Computational modeling of expressive music performance in hexaphonic guitar

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Contents

Motivation

- I'm a guitar player, really interested into machine learning and music.
- Polyphonic expressive music modelling has been mainly done in classical piano, but not in guitar.
- Previous work on monophonic expressive guitar performance modelling. [Giraldo 2016]
- Previous work on hexaphonic guitar recording and visualization. [Angulo 2016]

Objectives

- To propose a framework for hexaphonic (polyphonic) guitar modelling
- Generate machine learning models for polyphonic guitar music.
- Automatically produce expressive performances from polyphonic guitar scores.
- To generate an analyzed Dataset of hexaphonic expressive guitar performances.

State of the art

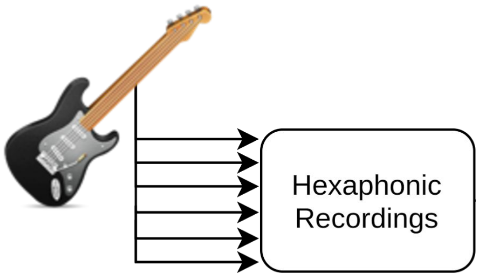
- Empirical studies: (analysis by synthesis)

Author	System	Instrument
KTH	Director Musices	General
Sundberg	Inter-Onset	Piano
Bresin	DM mapped to emotions	General

- Machine learning based studies:

Author	Method	Instrument	Mono/Poly
Arcos	Case based reasoning	Saxophone	monophonic
Bantula	Several methods	Jazz ensemble	polyphonic
Bresin	ANN	Piano	monophonic
Camurri	ANN	Flute	monophonic
Giraldo	Several methods	Guitar	monophonic
Gratchen	Case based reasoning	Saxophone	monophonic
Grindlay	HMM	Piano	monophonic
Kirke	Generative models	Piano	polyphonic
Miranda	Genetic Algorithms	Piano	monophonic
Puiggros	Several methods	Bassoon	monophonic
Ramirez	Several methods	Saxophone	monophonic
Widmer	Rule-based meta-learning	Piano	monophonic

Methodology - Hexaphonic Recordings



- Roland GK-3 divided pickup
- Breakout Box
- Recordings by H.Bantula
    - *Darn that dream (J.V.Heusen & E.DeLange)*
    - *Suite en la (M.M.Ponce)*

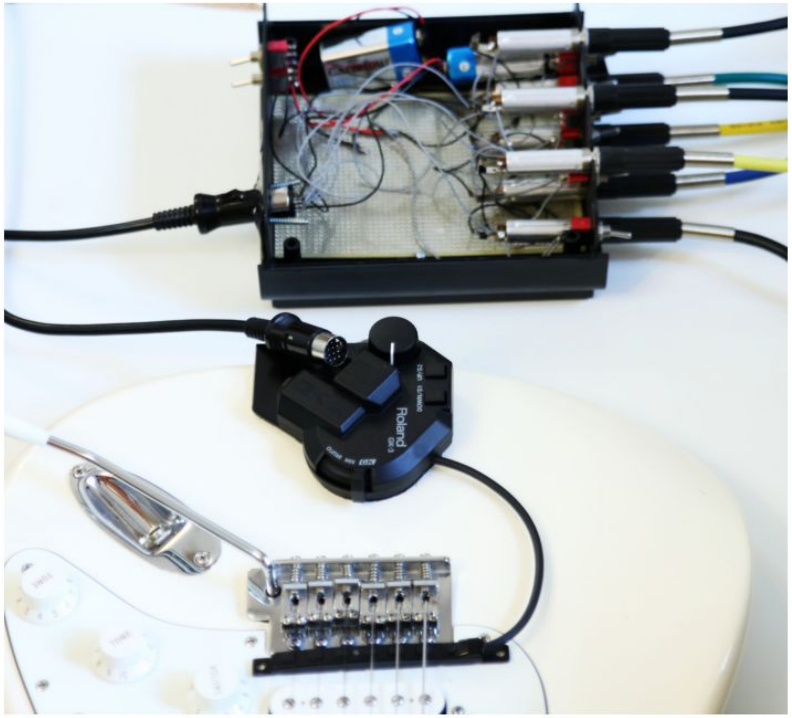
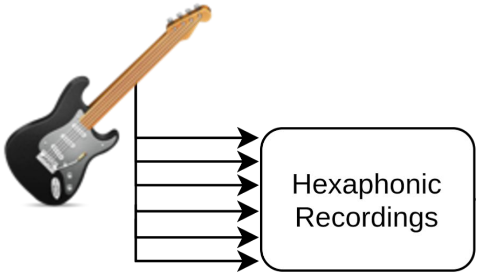


Fig.1 - Roland Gk-3 + Breakout Box [Angulo 2016]

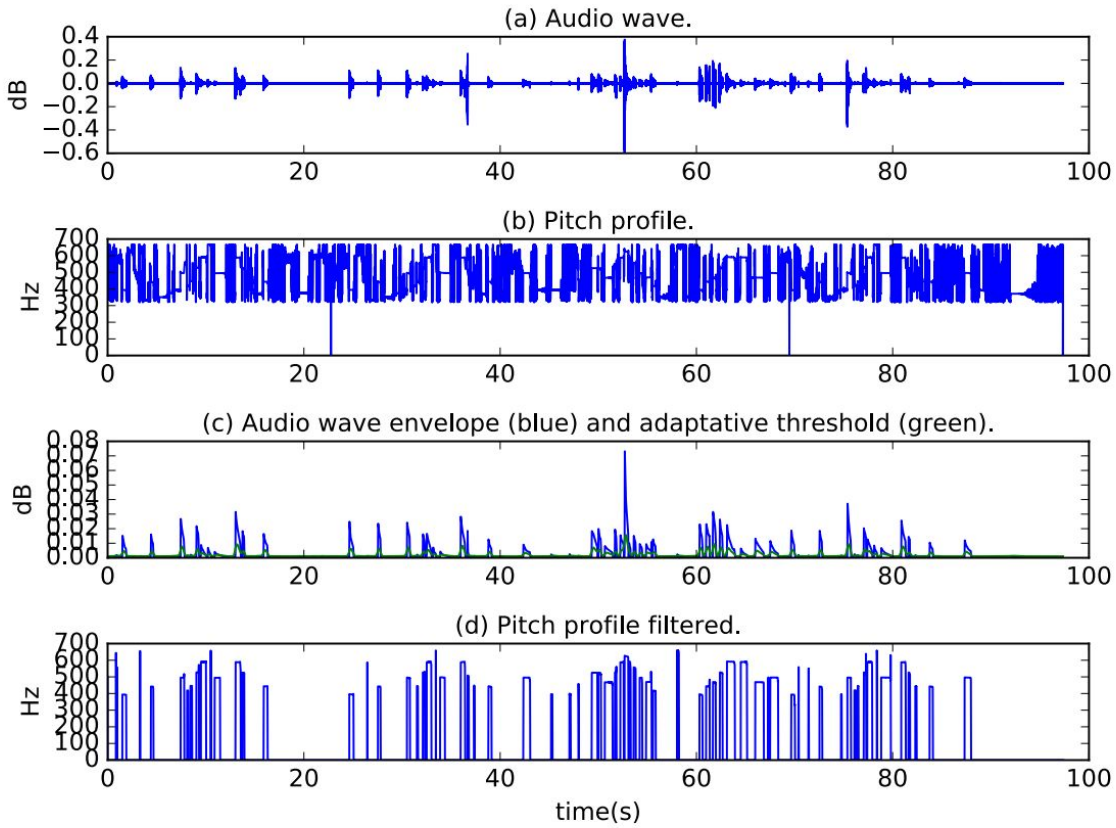
Methodology - Transcription



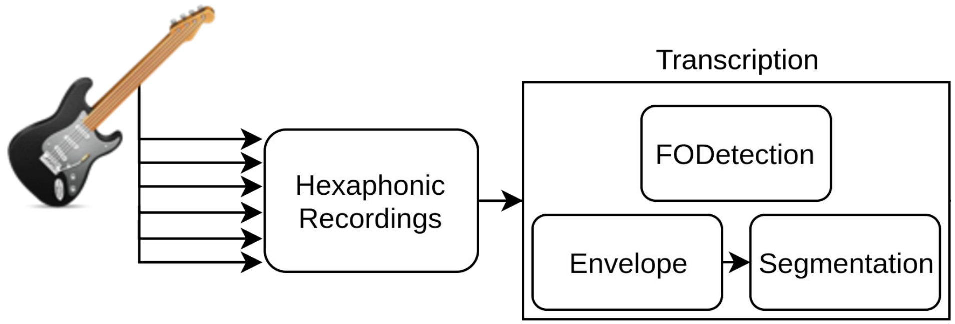
For each string:

- F0 detection → YIN algorithm
- Dynamic threshold over envelope
- F0 to midi note number
- Onset and duration
- Rules for note correction

Methodology - Transcription

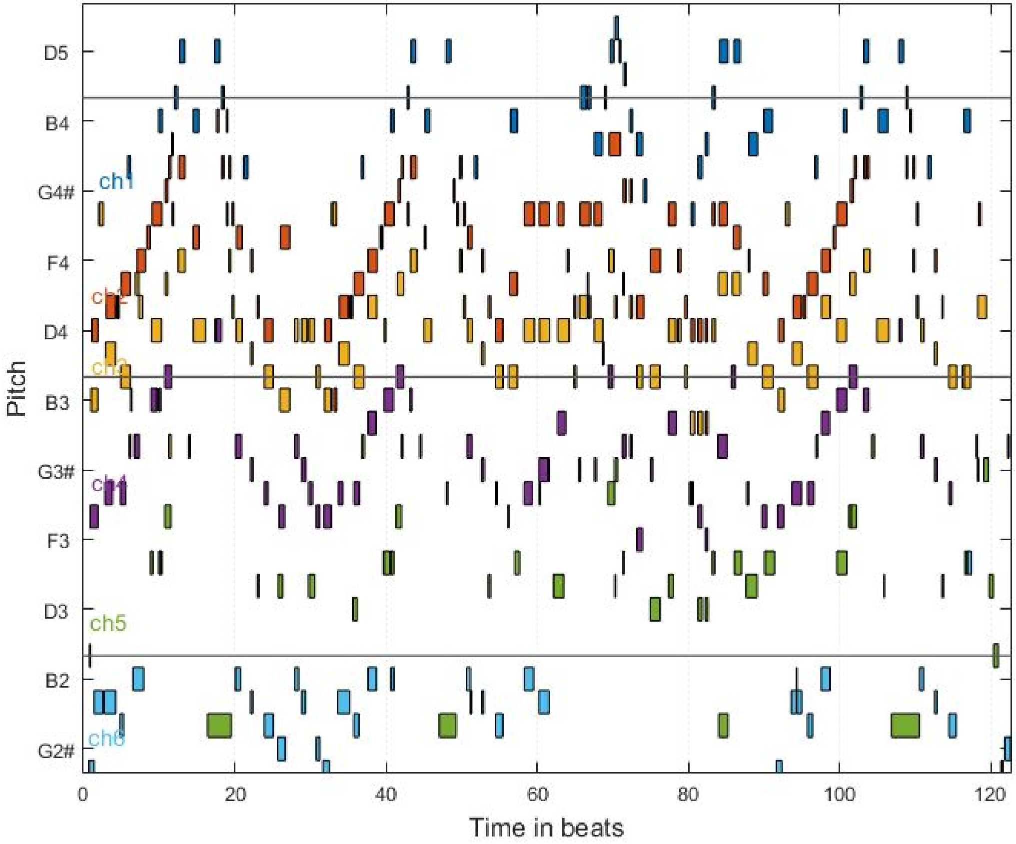


Methodology - MIDI Performances



- Each string → one midi channel
- Velocity → power envelope.
- One single midi file

Methodology - MIDI Performances



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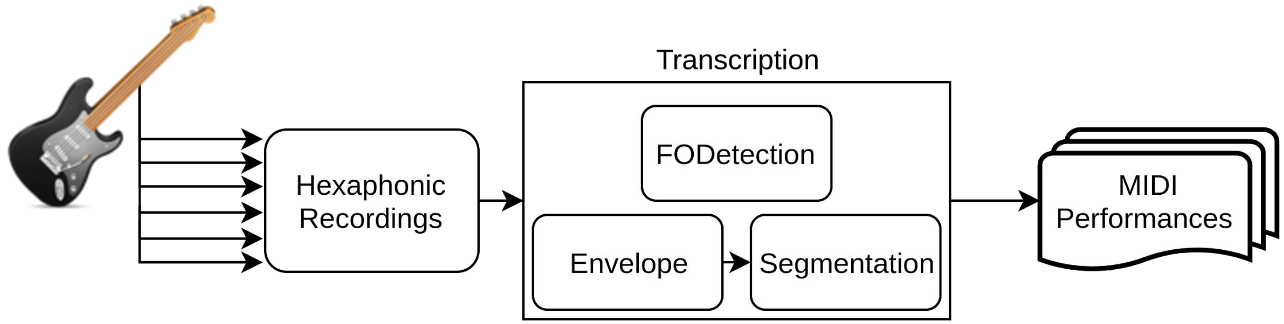
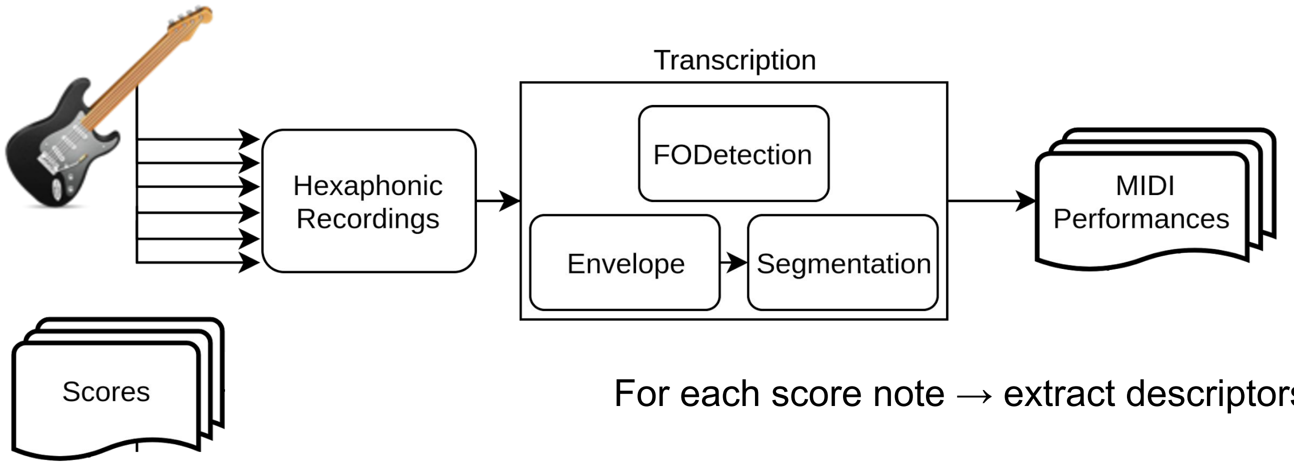
Methodology - Scores



- Scores in machine readable format
- Single channel xml
- Chord annotation

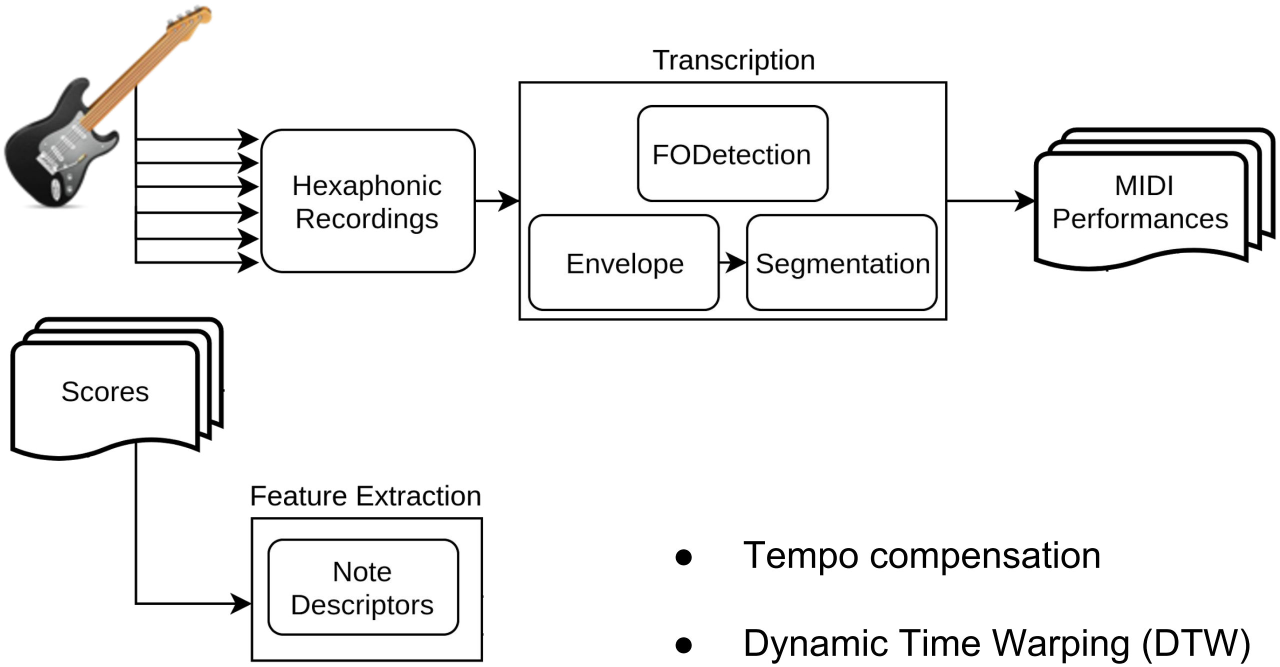
Methodology - Feature Extraction



For each score note → extract descriptors **(34 feat)**:

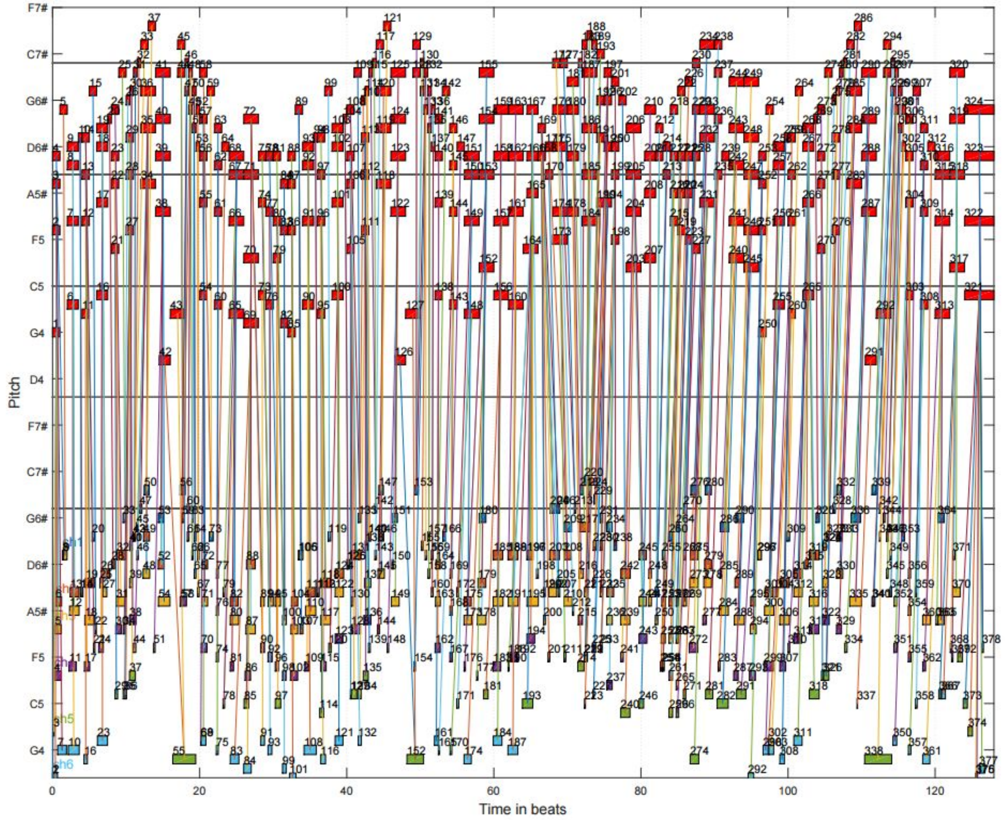
- Nominal descriptors
  Pitch, onset, duration, velocity, chroma, string,...
- Neighbouring descriptors
  Previous-next onset, duration, pitch, narmour, its chord, its pedal, nº simultaneous…
- Contextual descriptors
  Measure, tempo, chord, is chord note, note to key, metrical strength,...

Methodology - Performance to score alignment

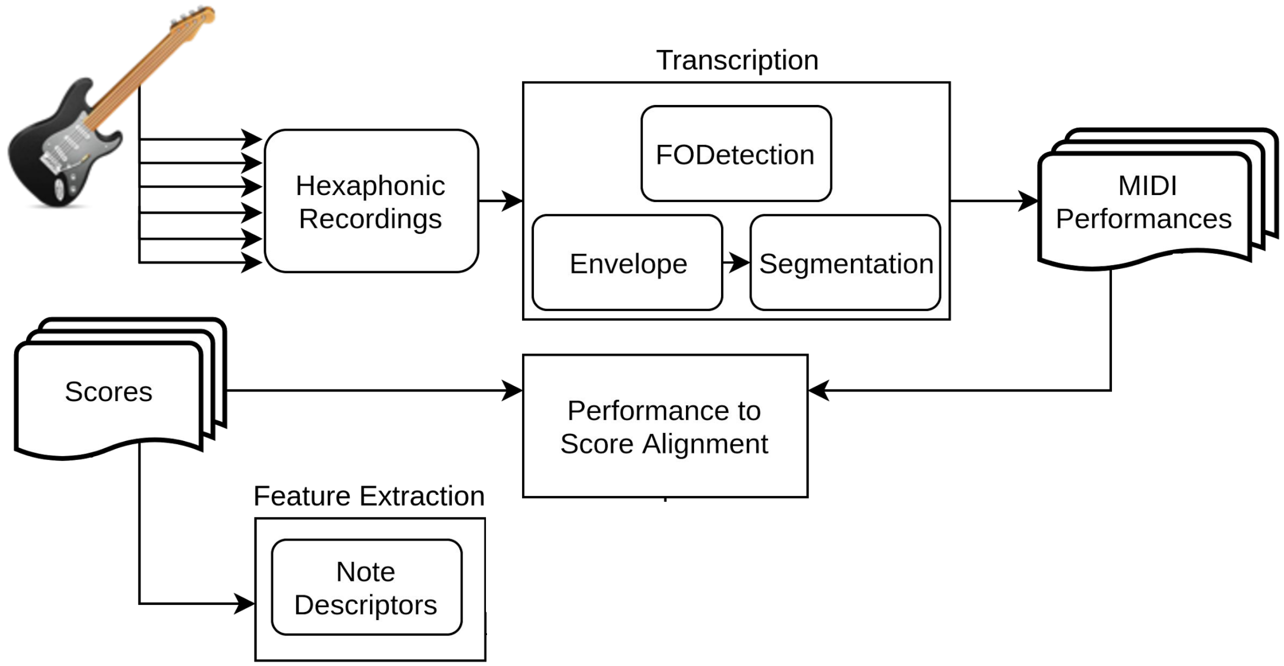


- Tempo compensation
- Dynamic Time Warping (DTW)
- Cost function based on pitch, onset, duration.

Methodology - Transcription



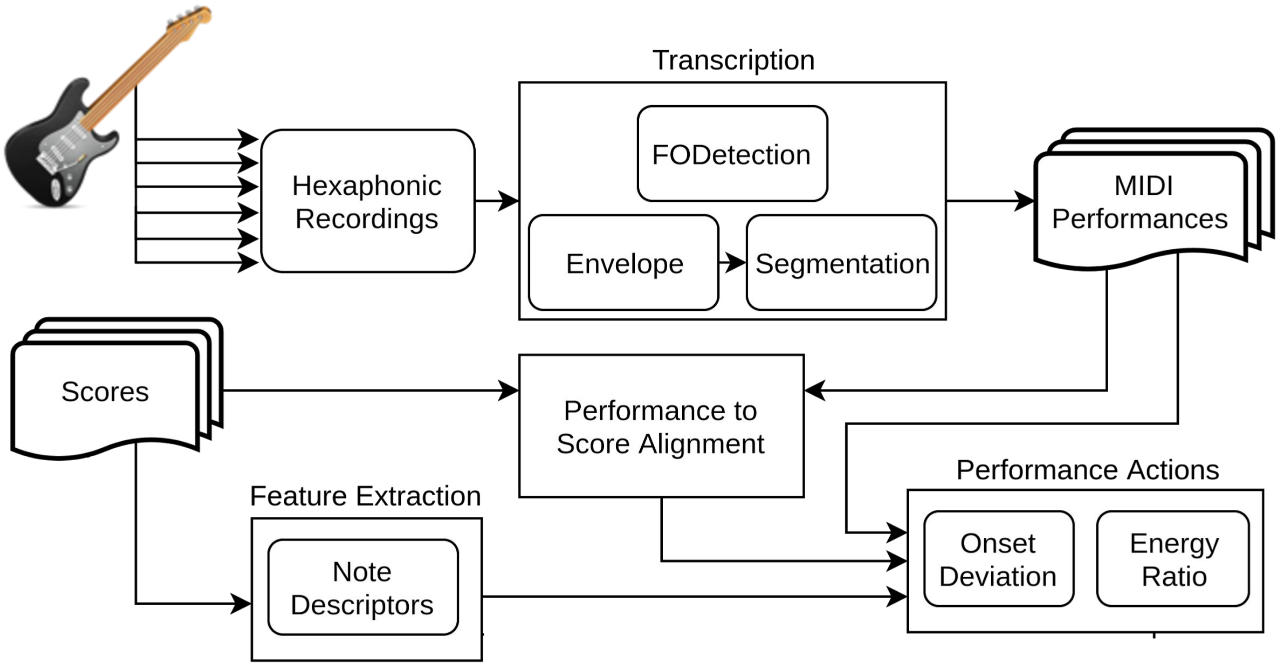
Methodology - Performance actions



Onset_dev = onset_perf - onset_score

Energy_ratio = energy_perf / energy_score

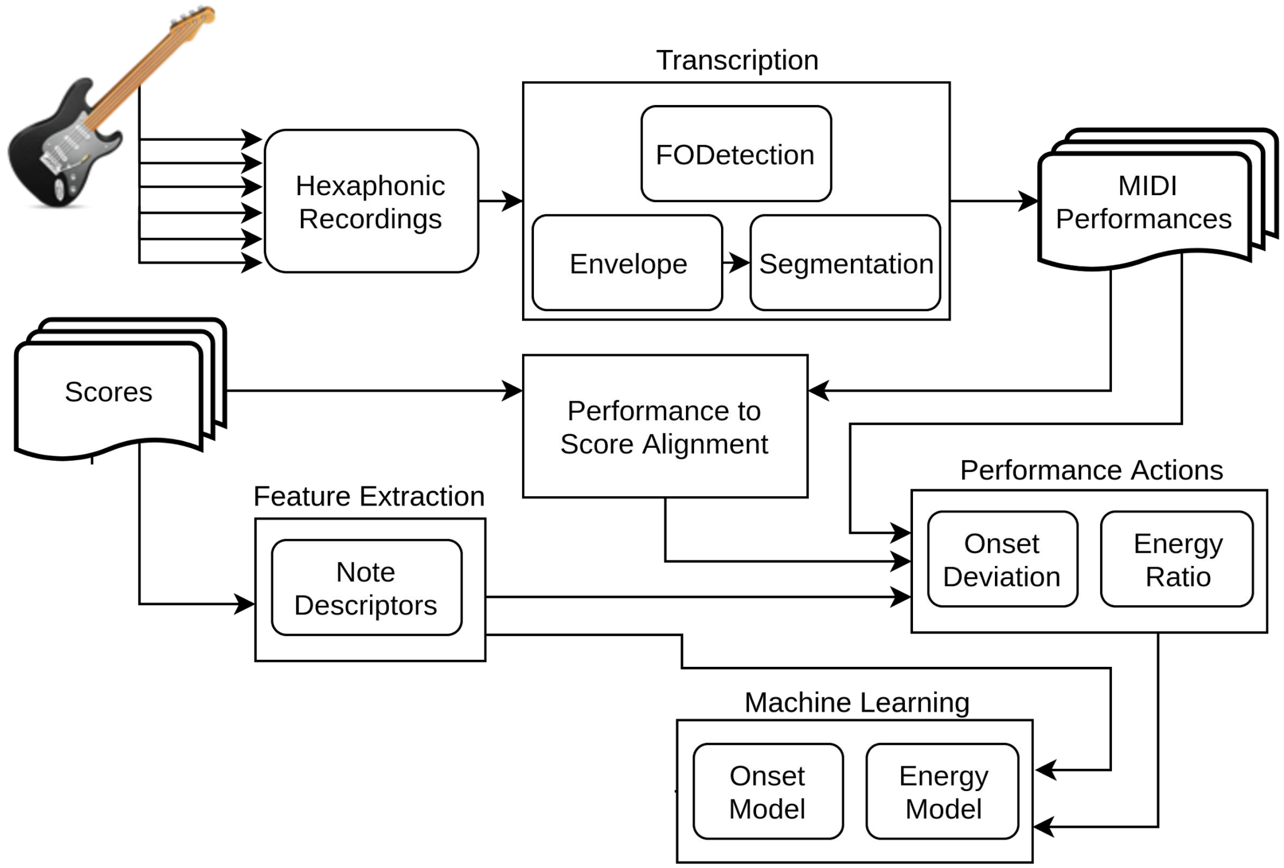
Methodology - Modelling



Testing different models:

Decission Trees, kNN, SVM, ANN,...

Methodology - Expressive Performances



Results - Audio Examples

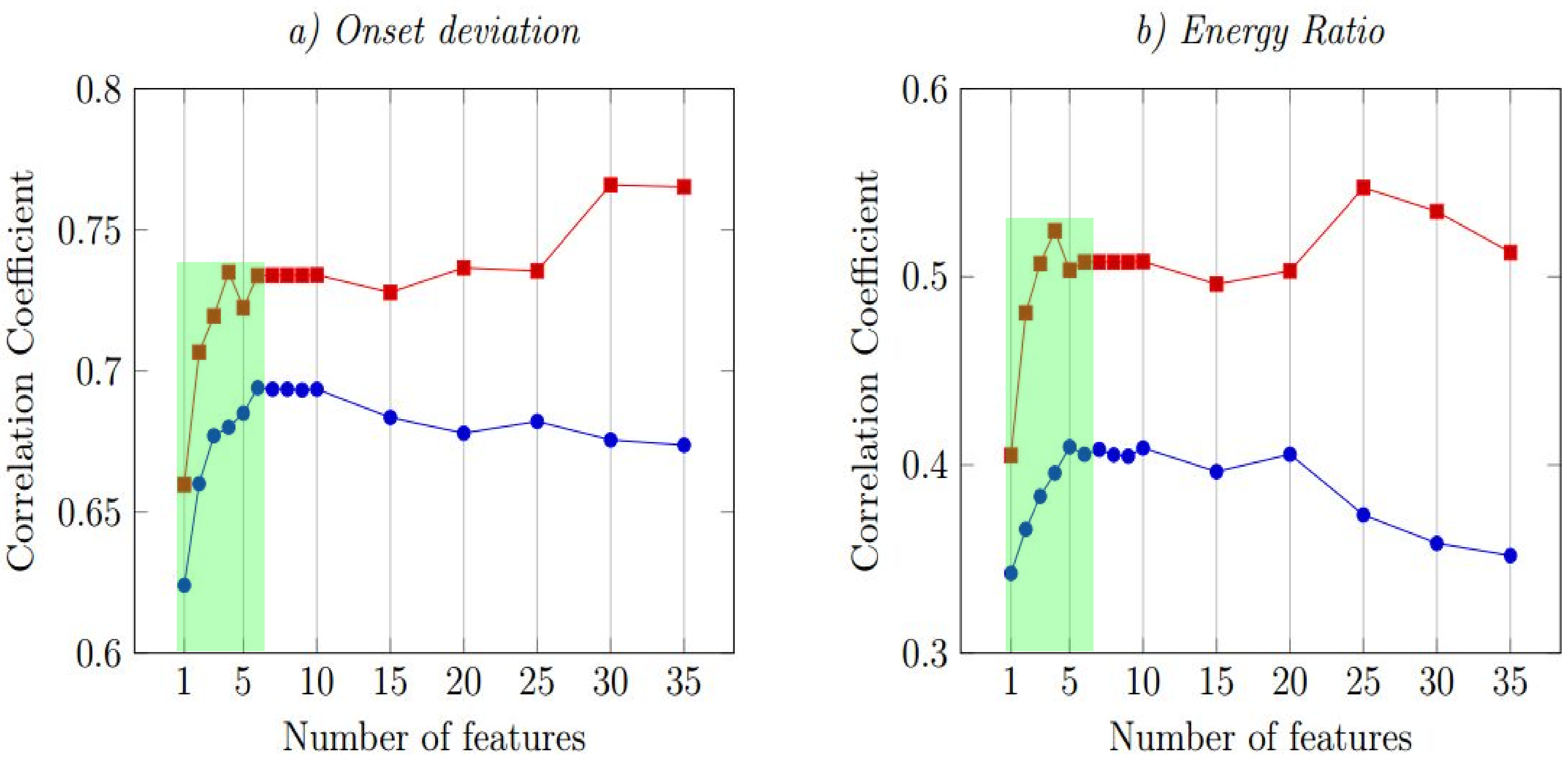
Results - Quantitative

Dataset (feature)	D.Tree cv/train	k_1NN cv/train	k_2NN cv/ train	k_8NN cv/train	SVM cv/train	ANN cv/train
'Darn (energy)'	0.37/0.53	0.18/1	0.27/0.78	0.28/0.52	0.37/0.55	0.26/0.98
'Darn (onset)'	0.70/0.87	0.35/1	0.42/0.83	0.52/0.69	0.57/0.68	0.47/0.99
'Suite (energy)'	0.35/0.59	0.24/1	0.31/0.77	0.32/0.53	0.23/0.38	0.17/0.70
'Suite (onset)'	0.77/0.88	0.28/1	0.35/0.80	0.33/0.53	0.30/0.40	0.29/0.79
'Suite2 (energy)'	0.32/0.70	0.21/1	0.24/0.77	0.17/0.45	0.19/0.31	0.18/0.66
'Suite2 (onset)'	0.83/0.92	0.43/1	0.48/0.85	0.51/0.85	0.44/0.52	0.40/0.78

Results - Quantitative

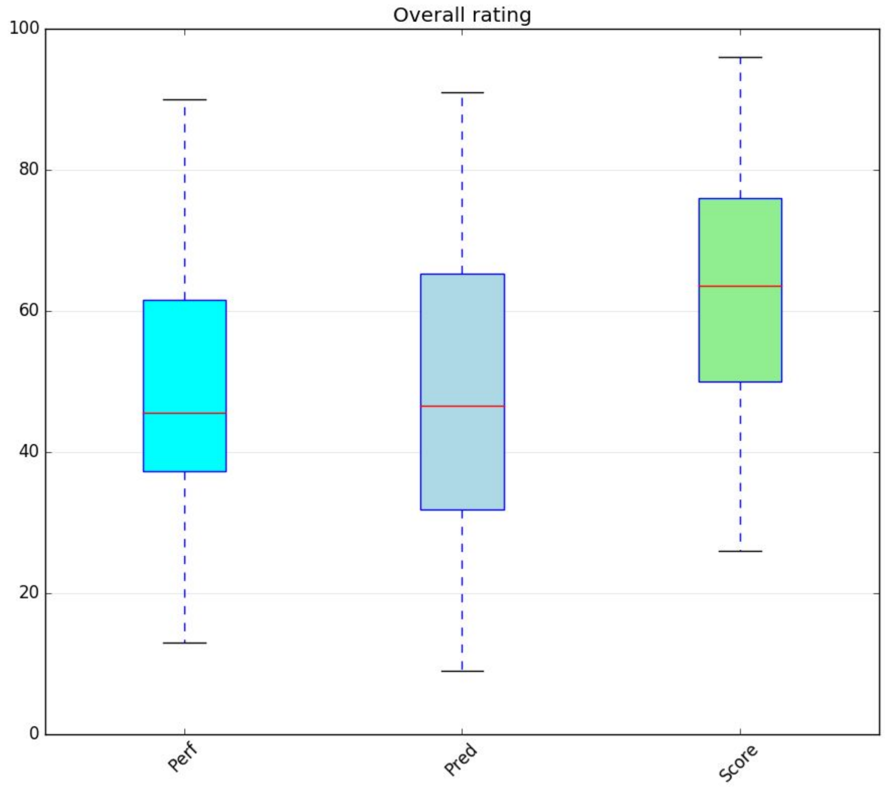
Train	Test	D.Tree		ANN	
		energy	onset	energy	onset
'Darn'	'Suite'	0.013	0.156	0.047	0.008
'Darn'	'Suite2'	0.091	0.183	0.033	0.075
'Suite'	'Darn'	0.017	0.140	0.107	0.032
'Suite'	'Suite2'	0.324	0.392	0.148	0.253
'Suite2'	'Darn'	0.043	0.099	0.079	0.027
'Suite2'	'Suite'	0.240	0.384	0.190	0.227

Results - Feature Selection



Results - Qualitative

- Online listening test: marcsiq2.github.io
- 4 different phrases, for each one:
  - Performance
  - Predicted
  - Score
- Rate how “human” are the audios
- 15 answers



Conclusions

- Proposed framework for hexaphonic guitar expression modelling:
    - Hexaphonic guitar transcription
    - Performance to score alignment
    - Feature extraction
    - Machine learning modelling
- Quantitative results
- Qualitative results

Contributions

- New problem (polyphonic guitar), as far as we know.
- Extended framework from monophonic guitar.
- Data-set analysis.
- GitHub with all code and data (marcsiq2.github.io/masterthesis)
- Paper submitted to:

  MML 2017 - 10th International Workshop on Machine Learning and Music

Future work

- More hexaphonic recordings:
    - Same performer different pieces.
    - Same piece different performers.
- Interpretability of the models
- How models generalize into same style
- Musical sense behind feature selection
- Sequential modelling.
- Work on improving the synthesis

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Thank you for your attention!

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