Towards an Automatic Detection of Rhetorical Patterns in the Renaissance Polyphonic Music

Víctor Padilla[1], Manuel Tizón[2], Francisco Gómez[3], Manuel Espigares[4], Edith Alonso[5]

[1,2,4,5] UNIR, [3]Universidad Politécnica de Madrid

victor.padilla@unir.net, manuel.tizon@unir.net, fmartin@etsisi.upm.es, manuel.espigares@unir.net, edith.alonso@unir.net

Abstract

In this paper we study the role and usage of rhetorical patterns in the vocal polyphonic music in the Renaissance period. We describe the main rhetorical patterns found in the masterpieces of that period and present algorithms to automatically find those patterns. To test our algorithms a ground-truth set was created by manually annotating rhetorical patterns in a few selected works. The annotation was made by expert musicologists in our research group (*OMITTED for blind review*).

Introduction

Musical discourse progresses through variation of musical material. Different musical traditions have used quite a vast range of strategies to transform the musical material and hence convey musical meaning. Among those strategies, we find imitations, repetitions, motivic treatment, and exposition of contrasting ideas, recapitulation of previous material, transformations in rhythm, pitch, harmony, or texture, among others. One way to endow the musical material with meaning is to borrow and adapt expressive devices from other domains; in the case of music, very often those means are borrowed from speech as in many cultural traditions speech possesses very elaborate and rich devices. In European Renaissance and Baroque music composers transferred many figures of speech to the music domain, and built a vocabulary, syntax and semantics out of them to express their musical ideas. In this work, we study how such transfer took place in the works of a few significant composers by identifying rhetorical patterns in their works.

The task of manually identifying patterns in large corpora is tedious, error-prone, time-consuming, and limited in scope. Computational methods in musicology can help enormously to automate that task. However, to build a system capable of analyzing and classifying the corpus of a composer in a reliable, sensible and meaningful manner is by no means an easy task. Our main goal with this paper is to examine the role of rhetorical patterns in vocal polyphonic pieces from the Renaissance period and identify stylistic differences between composers. More specifically, we will analyze features such as the particular rhetorical patterns, the length of the melodies in different composers, preferences for some patterns over others, or the distance between imitations and repetitions, among others.

Rhetoric in Music

Rhetorical theory was first developed in ancient Greece and Rome, where it reached high sophistication. It was later revived in the Renaissance and became a solid theory of artistic creation that also influenced music. It is important to point out that musical rhetoric is not a correct term, since rhetorical figure in music is artificial and depends on an applied discipline. In addition, music and speech share certain features such as repetition, dynamics changes, resting points, that create structural parallelism between both. Therefore, musical composition and verbal oratory were identified as to sharing similar terms: *dispositio* or formal organization of rhetorical speech, *decoratio* or the application of rhetorical figures (this is the most important element in this research), and *pronuntatio* or performance. In respect of the rhetorical figures, gave place to new musical techniques. As an illustration, below we list a few examples some figures of repetition (the list is by no means exhaustive; it is important to underline that sometimes is difficult to establish an one-to-one relationship between oratory and music, for this reason, some rhetorical figures may be ambiguous in its concept; all of this problems are reflected in the theoretical sources).

- *Anaphora*: polyphonic imitation of a voice, often found at the beginning of a phrase.
- *Epistrophe*: Repetition of a musical passage at the end of various phrases.
- *Anadiplosis*: Repetition of a part that closes a phrase at the beginning of the following phrase.
- *Epizeuxis*: Repetition of a passage several times in a row.

- *Complexio*: Repetition at the beginning and the end of a musical passage in other phrases.
- *Epanalepsis*: Repetition of the same passage at the beginning and the end of the same phrase.
- *Epanadiplosis*: It's an *epanalepsis* that encompasses larger sections.
- *Gradatio*: a descending or ascending sequence
- *Percusio*: brief exposition of musical passages that will be developed later on.
- *Mimesis*: an approximate rather than strict imitation of a subject at different pitches.

As we have just said, all these devices come from the adaptation of figures in speech to music. These rhetorical figures lent support to the doctrine of the affections, a theory holding that passions can be represented by their external signs. In this paper we seek to confirm the use of those rhetorical figures in the works of important composers by analyzing large corpora with the aid of automated methods of pattern detection.

Previous Research

The first obstacle we encounter when addressing the issue of rhetorical figures is that there is no universal consensus about which musical patterns should be considered as rhetorical figures. Those patterns vary as a function of time, geographical location, or style. For our work we have considered the most basic ones over which there is more agreement, and have followed authoritative sources such as Bartel (1997), whose analyses of the treatises and sources is thorough, as well as Saint-Dizier (2014) and McCreless (2008).

The idea to look for patterns in music in order to characterize is not new, especially since the advent of computers. For example, Giraud et al. (2015) developed several algorithms to perform an automated analysis of a fugue. They looked at the diatonic similarities between pitch intervals and their algorithm was able to detect subjects and countersubjects, among other patterns in the fugue. Knopke and Jürgensen (2009) designed a system based on suffix arrays that allows to find instances of melodic repetition in large collections of music. In particular, they applied their algorithms to the entire collection of Palestrina's masses. Gulati et al (2014) searched for melodic patterns in Carnati music by using time series mining techniques; their input was audio recordings and therefore they had to deal with further issues. However, the idea of using pattern-discovery algorithms to study rhetorical patterns has received scant attention. To the best of our knowledge, no work has been done to identify and find rhetorical patterns in the large collections of music.

For the rest of the previous work, we will cite it as the paper proceeds as the references are more technical and we need to introduce terminology first.

Working with Patterns

To find the rhetorical patterns, we will employ the concept of *viewpoints* (Conklin, 2010) from a horizontal perspective. Viewpoints are defined as a collection of independent views of the musical surface each of which models a specific type of musical phenomena. Each of this view can be combined into a higher-level description. A linked viewpoint is a combination of two or more viewpoints that model their interaction simultaneously. Each voice of a musical piece is cut into phrases that are separated by rests. This particular division of phrases is possible in Renaissance vocal music because the text segments the musical phrases, and rests are written between separate ideas, never as part of a musical idea.

Once the score is divided into phrases, each phrase is treated as a sequence of linked viewpoint values. The sequence of notes is converted to a sequence of features derived from the musical surface. Example of such features are absolute pitch (pitch), name of note (spell), melodic contour, duration contour, interval (diatonic), or an abstract interval class (scale-step), as will be explained below. A pattern is a sequence of features $(v_1, \dots, v_l)$ where each v_i is a feature.

The scale-step viewpoint (Padilla, 2016) groups successive intervals and is flexible enough to find patterns in music of Renaissance style. The values of that viewpoint are:

- Unison and Octave (J18)
- Minor second and Major second (Mm2)
- Minor third and Major third (Mm3)
- Perfect fourth and Perfect fifth (J45)
- Minor sixth – Major sixth (Mm6)
- Minor seventh - Major seventh (Mm7)

The repetitions of patterns in Palestrina are not merely exact transpositions of intervals. For example, a minor second can be converted to a major second, as shown in Figure 1. By using the syntax above, and taking into account the scale-step and contour duration, the following linked viewpoint

$$\text{scale-step} \otimes \text{contour(dur)}$$

is the pattern indicated in Figure 1 and would be represented as follows:

J45_-, Mm2_-, Mm3_=, Mm2_=, Mm2_=, Mm2_=, Mm2_+, Mm2_-, Mm2_+

Figure 1. *Kyrie from Ave Maris Stella, bars 1 to 4 altus part. T. L. de Victoria.*

Pattern Discovery

Data mining is the computational process of discovering interesting patterns in large data sets. Algorithms for sequential pattern mining are, among others: SPADE or sequential pattern discovery using equivalence classes, (Zaki, 2001); PrefixSpan or prefix-projected sequential pattern mining (Han, et al., 2001); GSP or generalized sequential pattern algorithm (Srikant & Agrawal, 1996); CloSpan or Closed Sequential pattern mining (Yan, Han, & Afshar, 2003); BIDE or bi-directional extension (Wang & Han, 2004); SPAM or sequential pattern mining using a bitmap representation (Ayres, Gehrke, Yiu, & Flannick, 2002).

In our paper we are using gap-BIDE (Li & Wang, 2008), an extension of the BIDE algorithm for mining closed sequential patterns with possible gap constraints. Currently, we are working at zero gap level ignoring gaps in the sequences.

Ranking Patterns

A huge number of patterns can typically be found in a piece. In this paper we establish a ranking of patterns based on a binomial distribution that computes the probability of obtaining an observed number of occurrences in a given number of sequence positions within the template piece.

The background probability of a pattern gives the probability of finding it in a random segment with the same zero-order distribution as the corpus*. The background probability (b_p) of a pattern $p = (v_1, \ldots, v_l)$. using a zero-order model of the corpus is:

$$b_p = \prod_{i=1}^{l} c(v_i)/N$$

where:

- $c(v_i)$ is the total count of feature v_i,
- N is the total number of places in the corpus where the viewpoint is defined.

To determine the importance of each pattern, we create a ranking based on its repetitions, length and the background probability. We assume that longer and more repeated patterns are more interesting. The interest $\mathbb{I}$ of a pattern, can be formally defined using the binomial distribution, which gives the probability of finding exactly k occurrences of the pattern in a sequence of length t, where the background probability is b. Then the negative logarithm of the probability of finding at least the observed number of occurrences of the pattern is

$$\mathbb{I}(p) = -\ln \mathbb{B}_{\geq}(k; t, b),$$

where:

- $\mathbb{B}_{\geq}$ gives the cumulative probability (right tail) of the binomial distribution,
- t approximates the maximum number of positions that can be possibly matched by the pattern,
- k is the number of times the pattern appears in the template piece.

Discussion

This is a work in progress to build a system that analyzes and compare different rhetorical aspects of Renaissance music. Figure 2 and 3 show the output obtained by the first version of our program implemented in Python, using the music21 library (Cuthbert & Ariza, 2010).

Figure 2*. Kyrie from Ave Maris Stella, bars 1 to 6. T. L. de Victoria. Detail of pattern 2.*

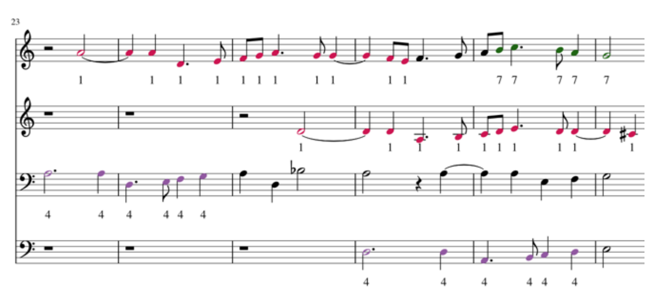

Figure 3*. Kyrie from Ave Maris Stella, bars 23 to 27. T.L. de Victoria. Detail of pattern 1 and 4.*

* The zero-order model has been created using 101 masses composed by Palestrina and published between 1554 and 1601, last seven after his death in 1594. The data has been obtained from music21, http://web.mit.edu/music21/, (accessed May 8, 2018), a Python-based toolkit for computer-aided musicology developed by MIT. The data of Victoria mases are from https://www.uma.es/victoria/index.html (accessed May 8, 2018),

The main constraints for our pattern discovery algorithm are 3 repetitions (at least) of 3 linked viewpoints. These figures show the detection of three different patterns. From the point of view of a human analysis, pattern 2 is an *anaphora* and patterns 1 and 4 are *inverted mimesis* of the same idea.

Using alignment algorithms (Mongeau & Sankoff, 1990; Needleman & Wunsch, 1970), it is possible to measure the melodic distance between the patterns and construct a phylogenetic tree (Rebelo, et al., 2012) that shows the relations between the patterns and, in fact, the structure of the whole piece.

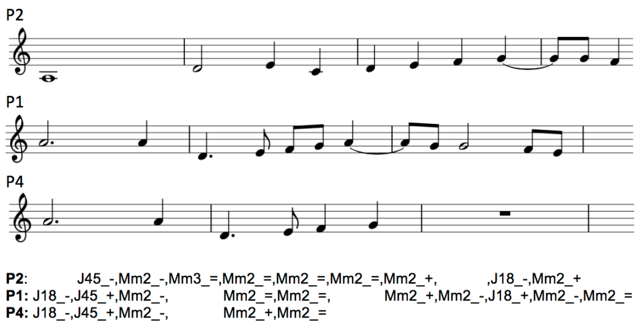

Figure 4. *Alignment of patterns. Kyrie from Ave Maris Stella, T.L. de Victoria.*

Conclusions and Next Steps

In this paper we present a work in progress for building a system that analyzes and classifies pieces from the Renaissance polyphonic music. Our research is at a preliminary stage, but results are very promising. The patterns in Renaissance and Baroque era are very flexible, adding or removing notes, changing rhythms, inverting parts of the pattern, etc., but clearly recognizable for a human musicologist. The main difficulty for our system is to provide the algorithms with the flexibility to fit and represent the human perception of music.

The examples shown in the previous section illustrate that A composer's use of patterns is not random, and can help understand his/her style and composition. As we discuss in a previous section, one piece can be constructed based on a few patterns and rhetoric presentations of those patterns. The next steps involve to design algorithms to group, compare and classify patterns from a rhetorical point of view. The inspiration comes from the bioinformatics and data mining where many algorithms have been developed to identify patterns, classify, align and build phylogenetic trees.

In order to test our research properly, a reliable groundtruth has to be built. The rigorous, standard way to do it is to gather a set of expert musicologists that would annotate the rhetorical patterns for a set of selected works. The output of the system would be tested against the results by the musicologists. However, we are aware that musicologists may not agree on this matter and therefore different analyses will, probably, focus on different aspects. A Turing test will help us to check if the output of our system is meaningful for a human analyst. Another possibility could be to carry out a Delphi round (Jorm, 2015), a process where experts are confronted with disagreeing views on a particular topic of their expertise in several rounds until they reach a certain degree of consensus.

The work with large volumes of musical information allows the musicologist to glimpse the possibility of the creation of machine learning models based on Big Data and the Knowledge Discovery in Databases concept, KDD, (Minarei- Bidgoli, 2004), applied to music analysis. From the results we have obtained so far, we observe interesting facts. Our system detected the rhetorical patterns that had been annotated by us. More surprisingly, the system identified more patterns, in general longer patterns, than the rhetorical patterns. We are still investigating what the meaning and function of those patterns is in the music.

References

Bartel, D. 1997. *Musica poetica: musical-rhetorical figures in german baroque music*. U of Nebraska Press.

Conklin, D. 2010. Discovery of distinctive patterns in music. *Intelligent Data Analysis, 14*(5): 547-554.

Cuthbert, M. S.; and Ariza, C. 2010. music21: A Toolkit for Computer-Aided Musicology and Symbolic Music Data. *In Proceedings of the International Conference on Music Information Retrieval*: 637–642.

Gómez, C.; Ruckhaus, E.; and Abad-Mota, S. 2007. An analysis of the Mongeau-Sankoff Algorithm for Music Information Retrieval. *ISMIR 07, 8th International Conference on Music Information Retrieval*. Vienna, Austria.

Giraud, M.; Groult, R., Leguy, E.; and Levé, F. 2015. Computational fugue analysis. *Computer Music Journal 39*(2): 77-96.

Gulati, S., Serrà J., Ishwar V., & Serra X. Melodic Pattern Extraction in Large Collections of Music Recordings Using Time Series Mining Techniques. *International Society for Music Information Retrieval Conference*. 2014.

Han, J.; Pei, J., Mortazavi-Asl, B.; Pinto, H.; Chen, Q.; Dayal, U.; Hsu, M. 2001. Prefixspan: Mining sequential patterns efficiently by prefix-projected pattern growth. *Proceedings of the 17th International Conference on Data Engineering*: 215-224. Washington, DC, USA: IEEE Computer Society.

Jorm, A.F. 2015. Using the Delphi expert consensus method in mental health research. Australian and New Zealand Journal of Psychiatry, 49(10):887–897.

Knopke, I.; and Jürgensen, F. 2009. A system for identifying common melodic phrases in the masses of Palestrina. *Journal of New Music Research* 38(2):171-181.

Li, C.; Wang, J. 2008. Efficiently Mining Closed Subsequences with Gap Constraints. *SIAM International Conference on Data Mining*: 313-322. Atlanta, Georgia, USA.

Needleman, S. B.; and Wunsch, C. D. 1970. A general method applicable to the search for similarities in the amino acid sequence of two proteins. *Journal of molecular biology* 48(3):443–453.

McCreless, P. 2008. Music and Rhetoric. In *The Cambridge History of Western Music Theory.* Edited by Thomas Christensen, University of Chicago. Cambridge University Press.

Saint-Dizier, Patrick.2014. Musical Rhetoric: Foundations and Annotation Schemes. Wiley.

Minarei-Bigdoli, B. (2004). *Data mining for a web-based educational system.* Michigan, US: Universidad de Michigan. Tesis doctoral.

Mongeau, M.; and Sankoff, D. 1990. Comparison of musical sequences, *Computer and the Humanities* 24:161–175.

Padilla, V., Conklin, D. 2016. Statistical generation of two-voice florid counterpoint. In *SMC 2016: 13th Sound and Music Computing Conference*: 380-387.

Rebelo, A.; Fujinaga, I.; Paszkiewicz, F.; Marcal, A. R.; Guedes, C.; and Cardoso, J. S. 2012. Optical music recognition: state-of-the-art and open issues. *International Journal of Multimedia Information Retrieval*, 1(3): 173–190.

Srikant, R.; and Agrawal, R. 1996. Mining sequential patterns: Generalizations and performance improvements. *International Conference on Extending Database Technology*: 1-17. Springer Berlin Heidelberg.

Yan, X.; Han, J.; and Afshar, R. 2003. CloSpan: Closed Sequential Patterns in Large Datasets. *Proceedings of the 2003 SIAM International Conference on Data Mining*: 166-177. San Francisco, California, USA.

Zaki, M. 2001. SPADE, An efficient algorithm for mining frequent sequences. *Machine learning:* 42(1-2): 31-60.