JINGJUMEL: THE MELODIC PATTERNS IN DIFFERENT JINGJU PERFORMANCE DIMENSIONS

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ABSTRACT

This study delves into the Jingju Music Scores Collection (JMSC) to explore melodic patterns across different Jingju performance dimensions, specifically focusing on *shengqiang* (vocal styles), *banshi* (tempo and meter) and role types (character categories). Employing a combination of melody detection algorithms and k-NN (k-Nearest Neighbors) classification, we analyze 108 MusicXML scores comprising 1084 melodic lines to identify prevalent melodies ranging from 3 to 8 notes in length and to determine their distribution across the mentioned categories. Our findings reveal significant alignment between *shengqiang* classifications and their corresponding melodic motifs, suggesting a strong correlation between specific *shengqiang* and their melodic patterns. Additionally, a notable association between melodic patterns and role types was observed, indicating potential character-specific melodies. In contrast, *banshi* classifications showed less correlation with melodic similarity, indicating a more nuanced relationship between rhythm and melody in Jingju. This study not only contributes to the fields of music information retrieval and computational ethnomusicology but also opens new avenues for understanding the interplay between melodic structure and theatrical roles in Jingju.

Keywords: Jingju, melody detection, k-NN classification, computational ethnomusicology. [1]

1. INTRODUCTION

The study of Jingju, offers a fascinating glimpse into the intricate interplay of musical and theatrical elements that define this traditional Chinese art form. Central to Jingju's musical identity are three critical dimensions: *shengqiang* ("声腔", vocal styles), *banshi* ("板式", rhythmic patterns), and role types ("角色", character categories with specific singing and acting styles). These elements not only serve to classify Jingju music pieces but also fundamentally shape the melodic contours, intervals, note density, and overall length of the performances. The motivation behind our research is twofold: firstly, to explore how melodies vary across three dimensions; secondly, to examine whether the most salient melodic patterns adhere to the expected contours dictated by the *shengqiang*.

To navigate the complexities of Jingju music, our study leverages a comprehensive dataset called JMSC (Jingju Music Scores Collection) provided by Caro Petto and Serra [1], which comprises a collection of music scores intended for corpus-based Jingju singing research. This dataset, in conjunction with music21, a versatile toolkit for computer-aided musicology, forms the backbone of our methodological approach. Through a detailed analysis of melodic patterns within these scores, we aim to unveil the nuanced ways in which melodic elements reflect the categorization into *shengqiang*, *banshi*, and role types.

Our research is positioned at the intersection of music information retrieval and computational ethnomusicology, drawing on the pioneering works of scholars who have applied computational methods to the study of musical traditions. Prior investigations into the automated analysis of music, such as those by Tzanetakis and Coo [2] and Müller et al. [3], provide the methodological inspiration for our study. These works underscore the potential of algorithmic approaches to uncover patterns and structures in music, paving the way for novel insights into Jingju's melodic dynamics.

This report is structured as follows: Section 2, "Methodology," outlines the computational techniques employed to identify and analyze melodic patterns across the Jingju music dataset. Section 3, "Results," presents our findings, highlighting the variation of melodic characteristics across *shengqiang*, *banshi*, and role types, and examining the alignment of salient melodic patterns with traditional expectations of the *shengqiang*. The Section 4: Conclusions reflects on the implications of our findings for the understanding and appreciation of Jingju music, and discusses potential avenues for future research in the domain of computational musicology.

2. METHODOLOGY

2.1 Dataset Descriptive Analysis

The Jingju Music Scores Collection (JMSC), developed within the CompMusic project, is pivotal for our study on

[1] Project repository available at: https://github.com/marioUPF/JingjuMel/tree/main

Jingju. It comprises 108 MusicXML scores, encapsulating 1084 melodic lines across various dimensions of Jingju's musical system, such as role type (*laosheng*, *dan*, *laodan*), *shengqiang* (*erhuang*, *xipi*, *nanbangzi*, *sipingdiao*), and *banshi* (rhythmic patterns). This rich dataset not only aids in exploring the complexity of Jingju music but also facilitates a deeper understanding of its melodic structures.

The JMSC is derived from printed editions, transnotated into staff notation from the original *jianpu* notation, which includes a separate accompaniment line (*jinghu*), enhancing the dataset's analytical depth. Detailed metadata and annotations are available in the scores_data.csv and lines_data.csv files within the MusicXML folder. These files provide exhaustive details on each score and line, including role type, *shengqiang*, *banshi*, line type, and lyrics, crucial for identifying and analyzing melodic patterns.

The distribution of scores and lines across role types and *shengqiang* reflects Jingju's musical diversity. Most scores are categorized under *erhuang* and *xipi*, the two predominant *shengqiang*, illustrating the dataset's focus on these modal systems. The annotations facilitate a granular analysis of melodic elements, enabling us to examine variations in melody across different Jingju dimensions.

Usage of the JMSC is strictly for non-commercial research purposes, under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International license, ensuring ethical compliance while leveraging this comprehensive resource.

Incorporating the JMSC into our research allows for an in-depth examination of Jingju's melodic patterns, providing insights into how these patterns vary across different musical dimensions. This dataset not only serves as a foundation for our methodology but also contributes to the broader field of music information retrieval and computational musicology, offering a pathway to new discoveries within the rich tradition of Jingju music.

2.2 Identifying Melodic Patterns in the Scores

The first step in order to find the most prominent melodies in each score was to think about what constitutes a melodic pattern. The main issue is that it is a lot more probable for very short melodies to be repeated within a piece, as opposed to melodies with a larger number of notes. Therefore, had we based our algorithm on repetition as the sole indicator of how representative a melody is, many longer melodies which are also common in the piece would have been ignored. As a solution to this, it was decided that for each musical piece six different melodies would be saved: the most common melodies formed by a number of notes ranging from 3 to 8. This way, both shorter and longer melodies would be taken into account.

The melody detection algorithm works with a sliding window approach. First, all notes from the scores are retrieved. Then, each note is taken as the possible starting point of a melody consisting of a certain number of notes, n. These n consecutive notes are stored, and each time one of these patterns is repeated, across the score, it is counted. This way, for each score in the dataset we obtain the most repeated sequence of notes, for a number of notes n that ranges from 3 to 8.

2.3 Finding Similar Pieces Using k-NN

Once every piece of the dataset has been characterized by obtaining six of its most repeated note patterns, it is time to match similar pieces to each other. However, it could happen that two pieces that are very similar feature slight variations in some of their melodic patterns. Therefore it was required that we implemented a system that wasn't based on exact matches, but rather a more tolerant similarity approach. As a result, we implemented a k-NN algorithm. In order to do so, the melodic patterns had to be vectorized.

For each musical piece in the dataset, we retrieve its 5 nearest neighbors. Then, we compare these pieces in terms of their classification: *shengqiang*, *banshi* and role type. By doing this, for each score we obtain the number of neighbors that share the same classification in each of these areas. Finally, we can calculate the distribution of number matching neighbors across the dataset for each category.

3. RESULTS

Table 1. Number of matching neighbors across different categories

# Matching	Shengqiang	Banshi	Role Type	All Dims
0	0.00%	6.48%	0.00%	8.33%
1	5.56%	38.89%	10.19%	49.07%
2	17.59%	18.52%	9.26%	21.30%
3	6.48%	25.00%	20.37%	15.74%
4	7.41%	8.33%	20.37%	5.56%
5	62.96%	2.78%	39.81%	0.00%

As detailed in Table 1, the distribution of matching neighbors across different categories highlights the varying degrees of similarity within the dataset.

When comparing a musical piece's *shengqiang* classification to its neighbors, in 62.96% of the cases all 5 neighbors match its categorization. Moreover, 76.85% of musical pieces had at least three neighbors belonging to their same *shengqiang*.

In terms of role type, the most common number of matching neighbors is 5, with 39.81% of musical pieces having all of their neighbors belonging to the same role type. Furthermore, 80.55% of the pieces have 3 or more neighbors that belong to the same character archetype.

Moving on to the rhythmic classification, the most common number of neighbors that belong to the same *banshi* is 1, which is the case for 38.89% of the pieces. In fact, for 63.89% of musical pieces, the number of neighbors that match their *banshi* category is 2 or less. Only in 2.78% of cases do all 5 neighbors match a piece's *banshi* classification.

Finally, we considered it would be interesting to look at the cases in which a musical piece's neighbors match all three categories. The most common number of matching neighbors was just 1, which is the case for 49.07% of the musical pieces. Furthermore, the percentage of pieces with two or less matching neighbors is 78.7%. This is understandable considering that this case study was by definition more restrictive than the previous ones.

4. CONCLUSIONS

Firstly, there are some limitations to this study that should be considered. There is an argument to be made that even if our approach retrieves common melodies within a piece, finding motifs that are musicologically significant shouldn't be done algorithmically, but rather on a case to case basis, applying domain knowledge and musical theory. Furthermore, we decided not to separate the vocal part and the accompaniment of musical scores, as we considered that accompaniments may also feature relevant melodic information for this research. Nonetheless, some may argue that conducting the research solely based on the vocal melodies would have been a more accurate representation of the musical tradition.

In terms of result analysis, the *shengqiang* of a musical piece relates directly to its motifs and melodic patterns, and therefore it was expected that neighboring pieces would usually share the same classification. This turned out to be true, and could be taken as a sign that the implemented methodology is sound. On the other hand, results seem to imply that there is no correlation between *banshi* and prominent melodic patterns. However, it must be said that the *banshi* categories in the dataset are more diverse and varied than those of the *shengqiang* and role types, and therefore it is harder to obtain matches with neighbors.

In our opinion, the most interesting result that we obtained was the apparent correlation between melodic similarity and role type. The distribution of matching neighbors was really positive, and somewhat similar to that of the *shengqiang*. This could imply that there are certain melodies and motifs that are associated with *dan* or *laosheng*, for example. The way these melodies could be shaped by a character's role within the story, or societal norms such as gender roles would be an interesting avenue for future work.

Future research could extend beyond the current dataset to include a wider array of performances and compositions, potentially uncovering further intricacies within Jingju's musical fabric. Additionally, exploring the impact of cultural, historical, and narrative contexts on the formation and evolution of melodic patterns could offer richer insights into the art form. A comparative analysis with other traditional Chinese opera genres could also shed light on the unique aspects of Jingju's musical system. Ultimately, by harnessing advanced computational methods, future work has the potential to further unravel the complex interplay between music, narrative, and cultural expression in Jingju, enriching our understanding of this venerable art form.

5. REFERENCES

[1] R. Caro Repetto and X. Serra, "A collection of music scores for corpus based jingju singing research," 2017.

[2] G. Tzanetakis and P. Cook, "Musical genre classification of audio signals," *IEEE Transactions on speech and audio processing*, vol. 10, no. 5, pp. 293–302, 2002.

[3] M. Muller, D. P. Ellis, A. Klapuri, and G. Richard, "Signal processing for music analysis," *IEEE Journal of selected topics in signal processing*, vol. 5, no. 6, pp. 1088–1110, 2011.