Audiovisual recognition of drum sequences

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Database

ENST-Drums: 10 Go of drum audio and video sequences, played by three different drummers on their own drum kit.

Four types of sequence: *hits*, *phrases*, *soli*, *accompaniment*. All sequences are annoted, with the time of each stroke and the corresponding instrument.

Possible instruments: snare drum, bass drum, cymbals (chinese ride, crash, splash, etc.), hi-hat, toms (low tom, mid tom, etc.)

Drum kit


crash cymbal
ride cymbal
cymbal stand
tom-toms
hi-hat cymbal
snare drum
cymbal stand
floor tom
hi-hat stand
bass drum
snare drum stand
bass drum pedal

Exercise

Different possible classification tasks:

- Recognize the drummer;
- Recognize the tool used to hit (stick, brush, mallet);
- The instrument that is hit (snare drum, bass drum, etc.);
- Or a higher-level category of instrument, or *taxonomy* (e.g. membranes versus plates).

We could use audio features, video features, or both of them.

Our goal

We use only audio features. The classification task we have chosen is to recognize the instrument within a *taxonomy*. We worked with four taxonomies:

- *Super-category:* membrane, plate.
- *Gillet's taxonomy:* bass drum, snare drum, hi-hat (75% coverage.)
- *Basic-level:* bass drum, snare drum, tom, cymbal, hi-hat.
- *Sub-category:* like *basic-level*, but toms are subdivised into low tom, low mid tom, etc., cymbals into splash, ride and crash cymbals.

Bibliography

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Overview

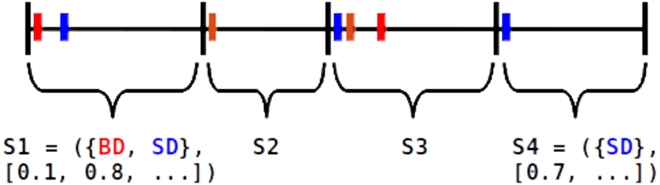
1. Data segmentation (separation of audio sequences into segments)
2. Feature extraction (transform an audio segment to a vector)
3. Feature selection (keep the best attributes)
4. Classification (transcription)
5. Results and conclusion

Data segmentation

Audio records are sequences of strokes. We must extract those strokes by:

- Detecting the beginning of each stroke. This process is called *onset detection*. In our case, we use the time defined in the annotations as an oracle.
- And defining a segment size. It could be either a fixed window (e.g. 200 ms) or the rest of the audio signal until the next stroke.
- We decided that instruments that are played within the same window of 50 ms belong to the same segment.

Feature computation



We used *Yaafe* to compute the features of each audio segment. For each of those features we compute the mean value, with an analysis window of 50 ms, and 50% overlap.

Feature list

Feature	Yaafe name	Dim
Mel Frequency Cepstrum Coef	MFCC	13
Spectral shape parameters	SpectralShapeStatistics	4
Temporal shape parameters	TemporalShapeStatistics	4
Energy ratio in octave frequency bands	OBSIR	9
Total energy	Energy	1
Zero crossing rate	ZCR	1
Linear prediction coefficients	LPC	6
Spectral flatness	SpectralFlatness	1
Perceptual sharpness	PerceptualSharpness	1
Perceptual spread	PerceptualSpread	1

We used three sets of features : *all features*, *manually chosen features* (MFCC and Spectral shape), and *automatically selected features* (by feature selection).

Feature selection

Feature selection consists in reducing the dimensionality of the feature vectors, by selecting a smaller number of attributes.

The algorithm *IRMFSP* finds the d best attributes, which maximize the inter-class dispersion, and minimize the intra-class dispersion.

Table : First 4 selected attributes

Instrument	Attributes
Bass drum	$OBSIR_3$, $OBSIR_2$, $MFCC_0$, $MFCC_1$
Snare drum	$OBSIR_2$, $MFCC_2$, $SpecShape_3$, $Spread_0$
Hi-hat	LPC_0, $TempShape_2$, $MFCC_4$, $OBSIR_8$

Classification task

Given a taxonomy with N instruments, determine for each of the instruments, whether it is played in the audio segment or not.

There are two approaches:

- A single classifier, with 2^N classes (one class for each combination of instruments.)
- N binary classifiers, which decide if the instrument is played or not.

Evaluation protocol

For both approaches, we tried two classifiers:

- SVM classifier, as *Gillet* proposed, with RBF kernel ($C = 2$, $\sigma = 1$)
- K-NN classifier, like *Herrera*, with $k = 5$

We used a 10-folds cross-validation. We reported, the *precision*, *recall* and *f-score* for each instrument.

$$precision = \frac{correct}{predicted},\ recall = \frac{correct}{true},\ f1 = \frac{2 \times P \times R}{P + R}$$

Results

Results for SVM, with *manual features*:

Table : Single SVM

Instrument	Precision	Recall	F1
Bass drum	91.4%	74.1%	81.9%
Snare drum	93.0%	79.6%	85.8%
Hi-hat	84.7%	93.2%	88.8%
Average	89.7%	82.3%	**85.5%**

Table : 3 binary SVM

Precision	Recall	F1
90.6%	76.1%	82.7%
92.8%	82.6%	87.4%
84.7%	94.1%	89.2%
89.4%	84.3%	**86.4%**

Results

Results for binary SVM and K-NN, with *all features:*

Table : 3 binary K-NN

Instrument	Precision	Recall	F1
Bass drum	88.5%	84.9%	86.6%
Snare drum	91.9%	90.8%	91.3%
Hi-hat	91.6%	92.7%	92.1%
Average	90.7%	89.5%	**90.0%**

Table : 3 binary SVM

Precision	Recall	F1
93.4%	75.9%	83.7%
95.5%	82.3%	88.4%
84.6%	97.1%	90.4%
91.2%	85.1%	**87.5%**

Results

Results for binary SVM, with *all features* and *auto features:*

Table : 3 binary SVM *(auto)*

Instrument	Precision	Recall	F1
Bass drum	86.6%	86.2%	86.4%
Snare drum	90.6%	86.3%	88.4%
Hi-hat	82.4%	94.4%	88.0%
Average	86.5%	89.0%	**87.6%**

Table : 3 binary SVM *(all)*

Precision	Recall	F1
93.4%	75.9%	83.7%
95.5%	82.3%	88.4%
84.6%	97.1%	90.4%
91.2%	85.1%	**87.5%**

Results

Average results for single SVM, with *manual features:*

Taxonomy	Precision	Recall	F1
Gillet ($N = 3$)	89.7%	82.3%	**85.5%**
Basic-level ($N = 5$)	87.7%	65.8%	**72.7%**
Sub-category ($N = 12$)	81.3%	44.4%	**52.3%**

Remarks

In Gillet's thesis, $F1 = 69.8\%$. Our results are comparatively good, because we skipped the *onset detection* step by using an oracle, and our evaluation protocol is less strict.

There is room for improvement:

- Better feature selection;
- Parameters tuning;
- Different type of classifier for each instrument;
- Use video features.

Here is our project's repository, feel free to take a look:
`https://code.google.com/p/drum-transcription/`