WHO'S PLAYING THAT SOLO? RECOGNIZING JAZZ MUSICIANS BY THEIR "UNIQUE SOUND"

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Outline

Motivation

”Jazz musicians have always acknowledged the importance of developing a ***unique*** *stylistic* ***voice*** *as a way of transcending from imitation and assimilation into innovation.”*

(Berliner, 1994)

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- What make jazz soloists recognizable by listeners?
  - Syntactical features (pitch, interval, rhythm, harmonic / metrical context)
  - Non-syntactical / expressive features (micro-timing, dynamics, intonation, pitch modulation, **timbre / sound**)

Motivation

- Which factors affect the recognition?[1]
  - **Instrument sound of performer**
  - Expressive tone modifications
    - Dynamics, articulations, pitch modulations, microtiming, ...
  - Sound of accompanying instruments (rhythm section)
  - Recording conditions
    - Recording setup, microphone characteristics, recording year, ...

[1] Audio example

Motivation

- Goals of this study
  - Focus on instrument sound as complementary part to other expressive features for jazz performance analysis
  - Focus on trumpet (tp), alto saxophone (as), and tenor saxophone (ts)
  - Evaluation scenarios: artist classification & similarity

Motivation

- Application Scenarios
  - Verification of known & discovery of unknown timbral similarities between jazz soloists
  - Automatic performer identification in jazz recordings
    - Content-based metadata enrichment & cleanup for jazz archives
  - Evolution of artist sound
    - Imitation strategies among jazz soloists

Outline

Related Work

- Timbre Research
  - Timbre = Difference between sounds of the same pitch & loudness
  - Among ”spectrographic attributes” [Benadon, 2003] with microtemporal deviations (microtiming) & expressive nuances (vibrato & pitch bending)
  - Previous studies often use perceptual scaling to indentify *underlying acoustic dimensions*
    - Note envelope, temporal change in spectrum
    - Rise time & quality of note attack
    - Spectral centroid

Related Work

- Jazz Performer Identification
  - [Benadon, 2003]
    - Music performance = *Calligraphic* (pitch, rhythm, contour) vs. *spectrographic* (timbre, microtiming, pitch modulation) aspects
    - Tenor saxophonist identification (*John Coltrane, Dexter Gordon, Sonny Rollins, Wayne Shorter*)
    - Listening tests (16 short 2-5 note sequences from post-bebop recordings)
    - Results: 7 subjects show average recognition score of 11.9/16
  - [Ramirez et al., 2010]
    - Analysis of monophonic saxophone solo recordings (4 standards, 2 tempi, 3 performers)
    - Spectral tone model, inter-note and intra-note features
    - Deviation patterns from pitch, timing, amplitude, timbre
    - Up to 98 % classification accuracy

Related Work

- Jazz Performer Identification
  - [Lazar and Lesk, 2016b]
    - Comparison of 3 trumpet performances of *St. Louis Blues* by *Louis Amstrong, Harry James, and Wynton Marsalis*)
    - Spectrogram-based observation of characteristic timbre propoerties
    - Note-level: sound fuzziness & sound clarity
    - Segment-level: sound complexity & note envelopes (rising time)
  - [Abeßer et al., 2015, Lazar and Lesk, 2016a]
    - Importance on vibrato features for jazz performer classification
- Similar approaches for identification of singers, cellists, piano players

Outline

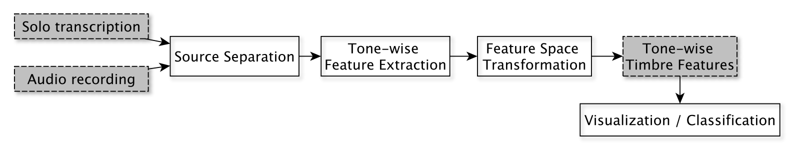
1. Motivation
2. Related Work
3. Proposed Method
4. Experiments & Results
    - Dataset
    - Artist Classification
    - Artist Sound Similarity
5. Conclusion & Outlook

Proposed Method

- How to analyze the ”sound” of a jazz soloist?
  - Data source: solos in commercial jazz recordings (multiinstrumental, polyphonic)
  - Use high-quality score information (Weimar Jazz Database) for “tone localization”
  - Isolate solo instrument from mixture signal (source separation)
  - Tone-level spectrogram-based analysis
  - Quantify different spectral & temporal properties of tones (state-of-the-art timbre features)
  - Use machine learning methods to learn artist-specific timbre patterns

Proposed Method

- Processing Flowchart

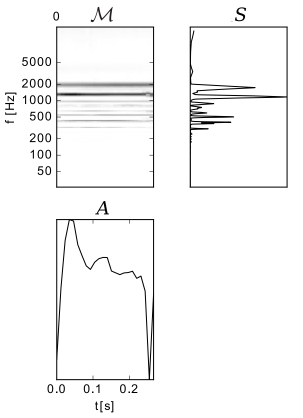


Proposed Method

- Pitch-informed solo & accompaniment separation [Cano et al., 2014]
  - Goal → isolate improvising solo instrument from accompaniment instruments (rhythm section)
  - Iterative **spectral modeling** of the solo instrument in the spectal domain
  - Includes musical instrument characteristics such as **common amplitude modulation**, **inharmonicity** & **magnitude and frequency smoothness**

Proposed Method

- Feature Extraction
  - One-Component Non-Negative Matrix Factorization NMF
    - Represent tone spectrogram M as product of spectral envelope S and temporal activation A



Proposed Method

- Feature Extraction
  - Spectral Features
    - Representation: S
    - $\rightarrow$ Statistics (centroid, spread, skewness, kurtosis)
    - $\rightarrow$ Shape (decrease, slope, flatness, roll-off)
    - Mel-Frequency Cepstral Coefficients (MFCC)
    - Spectral Contrast (octave-based, shape-based)
    - Inharmonicity
    - Relative Harmonic Magnitudes
    - Odd-to-even ratio
    - Tristimulus 1-3

Proposed Method

- Feature Extraction
  - Temporal Features
    - Representations: A, ΔA, 10-bin histogram over ΔA
    - $\rightarrow$ Statistics (centroid, spread, skewness, kurtosis)
    - $\rightarrow$ Shape (decrease, slope, flatness, roll-off)
    - Relative attack part length
    - Log attack / decay time
    - Multi-resolution gamma filterbank (correlation with prototype envelopes)

Outline

1. Motivation
2. Related Work
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4. **Experiments**
    - Dataset
    - Artist Classification
    - Artist Sound Similarity
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Experiments

- Dataset
  - Solos (audio + manual solo transcriptions) taken from *Weimar Jazz Database*[2]
  - Performer selection $\rightarrow \geq 4$ solos / performer
    - tp (7) $\rightarrow$ *Chet Baker, Dizzy Gillespie, Freddie Hubbard, Kenny Dorham, Miles Davis, Roy Eldridge*
    - ts (13) $\rightarrow$ *Bob Berg, Coleman Hawkins, David Murray, Dexter Gordon, Don Byas, John Coltrane, Joe Henderson, Joshua Redman, Lester Young, Michael Brecker, Sonny Rollins, Stan Getz, Wayne Shorter*
    - as (8) $\rightarrow$ *Art Pepper, Benny Carter, Cannonball Adderley, Charlie Parker, Lee Konitz, Ornette Coleman, Paul Desmond, Steve Coleman*
  - Note selection $\rightarrow$ first 100 tones / solo with ≥ 100 ms duration

[2] http://jazzomat.hfm-weimar.de/dbformat/dboverview.html

Artist classification

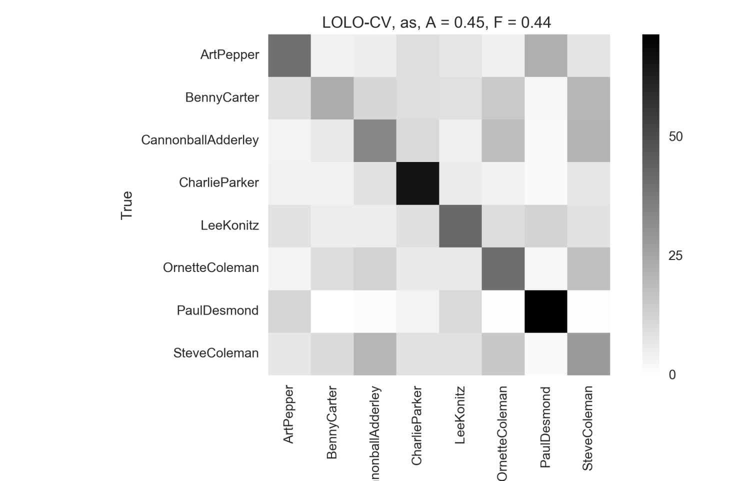
- Cross-validation strategy
  - Leave-one-label-out cross-validation (LOLO-CV)
    - Split of tones to training & test set strictly based on solo id
    - Realistic assumption: some solos of artist are known
- Optional majority voting over all tones of a given solo

Artist classification

Instrument	tp	as	ts
Number of Performers	7	8	13
Random baseline	0.14	0.13	0.08
LOLO-CV	0.36	0.45	0.28
LOLO-CV (majority voting)	**0.66**	**0.78**	**0.51**

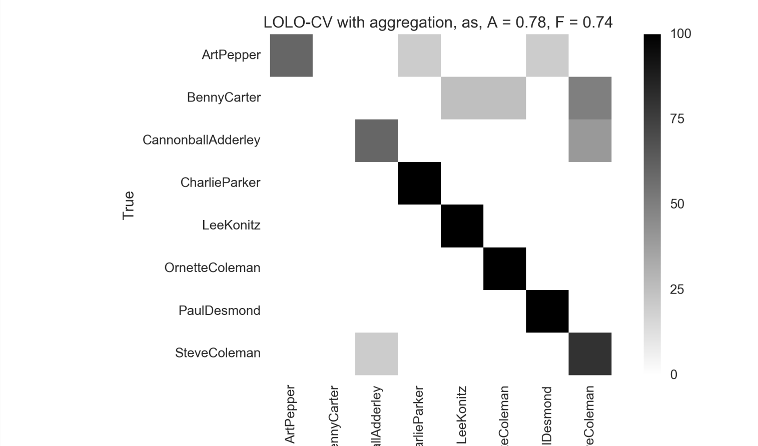
Artist classification (as)

- Example: alto saxophone - tone-wise classification



Artist classification (as)

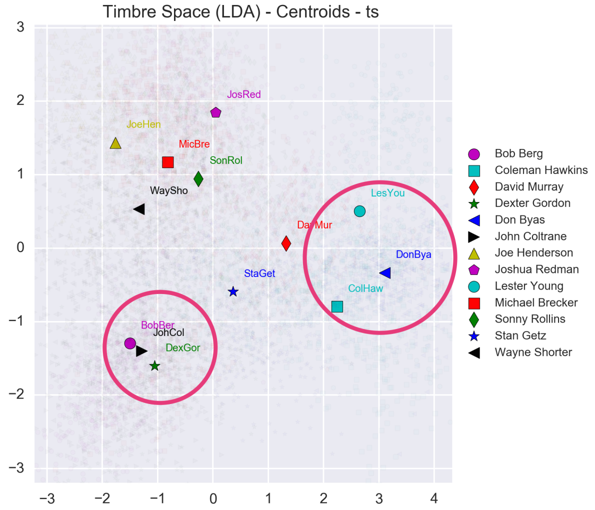
- Example: alto saxophone - solo-wise classification (majority voting over tones)



Artist Sound Similarity

- Explore reduced version of timbre feature space
- Transform feature space (127 dim. $\rightarrow$ 2 dim.) using Linear Discriminant Analysis (LDA) by
  - maximizing the variances between performers
  - minimizing the variances within performers
  - (Feature dimensions are linear combinations of existing features)
- Interpretation
  - Distance between class centroids $\rightarrow$ timbre similarity between performers
  - Clusters $\rightarrow$ Performers with similar sound

Artist Sound Similarity (ts)

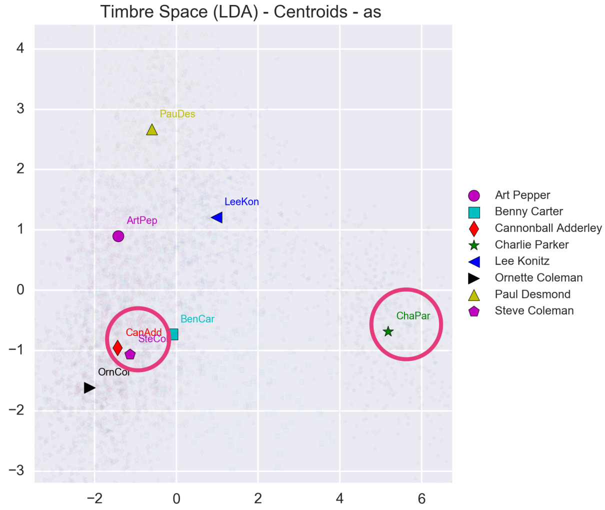


Artist Sound Similarity (ts)

- Obervations
  - Group 1: Coleman Hawkins, Lester Young, Don Byas
    - Swing tenor sax players
  - Cluster 2: John Coltrane, Bob Berg[3], Dexter Gordon
    - Dexter Gordon = early influence of John Coltrane[4]
    - Bob Berg: "The example of John Coltrane was a major influence on his playing [...]."[5]

[3] Audio example
[4] C. Woideck: John Coltrane: Development of a Tenor Saxophonist, 1950–1954, Jazz Perspectives, Vol. 2, Issue 2, 2008
[5] http://www.jazzhouse.org/gone/lastpost2.php3?edit=1039185731

Artist Sound Similarity (AS)

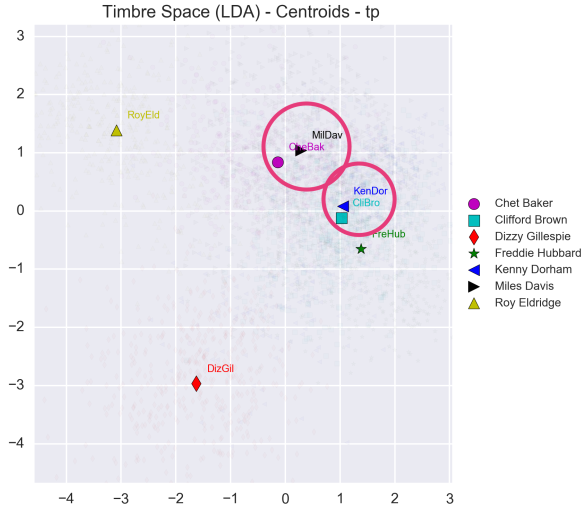


Artist Sound Similarity (AS)

- Obervations
  - Cluster: Steve Coleman, Cannonball Adderley[6]
  - Unique sound: Charlie Parker

[6] Audio example

Artist Sound Similarity (tp)



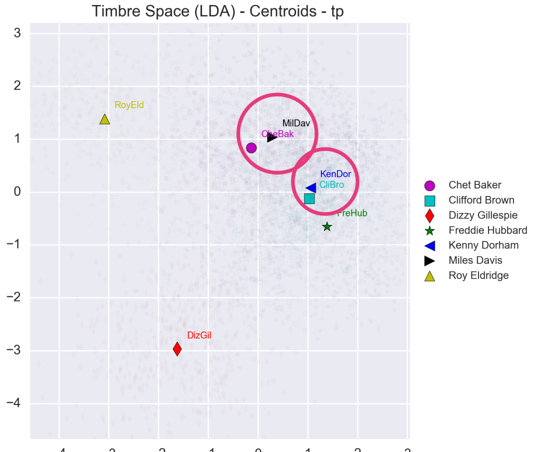
Artist Sound Similarity (tp)

- Observations
  - Unique sound: Dizzy Gillespie & Roy Eldridge
  - Cluster 1: Chet Baker, Miles Davis[7]
    - “[..] his small tone and limited range will remind some listeners of Miles Davis.”[8]
  - Cluster 2: Kenny Dorham, Clifford Brown[9]
    - Bebop trumpet players

[7] Audio example
[8] http://jazztimes.com/articles/20336-chet-baker-his-life-and-music-jeroen-de-valk
[9] Audio example

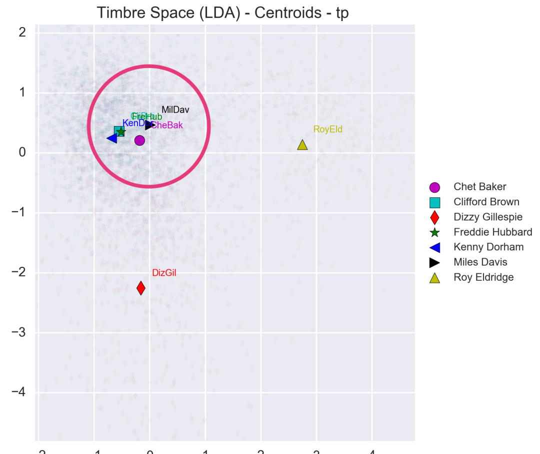
- Outlook: Influence of seperation method
  - More “strict” separation can lead to losing valuable timbre information (noise / transient properties)
  - More “loose” separation $\rightarrow$ Classifier might learn sound of recording / accompanying instruments
  - Example: Separability of trumpet players

- Spectral Harmonic Filtering



Artist Sound Similarity (tp)

- Source Separation



Outline

Conclusion

- New approach for score-informed timbre analysis in jazz solos
- Weimar Jazz Database allows for “large-scale” evaluation experiments
- Automatic soloist classification improved by
  - Knowledge of solo instrument
  - Majority voting over solos
- Timbre feature space confirms known / reveals unknown similarities between jazz soloists

Outlook

- Increase dataset size (artists, solos)
- Automatic Feature Learning (DNN)
- Quantify importance of different factors for artist recognition
  - Harmonic components (fundamental frequency, partials)
  - Noise components (attack transients, noise, subharmonic components)
- Combine timbre & style features (audio & symbolic) for artist & style classification
- Listening test $\rightarrow$ human performance?
- Artist sound evolution $\rightarrow$ imitation strategies among soloist

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Thank you very much for your attention!

Questions?