#### Automatic Chord Recognition using Neural Networks

Audio Signal Processing

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### Introduction

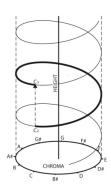
# A bit of music and history

- Automatic Chord Recognition, first start in 1991
- Classic methods: KNN, Logistic, HMM
- Leap in precision with the introduction of Neural Networks

#### Chords and Pitch

- Pitch: subjective perception of a note's height
- The pitch system is composed of 12 classes,
- An octave means a doubling of the frequency, each octave :  $f_n = 2^{\frac{1}{12}} f_{n-1}$
- Define an equivalence relation between notes
- A chord is combination of 2 or more pitches

### Chords and Pitch



			0.1		
	Octave				
Note	2	3	4	5	6
С	66 Hz	131 Hz	262 Hz	523 Hz	1046 Hz
C♯/D♭	70 Hz	139 Hz	277 Hz	554 Hz	1109 Hz
D	74 Hz	147 Hz	294 Hz	587 Hz	1175 Hz
D♯/E♭	78 Hz	156 Hz	311 Hz	622 Hz	1245 Hz
E	83 Hz	165 Hz	330 Hz	659 Hz	1319 Hz
F	88 Hz	175 Hz	349 Hz	698 Hz	1397 Hz
F♯/G♭	93 Hz	185 Hz	370 Hz	740 Hz	1480 Hz
G	98 Hz	196 Hz	392 Hz	784 Hz	1568 Hz
G♯/A♭	104 Hz	208 Hz	415 Hz	831 Hz	1661 Hz
A	110 Hz	220 Hz	440 Hz	880 Hz	1760 Hz
A♯/B♭	117 Hz	233 Hz	466 Hz	932 Hz	1865 Hz
В	124 Hz	247 Hz	494 Hz	988 Hz	1976 Hz

#### Features Extraction

#### Short-Time Fourier Transform

- Discrete FT on equally spaced segments of the song
- Frequency mapping can be scaled (Mel, Logarithmic)

#### Drawbacks:

- Constant resolution and frequency difference
- Not suited to represent the pitch class concept

### Constant Q Transform

$$f_k = f_{min}.2^{\frac{k}{B}} \tag{1}$$

where k is the frequency index,B is the number of bins per octave.

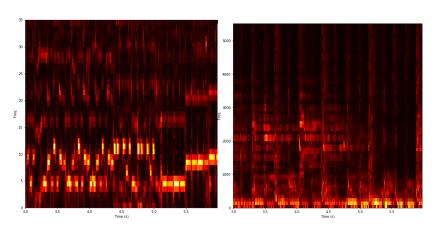
$$X(k;r) = \frac{1}{N_k} \sum_{n} x(nr)w(n)e^{j2\pi nQ/N_k} \qquad (2)$$

$$Q=rac{1}{2^B-1}$$
, and the resolution  $^{-1}N_k=[Qrac{f_s}{f_t}]$ 

## PCP, the first ACR System

- Can be seen as 1-bin Constant Q Transform
- Uses pitches pattern matching using NN and hand crafted score
- Takuya Fujishima, Realtime Chord Recognition of Musical Sound

## CQT vs STFT : who's the best ?



Muhammad Huzaifah, Comparison of Time-Frequency Representations.

# Features Processing

# Pre-processing

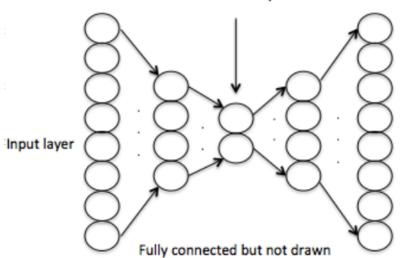
- Time slicing: concatenating adjacent frames
- First low pass filter :  $y_n = \alpha y_{n-1} + (1 \alpha)x_n$
- A pair of low pass filters: exponentially weighted mean

$$\sum_{i=-r} ra^{-|i|} x[.+r]$$

Other papers : Geometric mean/ Median filter

# Learning Architecture

#### Bottleneck Layer



# Deep Belief Networks

- Layers of fully connected layers of Restricted Boltzmann Machines
- A stochastic neural network :
- One layer of visible units : chords
- One layer of hidden units: latent variables
- the hidden units of layer i are the visible for the layer i+1
- Seen as an out-dated model in the Deep community

## Deep architectures

- Recurrent Neural Networks
  - Nicolas Boulanger-Lewandowski, Audio Chord Recognition with Recurent Neural Networks.
- Convolutional NN:
  - Anis Rojb al., Music Transcription by Deep Learning with Data and "Artificial Semantic" Augmentation

# Conclusion

#### Conclusions

- Improvement with the introduction with neural networks
- little difference in performance between different structures
- Smoothness of solutions to be improved
  - Matthias Mauch & Katy Noland & Simon Dixon (2009) Using Musical Structure to Enhance Automatic Chord Transcription.

#### Conclusions

