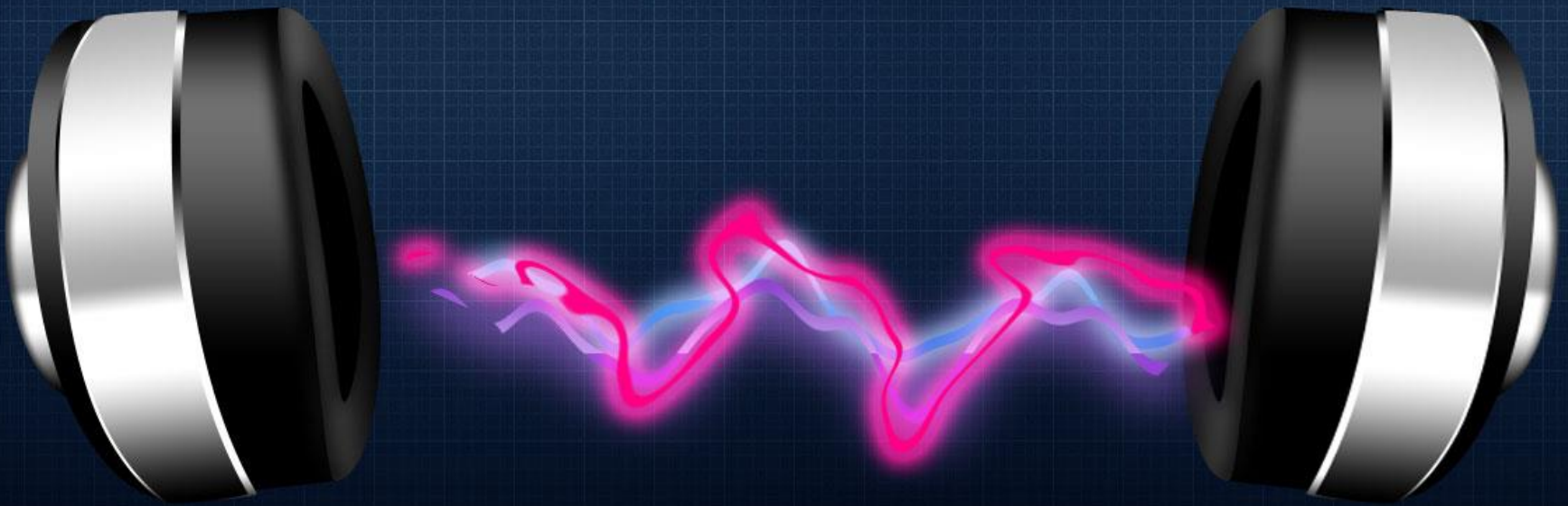# Topics in Computer Music

Instrument Identification

Ioanna Karydi

Presentation overview

- What is instrument identification?
- Sound attributes & Timbre
- Human performance
- The ideal algorithm
- Selected approaches
  - Overview
  - Steps
  - Results
- Conclusions

What is instrument identification?

Instrument identification

The procedure of training a learning machine to identify an instrument by hearing a sound clip.

fppt.com

Sound attributes

	Loudness	**Pitch**	**Timbre**	**Duration**
Pressure	+++	+	+	+
Frequency	+	+++	++	+
Spectrum	+	+	+++	+
Duration	+	+	+	+++
Envelop	+	+	++	+

Dependence of subjective qualities of sound on physical parameters.[1]

fppt.com

Timbre

Timbre:

"That attribute of auditory sensation in terms of which a listener can judge that two sounds similarly presented and having the same loudness and pitch are dissimilar" (American National Standards Institute)

Human performance

Musical instrument identification systems attempt to reproduce how humans can recognize and identify the musical sounds populating their environment. [1]

Number of instruments	Identification rates
2	97.6%
3	95.4%
9	90.2%
27	55.7%

An ideal Algorithm

- Characteristics:
  - Generalization
  - Robustness
  - Meaningful behavior
  - Reasonable computational requirements
  - Modularity
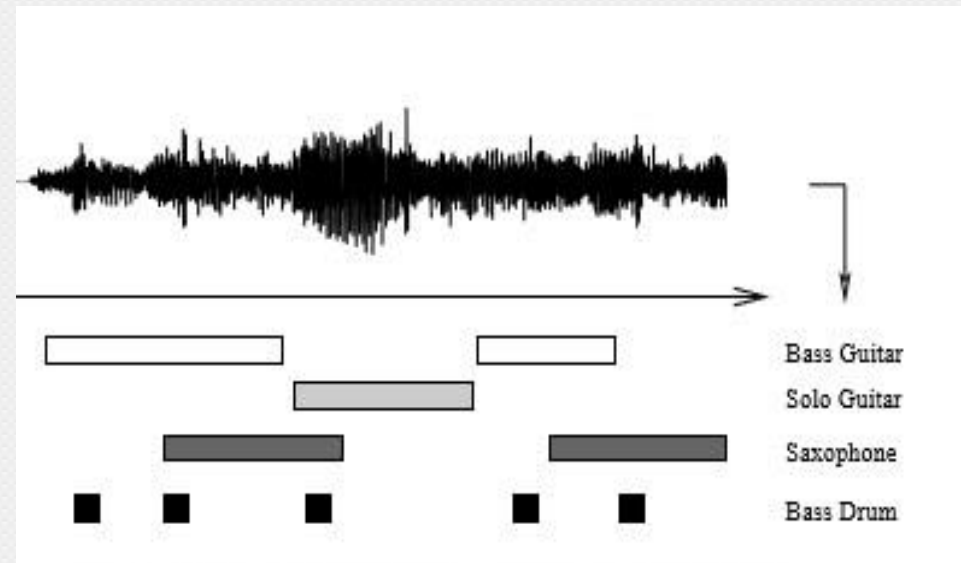
An ideal musical instrument identification system [1]

Agostini (1/4)

Overview

- Segmentation and estimation of pitch
- Features describe spectral characteristics of monophonic sounds (intended to be heard as a single channel of **sound** perceived as coming from one position)
- Dataset composed by 1.007 tones from 27 musical instruments (from orchestral sounds to pop/electronic instruments)
- Classification using pattern recognition techniques

Agostini (2/4)

Feature Extraction

A set of features related to the harmonic properties of sounds is extracted from monophonic musical signals

Steps:

• Audio Segmentation
• Pitch Tracking
• Calculation of Features

Classification Techniques

- Discriminant Analysis
  - Canonical discriminant analysis
    - Separates two instrument labels in a plane by means of a line
  - Quadratic Discriminant Analysis
    - the hyper-surfaces delimiting the regions of classification are quadratic forms

- Support Vector Machines
  - A representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible

- k-Nearest Neighbors
  - An object is classified by a majority vote of its neighbors, with the object being assigned to the instrument label most common among its k nearest neighbors

Agostini (4/4)

Results

	17	20	27
QDA	94.70	95.34	92.81
SVM	80.20	78.64	69.71
CDA	76.63	74.41	66.74
KNN	73.51	74.54	65.74
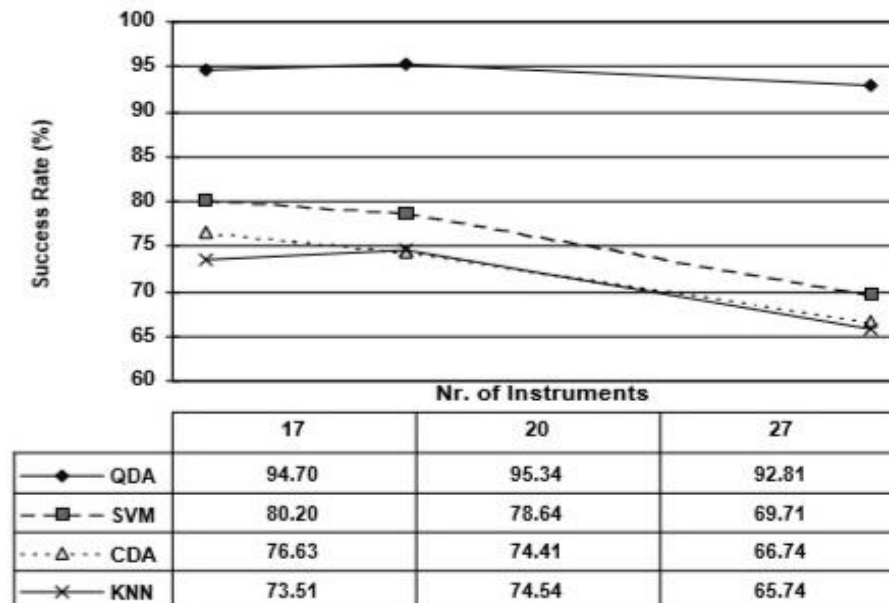
Classifiers performances for different number of instruments [2]

fppt.com

Barbedo –Tzanetakis (1/6)

Overview

- 4 instruments: alto saxophone (S), violin (V), piano (P) and acoustic guitar (G)

- Pairwise comparison scheme

- Requires single note from each instrument, the more isolated partials available the best accuracy

- Correct identification even in presence of interference

- Accurate estimates are possible using only a small number of partials, without requiring the entire note

- Using only one carefully designed feature more effective than traditional machine learning methods

Setting it up

- 1.000 mixtures used
- None of the instrument samples used in the test set

	SV	SP	SG	PV	VG	PG1	PG2
Acc.	90%	93%	94%	90%	93%	95%	83%

Separation accuracy for each pair of instruments [3]

Barbedo –Tzanetakis (3/6)

Setting it up

- Segment the signal
- Determine the number of instruments present in each segment
- Estimate the fundamental frequency (F0) of each instrument

Feature selection & extraction

- The features to be extracted depend directly on which instruments are being considered

- The feature selection for each pair aimed for the best linear separation

- The features are calculated individually for each partial

Instrument identification procedure

- Number of instruments and respective fundamental frequencies are known
- Pairwise comparison for each isolated partial - an instrument is chosen as the winner for each pair
- Repeat the same procedure for all partials related to that fundamental frequency
- Then, the predominant instrument is taken as the correct one
- Repeat the same procedure for all fundamental frequencies

Experimental results

Isolated partials available	Accuracy
One	Close to 91%
More than six	Up to 96%

3 factors for such good performance:

1. Only four instruments are considered

2. All instruments are taken from the same database

3. A very effective feature was found to the difficult pair piano - acoustic guitar, which significantly improved the overall results

Conclusions

- ## Agostini:

  Common used classifiers could not provide results similar to QDA, since extracted features follow such distribution.

  Feature set still lacking of temporal descriptors of the signal.

  Next steps: introduction of new features and inclusion of percussive sounds and live-instruments.

- ## Barbedo-Tzanetakis

  Robust and accurate results.

  Proved that pairwise comparison approach is effective.

  Next steps: more instruments and signals from other databases.

Thank you for your attention!

References

- [1] Nicolas D. Chétry , (2006), "Computer Models for Musical Instrument Identification" http://c4dm.eecs.qmul.ac.uk/papers/2006/Chetry06-phdthesis.pdf

- [2] G. Agostini, M. Longari, and E. Pollastri. Content-based classification of musical instrument timbres. International Workshop on Content-Based Multimedia Indexing, 2001. http://www.music.mcgill.ca/~ich/classes/mumt614/MIR/agostiniTimbre.pdf

- [3] Jayme Garcia Arnal Barbedo and George Tzanetakis (2010). "Instrument identification in polyphonic music signals based on individual partials." http://webhome.csc.uvic.ca/~gtzan/output/icassp2010gtzan.pdf

fppt.com