Guitar Tuning Detection

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Guitar Tuning Background

• Using alternate tunings involves changing which notes the open strings on a guitar are tuned to

 It's essential for a guitarist to know before learning a song



String	6	5	4	3	2	1
E Standard	Е	Α	D	G	В	Ε
Drop D	D	A	D	G	В	Ε
Drop C	С	G	С	F	А	D
D Standard	D	G	С	F	А	D
Open D	D	A	D	F#	А	D
Open G	D	G	D	G	В	D
F Maj 9	F	A	С	G	С	Ε



Nuances in Spectral Content Between Different Tunings



Goals

- Determine if a CNN and shallow classifier model is capable of distinguishing between different tunings using audio alone
 - We looked at the 7 different tunings
- Explore what might make tunings distinguishable

• Find ways to maximize the accuracy of the classifier

• Improve upon previous work, which found similar approach was promising with a limited dataset

String	6	5	4	3	2	1
E Standard	E	A	D	G	В	Ε
Drop D	D	Α	D	G	В	Е
Drop C	С	G	С	F	А	D
D Standard	D	G	С	F	А	D
Open D	D	A	D	F#	A	D
Open G	D	G	D	G	В	D
F Maj 9	F	A	С	G	С	Е

Dataset Collection

- No suitable dataset for our project existed, so we had to create our own
- All audio used contains only guitar as not to confuse the model in training
- Audio across all tunings contain clean tones, distortion, and other effects
- The dataset includes:
 - 96 ten-second clips of solo guitar, sourced from YouTube videos
 - 164 ten-second clips of stem-separated guitar, sourced from songs of many genres
- Clips were manually selected in an effort to make sure they were characteristic of their tuning

Model

• Generate feature embeddings with pre-trained OpenL3 model (256 Band Mel Spectrogram, embedding dimensionality of 6144, .5 second hop, 1 second window)

• Classify each frame of embeddings with Support Vector Machine (polynomial kernel)

• We can train multiple classifiers based on lowest detected pitch

Results



1.0 0.67 DropC -- 0.8 DropD DStandard - 0.6 True label EStandard 0.73 - 0.4 FACGCE -1 0.83 OpenD - 0.2 OpenG -1 0.0 DStandard EStandard FACGCE DropC DropD OpenD OpenG Predicted label Confusion Matrix of Classifier With All Pitches

Acc = 71.7%

Conclusions

• Achieved moderate success, but may be hitting limits of OpenL3

• Our model was trained on short frames of audio, which may introduce error, especially with single notes

- Differentiating between closely related tunings (multiple strings tuning to same pitch) might require music theory and/or genre information
 - Open Tunings: predominantly major chords and Folk/Indie genres
 - Drop Tunings: predominantly power chords and Rock/Metal genres

References

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