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Statistical analysis of the features of diatonic music using jMusic software.

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Introduction

Much has been written about the rules of melody writing and this paper reports on research that uses computer-based statistical analysis based upon these rules. As a first stage in a processes of computer generation of melodies we have devised computer software that analyses melodic features highlighted in melody writing literature. The results of this analysis identifies that not all melody writing rules are evident in historical practice, and thus reveals the usefulness of computer-based analysis in identifying those features that can be usefully applied to computer-generated composition. We also present details of the computer-based analysis software and the jMusic software environment in which it was built so that others might assess the application of these tools to their own music research.

Creative tasks, such as the composition of musical melodies, often defy the imposition of rules in the strict sense. In this paper we will outline our attempts to apply firm, at times brittle, digital implementations of compositional rules to Western diatonic music and show where these rules are indicative of coherent melodies and where they act more as guidelines or heuristics. In the process we will discuss some of the issues that arose in mapping linguistic rules to digital representations and how we were able to represent the results in multiple mediums. We found that the rules of melody writing were generally heuristic in nature but that despite wide standard deviations the features could usefully, if only loosely, differentiate coherent diatonic melodies from incoherent ones. They could alert us to “poor” melodies but not distinguish “good” from “average” melodies.

To explore the rule-adherence of existing melodies we developed software to automate the process. This software is now publicly available and so its operation and features will be described. It is hoped that others who require analysis of melodies for research might be able to utilise this software. Our research was also concerned with the support of melodic writing in school education and computer generation of algorithmic melodies and therefore these and other possible research extensions of our melodic analysis procedures will be briefly discussed.

Rules of melody writing

There are numerous books and courses on melody writing. Our first task was to survey this literature and distil the “wisdom” in them to develop a list of regularly occurring features. We limited our search to literature focused upon Western diatonic music and to rules aimed at beginner composers (Dunsby & Whittall 1988, Sturman 1995, 1995a, Stowasser 1989). We arrived at a list of 24 melodic features identified in the literature on composition. These are described briefly in figure 1 (for a more complete description see Towsey, Brown, Wright & Diederich 2000). The features are deliberately simplistic and do not include harmonic variation over time such as chord progression or modulation of key.

Melodic Features:

Pitch Features	**Rhythmic Features**
Pitch Variety The variety of pitches used.	*Note Density* The average number of notes per beat.
Pitch Range The distance between the lowest and highest pitch.	*Rest Density* The average number of rests per beat.
Key Centeredness The use of tonic and dominant pitches.	*Rhythmic Variety* The number of different rhythmic values used.
Tonal Deviation The use of non-scale pitches.	*Rhythmic Range* The difference between the shortest and longest rhythm value used.
Dissonance The use of dissonant intervals.	*Syncopation* The number of notes that sustain across the beat.
Overall Pitch Direction The upward or downward trend of the melody.	**Structural Features**
Melodic Direction Stability The number of times the melody changes pitch direction.	*Repeated Pitch Density* The use of two of the same pitches in a row.
Pitch Movement by Tonal Step The use of tonal steps, indicating pitch contour smoothness.	*Repeated Rhythmic Value Density* The use of two of the same rhythm values in a row.
Leap Compensation The use of rebounding direction after a large pitch leap.	*Repeated Pitch Patterns of Three* The occurrence of three of the same pitches in a row.
Climax Strength How often the highest note is used.	*Repeated Pitch Patterns of Four* The occurrence of four of the same pitches in a row.
Climax Position The location through the melody of the highest note.	*Repeated Rhythm Patterns of Three* The occurrence of three of the same rhythm values in a row.
Climax Tonality The use of a tonic or dominant pitch as the highest note.	*Repeated Rhythm Patterns of Four* The occurrence of four of the same rhythm values in a row.

Figure 1 – Melodic features identified in educational texts on composition.

Adapting features for computer analysis

The distilling of features from the literature was a step toward articulating the rules of melody writing for the computer which was a longer term goal of our research to support melody composition. At this stage we were keen to identify features without implying value judgements about their desirability. For example, pitch range may be narrow or wide as a feature but is usually recommended to be about an octave wide as a “rule”. Our process of statistical feature identification served well our purpose of checking adherence to established compositional rules. Other techniques of computational melodic analysis, often more sophisticated, have been developed but were either overly-complex or not easily adaptable to rule derivation. The interested reader is referred to methods by Huron, Thompson and Stainton in *Computing in Musicology* (1996) and by Maidín, Crawford et al., Lloyd et al., Howard, and Cope in the volume *Melodic Similarity* (1998) both edited by Hewlett and Selfridge-Field.

The next challenge was to represent features in a way where maximum and minimum values could be constrained (e.g. infinite values would never occur) and that the values from different melodies might be reasonably comparable. We chose to normalise all values as ratios of occurrence against potential occurrence. In many cases this was quite straight forward, for example in the case of tonal deviation the analysis returns the number of non-scale notes compared to the number of notes in the melody. However, in some cases it meant providing arbitrary limits on potentiality, as in the case of pitch range where “range” is theoretically limitless. In this case the maximum potential range was assumed to be three octaves from C3 to C6. Rhythm limitations of our implementation include the smallest rhythmic value being a semi-quaver and other rhythms being multiples of a semi-quaver. This, most significantly, does not allow for triplets or other duplets in melodies.

As a result of this normalisation all values produced by our analysis of a melody are in the range between 0.0 to 1.0. Normalisation enables reasonable comparisons to be drawn between melodies of different length, metre, and style. The key of a piece is the only additional attribute that is taken into account by the computer analysis procedures. This is done on a case-by-case basis.

Rule coherence with established repertoire

In order to test the validity of the features for indicating a well-formed melody we tested them against existing repertoire, assuming that that repertoire was “good”. Those features that showed a clustering of results were deemed to be informative—those whose data showed little or no coherence were considered unreliable.

The repertoire list of about 300 melodies included music by the following composers; Bach, Bartok, Beethoven, Du Fay, Gesualdo, Gibbons, Hadyn, Holst, Montiverdi, Mozart, Palestrina, Strauss and Tchaikovsky.

Features were calculated on each melody and the average result and standard deviation of each feature was calculated for the whole group, as described below. In order to determine which features might be most important in identifying well-formed melodies, T tests were run and significance assessed. A brief outline of the results is presented in figure 2. The features are grouped into three categories: 1) Highly reliable features, where all melodies generate similar results indicating that the factor is quite reliable as a predictor of melodic coherence; 2) mildly reliable features, those for which melodies vary considerably but tend toward the mean indicating that these features are partially indicative; and 3) Unreliable features, where melodies cluster into several regions indicating that these features are not consistent predictors of melodic coherence when analysed in this way. Details of the statistical results have been presented elsewhere (Towsey et al. 2000) and are not critical to the focus of this paper on the use of the computer in the process.

Highly Reliable	**Mildly Reliable**	**Unreliable**
Pitch Variety	*Pitch Range*	*Leap Compensation*
Tonal Deviation	*Key Centeredness*	*Climax Strength*
Dissonance	*Melodic Direction Stability*	*Climax Tonality*
Overall Pitch Direction	*Pitch Movement by Tonal Step*	*Rhythmic Range*
Note Density	*Climax Position*	
Rest Density	*Repeated Rhythmic Value Density*	
Rhythmic Variety	*Repeated Rhythm Patterns of Three*	
Syncopation	*Repeated Rhythm Patterns of Four*	
Repeated Pitch Density		
Repeated Pitch Patterns of Three		
Repeated Pitch Patterns of Four		

Figure 2 - Features as predictors of melodic coherence.

The results over all the repertoire melodies provide a useful indication of adherence to each feature which can be used as a basis for comparison with individual melodies. The overall results also reflect on the validity of features and the extent to which they are adhered to in practice.

In deference to space and time constraints two of the twenty-three features will be focused upon as examples, Key Centeredness and Climax Position.

The benchmark results from the repertoire melodies for these features are as shown in figures 3 and 4. The scale of these graphs are from 0 to 1 in 0.1 increments on the x axis and normalised heights indicating the numbers of melodies with scores in each range.

1. Key Centeredness: Mean: 0.31, Mode: 0.25

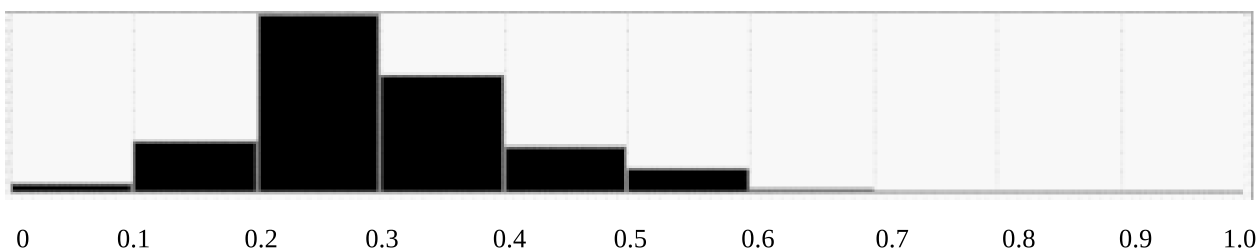

Figure 3 – The benchmark key centeredness results from the repertoire melodies.

2. Climax Position: Mean: 0.53, Mode: 0.75

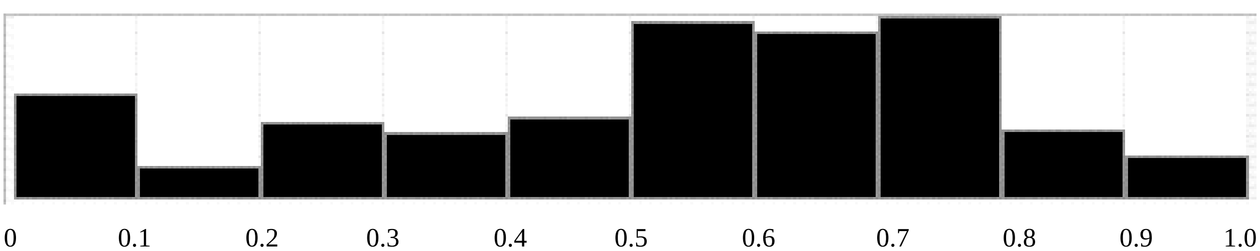

Figure 4 – The benchmark climax position results from the repertoire melodies.

To show how these results shed light on individual melodies we will compare the results from the repertoire melodies with two melodies, one by Claude Debussy and another computer-generated. The computer-generated melody results from a related research project. These examples will show how melodies (computer- or human-created) can be compared to traditional norms and how departure from those norms can be a prompt for further analysis.

The melody below is from *Nuages*, Nocturnes No. 1 by Claude Debussy.

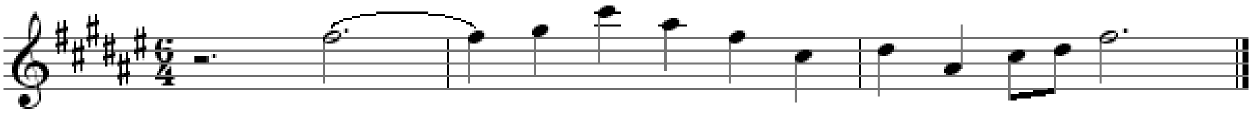

Figure 5 – A melody from Debussy's Nuages.

Its results of this melody for the chosen features are:

- Key Centeredness: 0.3
- Climax Position: 0.26

The melody by Debussy scores close to average with regard to Key centeredness because the notes used are all within the scale and there is prominent use of the tonic and other triadic pitches. The lower than average score for climax position simply reflects the reaching of the highest pitch by note three. This is earlier in the melody than average but not exceptional. Given the wide spread of climax positions in the repertoire melodies almost any position is acceptable despite the tendency toward climaxing about three quarters of the way through the melody.

The second example melody, below, was generated by a rule-based computer algorithm.

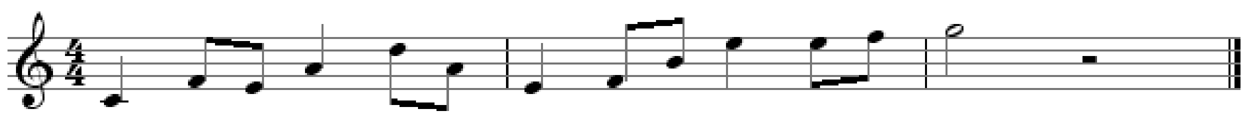

Figure 6 – A computer generated melody.

Its results for the chosen features are:

- Key Centeredness: 0.3
- Climax Position: 0.75

This melody and its results indicate that the statistics can be used to create reasonable melodies but also that statistics can be brittle at times. The score on key centeredness is consistent with the benchmark results which is to be expected given that the generative algorithm for note choice is highly biased toward conventional tonality and follows the same heuristics with regard to tonality used for the analysis software. The result for climax position is more interesting. The melody achieved a statistical result exactly in line with the benchmark results, however, when looking at the melody it is clear that the climax is at the end rather than three quarters of the way through. This is explained by understanding that the climax position is calculated by rhythmic value, rather than note count. The statistical result is influenced by the long length of the last note and the presence of a rest to complete the bar. Taking into account the rest the climax of this melody begins two thirds of the way through the melody's duration, and disregarding the rest four fifths of the way through. This degree of interpretation of the statistics regarding climax position does highlight the inherent brittleness of such endeavours and reinforces the need to use them as a guide and filter rather than absolute measure of musical features. In the case of our generative melody composition software we value the fact that such interpretations are possible and that the algorithm can surprise us with such novel suggestions.

We would make a final point about rule-based analysis of music, or other creative products. Rules like those found in the music theory books used in this study are best treated as norms rather than exemplars of excellence. It is for this reason that we refer to the melodic attributes as features. A melody that adheres to all the "rules" will be an unexciting melody indeed. Highly valued compositions are meaningful largely because of their deliberate avoidance of the expectations that arise from the history of experience from which the rules are derived (Manns 1994).

Phrase analysis software

The analysis of features used MIDI files as a readily available source of melodic data. Code was written in the Java language, using the jMusic libraries to handle the translation and analysis process.

The phrase analysis software provides an interface to the analysis procedures. It manages the reading of MIDI files, checks the key of the music (because all pitch functions are relative to key), selects phrase or phrases for analysis, displays analysis results as both numerical data and pictorial graphs, enables the mapping of statistical results back to particular phrases in a group, and can save the data in tabulated form to a file for use with other software.

Using the software is relatively straight forward given appropriate preparation. Specifically, the program requires type 1 MIDI files and reads only from one track (the first by default) and expects monophonic material (i.e., no chords or overlapping polyphonic parts). MIDI files of many well-known musical works are available on the Internet and these can be edited in sequencing software to extract and save just the melodies of interest. Alternately, sequencing or music publishing programs can be used to enter music for saving as standard MIDI files. Both of these methods were used to create the pool of melodies used in our research.

Once prepared, the MIDI files can be read into the phrase analysis software either individually or as a group within a particular folder/directory. Imported files can be analysed one at a time or as a group. All files in one group should be in the same key. Analysed files appear in a list that can be clicked to display the file as common practice notation and its statistics as a list of feature-value pairs.

A second screen displays graphs of the statistical results of all analysed files. A list of each analysis feature is shown. Selecting a feature brings up a column graph display and numerical data for mean and standard deviation. The resolution of the graph can be changed, from the 0.1 sized increments show in figures 3 and 4, to allow for more or less detailed distribution trends to be observed.

Pointing the cursor at any of the columns in the graph displays a list of the files that fit the values covered by the column. This can be quite useful in identifying outlying or exceptional files which may require closer manual analysis.

The results of the analysis can be saved as a tab-delimited text file. The file has the data tabulated with features as columns and files as rows. The overall statistics are listed after the individual files. This file can be easily read in other programs including Microsoft Excel or SSPS for further analysis. We utilised this feature to enable T tests, checks for correlations, and cluster analysis in our research.

The jMusic programming library

The music data format used for the analysis was that of the jMusic library. jMusic provides a musical data structure and methods for manipulating that structure, and was designed for music composition as well as analysis, though it is more often used for composition. All of the analysis functions used in this research are now part of the jMusic libraries and therefore available for use in other applications, some of which are described below. jMusic is a freely available open source project and its installation is required to run the phrase analysis software.

Online Music Tools

Many of the melodic feature analysis processes used here, and some additional ones, are available as online music tools accessible using a web browser. The visual display of the data is less compressive with the online analysis tools, but they do have the ability to analyse entire multi-part MIDI files. The online music tools were designed and programmed by Andrew Brown and Adam Kirby building on the research outlined in this paper.

Conclusion

The use of computer for analysis of diatonic melodies can be useful in the identification of interesting features often unobservable with manual analysis and provides a vehicle for the comparative analysis of individual melodies or classes of melodies. This paper has presented our work in melodic feature analysis based on simple rules of diatonic melody writing. Through the testing of these features against a data set of melodies from Western music history we were able to show which features are closely or loosely adhered to by composers in practice. We also showed how individual melodies can be compared against the norms to highlight interesting characteristics for further manual analysis.

Our music analysis software described in this paper makes the task of feature analysis relatively effortless, and its graphical presentation of results enables efficient and multi-modal communication of the data. We have outlined the basic operation of this software and provided details enabling others to access and perhaps modify the software for their needs. For example, one area of extension would be the provision of correlation between features.

The computer has prooved to be useful tool in focussing our thinking about diatonic music (in particular melodic construction), assisting with the analysis of large data sets, and in clarifying heuristics for algorithmic computational music creation.

Our research efforts are continuing in the direction of providing these and other analysis processes via a series of online music tools. These tools will go some way to addressing the limitations of our research to date. In particular, to consider larger musical structures, including multi-phrase parts and multi-part scores, and to provide greater acknowledgment of harmonic and structural features.

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