The 39th International Conference on Acoustics, Speech and Signal Processing (ICASSP 2014)

A Novel Cepstral Representation for Timbre Modeling of Sound Sources in Polyphonic Mixtures

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Introduction

Proposes a new cepstral representation named Uni Cepstrum (UDC) and its mel-scale variant (MUDC).

Ordinary Cepstrum (OC) - calculated from the

MFCC

Discrete Cepstrum (DC) Regularized DC (RDC)

Uniform DC (UDC)

magnitude spectrum - calculated from isola spectral points

- can model timbre of Mel-frequency UDC (MUDC) sources w/o source se

Derives mathematical relations between these repres

Relations of Cepstral Representations

Cepstrum: approximate log-amp spectrum with sinusoids $a(f) \approx c_0 + \sqrt{2} \sum_{i=1}^{p-1} c_i \cos(2\pi i f)$ (1)

- a(f) : log-amplitude spectrum at normalized frequency f • c_i 's : cepstral coefficients of order p
- ► Ordinary Cepstrum (OC): least square solution of Eq.(1) $\mathbf{a} = \mathbf{M}\mathbf{c}$

$$\mathbf{c}_{\mathsf{oc}} = (\mathbf{M}^T \mathbf{M})^{-1} \mathbf{M}^T \mathbf{a} = \frac{1}{N} \mathbf{M}^T \mathbf{a}$$

- a: discrete log-amplitude spectrum with N frequency bins
- M : the first p columns of a discrete cosine transform (DCT) matrix whose columns are orthogonal, so $\mathbf{M}^T \mathbf{M} = \frac{1}{N} \mathbf{I}$.



► MFCC: apply mel-scale filterbank before DCT Still approximating the mixture spectrum

References and Acknowledgement

[1] A. de Cheveigné and H. Kawahara, "Yin, a fundamental frequency estimator for speech and music", JASA, 111: 1917-1930, 2002.

[2] Z. Duan and B. Pardo, "Soundprism: an online system for score-informed source separation of music audio," *IEEE J-STSP*, 5(6): 1205-1215, 2011.

This work was partially supported by NSF grant 1116384.

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Ordinary Cepstrum (OC) of mixture signal

► DC: least square solution approximating selected points $\hat{\mathbf{a}} = \hat{\mathbf{M}} \mathbf{a}$

$$\mathbf{a} = \mathbf{M}\mathbf{c}$$

 $\mathbf{c}_{\mathsf{dc}} = (\mathbf{\hat{M}}^T \mathbf{\hat{M}})^{-1}$

- $\hat{\mathbf{a}}$: log-amplitudes of selected spectral points likely belonging to a source (e.g., harmonics of a pitched source)
- $\hat{\mathbf{M}}$: rows of \mathbf{M} corresponding to the spectral points • $(\mathbf{\hat{M}}^T \mathbf{\hat{M}})^{-1}$ is often poorly-conditioned due to large frequency gap
- between these points, i.e., approximated spectral envelope overfits these points and oscillates significantly at other frequencies.



► RDC: adding a regularizer to prevent overfitting $\mathbf{c}_{\mathsf{rdc}} = (\mathbf{\hat{M}}^T \mathbf{\hat{M}} + \lambda \mathbf{R})^{-1} \mathbf{\hat{M}}^T \mathbf{\hat{a}}$

• λR : parametric regularizer with strength λ

Proposed Cepstral Representations

- ► UDC: removing $(\hat{\mathbf{M}}^T \hat{\mathbf{M}})^{-1}$ in DC calculation $\mathbf{c}_{\mathsf{udc}} = \mathbf{\hat{M}}^T \mathbf{\hat{a}}$ $= \mathbf{M}^T \mathbf{\tilde{a}} = N(\mathbf{M}^T)$
- Eq. (8) shows that UDC is taking DCT on a sparse spectrum $\tilde{\mathbf{a}}$, which equals to \mathbf{a} at selected spectral points and 0 otherwise.
- the sparse spectrum $\tilde{\mathbf{a}}$ with sinusoids.
- Zeros in \tilde{a} serve as a natural and locally adaptive regularizer.



► Mel-scale UDC (MUDC)

• Let f be normalized mel-scale frequency 0.5mel(Hz)/mel(Fs/2).



 ${}^{1}\mathbf{\hat{M}}^{T}\mathbf{\hat{a}}$

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• Eq. (8) also shows c_{udc} is the least square solution of approximating

 \mathbf{M}^{T} (Discrete Cosine Transform) UDC of the source

► Fisher score analysis of timbre representations

- Calculate OC and MFCC from full spectrum



Instrument recognition in polyphonic audio



► UDC and MUDC use a more **natural and locally adaptive** regularizer to prevent overfitting the isolated spectral points. UDC and MUDC outperform the other representations in the task of instrument recognition in polyphonic audio mixtures.



Experiments

• 687 notes from 13 instruments of the University of Iowa dataset • 5 frames randomly selected from the sustain part of each note

• Detect pitch using YIN [1], then consider 50 harmonics as selected spectral points for DC, RDC, UDC, and MUDC

 Train 13-class SVM with 687 notes from the U lowa dataset • Test on 5000 random chords mixed with notes from RWC database Detect ground-truth pitches using YIN [1] prior to mixing • Calculate OC and MFCC from separated source spectrum, using a soft-masking-based separation method [2] with ground-truth pitches Calculate all the other features from first 50 harmonics of pitch

Conclusions