HIGH-LEVEL CHORD FEATURES EXTRACTED FROM AUDIO CAN PREDICT PERCEIVED MUSICAL EXPRESSION

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INTRODUCTION

- Music composers use harmonic progressions to express and induce particular emotional responses and to convey meanings.

→ e.g. association between minor chord and sadness
- Research in musicology: influence of harmonic progression on perceived emotion and meaning [1]
- Prior research in MIR: use chord information to predict genre membership [2] or to identify cover songs [3]
- Aims of present work:
  - Bridging the gap between both disciplines
  - Predicting perceived musical expression through automatically extracted chord features

→ **ABC_DJ project**

DEVELOPMENT OF NOVEL CHORD FEATURES

Basis: Chord progression → IRCAMchord [4]
Key/mode estimation → IRCAMkeymode [5]

Number of chords in a certain segment:

- *chords_total*: Total number of chords divided by the track duration (in seconds)
- *chords_unique:* number of unique chords divided by the track duration
- *chords_func*: number of functional chords divided by the total number of chords (→ Harmonic complexity)
- *chords_until_tonic*: average number of chord changes until the next tonic occurs (→ Harmonic tension)
- *chords_minor* / *chords_major*: number of minor and major chords, divided by the total number of chords

Number of specific cadences and turnarounds (selection):

- *authenticad:* number of authentic cadences (i.e. V-I chord progressions)
- *turnaround_blues:* number of basic Blues chord progressions (I-IV-I-V-IV-I).

METHOD

→ Validation of novel features by means of data from two online experiments

Sample:

- 10.047 participants (49.9% female) from three different countries, age cohorts, educational backgrounds (country-wise crossed-quotas)

Design:

- Rating of four (study part 1) or six (study part 2) randomly assigned 30-seconds music excerpts
- Stimuli: pool of 549 music titles (10 different genres and 61 styles)
- Measure: General Music Branding Inventory (GMBI, [6])

→ Perceived musical expression in branding contexts (four orth. factors: *Easy-going*, *Joyful*, *Authentic*, and *Progressive*)

Analyses:

- Estimation of four linear regression models ‘ (IV: Chord features, DV: GMBI factor scores averaged across participants, control variable: Genre tagged by experts)
- Procedure:
  - Initial stepwise regressions
    - 1. Entering dummy-coded genre variables as a whole block
    - 2. Stepwise entering of the chord features
  - Estimation of final general linear models (GLM) consisting of significant chord features and genre tags.

  → Additional testing of *chord features X genre* interaction effects

RESULTS

Easy-Going:

- Stepwise regression: three significant chord features (all $p < .01$):
  - *chords_minor* ($\beta = .147$)
  - *chords_func* ($\beta = .122$)
  - *chords_unique* ($\beta = .102$)
- GLM: Two significant interaction effects:
  - *chords_func X Folk* ($\beta = -.552$, $p < .05$)
  - *chords_unique X Jazz* ($\beta = .373$, $p < .05$)
- R^2 (variance explained by whole model) = 32.8% ($R^2_{adj} = 26.1\%$)
- η^2 (variance explained by chord features) = 4.6%
- η^2 (variance explained by interaction effects) = 0.9%

Joyful:

- Stepwise regression: three significant chord features (all $p < .01$):
  - *chords_total* ($\beta = 0.208$)
  - *chords_unique* ($\beta = -0.166$)
  - *chords_minor* ($\beta = -0.156$)
- GLM: No significant interaction effects
- R^2 (variance explained by whole model) = 23.7% ($R^2_{adj} = 22.0\%$)
- η^2 (variance explained by chord features) = 6.1%

Authentic:

- Stepwise regression: one significant chord feature ($p < .01$):
  - *chords_unique* ($\beta = 0.193$)
- GLM: No significant interaction effects
- R^2 (variance explained by whole model) = 38.1% ($R^2_{adj} = 36.9\%$)
- η^2 (variance explained by *chords_unique*) = 3.5%

Progressive:

- Stepwise regression: one significant chord feature ($p < .01$):
  - *chords_unique* ($\beta = -0.132$)
  - *chords_minor* ($\beta = 0.086$)
- GLM: No significant interaction effects
- R^2 (variance explained by whole model) = 50.4% ($R^2_{adj} = 49.4\%$)
- η^2 (variance explained by chord features) = 1.7%

DISCUSSION

- Significant contribution of chord features in predicting perceived musical expression
- Additional explanatory gain (4.1% on average) above genre information

→ Valuable additional set of predictors for diverse MIR scenarios
- Most important features: *chords_unique*, *chords_total*, *chords_minor*
- Almost no interaction effects between chord features and genre

→ Effects of chord progressions on perceived musical expression are stable across different genres
- Future work: Development of novel features detecting bass notes and additional notes (e.g. sixths, ninths)

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