

HPCP-based music classification

Louis Dorard¹ and John Shawe-Taylor¹

Department of Computer Science
University College London
London, WC1E 6BT
United Kingdom
{l.dorard, jst}@cs.ucl.ac.uk

Centre for Computational Statistics and Machine Learning
<http://www.csml.ucl.ac.uk/>

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Abstract

Chord chroma representations have proven quite successful for chords detection from audio as they allow to infer chord labels¹. These chroma representations, and more specifically Harmonic Pitch Class Profiles (HPCPs), can also be derived from chords in symbolic notation (e.g. [E2 G#3 B3 E4]).

Paiement et al.² have shown how the Euclidian distance between HPCPs matches perceptual closeness of chords. We are therefore interested in using HPCPs as a low-dimensional representation of chords in a “psycho-acoustic space”, for the purpose of classifying music based on harmonic information owing to Machine Learning techniques.

Symbolic music can be represented as discrete-time time series of musical events which can have several features, such as HPCP and melody pitch for instance. In order to be insensitive to transpositions, we consider the deltas of these features ($feat(t + 1) - feat(t)$: melody pitch becomes melodic interval). Notice that HPCP deltas stay equivalent by circular permutation. The musical time series can then be compared using Dynamic Time Warping in order to handle time axis gaps³.

This idea can be extended to use HPCPs extracted from audio, however this will probably introduce noise in the representation.

¹ Helene Papadopoulos and Geoffroy Peeters: Large-scale study of chord estimation algorithms based on chroma representation and HMM (IEEE 2007)

² Jean-François Paiement, Douglas Eck, Samy Bengio and David Barber: A Graphical Model for Chord Progressions Embedded in a Psychoacoustic Space (ICML 2005)

³ The reader can find an explanation of DTW and good illustrations in Remi Gaudin and Nicolas Nicoloyannis: An adaptable time warping distance for time series learning (ICMLA 2006)