train horn
3k, mono, 8-bit, 8000 Hz, 0.4 seconds (show page | e-mail this sound)

Sound Designers, click here

2.

http://www.srim.org/IMAGES/Trainhorn.wav
train whistle
5k, mono, 8-bit, 11025 Hz, 1.6 seconds (show page | e-mail this sound)

3.

http://newton.umsl.edu/exhibit/doppler-aux.au
train whistle
7k, mono, 8-bit, 8000 Hz, 0.8 seconds (show page | e-mail this sound)

If you like FindSounds.com, you will love FindSounds Palette!

4.

http://www.tux.org/pub/X-Windows/games/freeciv/incoming/sounds/TRAINW.WAV
train whistle
7k, mono, 8-bit, 11025 Hz, 2.9 seconds (show page | e-mail this sound)

If you like FindSounds.com, you will love FindSounds Palette!

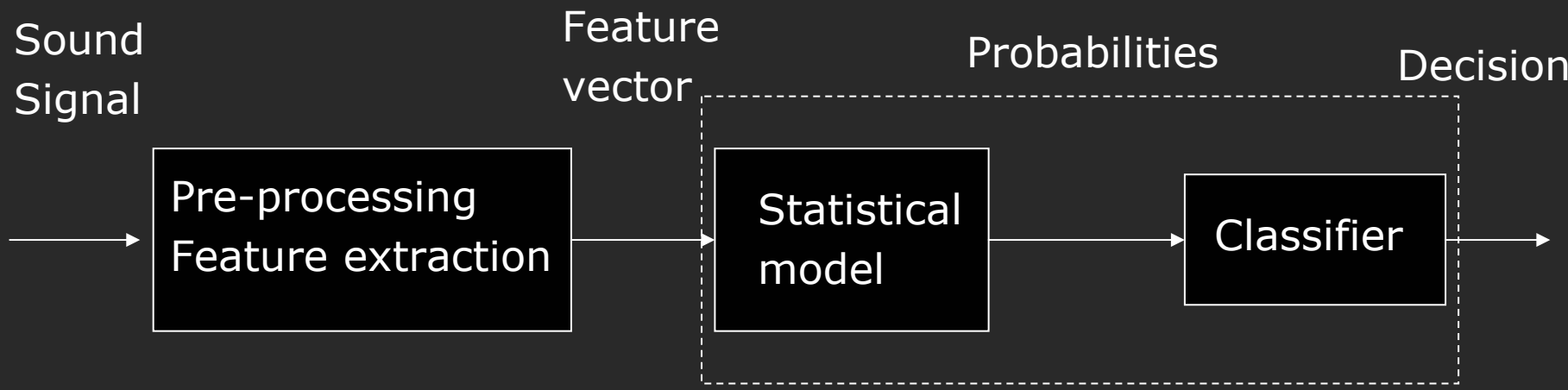
5.

http://ftp.megamirror.com/pub/games/freeciv/contrib/sounds/dubious/sounds/TRAINW.WAV
train whistle

Problems with Music Genre

- Genres are subjectively defined – not an intrinsic property *[Aucouturier02]*
  - Different labelling schemes from e.g. Amazon, iTunes, Gracenote, Freedb
  - Cultural background
- Decision-time horizon problems *[Ahrendt04, Meng04]*

Typical Audio Classification System



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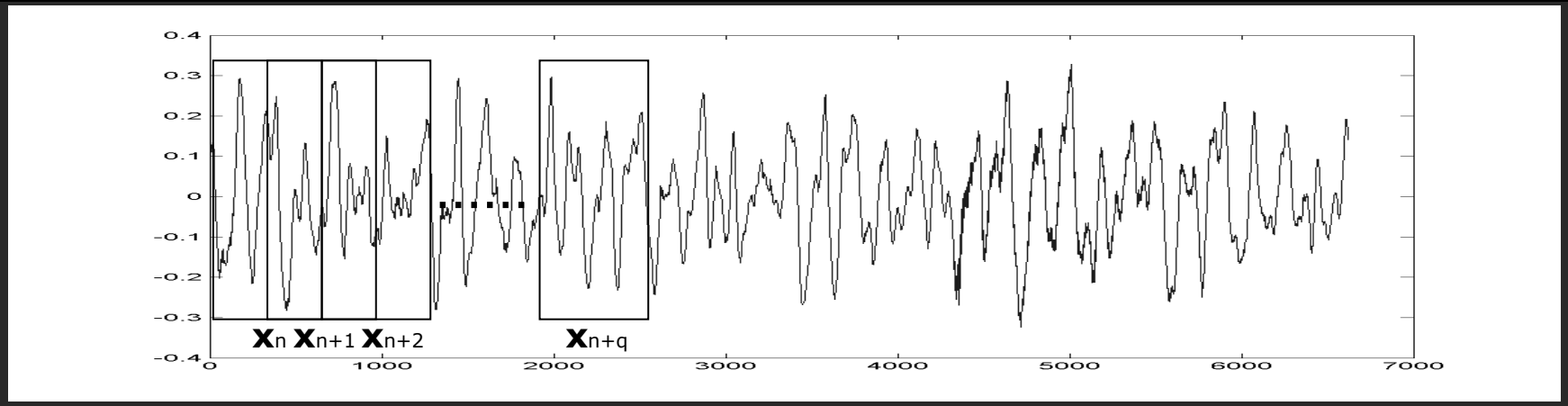
Feature Extraction

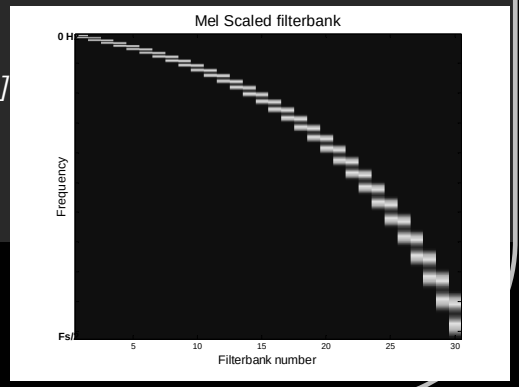


$$\mathbf{x}_n = \begin{bmatrix} x_n^1 \\ x_n^2 \\ \vdots \\ x_n^D \end{bmatrix}$$

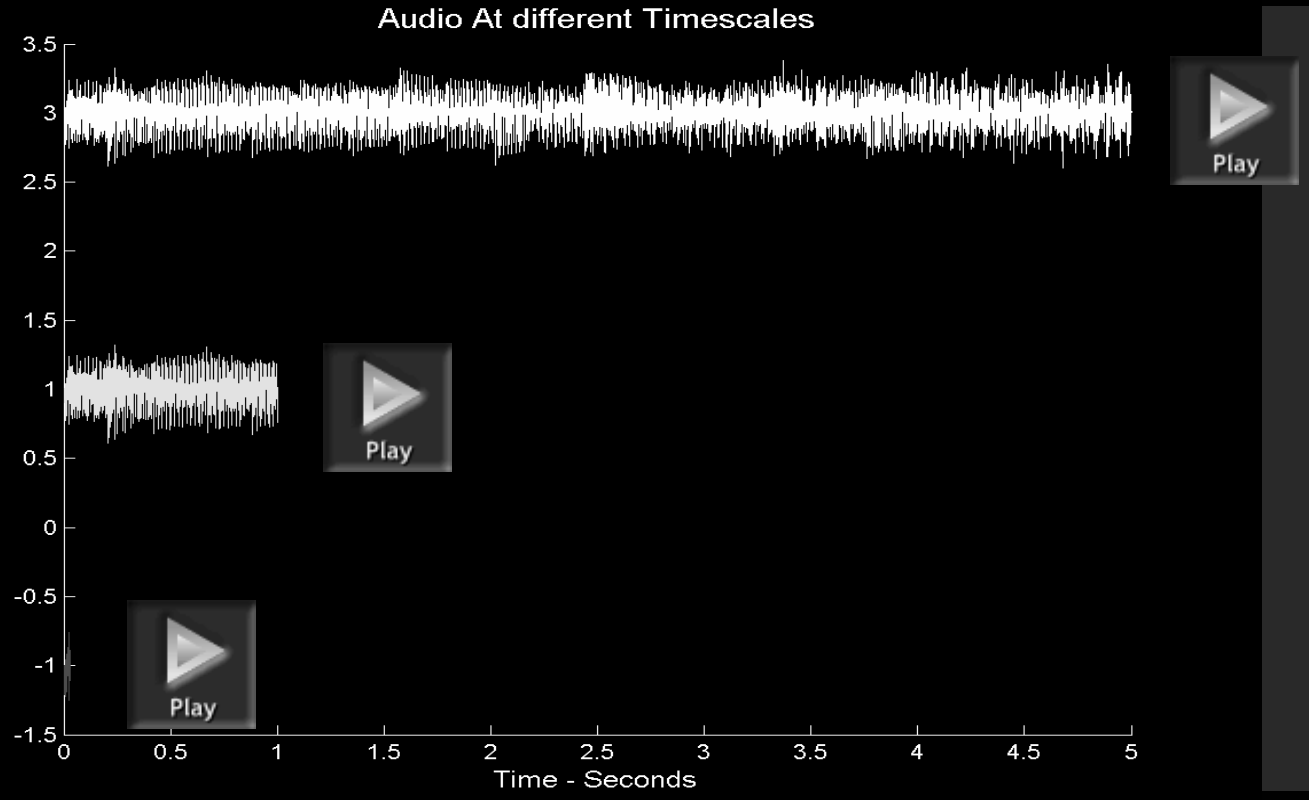
- Typical frames is 10-30ms long, and normally overlap.
- Time or/and frequency features are extracted. Features at similar time levels are stacked.
- A piece of audio (say p) can be expressed as a D x N_p matrix.

Some features

- **Short Time Features (10-30 ms)**
  - Mel Frequency Cepstral Coefficients (MFCC, orig. for automatic speech recognition(ASR), see e.g. *[Davis80]*),
  - Linear Predictive Coefficients (LPC, orig. for ASR). See e.g. *[Makhoul75]*
  - Time Zero Crossing Rate (segmentation). See e.g. *[Tzanetakis02]*
  - Short Time Energy (silence detection).
  - MPEG-7 features (Audio Spectrum Centroid, Audio Spectrum Spread, Spectral
  - Flatness), see e.g. *[Ahrendt04]*
  - Pitch estimators (Speaker recognition / gender recognition)
- **Sound Texture Windows (400msec. – 1 second)**
  - Mean/variance (or some other model) of short time features (feature integration), see e.g. *[Tzanetakis02]*
- **Long time features** (several seconds)
  - Beat estimators (Music analysis, transcription) *[Tzanetakis02]*
  - Feature integration from short time features, *[Tzanetakis02,Ahrendt04,meng04]*



So why does time matter ?



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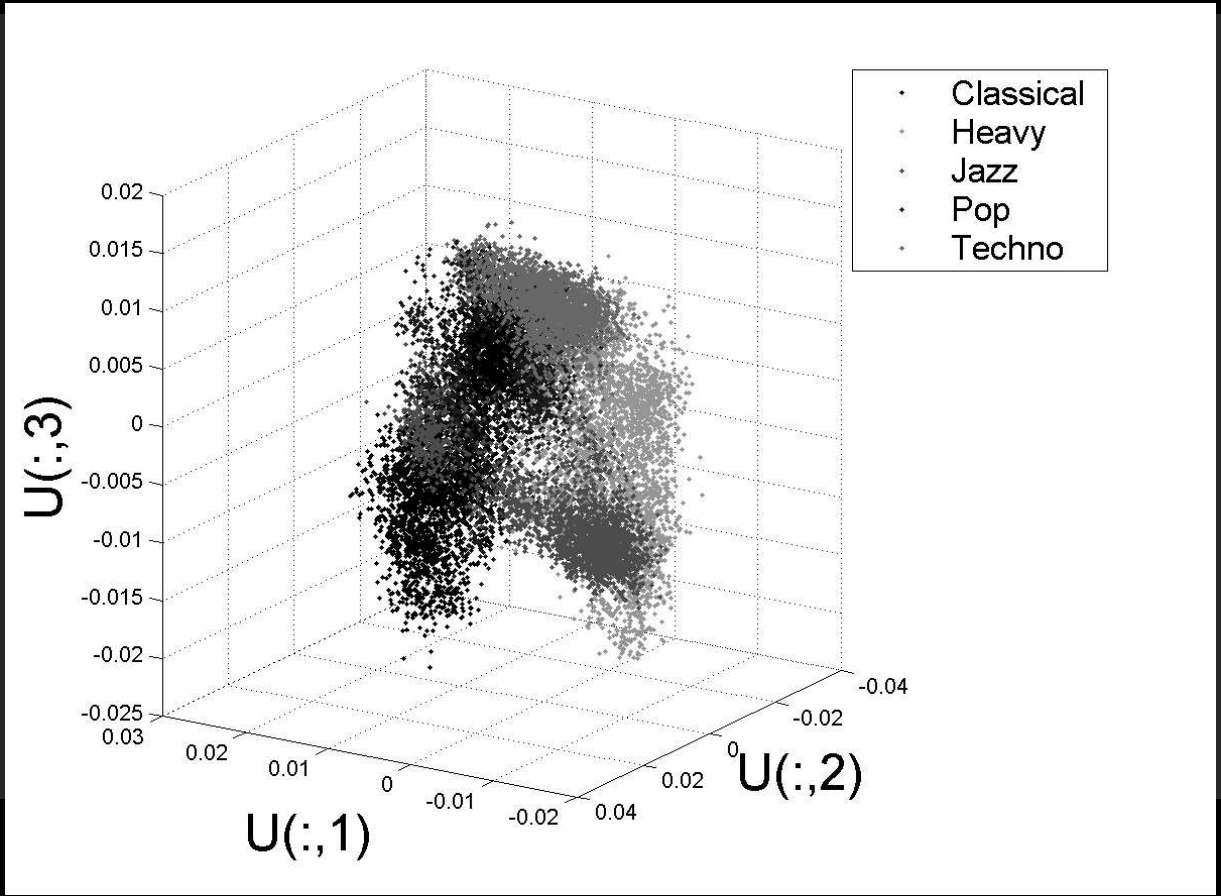
Projection of songs



- Each song is 30 sec.

Statistical Model

Desired (posterior probability) : P(C | **x**) (class C and features **x**)

Investigated models :

- Linear and non-linear neural networks
- Gaussian distribution
- Gaussian Mixture Model
- Hidden Markov Model

Decision time horizon

- What is early and late information fusion *[Ahrendt04]*
  - **Early information fusion**: operation on short time features **before** classification (and decision making).
  - L**ate information fusion :** assembles information on the basis of the outputs from classifier.
- Early information fusion (Feature integration):
  - Dynamic PCA. *[Wu95]*
    Time stacking of features and perform a PCA as to decorrelate features in both time and between the features.
  - Texture windows
    Mean / Variance of features
    Model temporal characteristics using e.g. an Autoregressive Model *[Meng04]*
- Late information fusion *[Kittler98]* :
  - Sum Rule , Median Rule or Majority voting.

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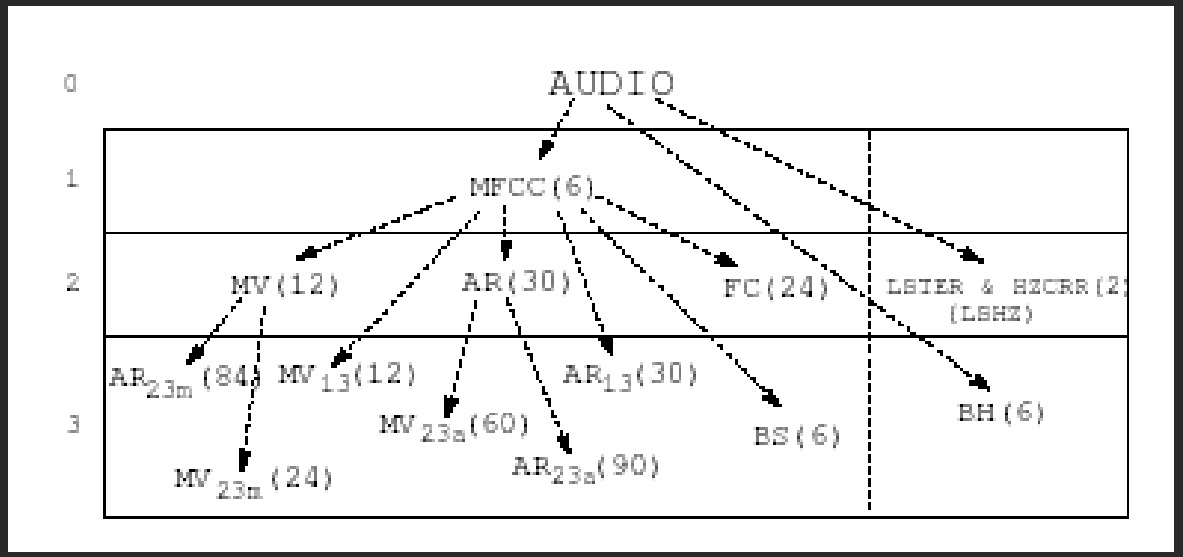
Feature Integration project *[Meng04]*, setup

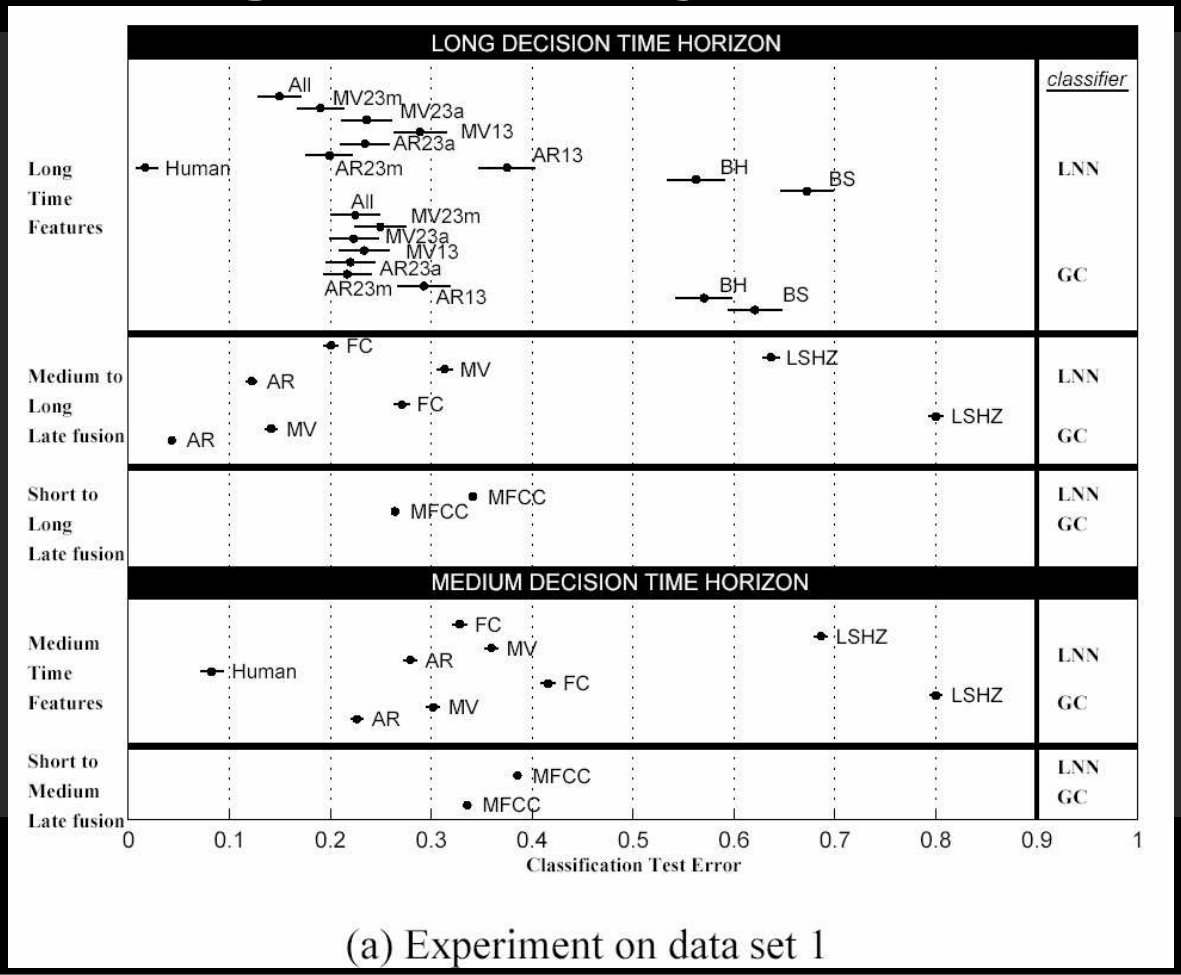
- Goal
  - Music Genre Classification
  - 5 Genres (Rock, Classical, Jazz, Pop, New-Age)
  - Find best features at timescales from 30ms to 5 seconds and compare with human performance
- Features
  - Short time, Mel Frequency Cepstral Coefficients (MFCC)
- Method
  - Combining early and late information fusion. Compare with human performance.
- Classifiers
  - Linear Neural Network (Trained Discriminately)
    - No. Parameters : ~ 5D
  - Gaussian Classifier (GC)
    - No. Parameters : ~ 5D(D/2+2)

Feature integration project – early fusion

1. ~ 30 ms
2. ~ 1 second
3. ~ 5 seconds



Feature Integration Project, outcome



(a) Experiment on data set 1

Feature Integration Project, outcome

- Combination of feature integration and late information fusion improves performance.
- Temporal information in short time features are important in Music Genre Classification.
- Generalizes to other areas such as playlist-generation, retrieval.

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Summary

- The area of audio mining is expanding.
- Music Genre Classification can to some extend be used as a test-bench for new music features.
- A more natural approach to music genre is the use of multi-labels.
- Music genre is a first step to music navigation.

References

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