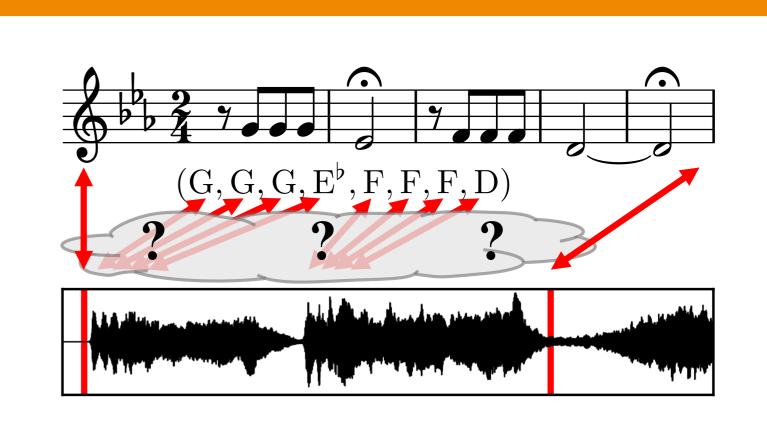
ISMIR

Using Weakly Aligned Score-Audio Pairs to Train Deep Chroma Models for Cross-Modal Music Retrieval

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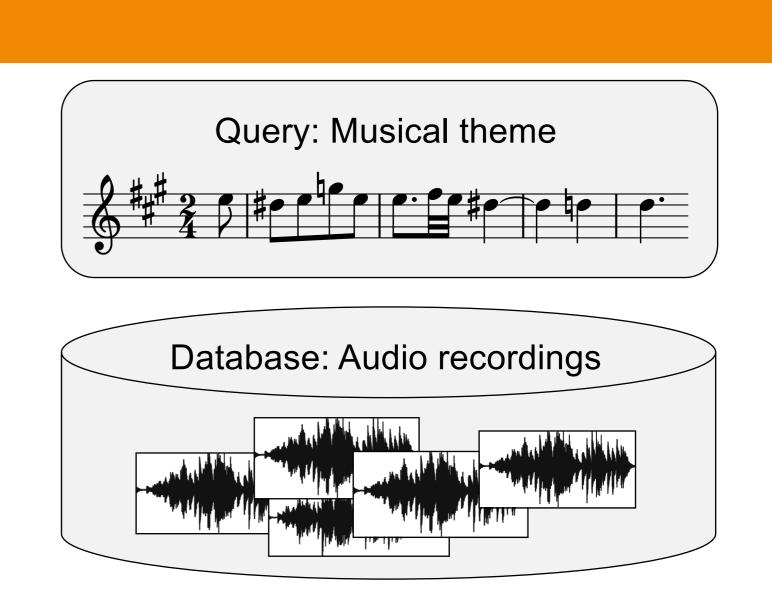
Summary

- Cross-modal retrieval application with monophonic symbolic musical themes as queries and audio database of polyphonic music
- Learn **enhanced chroma variant** for musical themes
- Only use weakly aligned training pairs
- Adapt a deep salience model and train with the Connectionist Temporal Classification (CTC) loss for computing chroma features
- Improved state-of-the-art results for cross-modal retrieval application



1. Cross-Modal Retrieval

- Query: Monophonic theme in symbolic encoding
- Database: Polyphonic audio recordings of Western classical music
- Aim: Find relevant recordings where theme is played
- **Approach:** Retrieval based on subsequence dynamic time warping and chroma features [1]
- **Problem:** Monophonic–polyphonic difference between query and database
- **Solution:** Learn enhanced audio chroma features for musical themes



Mean Dur.

00:00:09

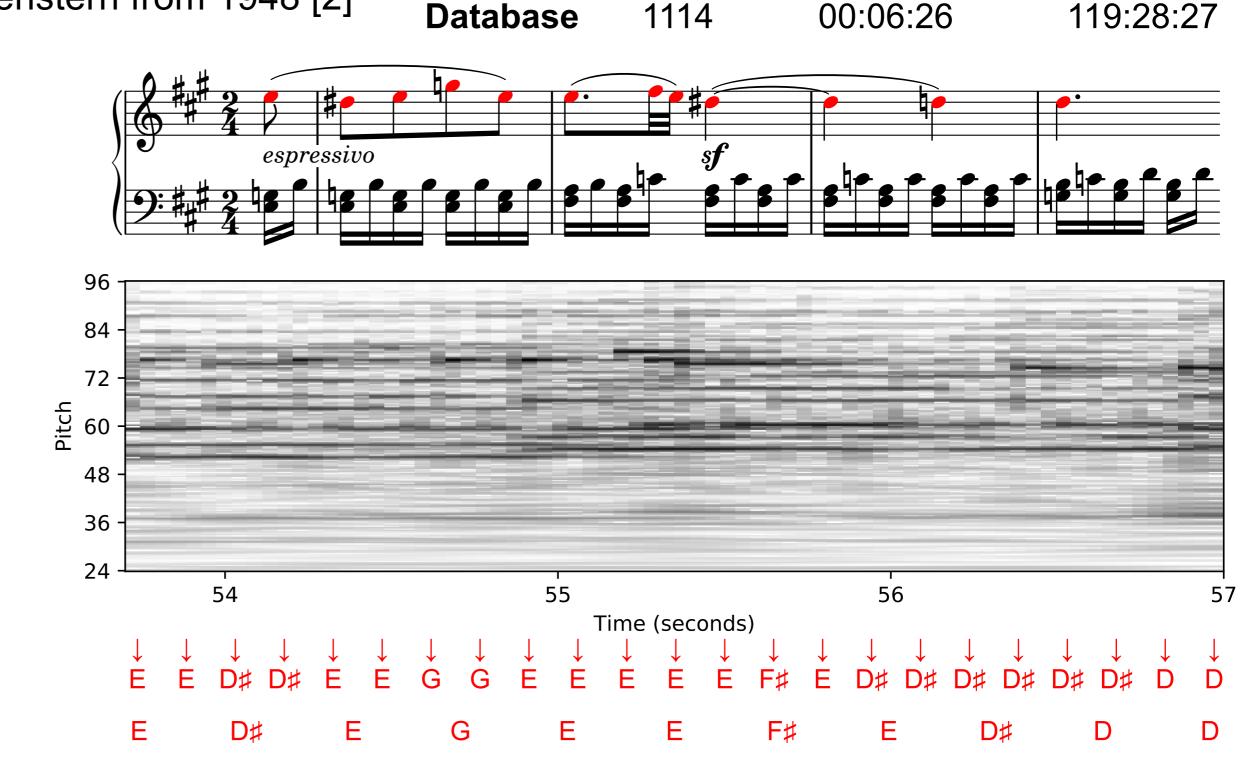
Total Dur.

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2. Data: Weakly vs. Strongly Aligned

- Dataset with more than 2000 musical themes
- Based on dictionary by Barlow and Morgenstern from 1948 [2]
- Publicly available as Musical Theme Dataset (MTD) [8]
- Standard training procedure: Using strongly aligned training pairs (chroma labels are annotated for each spectral frame)
- Creating strong alignments is very labor intensive
- Our aim: Using weakly aligned training pairs (only the beginning and end of the theme is annotated)

Strongly aligned Weakly aligned

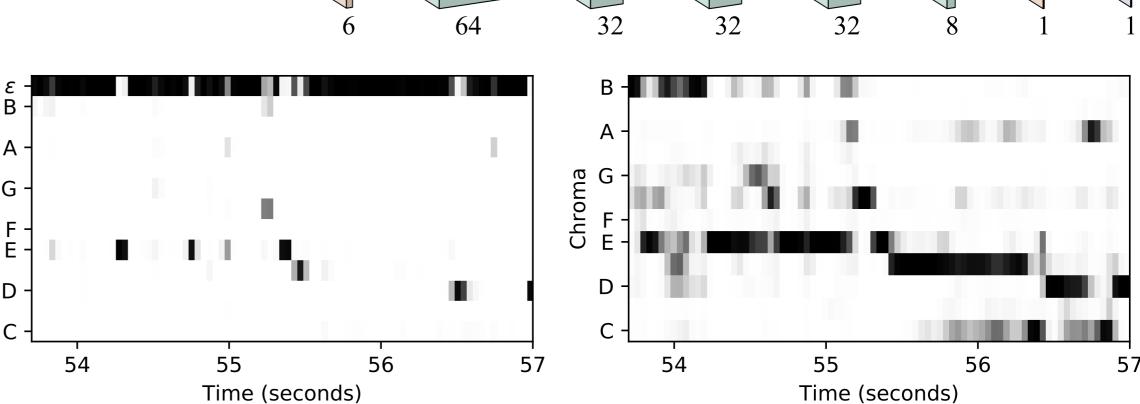


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Queries

3. Approach: Connectionist Temporal Classification

- Adapt deep salience model [3] to have fewer parameters and to output a chroma representation
- Training with Connectionist Temporal Classification (CTC) loss [5]
- Input: HCQT tensor of theme recording
- Output: probability distribution over symbol alphabet of chroma labels and
- chroma label sequence
- Training aim: Maximize output probability
- for all possible alignments between input features and chroma label sequence
- blank symbol ε (*left matrix*) Given for training: Weakly aligned Syn 55 56 54 Time (seconds)



After training: Remove blank symbol probabilities, normalize frames (right matrix)

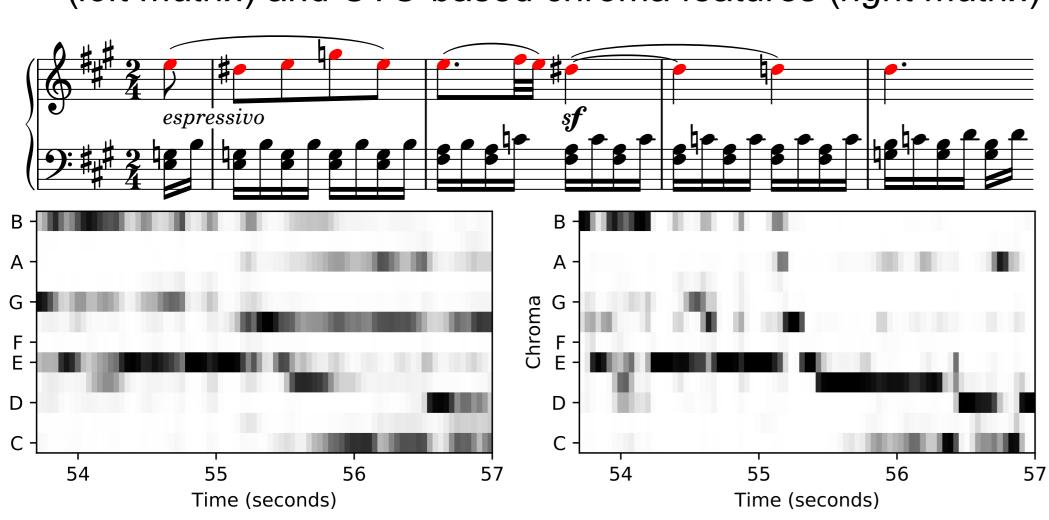
4. Results

SMC 2016.

research, accepted at TISMIR, to appear.

Qualitative comparison of standard chroma features

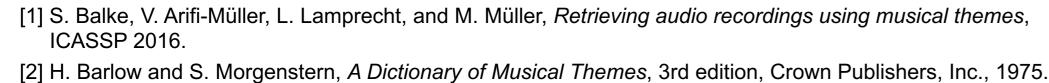
(left matrix) and CTC-based chroma features (right matrix)



Quantitative comparison against state-of-the-art baselines [7] using retrieval-based evaluation

Measure	СТС	Bittner et al. [3]	Bosch/Gómez [4]
Top-01	0.865	0.763	0.820
Top-05	0.925	0.844	0.892
Top-10	0.941	0.867	0.910
MRR	0.893	0.802	0.854

References, Acknowledgments, Demos, and Code



[3] R. Bittner, B. McFee, J. Salamon, P. Li, and J. Bello, Deep salience representations for F0 tracking in polyphonic music, ISMIR 2017.

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[7] F. Zalkow, S. Balke, and M. Müller, Evaluating salience representations for cross-modal retrieval of Western classical music recordings, ICASSP 2019. [8] F. Zalkow, S. Balke, V. Arifi-Müller, M. Müller, MTD: A multimodal dataset of musical themes for MIR https://www.audiolabs-erlangen.de/ resources/MIR/2020-ISMIR-ctc-chroma



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