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CATEGORIZATION OF CHORD INVENTORIES AND CHORD PROGRESSIONS IN GEORGIAN POLYPHONY

Introduction

In this presentation, we want to report on the status of our work to determine the characteristic properties of chord inventories and chord progression structures in traditional Georgian polyphonic vocal music. The goal of the work that we are presenting today is to develop a workflow for the computational determination of the home region and/or the genre of a randomly chosen traditional Georgian song, based simply on a digital score (a musicXML file). This work involves multiple and varied challenges: conceptual, technical, musicological, and perceptual (to name a few), which we will not be able to exhaustively address in detail today. We should also mention that this project has a longer prehistory:

- First steps in the direction of our present work: (Arom & Vallejo, 2008, 2010). At that time, only Simha Arom and Frank Kane had met (1990).
- Between 2010 and 2015, Frank Kane and Frank Scherbaum (2010), Simha Arom and Frank Scherbaum (2014), and Simha Arom and Florentt Caron-Darras (2015) started to work together. This led to a first series of short studies on sub-problems of our current work which helped us to identify some of the major hurdles we are facing: (Arom et al., 2018; Scherbaum et al., 2015, 2016b, 2016a).

The first major problem, which we can only now solve to our satisfaction, is how to deal with the fact that the tonal organization of traditional Georgian music does not correspond to the 12TET (12-tone equal temperament) system on which Western notation is based. It took several acoustical studies (Scherbaum et al., 2020, 2022) and the exploration of a number of conceptual dead-ends (e.g. determination of western church modes, *finalis* as reference notes) before we found the current work approach.

The second major hurdle that needed to be overcome was that before Ana Lolashvili joined the team in 2021, there were no Georgians on the team, and we were therefore worried that our working hypotheses, e.g. what are essential and what are ornamental aspects of a piece, what are the tonal centers and/or reference notes, might not stand up to rigorous questioning from our Georgian colleagues.

Between 2019 and 2021, in order to determine temperaments and scales, we had to move away from transcriptions because they constrained the music to a tonal and tempered organization with, for example, the presence of key signatures, semitones, and modulations. We had to move towards an exclusively acoustic analysis. Today, having established that Georgian polyphonies are based on an approximately unitonic heptatonic scale, with notably vertical adjustments for pure fourths and fifths, we were able to pursue our structural and syntactic research. Scores then re-entered our research corpus, but we adopted a new point of view towards them. These scores are essential in our process because they are a symbolization of the acoustic field, and this symbolization leads to simplification and standardization. They allow us to speak in notes rather than in frequencies. Above all, when these scores are obtained in digital format, they constitute the primary material of our database for computational analysis. We can thus handle a very large number of songs to consolidate our analyses.

Current Workflow

Our current preprocessing workflow consists of several steps.

1. Cleaning the digital scores: Separating the 3 voices of the song onto different staves (for technical reasons), removing passing tones, neighboring, escape tones, ornaments, appoggiaturas, anticipations, and suspensions, so that the cleaned scores contain only the notes from the three voices, one per staff, and nothing else (Arom, 2017). This is a purely technical preprocessing step which, however, requires great care and can become rather time-consuming.

2. Reducing the scores to their “harmonic pillars”: leaving only structural chords. Removing “invisible notes” in digital scores.

3. Converting scores to music XML files.

4. The next step in the processing chain involved correction of the digital score for its representation in an inappropriate Western five-line staff notation which is intrinsically based on the assumption of a 12-tone equal temperament (12TET) scale. Acoustical analyses of the tonal organization of old as well as recent recordings (Scherbaum et al., 2020, 2022) clearly indicate that this is inappropriate. This is also the consensus among our Georgian colleagues. In our opinion, the description of the tonal organization of traditional Georgian vocal music seems to require more than just a single fixed scale, since the harmonic and melodic scales are different from each other (at least with respect to the 2nd). In addition, melodic step sizes (as the third aspect of tonal organization) are highly variable and again tell a different story (taking the modal value of the melodic step size distribution would even suggest an equidistant melodic scale). In the context of our work, we avoid having to decide on a particular tuning system. We instead make the assumption that:

- a. the melodic scale is heptatonic (with unknown exact interval structure in cents) and
- b. that if we remove all the accidentals and take the differences of the scale degrees between two voices, we obtain the corresponding harmonic interval. In order to allow for comparison of the relative bass voice scale degrees, we define the scale degree of the ending bass note as 0, scale degrees below that with negative numbers, and scale degrees above with positive numbers. This is simply for convenience to make the scores comparable. Example: bass voice scale degree: -1, middle voice: 3, top voice: 4. The resulting chord would be {-1, 4, 5}, with the first number being the bass voice scale degree and the second and third numbers the intervals from the bass to the middle and from the bass to the top voice, respectively.

Using this processing strategy, we obtain a table containing the complete chord progression for each song (Fig. 1).

Dataset and Preliminary Results

For the study in its current state, we processed a total of roughly 120 songs from six different collections: GEL (Gelati), KAR (Kakheti-Kartli liturgical), SHE (Shemokmedi), FO1 (folk songs), GUR (Gurian folk songs), KCH (Kakheti-Kartli folk songs)

The datasets were chosen based on the collections of sheet music which were available in XML format at the time to Ana Lolashvili, with an aim to achieve a certain variety, and with the goal of increasing the number of songs in each category in the longer term.

Once the chord progression tables (cf. Fig. 1) have been prepared, there are many different ways to use the information that they contain. An obvious one is to simply analyze the frequencies of occurrence of particular chords or chord progression patterns (Fig. 2).

As a final example and an outlook for the next steps of our project, we briefly illustrate the

results of training different types of commonly used classification algorithms on this dataset and examine how well they perform in classifying as yet uncategorized songs. Since the datasets are still small, we emphasize that this is a very preliminary result. Specifically, we used $\frac{3}{4}$ of the corpus for training and $\frac{1}{4}$ for testing. The different classifiers: Markov, Random Forest, Naïve Bayes, Support Vector Machine, Nearest Neighbor, and Logistic Regression, performed quite differently, with the best one (Markov) correctly classifying about 95% of the test data. The resulting confusion matrix is shown in Fig. 3.

Why does it Work so Well?

There are at least two possible reasons why the classification works so well. First, it might be that the chord inventories of the different sub-corpora are significantly different, which – sloppily speaking – makes it easy for the classification algorithm to find the proper association for a previously ‘uncategorized’ song. For this to happen, the frequency of occurrence of particular chords will differ strongly between the subsets. In cases where the chord inventories are not significantly different, however, it might be that the chord progressions (not the chords themselves) differ between the subsets. In other words, the different sub-corpora make different use of the chords. In order to test this, we calculated the frequency of occurrence profiles for the most frequent jointly used chords in the different subsets (Fig. 4)

Fig. 4 shows that based on the chord profiles between the individual sub-corpora there are significant differences in the use of particular chords (e.g. the (3–7), the (4–8)). Consequently, the chord progression features will also be different. Sloppily speaking, the classification algorithm offers many features for use. However, we want to emphasize that the dataset is still fairly small and there is still a lot of additional work ahead of us before we will feel ready to draw general conclusions.

What Next?

The next steps will involve increasing the size of our corpus and testing the stability of the results. This is already underway.

Conclusions and Outlook

The results are very encouraging since they tell us that the chord progression table seems to contain enough characteristic patterns to sort the current dataset quite successfully and correctly. As stated above, we don’t see this as a final result but rather as an important intermediate step forward in our ongoing journey to find the rules for the harmonic organization of Georgian polyphony.

If you are interested in contributing digital scores to this project, we invite you to join our team.

Acknowledgments

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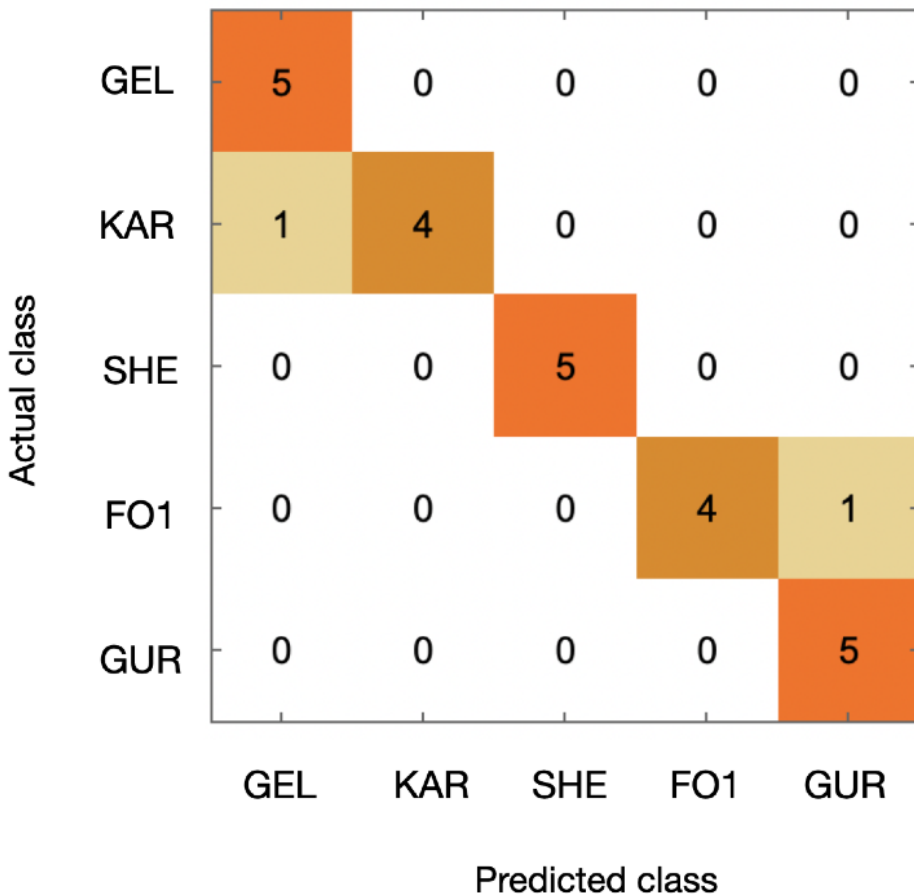
სურათი 2. აკორდებისა და მათი თანმიმდევრობის აღრიცხვა ყველაზე ხშირი აკორდებისთვის და აკორდული თანმიმდევრობისთვის სრულ კორპუსში. პირველი რიცხვი თითოეულ სვეტში არის კორპუსში მოტივის გამოჩენის რაოდენობა.

Figure 2. Chord inventory and chord progression inventories for the most frequent chords and chord progressions in the complete corpus. The first number in each column is the number of occurrences of a pattern in the corpus

Inventory	Single step	Double step	Triple step
321 (-1/3/5)	88 (0/3/5)→(-1/3/5)	45 (-2/3/5)→(-1/1/3)→(0/1/1)	11 (-3/5/7)→(-2/3/5)→(-1/1/3)→(0/1/1)
248 (-2/3/5)	86 (-1/1/3)→(0/1/1)	25 (-2/6/8)→(-2/5/7)→(-1/3/5)	9 (-4/4/8)→(-5/4/8)→(-4/3/7)→(-3/1/5)
206 (0/3/5)	65 (-1/3/5)→(0/1/5)	23 (0/3/5)→(-1/3/5)→(-2/3/5)	9 (-1/3/5)→(-2/3/5)→(-1/1/3)→(0/1/1)
144 (-2/6/8)	63 (-1/3/5)→(-2/3/5)	22 (-5/4/8)→(-4/3/7)→(-3/1/5)	8 (-6/6/10)→(-5/4/8)→(-4/3/7)→(-3/1/5)
142 (0/1/1)	47 (-2/3/5)→(-1/1/3)	20 (-1/6/8)→(-1/5/7)→(0/3/5)	8 (-2/5/9)→(-2/4/8)→(-1/3/7)→(0/1/5)
140 (-3/3/5)	42 (-2/3/5)→(-3/3/5)	18 (-2/4/8)→(-1/3/7)→(0/1/5)	8 (-2/4/6)→(-2/3/5)→(-1/1/3)→(0/1/1)
127 (-1/6/8)	39 (-1/3/7)→(0/1/5)	18 (0/3/5)→(-1/3/5)→(0/1/5)	8 (-2/3/5)→(-1/1/3)→(0/1/1)→(-2/3/5)
122 (0/1/5)	36 (-2/5/7)→(-1/3/5)	17 (-1/4/6)→(-1/3/5)→(0/1/5)	8 (-1/6/8)→(-1/5/7)→(0/3/5)→(-1/3/5)
117 (0/0/0)	34 (-2/6/8)→(-2/5/7)	15 (-1/3/5)→(-2/3/5)→(-1/3/5)	8 (-1/5/7)→(-2/5/9)→(-1/3/7)→(0/1/5)
106 (-1/5/7)	33 (-3/3/5)→(-2/3/5)	14 (0/4/6)→(0/3/5)→(-1/3/5)	8 (0/3/5)→(-1/3/5)→(-2/3/5)→(-1/3/5)
96 (-4/3/5)	33 (-1/4/6)→(-1/3/5)	13 (-2/5/9)→(-1/3/7)→(0/1/5)	7 (-2/3/5)→(-2/4/6)→(-2/5/7)→(-2/6/8)
96 (-3/6/8)	30 (-1/6/8)→(-2/6/8)	13 (-2/2/4)→(-1/1/3)→(0/1/1)	7 (-1/6/8)→(-1/5/7)→(0/3/5)→(-1/5/7)
92 (-2/5/7)	29 (-1/5/7)→(0/3/5)	13 (-1/3/5)→(-2/3/5)→(-3/3/5)	7 (-1/6/8)→(-1/4/6)→(-1/3/5)→(0/1/5)
92 (-1/1/3)	27 (-2/3/5)→(-1/3/5)	12 (-1/5/7)→(0/3/5)→(-1/3/5)	7 (-1/3/7)→(0/1/5)→(-1/6/8)→(-2/6/8)
86 (-4/6/8)	27 (-1/6/8)→(-1/5/7)	11 (-3/5/7)→(-2/3/5)→(-1/1/3)	7 (-1/3/5)→(0/4/6)→(0/3/5)→(-1/3/5)
78 (1/3/5)	27 (-1/3/5)→(0/3/5)		6 (-5/6/8)→(-6/6/10)→(-5/4/8)→(-4/3/7)
75 (-5/6/8)	25 (-4/3/5)→(-3/1/5)		6 (-2/6/8)→(-2/5/7)→(-1/3/5)→(-2/3/5)
65 (-2/4/8)	24 (0/4/6)→(0/3/5)		6 (-2/5/7)→(-2/6/8)→(-2/5/7)→(-1/3/5)
63 (-3/5/7)	23 (-3/5/7)→(-2/3/5)		6 (-2/5/7)→(-1/3/5)→(-2/3/5)→(-3/5/7)
59 (-4/5/7)	23 (-2/5/7)→(-2/6/8)		6 (-2/4/8)→(-1/3/7)→(0/1/5)→(-1/6/8)
59 (-2/5/9)	22 (-5/4/8)→(-4/3/7)		6 (-2/4/6)→(-2/5/7)→(-2/6/8)→(-2/5/7)
52 (-3/1/5)	22 (-4/3/7)→(-3/1/5)		6 (-2/3/5)→(-3/5/7)→(-2/3/5)→(-1/1/3)
49 (0/4/6)	21 (-4/5/7)→(-3/3/5)		6 (-1/5/7)→(-2/5/9)→(-2/4/8)→(-1/3/7)
47 (-5/3/5)	21 (-2/4/6)→(-2/3/5)		6 (-1/3/5)→(-2/3/5)→(-3/5/7)→(-2/3/5)
47 (-1/4/6)	21 (1/3/5)→(0/3/5)		6 (-1/1/3)→(0/1/1)→(-2/3/5)→(-2/4/6)
45 (-2/4/6)	20 (-2/3/5)→(-1/1/5)		6 (0/4/5)→(-1/5/7)→(-2/5/9)→(-2/4/8)
44 (-1/3/7)	20 (-1/1/1)→(0/1/1)		6 (0/3/5)→(-1/3/5)→(-2/5/7)→(-2/6/8)
43 (-4/5/9)	19 (-3/3/5)→(-4/3/5)		6 (0/3/5)→(-1/3/5)→(-2/3/5)→(-3/3/5)
43 (-4/4/8)	19 (-2/4/8)→(-1/3/7)		
43 (-3/4/8)	18 (-3/6/8)→(-1/3/5)		
43 (0/4/5)	17 (-4/6/10)→(-3/6/8)		
39 (-1/1/5)	17 (-2/6/8)→(-1/6/8)		
37 (-3/5/9)	17 (0/3/5)→(-1/5/7)		
35 (0/6/8)	16 (-4/6/8)→(-2/3/5)		
34 (-2/4/5)	16 (-2/6/8)→(0/3/5)		
33 (-5/5/7)	16 (-1/5/7)→(-2/5/9)		

სურათი 3. მარკოვის კლასიფიკატორზე დაფუძნებული უნესრიგობის მატრიცა ტესტის მონაცემების კლასიფიკაციისთვის, რომელიც მომზადებულია სრული კორპუსის 3/4-ზე. შედეგი იყო ის, რომ ხუთი ქვეჯგუფიდან სამი იდეალურად იყო კლასიფიცირებული, ხოლო KAR-ის 5 სიმღერიდან 1 შეცდა GEL-ში და FO1-დან ერთი სიმღერა შეტანილი იქნა GUR კლასში (რაც, შეიძლება, იყოს რეალურად სწორი, რადგან FO1 მონაცემთა ნაკრები შეიცავს სიმღერებს სხვადასხვა რეგიონიდან).

Figure 3. Confusion matrix for the classification of the test data based on a Markov classifier trained on 3/4 of the complete corpus. The result was that three of the five subsets were classified perfectly while 1 of 5 songs from KAR was mistaken for GEL and one of the songs from FO1 was put into the GUR class (which may actually be correct because the FO1 dataset contains songs from different regions).



სურათი 4. სხვადასხვა ქვეჯგუფის აკორდების პროფილები მთელი კორპუსის აკორდული თანმიმდევრობის საშუალო პროფილთან შედარებით. აკორდის ეტიკეტებზე მითითებულია ინტერვალები ბანსა და შუა ხმას და ბანსა და ზედა ხმას შორის, შესაბამისად. თითოეული აკორდის ჰისტოგრამის ზოლები მიმაგრებულია ამ აკორდის საშუალო სიხშირეზე მთელ კორპუსში. საშუალო ხაზის ზემოთ მყოფი ზოლები მიუთითებენ იმაზე, რომ ამ კორპუსში შესაბამისი აკორდი (იხ. ფერის კოდი) გამოიყენება საშუალოზე უფრო ხშირად, ხოლო ქვემოთ მდებარე ზოლები მიუთითებენ იმაზე, რომ ის ნაკლებად ხშირად გამოიყენება.

Figure 4. Chord inventory profiles for the different subsets in comparison to the average chord progression profile for the whole corpus. The chord labels indicate the intervals between the bass and the middle part and the bass and the top part, respectively. The histogram bars for each chord are anchored to the average occurrence frequency of this chord in the whole corpus. Bars going above the average line indicate that the corresponding chord in this corpus (see color code) is used more often than average, while bars going below indicate that it is less frequently used.

