SOMphony: Visualization and Comparison of Symphonies Through Application of Time Series on 3D SOM

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Abstract

Symphonies are musical compositions for orchestras that consist of several large sections called movements. There are five major musical periods namely the Baroque Period, Classical Period, 19th Century, Romantic Period, and the 20th Century that played a big role during the height of symphonies. This research will compare pairs of symphonies to determine their similarity, and create a visualization method to represent the comparison. From a previous research work by Azcarraga & Flores (2016) that compared symphonies though self-organizing maps (SOM), this research work will compare symphonies through visualization in a 3D SOM. By having a visual representation, the research provides an interactive and straightforward way to identify which parts of the symphonies are most similar and by adding the concept of time series on the clustering of the 3D SOM, more accurate results can be made. Quantitative data will be gathered through cluster analysis and using Euclidean distance to measure the musical trajectories of each musical segment of the symphony to produce the overall 3D SOM. T-SNE will also be experimented upon to see if it also produces optimal visualization for symphonies like with SOM.

Keywords: Machine Learning, Music, Time Dimension, Self-Organizing Map, K-Means Clustering.

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Chapter 1

Research Description

1.1 Overview of the Current State of Technology

Music has been a part of peoples culture for hundreds of years, classical music being one of the oldest genres of music. Classical music is rooted in the traditions of early western music and to this day, many people refer to classical music as serious music. Musicians, however, use classical music to refer to music composed during 1750 to 1825, otherwise known as the Classical Era (Bernstein, 1959). The central norms of classical music became established between 1550 and 1900, which is known as the common-practice period. The common-practice period contains the majority of what we now know as classical music. Under this period there are 3 musical eras: Baroque, Classical and Romantic. Music from the Baroque period are decorated and elaborate, with little to no expression. Works from the Classical era contain repetitive dynamics and clean transitions. In contrast to music from the Baroque period, music from the Romantic period are expressive and emotive, having the ability to paint a vivid picture in the minds of the listeners (Grout & Palisca, 1996); however, Dahlhaus (1981) points out that another musical era existed between the Classical and the Romantic period and he refers to this as the 19th century era. This era serves as the transition period for classical and the romantic period, thus having similarities in style with both eras. After the common-practice period comes the 20th century era, which explores modernism, impressionism, neoclassicism and experimental music.

It was in the common-practice era when symphonies began to be composed. Libin (2014) describes symphonies as lengthy forms of musical compositions which are almost always written for orchestras and are consisting of several large movements. They are composed of three to five movements, depending on the time period and are constructed by many different composers (Libin, 2014). There are five major musical periods namely the Baroque Period, Classical Period, 19th Century, Romantic Period, and the 20th Century. Musical pieces from each era share certain characteristics and styles that are representative of the era. With a history of almost 300 years, symphonies today are viewed as the very pinnacle of classical music where Beethoven, Brahms, Mozart and other renowned composers were able to find a venue for transcending their creativities and overall influencing them heavily on their music. During the course of the 18th century, the tradition was to write four-movement symphonies (Hepokoski & Darcy, 2006).

Throughout time, different styles have developed, each having features unique to themselves. Tilden (2013) notes the historical influence of composers with each other and how similar the methods of composing classical music are with pop music. Due to these facts presented, symphonies written in the early 20th century may be influenced by the great composers and compositions of the previous eras. Analyzing these musical relationships and comparing one to another is a research area that could be done through both manual and machine learning methods.

McFee, Barrington & Lanckriet (2012) compare the use of context-based manual semantic annotation versus their proposed optimized content-based similarity learning framework. With machine learning, the use of high-quality training data without active user participation and the analysis of more data is possible than with feedback or survey data from active user participation. Human error in the analysis process can also be minimized with machine learning since human-supervised training is minimal. Corra & Rodrigues (2016) shows the analysis of music features using machine learning techniques. According to the MIR community (Silla & Freitas, 2009), the two main representation of music feature content are either audio-recorded or symbolic-based. The former employs the explicit recording of audio files while the latter uses symbolic data files such as MIDI or KERN.

SOMphony, a research paper by Azcarraga & Flores (2016), aims to understand the relationship of compositions between the same composer to denote style as well as to determine the similarities between compositions of different periods of music to denote influence between time periods. The research showed the relationships and influences between composers from 5 major musical periods, namely the Baroque Period, Classical Period, 19th Century music, Romantic Period and the 20th century. The research focuses on self-organizing maps (SOM) that are trained using 1-second music segments extracted from the 45 different symphonies. The trained SOM is then further processed by doing a k-means clustering of the node vectors, allowing quantitative comparison music trajectories between symphonies. Their research showed that using SOM is indeed helpful in visualizing the musical features of a symphony, making it easier to create insights about the relationships within the different pieces and composers. The research concludes that a larger dataset would be needed to confirm whether the approach is indeed valid.

SOMphony, however, does not take into consideration the notion of time. In time series data, each instance represents a different time step and the attributes give values associated with that time (Witten & Frank, 2005). To be able to generate time sensitive musical analysis, this research will add in the time dimension variable to the SOM and a new visualization in 3D space would need to be created.

In another research work by Maaten & Hinton (2008), they introduce a new visualization technique for assigning data points in a two dimensional or three dimensional map called t-Distributed Stochastic Neighbor Embedding or t-SNE, which is a variant of Stochastic Neighbor Embedding or SNE. Since t-SNE produces almost very distinct visualizations as will be discussed in more detail in Chapter 2 and Chapter 3 based on the experiment performed by their research work, this technique for visualizing individual symphonies may be more optimal than SOM in terms of both accuracy and efficiency.

1.2 Research Objectives

1.2.1 General Objective

To visualize symphonies using time dimension

1.2.2 Specific Objectives

The research aims to:

1. Perform feature selection to decrease number of features for faster training time in machine learning;
2. Find time-dependent distance measures to compare trajectories;
3. Create a 3D visualization model for the music data;
4. Determine feasibility of t-SNE as another form of visualization for comparison of symphonies;

1.3 Scope and Limitations of the Research

To expand the data set of SOMphony, the proponents will add an additional 2 symphonies to the existing 3 symphonies for each of the 15 total composers from the previous work and add in 2 additional composers for each era with the same number of compositions for each one. This will result to a total of 125 symphonies in total. By having an equal number of symphonies per composer, a balanced data set for all composers can be maintained. The criteria for choosing the symphonies to be added would be random due to the availability of musical pieces and this would also provide a better grasp on the general style of the composer.

To be able to generate a self-organizing map, the proponents will use jAudio to extract 436 audio features from musical segments generated from the symphony (See Appendix C). The 436 audio features would be trimmed down through feature selection. Decision Trees will be used to trim excess features and retain only the most relevant ones in order to speed up SOM training without losing too much accuracy (Yang & Pedersen, 1997). The proponents will experiment on different numbers of of features (n) to be used. By selecting only the n most influential features, the time it would take to train the SOM would not be as time consuming compared to using all 436 features, however, this will be at the cost of some of its accuracy in plotting the symphonys musical trajectory.

In incorporating the time dimension, the musical piece is divided into 1 second segments in order to be uniform all throughout the piece and to avoid incomplete notes. A 0.5 second overlap is used to be able to consider transitions between each second.

To create a 3D model to represent the symphony, the proponents will assign each generated SOM to a point in time and will be used to create a graph representing each map in a time series. As a result of using time dimension, this research will be able to better differentiate symphonies that use similar themes but at different periods of time in the composition.

Similar to SOMphony, the proponents will focus on representation of symphonies using SOMs for the purpose of comparison to other symphonies. T-SNE will also be used as a visualization technique for the musical features of each individual symphonies. The results from t-SNE will then be used to validate if t-SNE is an optimal visualization tool for visualizing symphonies.

1.4 Significance of the Research

As this study focuses on comparing different symphonies and analyzing to see how similar they are, the results of this study will help in the simplification of one to two long hours of music into a single visual representation. The study can help in the comparison of music using time series and some quantitative data. It can prove that visualization can be achieved, allowing comparison of simplified time series data. By using qualitative and quantitative means, the results of the study may also determine the similarity between two compositions. The results of the study may also help prove the benefits and possibilities of SOM when transitioning from 2D to 3D with basis on the time series.

Some possible future application of the results of this study would include the improvement of existing music information retrieval (MIR) techniques used by music databases. Similarly, this research can also be used to further improve the algorithms used by playlist managers for the retrieval of similar songs from music databases using the comparison of the trained SOMs.

The application of time series in machine learning would benefit studies outside of music that incorporates the use of time sensitive data. It can be used in future works regarding traffic modelling, weather monitoring, prediction, and other time sensitive fields.

1.5 Research Methodology

This section contains phases and activities that will be performed to accomplish the research. The phases listed here will be arranged sequentially unless otherwise stated.

1.5.1 Concept Formulation and Review of Related Literature

This phase will concern the consolidation of the thesis requirements such as the objective of the research, the research problem to be tackled, and the scopes and limitations of such research. Research related to music comparison, machine learning algorithms in music and music visualization will be part of the Review of Related Literature.

1.5.2 Data Gathering

This phase will concern the gathering of the additional symphonies to be used for the research. The original music dataset for SOMphony is composed of 75 symphonies spread across 5 periods, each having 3 composers. To expand the dataset, 2 symphonies will be added to each composer, summing up to a total of five symphonies per composer and 2 composers will also be added with the same number of symphonies for each era summing to a total of 125 symphonies. The proponents have decided to maintain 5 symphonies per composer so that the data set will be balanced. The process of selecting which symphonies to be added would be by random to have a better grasp of the general style of the composer. The audio files would be retrieved from online sources and physical means. The researchers would not take into consideration the file type and bitrate of the audio files since music data that is free for use is limited.

1.5.3 Pre-processing

To start pre-processing, the audio files would be converted into wav files in preparation for splitting. WaveSplitter will be used in splitting the audio file into 1 second segments at intervals of 0.5 second. These segments would undergo feature extraction using jAudio. The result would be an xml file containing all the features determined for each segment. The researchers would then run RegEx to extract the unnecessary text in preparation for labeling. Since the proponents would have supervised learning, the data needs to be labelled according to their composer, composition and file name.

1.5.4 Feature Selection

In this phase, the proponents will trim down the 436 features that jAudio has extracted. With decision trees, the top n nodes will be selected as the top n features. Aside from decision trees, the proponents will explore other statistical techniques such as PCA or Pearson correlation for feature selection which may prove more efficient or optimal than decision trees. By doing feature selection, the data set would have a uniform number of features for all symphonies and it would also enhance the efficiency of training the SOM.

1.5.5 Visualization

Frequency cluster counting will be mainly used for quantitative measurements to determine if a pair of symphonies are alike as will be discussed in more detail in Chapter 3. The resulting visualization from SOM and t-SNE will then be used to verify both methods accuracy by comparing for example if two symphonies by composer A have a much similar visualization. If the resulting visualizations show that the compositions by the same composer are alike, then it may be able to prove the accuracy of the visualization technique used.

1.5.6 Performance Evaluation

In this phase, the proponents limit themselves to 50 participants. The participant profile would be people that have experience with classical music. In the case that the target amount is not reached within two months, the researchers will proceed to analyze the results they have. The participants would be presented with a 3D graph and two music players. They are tasked to annotate specific regions of the symphony and verify if they are indeed similar. However we do not limit the participants to the specified regions, the participants are free to annotate parts that they believe sound similar.

1.5.7 Documentation

This phase will be done all throughout the whole research timeframe. The previously mentioned stages and their corresponding findings would also be documented duly.

1.6 Calendar of Activities

Table 1.1 shows the time table for the activities involved with the research for 2017 and Table 1.2 shows the activities for 2018. The numbers represent the number of weeks worth of activity. The # symbol represents the number of weeks allotted for the month.

Calendar of Activities							
Activities for 2017	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Concept Formulation and RRL	###	####	#				
Data Gathering			#	###	##		
Pre-processing				##	##	####	##
Feature Selecion							
Visualization Development				##	##	##	#
Performance Evaluation							
Documentation	##	###	##	###	####	####	##

Table 1.1 Timetable of Activities for 2017

Calendar of Activities							
Activities for 2018	Jan	Feb	Mar	Apr	May	Jun	Jul
Concept Formulation and RRL							
Data Gathering							
Pre-processing							
Feature Selecion	###	####					
Visualization Development			####	####	####		
Performance Evaluation					####	####	
Documentation	###	####	####	####	####	####	##

Table 1.2 Timetable of Activities for 2018

Chapter 2

Review of Related Literature

This chapter discusses existing research on musical data representations. It also discusses the application of machine learning in music and visualization techniques for musical compositions. A summary of each section in this chapter is presented prior to the discussion of each section.

2.1 Musical Data Representation

Musical Data Representation and Interpretation			
Authors &Year	Title	Research Problem	Approach
Correa & Rodrigues (2016)	A survey on symbolic data-based music genre classification	Expanding music database needs more accurate tools for music information retrieval	Symbolic-based music feature are used to train system for genre classification.
McEnnis, McKay, Fujinaga, & Depalle (2005)	JAudio: A Feature Extraction Library	Solving existing problems in feature extraction systems	They developed jAudio to make extracting features a lot more convenient for researchers.
Cambouropoulos & Widmer (2000)	Automated Motivic Analysis via Melodic Clustering	Finding similarity in music patterns.	Their method uses differences in pitch-intervals and rhythm as basis for splitting one musical motive (small bits of music) from another.

As music grows continuously over time, a constant need for an upgrade to satisfy the number and size of music databases causes the development of more accurate tools for music information retrieval (MIR). MIR is the research field responsible for the development of algorithms or other computational means for the retrieval of useful information from music and the classification of music based on their categories. According to Corra & Rodrigues (2016), the ever increasing research on machine learning, the ever expanding abundance of digital audio formats, the growing quality and availability of online symbolic music data, and availability of tools for extracting musical properties motivate this study on machine learning and MIR. One of the main problems in MIR involves the classification of music based on their genre which this research work tackles. The automatic genre classification of music plays a key role in online music databases where websites or device music engines manage and label music content for retrieval. The main goal of this research work is to be able to compare music samples and give them their own groups or tags in the database so that they can be easily retrieved whenever needed.

Symbolic-based data are music features extracted from symbolic data formats such as MIDI and KERN. In the MIR community, two main representations of music content for MIR research are followed, either the audio-recorded or the symbolic content. Audio-recorded content produce low-level and middle-level features, whereas symbolic content produce high-level features. When analyzing music content, it is preferable to extract more features with the high-level feature of the symbolic content since it is closer to the human perception of music. Due to these reasons, symbolic-based content is used for the research. This research further provides overviews of important approaches regarding music genre classification with the use of symbolic-based music features. The research, as a result, reveals that pitch and rhythm are the best musical aspects to be explored in symbol-based music feature classification that lead to accurate results. Some limitations for further improvement on future works however are present such as the small amount of music dataset used in the research, the bias of using western culture music, and the lack of comparison means for the result of the research due to the lack of previous research works regarding symbolic-based music genre classification.

McEnnis, McKay, Fujinaga, & Depalle (2005) introduced a feature extraction software for audio files called jAudio. jAudio provides an easy to use GUI and a command line interface for selecting which features to select/deselect from the list of features in jAudios current library of feature extraction algorithms which can be found in Appendix C. The software accepts any audio file as input and outputs ACE XML or ARFF format for the features extracted from the audio file. The proponents in this research encountered many problems with regards to existing feature extraction softwares at the time of their research such as there was great difficulty in extracting perceptual features such as meter or pitch from a signal. Another problem was that there was no existing repository of feature extraction algorithms and researchers would have to implement their own feature extraction algorithm whenever they need it and there will be a big chance that they implement the algorithm incorrectly. There was also no existing feature extraction software that produced a standard output format. Feature extraction code was also restricted and not made available to users, thereby denying researchers from developing more feature extraction algorithms.

JAudio tackles these problems by being a Java-based software, making it easy to acquire and making it compatible with any platform. It produces a standard output format and handles dependencies well by executing all dependencies of a feature extraction algorithm before executing it. For example, the magnitude spectrum of a signal is used by a lot of other features so jAudio would prioritize extracting this first before the others to avoid repeating any extraction process.

JAudio also supports metafeatures which are just features that are used by all other features. Examples of this would be derivatives and mean.

Cambouropoulos & Widmer (2000) stated that music could be categorized into small bits called "motives". These motives are extracted from a musical piece by determining which clusters of musical data can be grouped together while maintaining melodic and rhythmic coherence. This is achieved by representing a melodic segment as a series of notes while minding musical closeness.

Their paper outlines a method that uses differences in pitch-intervals and rhythm as basis for splitting one musical motive from another. For example, two segments can be considered similar if they share a certain number of component notes or intervals using approximate pattern matching. The segments can also be considered similar if they contain shared elements at different pitches. However, this would require a more advanced pattern matching and data structure.

2.2 Machine Learning

Machine Learning			
Authors & Year	Title	Research Problem	Approach
Raphael (2010)	Music Plus One and Machine Learning	Computer driven musical accompaniment	Hidden Markov Models and Gaussian Graphical Models
Dubnov, Assayag, Lartillot, & Bejerano	Using Machine-Learning Methods for Musical Style Modeling	Predicting and determining musical context based on relevant past sample is very difficult because the length of the musical context varies widely	Two approaches, incremental parsing (IP) and the prefix suffix trees (PST), are used in designing predictors that can handle data with very large length.

Comparing trends in musical scores and generating a seemingly new work based on the past works of a certain composer has been the focus of another study. In Dubnov, et. al. (2003)s research, they stated that predicting and determining musical context based on relevant past samples is very difficult because the length of the musical context varies widely. The proponents formulated then that by using statistical and information theoretic tools, one can capture important trends present in the musical scores for further analysis with machine learning to derive mathematical models for inferring and predicting a seemingly new work from this particular composer. Large contexts make it very difficult to estimate because the number of parameters, computational costs, and data requirements for reliable estimation increases exponentially. To address this problem, the usage of predictors that can handle data with very large length is necessary. Two algorithms are used to design such a predictor for generating new works from old music scores, namely the incremental parsing (IP) and the prefix suffix trees (PST).

The IP algorithm was first suggested by Ziv & Lempel (1978). Given a string as input, the algorithm first builds a dictionary of distinct patterns by traversing from left to right of a sequence once and adding to the dictionary every time a new phrase with a different last character from the longest match that already exists in the dictionary. In representing the dictionary with a tree, every node contains a string in the dictionary and each time the algorithm reaches a node, it means that the string input contains the string assigned to the node but is longer. In this case, a new child node will be added to the tree.

PST was developed by Ron, Singer & Tishby (1996). This algorithm is very similar to IP, but it only adds to its dictionary if and only if the pattern or motif appeared a significant number of times in the string input and will prove to be useful in predicting for the future. Due to this, the main advantage that IP has over PST is that IP is a lossless compression algorithm, since in PST, some patterns are not added to dictionary, especially if they are not significant. PST, however, is more efficient that IP as a parsing algorithm.

Aside from music comparison, machine learning is also applied in automatic music accompaniment. These accompaniment systems serve as musical partners for live musicians that are performing music that is centered on the soloist. Raphael (2010) developed an accompaniment system with three modules namely Listen, Predict, and Play. The first module interprets the audio input of the live soloist in real-time, identifying note onsets with variable detection latency using hidden Markov model-based score following. However, there will be some detection latency due to the fact that a note must be heard first before it could be identified. To resolve this issue, the Predict module, implements a Gaussian graphical model that times the accompaniment on the human musician, continually predicting the evolution as more information comes.

2.3 Music Visualization

Musical Visualization			
Authors & Year	Title	Research Problem	Approach
Azcarraga, A., Caronongan, A., Setiono, R., & Manalili, S. (2016)	Validating the Stable Clustering of Songs in a Structured 3D SOM	Will constructing the classic 2D SOM as a 3D map be feasible, with the learning algorithm still the same as the 2D map?	The 3D map is designed as a $3X3X3$ cube with $9X9X9$ nodes. The cube is divided into one core cube and 8 corner cubes. The Euclidean distance from core to each corner represents the quality of the different categories or genres.
Barrington, Chan, & Lanckriet (2010)	Modelling Music as a Dynamic Texture	Addressing the lack of time-dependency between feature vectors	Dynamic Texture to represent a sequence of audio features
Maaten & Hinton (2008)	Visualizing Data Using t-SNE	To construct a dimensionality reduction visualization technique that can outperform other existing visualization techniques	Modify SNE to produce a more optimal visualization technique by replacing some steps in the algorithm like the cost function of SNE and by replacing the Gaussian distribution with Student t-distribution

Musical Visualization			
Authors & Year	Title	Research Problem	Approach
Foote (1997)	Visualizing music and audio using self-similarity	Is it possible to display the acoustic similarity between any two instants of an audio file as a two-dimensional representation	Audio similarity is computed by parameterizing them into MFCCs and getting the autocorrelation of two MFCC feature vectors V_i and V_j that were derived from audio windows.

Modeling music is representing the audio file in a machine-readable form. (Barrington et al., 2010) raises the issue of the lack of time dependency between feature vectors and stresses the need to have the feature vectors ordered in time. When time is ignored, the feature vectors fail to represent the musical dynamics of an audio fragment. The research addresses these limitations and proposes a visualization model for short temporal fragments of music and calls it a dynamic texture.

In another research work regarding the visualization of symphonies using SOM and also the previous research work this research work desires to expand on, Azcarraga & Flores (2016) focused on whether the music of certain composers and centuries are influenced by prior works of other composers. Their approach relied upon SOMs and k-means clustering where each section on the map represented a specific type of sound. When fed the data from a symphony, a line would be drawn and move from section to section which would represent the different types of sound the SOM would encounter during playback. The result would look like a scribble of lines superimposing each other. By comparing whether this signature of the symphony was similar to one of another symphony, the researchers were able to detect the stylistic influence that one composer has with another.

Azcarraga, Caronongan, Setiono, & Manalili (2016) presents a variant of the classical 2D SOM, a 3D SOM, that is stable with the general clusters not moving around on every training phase. A structured 3D SOM is an extension of a 2D Self-Organizing Map to 3D with a predefined structure. The 3D SOM is represented as a 3x3x3 cube with 27 sub-cubes of the same size. Each sub-cube is further divided into 9x9x9 nodes. The structured 3D SOM is a collection of one distinct core cube in the center and 26 exterior cubes surrounding it, hence summing to a total of 27 sub-cubes. Alongside 3D SOMs built in structure, the learning algorithm used in this 3D SOM includes a four-phase learning and labelling phase. The first phase of training involves the semi-supervised training of the core cube. The second phase involves yet another semi-supervised training, but for the eight corner cubes. The third phase involves training the core cube again, but the training will be unsupervised. The fourth and final phase will be the labelling phase. This phase involves the uploading of the music files into the cube and labelling them accordingly. The music dataset used in this research includes songs from 9 genres: blues, country, hip-hop, disco, jazz, metal, pop, reggae, and rock. Each genre has 100 songs, thus summing to a total of 900 songs.

SOM is usually represented as a 2D map with the input elements being similar to the input environment. This research verifies that designing the SOM as a 3D map is very feasible, with the learning algorithm still the same as with the 2D map. By extending the SOM from 2D map to 3D, the map is further distinguished into the sub-cubes: eight corner cubes and one core cube in the center. Each corner cube represents a music genre while the core cube represents the song itself. The 3D SOM will be able to identify the quality of the different categories or genres of music albums based on a measure of distortion values of music files with respect to their respective music genres. Distortion value is measured by the Euclidean distance between the core cube and a corner cube.

Maaten & Hinton presents a visualization technique using dimensional reduction of high dimensional data into a 2D or 3D map called t-SNE as was briefly discussed in the introduction. This technique aims to transform high dimensional data into low dimensional data representation for data plotting in the map using a series of computational steps or algorithm which will be discussed in more detail in Chapter 3.

In their research work, they compared t-SNE with other techniques for dimensionality reduction for visualization of data which includes Sammon mapping, Isomap, and LLE using the MNIST data set, the Olivetti faces data set, and the COIL-20 data set. The resulting visualizations by t-SNE for all three types of data set proved to be superior to the three other techniques as t-SNE was able to cleanly cluster the different data classes together for each data set as compared to the other three techniques.

The main advantage of using t-SNE to other techniques is that t-SNE models dissimilar data points by means of large pairwise distances and models similar data points by means of small pairwise distances. This would result in a visual image that have similar data points grouped together and are far apart from data points that are very dissimilar with them. T-SNE also uses either of two tricks which they label as early compression and early exaggeration. Early compression is when the map points are forced to stay together at the start of the optimization and early exaggeration is when map points are forced to have large gaps between their respective clusters by multiplying all of the high dimensional probabilities with a certain constant value so that the modelled data points will have larger values. When the data points are closely packed together in early compression, the clusters will be able to move much easier. Similarly, when there are large gaps among the different data points, the clusters will also be able to much easier to find a good global optimization.

Foote (1997) presented a paper on Visualizing Music and Audio using Self-Similarity. In this paper, the acoustic similarity between any two instants of an audio file is calculated and displayed as a two-dimensional representation. Structure and repetition is a general feature of nearly all music, with parts resembling certain parts of the song that came before it. This paper presents a method of visualizing the structure of the music by its acoustic similarity or dissimilarity in specific instances of time through grayscale gradation patterns.

Before getting the similarity measures, the two instants are first parameterized into Mel-frequency cepstral coefficients (MFCCs) plus an energy term. The similarity measure $S(i, j)$ is computed by getting the autocorrelation of two MFCC feature vectors V_i and V_j that were derived from audio windows. A simple metric of vector similarity S is the scalar product of the vectors. A better similarity measure can be obtained by computing the vector correlation over a window w. This captures the time dependence ofthe vectors. To have high similarity measure, the vectors must not only be similar, but their sequence must be similar as well.

Given the similarity measures $S(i, j)$ computed for all window combinations, an image is constructed so that each pixel at location (i, j) is given a grayscale value proportional to the measure. The maximum similarity measure is given maximum brightness. Visually, regions of silence or long sustained notes appear as bright squared on the diagonal. Repeated figures such as choruses and phrases will appear as bright off-diagonal rectangles. If the music has a high degree of repetition, it will show up as diagonal stripes or checkerboards that are offset from the main diagonal. Longer audio files would result to larger images due to the rapid rate of feature vectors. To reduce the image size, the similarity is only calculated for certain time indexes and since S is already calculated at window size w, the paper only looks at time indexes that are an integer multiple of w.

Chapter 3

Theoretical Framework

This chapter contains theories and concepts that are related to the research.

3.1 Symphonies

3.1.1 Basic Structure of a Symphony

The Classical and Romantic symphony is mainly written in four movements, namely the fast tempo or sonata allegro form, the slow tempo, the medium/fast tempo or minuet, and the fast tempo again. The sonata form makes up the main form of Classical and Romantic symphonies. It is composed of two contrasting themes, the aggressive and the passive and is further divided into several sections, namely the introduction, exposition, development, recapitulation, and coda. The introduction section is purely optional and is slow and solemn in nature. The exposition section is where the themes of the symphony are exposed or presented for the first time and will consequently be repeated all throughout. The development section is where the themes are altered and manipulated. The recapitulation section is where the themes return to their original forms from before they were altered. The code section finally represents the end of the movement and this is where the original tone from the exposition section is repeated or recapped to form the ending for the movement (Heikkinen, 2017 & BBC, 2014).

3.1.2 Music Features

A feature is a characteristic used to distinguish one entity from another and in a sense defines its uniqueness. Music features, therefore, are what makes music similar to or different from one another. By comparing the values for each music feature and by examining if a feature is present at all or not, comparison of music by mathematical means is very possible (Huron, 2001).

Today, music information retrieval (MIR) has become an important area of research especially because of the ever expanding database for music through the years. The features extracted from music can be used in many areas of MIR research. It can be said that when two songs share closer values for each music feature, then they are more similar than with others (Corra & Rodrigues, 2016).

MFCC

MFCC, also known as Mel-Frequency Cepstral Coefficients, is the most commonly used feature in speech analysis and since speech analysis and music research are closely interrelated as pointed out by Loughran, Walker, ONeill, & OFarrell (2008), then MFCC will likely be the most commonly used feature in music feature extraction.

According to Lutter (2014), MFCC is based mainly from experiments on human misconceptions of words such as when a person misunderstands what another person says. This feature extraction method was first developed by Bridle and Brown in 1974 and was further developed by Mermelstein (1976). The MFCC feature extraction method involves mimicking some parts of the human speech production and speech perception. This feature extraction involves five steps, namely the fourier transform, the mel-frequency spectrum, the logarithm, cepstral coefficients, and the derivatives. The first step, fourier transform makes use of the formula $C_{r,k} = |\frac{1}{N}\sum_{j=0}^{N-1} fjexp[-i2\pi\frac{jk}{N}]|$, where $k = 0, 1, ..., (\frac{N}{2}) - 1$ and N is the number of samples within a speech or time frame.

The mel-frequency spectrum closely mimics the sensation of the human ears auditory system and the process involves filtering the spectrum with different band-pass filters, devices that pass frequencies within a certain range and reject all others, and the power for each band-pass filter is computed accordingly (Agarwal, 2017). The computation makes use of the formula $C_{T,j} = \sum_{k=0}^{\frac{N}{2}-1} d_{j,k}\, C_{T,k}$, where $j = 0, 1, ..., N_d$ and d is the amplitude of the band-pass filters at index j and frequency k, to produce the corresponding filter bank for the spectrum.

The third step, logarithm involves mimicking the perception of loudness by the human ear and is represented by the formula $C_{T,j} = log(C_{T,j})$ where $j = 0, 1, ..., N_d$.

In cepstral coefficients, the main goal here is to remove the speaker or the music dependent characteristics. The computation of cepstral coefficients results in the inverse of the fourier transform of the estimated spectrum of the signal and is represented by the formula $C_{T,j} = \sum_{j=1}^{N_d} C_{T,j}\, cos[\frac{k(2j-1)\pi}{2} N_d]$ where $k = 0, 1, ..., N_{m,c} < N_d$ and $N_{m,c}$ is the chosen cepstral coefficient for further processing.

Lastly, the derivative represents the dynamic nature of speech or the music.

3.2 Preprocessing

3.2.1 Data Collection

In gathering data, a careful lookup for patent or copyright issues must strictly be observed. Symphonies are musical pieces that were generally composed a long time ago and as such copyright on the actual symphonies are nonexistent. The only copyright issues to be possibly encountered here would be the source of the recreated symphony. For example, when the symphony is uploaded by a certain person in Youtube then the standard youtube license or the creative commons would apply (Brown, 2017).

3.2.2 Preparation of Dataset

In Azcarraga & Flores (2016)s research regarding visualization and comparison of symphonies through SOM, the preparation of dataset was done by first cutting the symphony into multiple 1 second music segments with an overlapping interval of 0.5 second to provide a smoother transition of the segments when represented later visually in addition to taking consideration of sections or notes that have been abruptly cut during the splitting process. In this way, after the feature is extracted and trained in the SOM, the multiple music segments will make up different musical trajectories which makes up the map visualization.

3.2.3 Feature Extraction

Feature extraction is the means of extracting relevant and effective data to train machine learning algorithms. Not all features, however, may be useful and others may be irrelevant individually but can be useful when combined with other features. The input data or raw data often need to be converted into a set of useful features through preprocessing transformations such as, standardization, normalization, signal enhancement, nonlinear expansion, et al. The resulting data may also be pruned of excess features in order to achieve improved algorithm speed and or predictive accuracy (Guyon & Elisseeff, 2006).

Feature extraction for music can be done using jAudio, a Java project/program developed by McEnnis, McKay, Fujinaga, & Depalle (2005). JAudio is a feature extraction system that provides a user friendly GUI and a command line interface to suit user needs for selecting their desired features to be extracted for the audio. The system accepts audio files as input and outputs XML or ARFF files. This output file contains the values for each feature of the audio file selected by the user.

3.2.4 Feature Selection

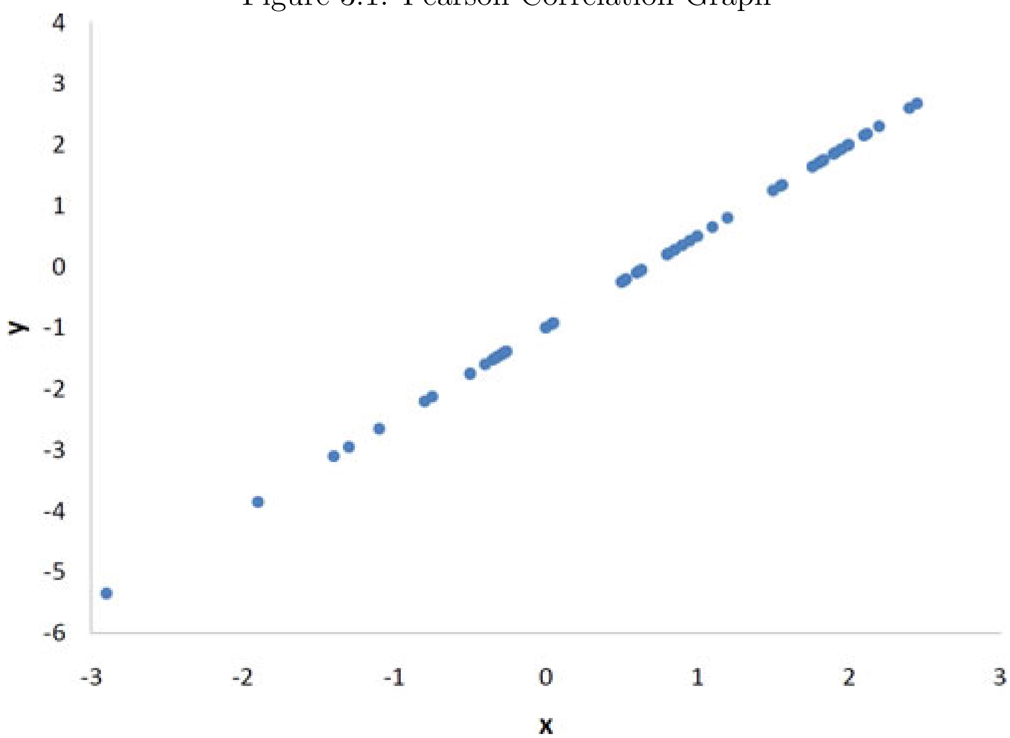
Gupta (2017) defines decision tree as a binary tree that branches down from the root. The term tree-walking is used to continuously make decisions on every level of the tree starting from the root node until the leaf nodes are reached or a satisfactory answer is found. In this way, it can be derived that the nodes found at the top of the tree are more important than its child nodes and all others beneath them. Decision trees are useful for inferring what features of a dataset can greatly or weakly influence its outcome (Mitchell, 1997).

Feature selection is the automatic selection of attributes in the dataset that are most relevant to a specific predictive model. It seeks to identify the out of the ordinary features among all the others and it helps in reducing the number of data attributes being used while still retaining a good or accurate predictive model. Aside from reducing the number of features or data attributes, it can also help in removing unwanted attributes that may decrease the accuracy of the predictive model (Brownlee, J., 2014).

Grabczewski & Jankowski (2005) explains that decision tree algorithms are best used for feature selection because of the inherent characteristic of decision trees that allows them to separate the different features and showcase the more important features since it will appear at the root of the decision tree.

Some simple but successfully tested algorithms for feature selection would include Pearsons correlation coefficient and Fisher-like criterion. Pearsons correlation coefficient or Pearsons R is widely used in the computation of statistics and this involves detecting linear correlation, which is the representation of how close the data points are in making a straight line in a graph, just as shown in Figure 3.1.

Figure 3.1: Pearson Correlation Graph



PCA is another statistical procedure that transforms a set of data points using orthogonal transformation, which scales the set of points by a certain value, into a set of linearly uncorrelated values called principal components. Principal components are ordered such that the variance from the original variable decreases. It will always turn out that the first principal component will have the largest variance that was present in the original variable.

In machine learning, PCA is used to reduce the dimensionality of a set of data points. In implementing PCA on a 2D data set, the mean and the covariance of the data set would first have to be computed first. Mean is computed using $m = \frac{1}{P}\sum_{\mu=1}^{p} x^{\mu}$ and Covariance is measured using $S = \frac{1}{P-1}\sum_{\mu=1}^{P}(x^{\mu} - m)(x^{\mu} - m)^{T}$ (Storkey, 2017).

The eigenvalue and the eigenvector would also have to be computed. Eigenvector is computed using the formula $det(\lambda I - A) = 0$, where λ is the eigenvalue, I is the identity matrix of A, det is the determinant of the matrix, and A is the covariance matrix from the previous step. Eigenvalue is computed using the formula $(\lambda I - A)v = 0$.

For each data point x^n, the lower dimensional representation is $y^\mu = E^T(x^\mu - m)$ and the approximate reconstruction of the original data point x^n is $x^\mu = m + Ey^\mu$. The total squared error over all the training data made is given by $(P-1)\sum_{j=M+1}^{N} \lambda j$ where $\lambda j, j = M+1...N$ are the eigenvalues discarded in the projection.

The last step is to choose the components and to form the feature vector. The number of eigenvectors and eigenvalues is equal to the number of data in the dataset. The eigenvector corresponding to the highest eigenvalue is the principal component of the dataset. To form the feature vector, the top k eigenvectors with top eigenvalues will be used. To compute for the principal component, the transposed version of the feature vector is left-multiplied with the transposed version of the scaled version of the original dataset.

Fisher-like criterion makes use of the formula $\frac{m_0 - m_1}{s_0 - s_1}$, wherein m is the mean value of the feature for the$i$-th element and s is the corresponding standard deviation. This algorithm can only be used, however, when dealing with binary classifications.

Feature selection, in general however, can be classified into three categories, namely the filter methods, wrapper methods, and the embedded methods. Filter method involves labelling each feature with a statistical measure and by comparing these measures, the more important features can be selected. Wrapper method involves grouping different combinations of features together to see which combinations work best. Embedded methods involve learning which features best contribute to the accuracy of the model while the model is simultaneously being created. Some more examples of feature selection algorithms would include best-first search, hill-climbing algorithm, and the usage of heuristics. Best-first search and hill-climb fall under the wrapper methods wherein different combinations are used until the top n features are found. Heuristics falls under the filter method wherein a heuristic score is given to each feature using a statistical measure such as Euclidean distance for example, and the features with the high scores will be the ones selected.

3.3 Machine Learning

Machine learning as defined by Ng (2017) is the science behind computers acting on a certain stimulus without being explicitly programmed to do so. Some examples of impact led by machine learning would be self-driving cars and web search suggestions from Google. Machine learning is also widely used in many different fields of research such as in artificial intelligence, data mining, natural language processing, image recognition, and expert systems (McCria, 2014). In machine learning, the concept of training the system to perform a unique task given a certain amount of data received has two main underlying categories, unsupervised learning and supervised learning.

3.3.1 Supervised Learning

Supervised learning, as defined by Brownlee (2016), is a type of machine learning wherein an input variable and an output variable is defined and an algorithm is used to map the input to the output variable. The goal of this type of learning is to map the input variables to their respective output variables by approximation so that when a new input variable is presented, an output can be predicted by the system. The main difference of supervised learning over unsupervised is that there is no third party that supervises and corrects the training of data in unsupervised but in supervised, intervention of the supervisor is necessary in order to achieve an acceptable level of performance by the system. Supervised learning can be further divided into two groups, namely regression and classification. Regression is used when the output is a real value, for example, weight, height, or age. Classification is used when the output is a category or group, for example, colors, sizes.

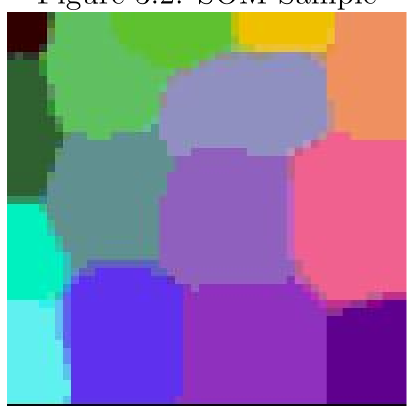
3.3.2 Unsupervised Learning

Brownlee (2016) defines unsupervised learning as having no corresponding output variable. Unsupervised learning is analysing the structure and distribution of the data in order for system to learn. Unsupervised learning can be further classified into two groups of algorithms, namely the clustering and the association. Clustering is used for discovering the groupings of data through clusters and association is used for discovering rules that describe the provided data.

SOM

Teuvo Kohonen (1995) defines SOM as a data visualization technique developed by Professor which reduces the dimension of data through the use of self-organizing neural networks. As SOM reduces the dimension of data, it also groups similar data items together; therefore, it not only reduces the dimension of data but also groups similar ones together. Figure 3.2 shows a basic example of a SOM. Note in this example that the data represented by colors are grouped according to their similarity (eg. yellow is near orange, dark teal is between blue and green).

Figure 3.2: SOM Sample



Rumelhart & Zipser (1985) defines a class under supervised learning called competitive learning. Here, neurons compete among themselves in a winner-takes-it-all scenario wherein only one neuron wins and is activated at any one time. Implementation of this competition is done through the use of lateral inhibition connections, which are structures of a network in which neurons inhibit their neighbors. When neurons are forced to organize themselves through this scenario, then the result would be a map that is self-organized, thus a SOM.

K-Means Clustering Algorithm

K-means clustering algorithm is a type of unsupervised learning algorithm wherein a set of unlabeled data will be grouped together and these groups are defined as the k variable. The algorithm will assign the different data points to their respective k-groups based on the selected features. Data points will then end up being clustered based on their feature similarities. The algorithm has two main iterative steps, , the data assignment step and the centroid update step, that repeats until either data points change clusters, the sum of the distances is minimized, or some maximum number of iterations is reached. Before starting with these two steps, the centroid for each k-cluster is computed first. In data assignment, each data point is placed in their nearest centroid value computed with squared Euclidean distance. In centroid update, the centroid is recomputed by taking the mean of all the data assigned to the centroids cluster (Hartigan & Wong, 1979).

t-SNE

Maaten & Hiton (2008) introduces t-SNE as a variant of the Stochastic Neighbor Embedding (SNE) which seeks to visualize high dimensional data by plotting these data points in a two or three dimensional map. Since t-SNE is a variant of SNE, SNE would have to be discussed first before transitioning to t-SNE. SNE starts by transforming the Euclidean distances of the high-dimensional data points into conditional probabilities that represent similarities. For example with $p_{j|i}$, this would represent the similarity from X_j to X_i, that X_i would pick X_j as its neighbor if neighbors were picked in proportion to their probability density under a Gaussian centered at X_i. The conditional probability of $p_{j|i}$ is given with $p_{j|i} = \frac{exp(-||x_i - x_j||^2/2\delta_i^2}{\sum_{k \neq i} exp(-||x_i - x_k||^2/2\delta_i^2}$ where δi is the variance of the Gaussian that is centered in X_i. $p_{i|i}$ is set to 0 since only pairwise similarities will be considered. For the low dimensional counterpart of X_i and X_j, the probability is computed by $q_{j|i} = \frac{exp(-||y_i - y_j||^2}{\sum_{k \neq i} exp(-||y_i - y_k||^2)}$.

As with its high dimensional counterpart, $q_{i|i}$ is set to 0. In order for SNE to find a low dimensional data representation that represents the mismatch between $p_{j|i}$ and $q_{j|i}$, a cost function is used, $C = \sum_i KL(P_i||Q_i) = \sum_i \sum_j p_{j|i} log \frac{p_{j|i}}{q_{j|i}}$,where KL is the Kullback-Leibler divergences, P_i is the conditional probability distribution over all other data points given data point X_i, and Q_i is the conditional probability distribution over all other data points given data point Yi.

With the variance δi of the Gaussian that is centered over each high-dimensional data point X_i, it is important to note that the density of all data points in a data set are not uniform and it is more appropriate to use a smaller δi value in denser regions than in sparser regions. Any value of δi influences a probability distribution P_i over all other data points. This probability distribution has an entropy value which increases as δi increases. SNE seeks for a value of δi that has a P_i with fixed perplexity specified by the user using binary search. The perplexity is computed by $Perp(P_i) = 2^{H(P_i)}$ where the $H(Pi)$ or the Shannon entropy of P_i is further computed using $H(P_i) = -\sum_j p_{j|i} log_2 p_{j|i}$. The smooth measure of the effective number of neighbors can also be identified as the perplexity and the typical values for this would range from 5 to 50. The cost function shown earlier can also be minimized into $\frac{\delta C}{\delta y_i} = 2\sum_j (p_{j|i} - q_{j|i} + p_{i|j} - q_{i|j})(y_i - y_j)$.

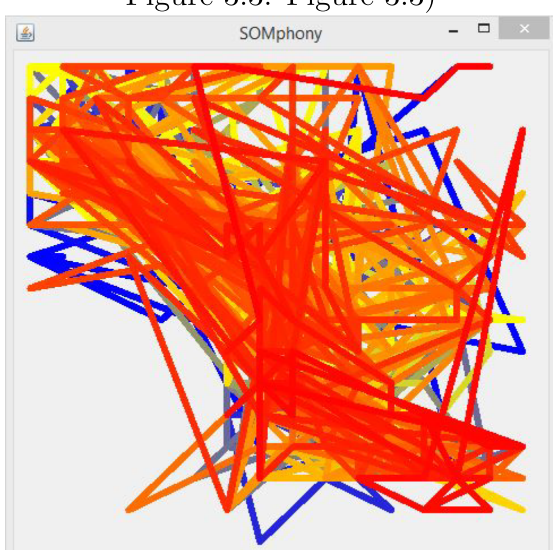
The gradient can be thought of as a spring force from a map point y_i to any y_j along the map. As the force is computed with $y_i - y_j$, the resulting force can either make the points repel or attract each other depending if the distance between the two is too small or too large. To speed up the optimization and to avoid poor local minima, a gradient update with a momentum term is done using $y^{(t)} = y^{(t-1)} + \eta\frac{\delta C}{\delta y} + \alpha(t)(y^{(t-1)} - y^{(t-2)})$ where y^t indicates the solution at iteration t, η indicates the learning rate, and $\alpha(t)$ represents the momentum at iteration t.

3.4 Visualization

3.4.1 Single Image

Just as done in Azcarraga & Flores (2016) research work, visualization for the result of the SOM can be done in a single image. The BMU or best matching unit, which will be explained further in section 3.5.1, represents the music trajectory of a certain 1 second music segment from the symphony. This sequence of BMUs make up the visual image representation of a certain symphony. A color coding scheme was also used to denote the time sequence of a certain music trajectory in the image, blue representing the start and going to red as the music progresses as shown in Figure 3.3.

Figure 3.3: Figure 3.3)



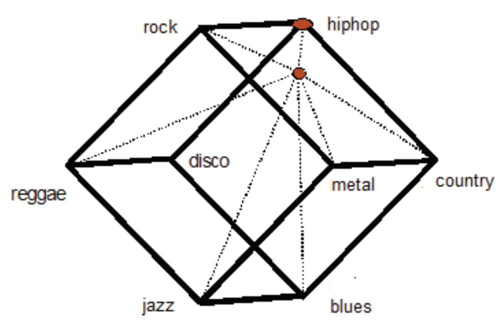
3.4.2 Video

Aside from representing the result of the SOM in a single image, it can also be represented in a video or multiple images. Video can be produced for the results of this research by collating each 1 second segment result in order to show the progression of the musical trajectory grow from the start of the symphony to the end. This allows clearer visualization of the data to have more accurate analysis. Using this kind of visualization also greatly helps the survey user in the outcome of this research.

3.4.3 3D Models

In Azcarraga, Caronongan, Setiono, & Manalili (2016)s research work, they incorporated the use of a structured 3D SOM instead of the regular SOM which will result in a single image. They represented the 3D map as a 3x3x3 dimensional cube with 27 subcubes each of the same sizes. Each subcube is further divided into 9x9x9 nodes. Here, they introduced the concept of a core cube at the center and the other 26 corresponding exterior cubes surrounding it. The training phase of the cube involved a four step labelling phase which was discussed in greater detail back in chapter 2. The resulting 3D SOM was then used to identify the proximity of a certain music to a particular genre. Each genre represented one corner of the cube as shown in Figure 3.4.

Figure 3.4: Figure 3.4)



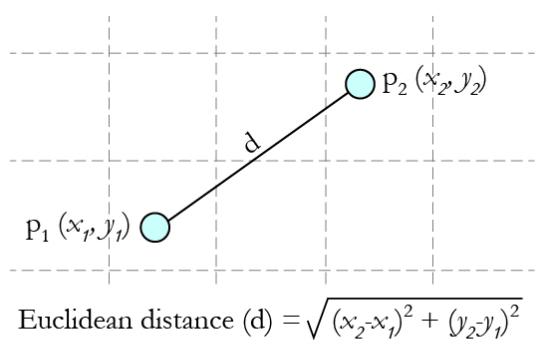
3.5 Metrics

There are two general types of data, qualitative and quantitative data. Qualitative data are data that cannot be measured by numbers while quantitative can be measured by numbers.

3.5.1 Quantitative

When using clustering as the method for machine learning, for example k-means clustering, there will result in k number of clusters after the algorithm is performed. Azcarraga & Flores (2016) used k-means clustering in clustering the 1 second music segments. The best matching unit (BMU) for each 1 second music segment is first computed using Euclidean distance, which is the square root of the square of the difference between the x-axis of the first and second point added to the square of the difference between the y-axis of the first and second point, as shown in Figure 3.5.

Figure 3.5: Figure 3.5)



Each time a 1 second music segment has a BMU inside a cluster, the frequency count for that cluster is incremented. In this way, only the clusters that are mainly used by the music or symphony will have a high frequency count. The frequency counts are then normalized by dividing the counts of a certain composition by its total number of 1 second music segments. Once these normalized frequency counts are summarized, the resulting percentages can then be used to perform pair-wise comparisons between symphonies as shown in Appendix D.

3.5.2 Qualitative

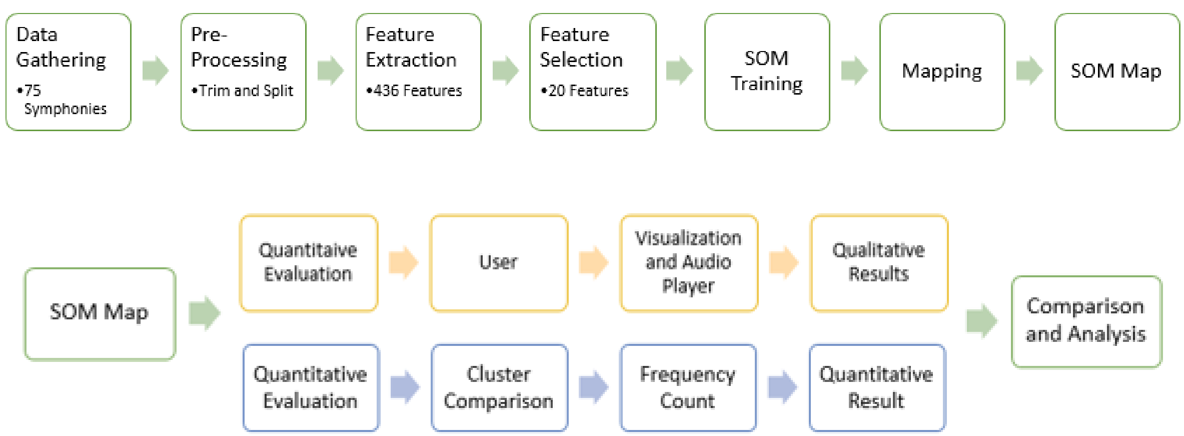
In theory, the main purpose of conducting surveys is to generate results for a certain research work; however, surveys can also be used to validate the results of a research by comparing the results of the surveys and the results produced initially by the research work. In performing research regarding the usage of algorithms in visualizing and comparing symphonies, it would be sound to say that performing surveys that require participants to listen to two symphonies that have been calculated by the SOM to have a large degree of similarity and asking the surveyees for their opinion on the closeness of the two symphonies can help validate the research work if it really produced reliable or accurate results.

Chapter 4

Research Overview

This chapter contains procedures that propoenents will follow for the research based from theories and concepts discuess in chapter 3 and the methodologies discussed in chapter 1.

4.1 System Architecture



4.2 Preprocessing

After acquiring the symphonies from online sources or through physical means, omitting segments of the music file which has no sound in it will be done using

Audacity. This is done so that the output produced later will have no empty values since no sound will result in empty values. After the music files are cleaned, they will then be cut into one second music segments with a half second overlapping interval just as discussed in section 1.5.3 using Direct WAV MP3 Splitter. The music segments will then have their features be extracted using jAudio, producing an output file of XML. The XML file will then be converted to CSV format. The consolidated CSV file of all symphonies will then be used for feature selection to select only the more important features just as discussed in section 3.2.4. After the features have been selected, audio feature extraction will be done again, but only for these selected features. The resulting CSV file will then be used for machine learning using RapidMiner to be used in producing the SOM.

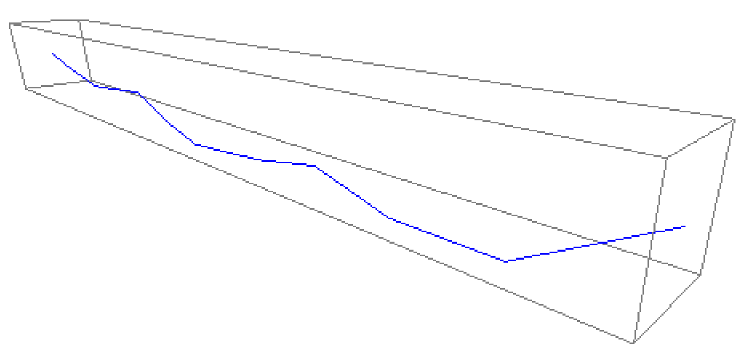
4.3 Visualization Components

4.3.1 Function

The program will allow the proponents to visualize the SOM in 3D by plotting the BMU of each music segment on a 2D plane and then collating the results of all segments in the composition in time series. The result is a line T(x, y, z) where (x, y) denotes the coordinates of the BMU of a particular music segment on the SOM and z being the index of the segment in the time series.

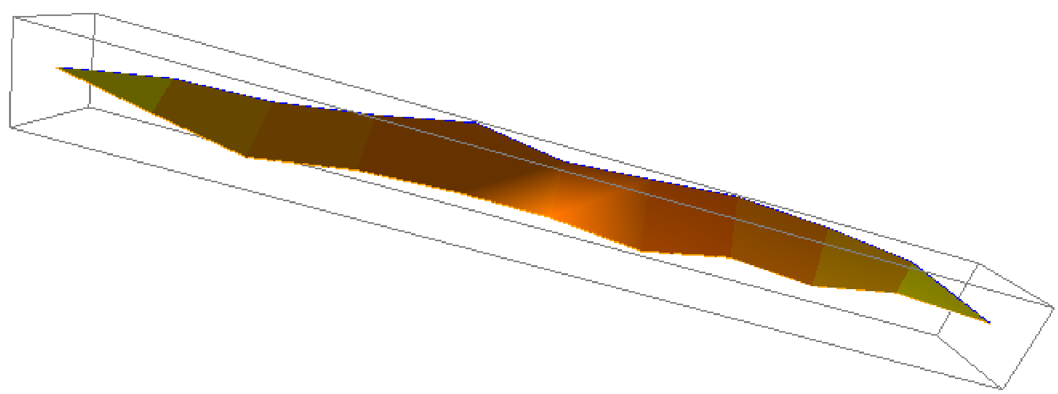
4.3.2 Screenflow

Figure 4.1: Figure 4.1)



Displaying the data of one symphony will plot a line that represents the musical trajectory or progression of the symphony in the SOM from start to finish. Each point on the z-axis (longest axis) represents the position of the BMU on the SOM at a particular interval in the time series as shown in Figure 4.1.

Figure 4.2: Figure 4.2)



Alternatively, when comparing two symphonies, two lines will be generated representing the musical trajectories of both symphonies. As shown in Figure 4.2, the area between the two lines will be colored depending on the Euclidean distance between the two BMUs in the same time axis.

4.4 Testing and Methodology

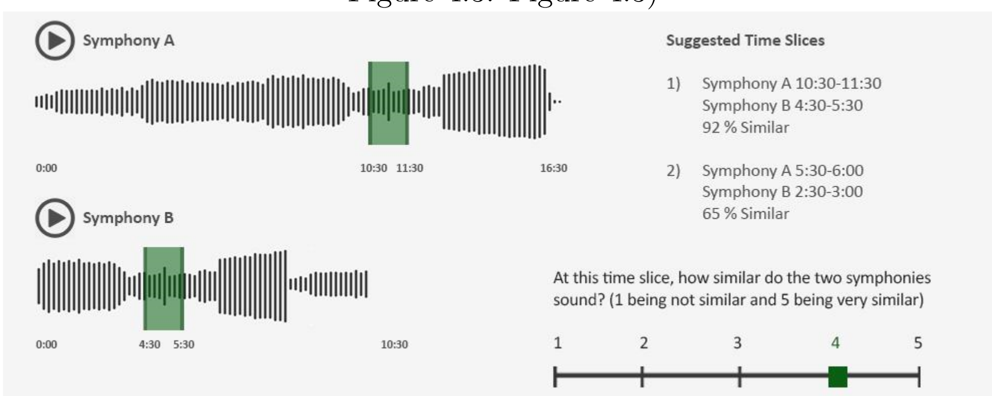
4.4.1 Quantitative

K-means clustering algorithm will be used as the algorithm for machine learning and Euclidean distance will be used for calculating the BMUs for each cluster to compare the similarities of symphonies just as discussed in section 3.5.1.

4.4.2 Qualitative

A survey form deployed online will be used to validate the result for the quantitative measurements starting April 2018 to June 2018. In the survey, the participant will first be asked for their voluntary consent as shown in Appendix E. Then, upon consenting, they will be asked to listen to two symphonies that are found to be similar using the quantitative measure used in the research as seen in figure 4.3. The system will provide suggested time slices for them to annotate. An annotation module is provided for the user to rate the similarity from 1 to 5, with 1 being dissimilar and 5 as similar. They may also choose to annotate which part/parts in the symphony that was not suggested yet they believe were similar. Upon selecting time slices, the coloration of the time slices would change depending on the % similarity of the selected slice. A spectrum of red to green would be used, with red representing a low % similarity and green representing a high % similarity. The results from these should help validate if this research works methodology and speculated results prove true.

Figure 4.3: Figure 4.3)



50 participants will be asked to answer these survey forms. The participants profile will come in the form of either musical inclined people or just regular people who may not know much about music. An estimate of around 60% of the survey forms must be answered by musical inclined people and about 40% answered by regular people because musical inclined people know best about music and are reliable sources for comparison but they may also hold biases with regards to the music they listen to or whether they like listening to this particular composer or not; therefore, including regular people in the survey will help lessen the bias since no knowledge over something will result in no bias.

Appendix A

Research Ethics Documents

This section contains all documents related to research ethics.

DE LA SALLE UNIVERSITY
General Research Ethics Checklist

This checklist is to ensure that the research conducted by the faculty members and students of De La Salle University is carried out according to the guiding principles outlined in the Code of Research Ethics of the University. The investigator is advised to refer to the De La Salle University Code of Research Ethics and Guide to Responsible Conduct of Research before completing this checklist. Statements pertinent to ethical issues in research should be addressed below. The checklist will help the researchers and evaluators determine whether procedures should be undertaken during the course of the research to maintain ethical standards. The University's Guide to the Responsible Conduct of Research provides details on these appropriate procedures.

Details of the Research	
Students	Cruz, Edwardo Dionisio, Jefferson Fukouka, Kenji Portales, Naomi
Thesis Adviser	Flores, Fritz
Department	Software Technology Department
Title of the Research	SOMphony: Visualization and Comparison of Symphonies Through Application of Time Series on 3D SOM
Term(s) and Academic year in which research is to be conducted	AY 2017-2018 Term 1,2,3

This checklist must be completed AFTER the* De La Salle University Code of Ethics *has been read and BEFORE gathering data.

Questions	Yes	No
1. Does your research involve human participants (this includes new data gathered or using pre-existing data)? If your answer is **yes**, please answer **Checklist A (Human Participants).**	✔	
2. Does your research involve animals (non-human subjects)? If your answer is **yes**, please answer **Checklist B (Animal Subjects).**		✔
3. Does your research involve Wildlife? If your answer is **yes**, please answer **Checklist C (Wildlife)**.		✔
4. Does your research involve microorganisms that are infectious, disease causing or harmful to health? If your answer is **yes**, please answer **Checklist D (Infectious Agents).**		✔

5. Does your research involve toxic/chemicals/ substances/materials? If your answer is **yes**, please answer **Checklist E (Toxic Agents).**		✔

Research with Ethical Issues to address:

If you have a YES answer to any of the above categories, you will be required to complete a detailed checklist for that particular category. A YES answer does not mean the disapproval of your research proposal. By providing you with a more detailed checklist, we ensure that the ethical concerns are identified so these can be addressed in adherence to the University Code of Ethics.

Declaration of Conflict of Interest

[✔] I do not have a conflict of interest in any form (personal, financial, proprietary, or professional) with the sponsor/grant-giving organization, the study, the co-investigators/personnel, or the site.

[ ] I have a personal/family or professional interest in the results of the study (family members who are co-proponents or personnel in the study, membership in relevant professional associations/organizations).

Please describe the personal/family or professional interest:

[ ] I have propriety interest vested in this proposal (with the intent to apply for a patent, trademark, copyright, or license)

Please describe propriety interest:

[ ] I have significant financial interest vested in this proposal (remuneration that exceeds P250,000.00 each year or equity interest in the form of stock, stock options or other ownership interests).

Please describe financial interest:

Declaration

We certify that we have read and understand the De La Salle University Code for the Responsible Conduct of Research and will abide by the ethical principles in this document. We will submit a final report of the proposed study to the DLSU-Research Ethics Office. We will not commence with data collection until we receive an ethics review approval from the College Research Ethics Committee.

Name and Signature of Student 1	Name and Signature of Student 2
Name and Signature of Student 3	Name and Signature of Student 4

Endorsement from thesis adviser to the thesis panel for proposal defense…

Name and Signature of Adviser	Date

Endorsement from thesis adviser to the thesis panel for final defense…

This is to certify that the research was conducted in a manner that adheres to ethical research standards. I am thus endorsing the group for final defense.

Name and Signature of Adviser	Date

De La Salle University	**Research Ethics Review Committee** Research Ethics Office, 3F Henry Sy Sr. Hall De La Salle University Manila 2401 Taft Avenue, Manila 1004, Philippines REO@dlsu.edu.ph (632) 524-4611 loc. 513	SOP No.: 2 Form No.: 2.03 Version No.: 1 Effectivity Date: July 2016

DE LA SALLE UNIVERSITY

Checklist A

Research Ethics Checklist for Investigations involving Human Participants

This checklist must be completed AFTER the* De La Salle University Code of Research Ethics and Guide to Responsible Conduct of Research *has been read and BEFORE gathering data. The University Code of Research Ethics is available at http://www.dlsu.edu.ph/offices/urco/forms/URCO-Code-of-Research-Ethics_August2011.pdf

NOTE: This checklist is completed after the research proponent fills out the General Checklist Form.

Only answer this Checklist if you answered YES on question 1 of the General Checklist.

Researcher Details	
Students	Cruz, Edwardo Dionisio, Jefferson Fukuoka, Kenji Portales, Naomi
Thesis Adviser	Flores, Fritz
Department	Software Technology Department
Title of the Research	SOMphony: Visualization and Comparison of Symphonies Through Application of Time Series on 3D SOM
Term(s) and Academic year in which research is to be conducted	AY 2017-2018 Term 1,2,3

Provide a brief description of the data collection procedure to be undertaken in the research:

Human participants will be tasked to listen to small music samples to be used for comparison in the research. They can also opt to annotate the parts they listen to for additional comments.

The following should be attached to the checklist:

- A copy of the informed consent form to be used in the study.
- A copy of the instrument/tool that will be administered to the participants.
- If applicable, a copy of the letter seeking permission to collect data from participants who are under the supervision of an agency, institution, department, or office.
- If applicable, a copy of the parental consent form for participants below 18 years old.

The following items refer to important ethical considerations in the conduct of research with human participants. Provide a check for the appropriate answer to each question.

Source of data

Please check all that apply:

	1. New data will be collected from human participants If you checked this item, how will the new data be gathered? Please check all that apply. **After answering this question, please proceed to page 3**	
		Experimental Procedures/Intervention/ Treatments
		Focus Group
		Personal Interviews
		Self-administered Questionnaire
		Researcher-administered Questionnaire
	✔	**Internet survey**
		Observation
		Telephone survey
		Others, please specify:
	2. Pre-existing data from human participants, i.e., from a dataset **If you checked this item, please proceed to page 7**	

If both options are checked (both new data and pre-existing data), **answer all of the questions in this document.**

ONLY ANSWER IF NEW DATA WILL BE COLLECTED (item 1 above)

Sampling Details	
Number of Participants/Subjects	**50**
Location where the participants will be recruited/ where subjects will be obtained?	**Online**
How long will the data collection take place?	**3 months**
Who will perform the data collection?	**Self-administered**
Location(s) where data collection will take place	**Online**
What procedures will be employed to ensure voluntary consent from participants?	**Participant will be asked shown the informed consent form first and upon consenting, they will be led to the survey page.**
Data Retention	
How long will data with participant identifiers be kept after the publication of the first paper from the project?	**There will be no personal identifiers of participants since they shall remain anonymous.**
How long will anonymized data be kept after the publication of the first paper from the project?	**Anonymized data shall be kept in archive for future works.**
Procedure for Informed Consent	
How will informed consent be recorded? (check all that applies) Reminder: please attach informed consent that will be used in the study	[ ] Written Consent [ ] Audio-recorded Consent [✔] Online/Email recorded Consent [ ] Others, please specify:

If you will not obtain a recorded informed consent, answer the questions that follow:

Why does the waiver of informed consent not pose a threat to the welfare and rights of the participants?

Why is recording an informed consent not practical for the proposed study?

	Yes	No	Not Applicable
1. Will the research involve students who will be receiving course credits for their participation? **If YES, please attach a copy of the consent form and a summary of the debriefing process that will help participants understand how their participation in the research has provided a relevant learning experience to the crediting course.**		✔	
2. Does the study involve participants below 18 years old or those who are unable to give their informed consent? **If YES, please attach a copy of the parental consent form.**		✔	
3. Is there a possibility that the research can induce physical and/or psychological harm to the participants? Will they experience pain or some discomfort as a result from their participation in the research? **If YES, please attach an acceptable argument that outlines the benefits of doing the research and how they outweigh the cost of harming the participants.**		✔	
4. Will the participants be deliberately falsely informed or made unaware that they are being observed? Will they be misled in a way that they will possibly object to or show unease when told of the real purpose of the study?		✔	

If YES, please attach an acceptable argument that outlines the benefits of doing the research and how they outweigh the cost of harming the participants.			
5. Will the research involve the discussion of, or questions on, sensitive topics (e.g. sexual activity, substance abuse, or mental health)? **If YES, please make sure that the informed consent form explicitly states that sensitive questions will be posed and that you will safeguard the anonymity of the participants and ensure confidentiality. Please attach a copy of your informed consent form and your instrument.**		✔	
6. Will the research involve the administration of drugs, or other substances to the participants? **If YES, please attach an acceptable argument that outlines the benefits of doing the research and how they outweigh the cost of harming the participants.** **Please also attach a description of the procedure that will ensure that the participants will be brought back to their physical and psychological states prior to their participation in the research.**		✔	
7. Will biological samples (e.g. blood, saliva, urine) be obtained from the participants? **If YES, will this involve invasive procedures? Please attach a description of these procedures.**		✔	
8. Will genetic materials be obtained from the biological samples?		✔	

If YES, please attach a description of the procedures that will ensure confidentiality. Please attach the informed consent form.			
9. Will financial inducements (other than reasonable expenses, like transportation or meal allowances) be offered to the participants for their participation in their research? **If YES, the researcher(s) should be mindful of how the inducements can influence the participants' responses or behaviors during the research. Indicate the financial inducements offered to the participants:** ____________________________________		✔	
10. Is there a possibility for groups or communities to be harmed by the dissemination of the research findings? **If YES, please attach a description of procedures to ensure the anonymity and confidentiality of the research findings.**		✔	

Answering YES to most of the above items will signal an ethical issue that needs to be addressed. Some actions that will allow adherence to research ethical principles are provided with each item. The researcher is advised to refer to the University's Guide to the Responsible Conduct of Research for the appropriate procedures to ensure adherence to ethical principles in the conduct of research.

Declaration

We certify that we have read and understand the De La Salle University Code for the Responsible Conduct of Research and will abide by the ethical principles in this document. We will submit a final report of the proposed study to the DLSU-Research Ethics Office. We will not commence with data collection until we receive an ethics review approval from the College Research Ethics Committee.

Name and Signature of Student 1	Name and Signature of Student 2
Name and Signature of Student 3	Name and Signature of Student 4

Endorsement from thesis adviser to the thesis panel for proposal defense…	
Name and Signature of Adviser	Date

Endorsement from thesis adviser to the thesis panel for final defense… This is to certify that the research was conducted in a manner that adheres to ethical research standards. I am thus endorsing the group for final defense.	
Name and Signature of Adviser	Date

FOR PROPONENTS WHO WILL GATHER NEW DATA ONLY, PLEASE STOP ANSWERING.

Use of Pre-existing Data collected from Human Participants		
Indicate the dataset from which the data for the study will be sourced		
		Yes Please indicate where the dataset is available:

Is the data publicly available, i.e., the access to which does not necessitate an approval process?		No Please indicate/attach the approval authority for access:
Was the original dataset originally collected for the present study's purpose?		Yes **Please attach the Consent Form used in the original study.**
		No **Please attach the Information Collection Statement (i.e., the statement given to informants providing them with the rationale for the collection of specific information).**
Does the original data set contain sensitive data, that is information that an individual would not likely want to be disclosed publicly, e.g., data on sexual activities, substance use?		Yes **Please describe the type of sensitive data to be used in the present research:**
		No
Does the original dataset have personal identifiers?		No *(This means that neither the researcher nor the participant provided any personal identifiers)*
		Yes, specifically: ______ Direct *(i.e., the participant provided personal details like name and address)* _____ Indirect (*i.e., the participant was given a respondent code to make the participant identifiable)*
Will new data be collected and analyzed along with data from the existing dataset?		Yes **Please answer questions on page 3-5.**
		No

<u>Declaration</u>

We certify that we have read and understand the De La Salle University Code for the Responsible Conduct of Research and will abide by the ethical principles in this document. We will submit a final

report of the proposed study to the DLSU-Research Ethics Office. We will not commence with data collection until we receive an ethics review approval from the College Research Ethics Committee.

Name and Signature of Student 1	Name and Signature of Student 2
Name and Signature of Student 3	Name and Signature of Student 4

Endorsement from thesis adviser to the thesis panel for proposal defense…

Name and Signature of Adviser	Date

Endorsement from thesis adviser to the thesis panel for final defense…

This is to certify that the research was conducted in a manner that adheres to ethical research standards. I am thus endorsing the group for final defense.

Name and Signature of Adviser	Date

Thesis Informed Consent Form

Good day participant! We are undergraduate students in De La Salle University-Manila currently taking up our thesis as per required by the curriculum of BS Computer Science with specialization in Software Technology. Our research is about visualizing symphonies using 3D Self-Organizing Maps and comparing their visual results. In this survey, we will be providing you with parts of two symphonies that are deemed by our software as very similar. The purpose is to affirm that the visualizations and comparisons made by our software coincide with how humans determine similarity among symphonies. The survey shall only take up about 10-20 minutes of your time. Participation is voluntary and without incentive. Withdrawal from participation will not merit any sanctions or consequences. No sensitive information will be asked except for the name which will be kept absolutely confidential and only the researchers will have access to the name provided. Lastly, you must be 18 years old or above to participate in this survey. If you have any concerns and clarifications, please contact us at jefferson_dionisio@dlsu.edu.ph

RESEARCH ETHICS CLEARANCE FORM For Thesis Proposals[1]				
Names of student researcher/s :	*Cruz, Edwardo* *Dionisio, Jefferson* *Fukuoka, Kenji* *Portales, Naomi*			
College:	College of Computer Studies			
Department:	Software Technology Department			
Course:	BS Computer Science with specialization in Software Technology			
Expected duration of project:	from:	September 2017	to:	July 2018

Ethical considerations

<list down the ethical concerns as listed in your defense form; also include steps made to resolve them>
Human participants who will compare data for validation of research findings:

1. *Consent forms shall be processed first before any data will be gathered from the participants.*
2. *Human participants shall only be above 18 years old.*
3. *On-site participants shall be informed at least a week before data collection.*
4. *Participants can back out at any time during the course of the data gathering session.*

To the best of our knowledge, the ethical issues listed above have been addressed in the research.

<name of adviser>
Name and signature of adviser/mentor
Date:

<name of panelist 1>
Name and signature of panelist
Date:

<name of panelist 2>
Name and signature of panelist
Date:

[1]The same form can be used for the reports of completed projects. The appropriate heading need only be used.

Appendix B

Turnitin Similarity Report

This section consists of the first page of the Turnitin Originality Report.

SOMphony: Visualization and Comparison of Symphonies Through Application of Time Series on 3D SOM

ORIGINALITY REPORT

13%	6%	9%	4%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Arnulfo Azcarraga, Arturo Caronongan, Rudy Setiono, Sean Manalili. "Validating the stable clustering of songs in a structured 3D SOM", 2016 International Joint Conference on Neural Networks (IJCNN), 2016 Publication	1%
2	Submitted to De La Salle University - Manila Student Paper	1%
3	"Neural Information Processing", Springer Nature, 2016 Publication	1%
4	Corrêa, Débora C., and Francisco Ap. Rodrigues. "A survey on symbolic data-based music genre classification", Expert Systems with Applications, 2016. Publication	1%
5	netcentric.dlsu.edu.ph Internet Source	1%
	pi3.informatik.uni-mannheim.de	

Appendix C

List of Features and Definitions

This section consists of the list of features extractable in jAudio and their corresponding definitions.

Spectral Centroid Overall Standard Deviation	The centre of mass of the power spectrum. This is the overall standard deviation over all windows.
Derivative of Spectral Centroid Overall Standard Deviation	Derivative of Spectral Centroid. The centre of mass of the power spectrum. This is the overall standard deviation over all windows.
Running Mean of Spectral Centroid Overall Standard Deviation	Running Mean of Spectral Centroid. The centre of mass of the power spectrum. This is the overall standard deviation over all windows.
Standard Deviation of Spectral Centroid Overall Standard Deviation	Standard Deviation of Spectral Centroid. The centre of mass of the power spectrum. This is the overall standard deviation over all windows.
Derivative of Running Mean of Spectral Centroid Overall Standard Deviation	Derivative of Running Mean of Spectral Centroid. Running Mean of Spectral Centroid. The centre of mass of the power spectrum. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Spectral Centroid Overall Standard Deviation	Derivative of Standard Deviation of Spectral Centroid. Standard Deviation of Spectral Centroid. The centre of mass of the power spectrum. This is the overall standard deviation over all windows.
Spectral Rolloff Point Overall Standard Deviation	The fraction of bins in the power spectrum at which 85% of the power is at lower frequencies. This is a measure of the right-skewedness of the power spectrum. This is the overall standard deviation over all windows.
Derivative of Spectral Rolloff Point Overall Standard Deviation	Derivative of Spectral Rolloff Point. The fraction of bins in the power spectrum at which 85% of the power is at lower frequencies. This is a measure of the right-skewedness of the power spectrum. This is the overall standard deviation over all windows.
Running Mean of Spectral Rolloff Point Overall Standard Deviation	Running Mean of Spectral Rolloff Point. The fraction of bins in the power spectrum at which 85% of the power is at lower frequencies. This is a measure of the right-skewedness of the power spectrum. This is the overall standard deviation over all windows.
Standard Deviation of Spectral Rolloff Point Overall Standard Deviation	Standard Deviation of Spectral Rolloff Point. The fraction of bins in the power spectrum at which 85% of the power is at lower frequencies. This is a measure of the right-skewedness of the power spectrum. This is the overall standard deviation over all windows.
Derivative of Running Mean of Spectral Rolloff Point Overall Standard Deviation	Derivative of Running Mean of Spectral Rolloff Point. Running Mean of Spectral Rolloff Point. The fraction of bins in the power spectrum at which 85% of the power is at lower frequencies.

	This is a measure of the right-skewedness of the power spectrum. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Spectral Rolloff Point Overall Standard Deviation	Derivative of Standard Deviation of Spectral Rolloff Point. Standard Deviation of Spectral Rolloff Point. The fraction of bins in the power spectrum at which 85% of the power is at lower frequencies. This is a measure of the right-skewedness of the power spectrum. This is the overall standard deviation over all windows.
Spectral Flux Overall Standard Deviation	A measure of the amount of spectral change in a signal. Found by calculating the change in the magnitude spectrum from frame to frame. This is the overall standard deviation over all windows.
Derivative of Spectral Flux Overall Standard Deviation	Derivative of Spectral Flux. A measure of the amount of spectral change in a signal. Found by calculating the change in the magnitude spectrum from frame to frame. This is the overall standard deviation over all windows.
Running Mean of Spectral Flux Overall Standard Deviation	Running Mean of Spectral Flux. A measure of the amount of spectral change in a signal. Found by calculating the change in the magnitude spectrum from frame to frame. This is the overall standard deviation over all windows.
Standard Deviation of Spectral Flux Overall Standard Deviation	Standard Deviation of Spectral Flux. A measure of the amount of spectral change in a signal. Found by calculating the change in the magnitude spectrum from frame to frame. This is the overall standard deviation over all windows.
Derivative of Running Mean of Spectral Flux Overall Standard Deviation	Derivative of Running Mean of Spectral Flux. Running Mean of Spectral Flux. A measure of the amount of spectral change in a signal. Found by calculating the change in the magnitude spectrum from frame to frame. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Spectral Flux Overall Standard Deviation	Derivative of Standard Deviation of Spectral Flux. Standard Deviation of Spectral Flux. A measure of the amount of spectral change in a signal. Found by calculating the change in the magnitude spectrum from frame to frame. This is the overall standard deviation over all windows.
Compactness Overall Standard Deviation	A measure of the noisiness of a signal. Found by comparing the components of a window's magnitude spectrum with the magnitude spectrum of its neighbouring windows. This is the overall standard deviation over all windows.

Derivative of Compactness Overall Standard Deviation	Derivative of Compactness. A measure of the noisiness of a signal. Found by comparing the components of a window's magnitude spectrum with the magnitude spectrum of its neighbouring windows. This is the overall standard deviation over all windows.
Running Mean of Compactness Overall Standard Deviation	Running Mean of Compactness. A measure of the noisiness of a signal. Found by comparing the components of a window's magnitude spectrum with the magnitude spectrum of its neighbouring windows. This is the overall standard deviation over all windows.
Standard Deviation of Compactness Overall Standard Deviation	Standard Deviation of Compactness. A measure of the noisiness of a signal. Found by comparing the components of a window's magnitude spectrum with the magnitude spectrum of its neighbouring windows. This is the overall standard deviation over all windows.
Derivative of Running Mean of Compactness Overall Standard Deviation	Derivative of Running Mean of Compactness. Running Mean of Compactness. A measure of the noisiness of a signal. Found by comparing the components of a window's magnitude spectrum with the magnitude spectrum of its neighbouring windows. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Compactness Overall Standard Deviation	Derivative of Standard Deviation of Compactness. Standard Deviation of Compactness. A measure of the noisiness of a signal. Found by comparing the components of a window's magnitude spectrum with the magnitude spectrum of its neighbouring windows. This is the overall standard deviation over all windows.
Spectral Variability Overall Standard Deviation	The standard deviation of the magnitude spectrum. This is a measure of the variance of a signal's magnitude spectrum. This is the overall standard deviation over all windows.
Derivative of Spectral Variability Overall Standard Deviation	Derivative of Spectral Variability. The standard deviation of the magnitude spectrum. This is a measure of the variance of a signal's magnitude spectrum. This is the overall standard deviation over all windows.
Running Mean of Spectral Variability Overall Standard Deviation	Running Mean of Spectral Variability. The standard deviation of the magnitude spectrum. This is a measure of the variance of a signal's magnitude spectrum. This is the overall standard deviation over all windows.

Standard Deviation of Spectral Variability Overall Standard Deviation	Standard Deviation of Spectral Variability. The standard deviation of the magnitude spectrum. This is a measure of the variance of a signal's magnitude spectrum. This is the overall standard deviation over all windows.
Derivative of Running Mean of Spectral Variability Overall Standard Deviation	Derivative of Running Mean of Spectral Variability. Running Mean of Spectral Variability. The standard deviation of the magnitude spectrum. This is a measure of the variance of a signal's magnitude spectrum. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Spectral Variability Overall Standard Deviation	Derivative of Standard Deviation of Spectral Variability. Standard Deviation of Spectral Variability. The standard deviation of the magnitude spectrum. This is a measure of the variance of a signal's magnitude spectrum. This is the overall standard deviation over all windows.
Root Mean Square Overall Standard Deviation	A measure of the power of a signal. This is the overall standard deviation over all windows.
Derivative of Root Mean Square Overall Standard Deviation	Derivative of Root Mean Square. A measure of the power of a signal. This is the overall standard deviation over all windows.
Running Mean of Root Mean Square Overall Standard Deviation	Running Mean of Root Mean Square. A measure of the power of a signal. This is the overall standard deviation over all windows.
Standard Deviation of Root Mean Square Overall Standard Deviation	Standard Deviation of Root Mean Square. A measure of the power of a signal. This is the overall standard deviation over all windows.
Derivative of Running Mean of Root Mean Square Overall Standard Deviation	Derivative of Running Mean of Root Mean Square. Running Mean of Root Mean Square. A measure of the power of a signal. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Root Mean Square Overall Standard Deviation	Derivative of Standard Deviation of Root Mean Square. Standard Deviation of Root Mean Square. A measure of the power of a signal. This is the overall standard deviation over all windows.
Fraction Of Low Energy Windows Overall Standard Deviation	The fraction of the last 100 windows that has an RMS less than the mean RMS in the last 100 windows. This can indicate how much of a signal is quiet relative to the rest of the signal. This is the overall standard deviation over all windows.
Derivative of Fraction Of Low Energy Windows Overall Standard Deviation	Derivative of Fraction Of Low Energy Windows. The fraction of the last 100 windows that has an RMS less than the mean RMS in the last 100 windows. This can indicate how much of a signal is quiet relative to the rest of the signal. This is the overall standard deviation over all windows.

Running Mean of Fraction Of Low Energy Windows Overall Standard Deviation	Running Mean of Fraction Of Low Energy Windows. The fraction of the last 100 windows that has an RMS less than the mean RMS in the last 100 windows. This can indicate how much of a signal is quiet relative to the rest of the signal. This is the overall standard deviation over all windows.
Standard Deviation of Fraction Of Low Energy Windows Overall Standard Deviation	Standard Deviation of Fraction Of Low Energy Windows. The fraction of the last 100 windows that has an RMS less than the mean RMS in the last 100 windows. This can indicate how much of a signal is quiet relative to the rest of the signal. This is the overall standard deviation over all windows.
Derivative of Running Mean of Fraction Of Low Energy Windows Overall Standard Deviation	Derivative of Running Mean of Fraction Of Low Energy Windows. Running Mean of Fraction Of Low Energy Windows. The fraction of the last 100 windows that has an RMS less than the mean RMS in the last 100 windows. This can indicate how much of a signal is quiet relative to the rest of the signal. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Fraction Of Low Energy Windows Overall Standard Deviation	Derivative of Standard Deviation of Fraction Of Low Energy Windows. Standard Deviation of Fraction Of Low Energy Windows. The fraction of the last 100 windows that has an RMS less than the mean RMS in the last 100 windows. This can indicate how much of a signal is quiet relative to the rest of the signal. This is the overall standard deviation over all windows.
Zero Crossings Overall Standard Deviation	The number of times the waveform changed sign. An indication of frequency as well as noisiness. This is the overall standard deviation over all windows.
Derivative of Zero Crossings Overall Standard Deviation	Derivative of Zero Crossings. The number of times the waveform changed sign. An indication of frequency as well as noisiness. This is the overall standard deviation over all windows.
Running Mean of Zero Crossings Overall Standard Deviation	Running Mean of Zero Crossings. The number of times the waveform changed sign. An indication of frequency as well as noisiness. This is the overall standard deviation over all windows.
Standard Deviation of Zero Crossings Overall Standard Deviation	Standard Deviation of Zero Crossings. The number of times the waveform changed sign. An indication of frequency as well as noisiness. This is the overall standard deviation over all windows.

Derivative of Running Mean of Zero Crossings Overall Standard Deviation	Derivative of Running Mean of Zero Crossings. Running Mean of Zero Crossings. The number of times the waveform changed sign. An indication of frequency as well as noisiness. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Zero Crossings Overall Standard Deviation	Derivative of Standard Deviation of Zero Crossings. Standard Deviation of Zero Crossings. The number of times the waveform changed sign. An indication of frequency as well as noisiness. This is the overall standard deviation over all windows.
Strongest Beat Overall Standard Deviation	The strongest beat in a signal, in beats per minute, found by finding the strongest bin in the beat histogram. This is the overall standard deviation over all windows.
Derivative of Strongest Beat Overall Standard Deviation	Derivative of Strongest Beat. The strongest beat in a signal, in beats per minute, found by finding the strongest bin in the beat histogram. This is the overall standard deviation over all windows.
Running Mean of Strongest Beat Overall Standard Deviation	Running Mean of Strongest Beat. The strongest beat in a signal, in beats per minute, found by finding the strongest bin in the beat histogram. This is the overall standard deviation over all windows.
Standard Deviation of Strongest Beat Overall Standard Deviation	Standard Deviation of Strongest Beat. The strongest beat in a signal, in beats per minute, found by finding the strongest bin in the beat histogram. This is the overall standard deviation over all windows.
Derivative of Running Mean of Strongest Beat Overall Standard Deviation	Derivative of Running Mean of Strongest Beat. Running Mean of Strongest Beat. The strongest beat in a signal, in beats per minute, found by finding the strongest bin in the beat histogram. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Strongest Beat Overall Standard Deviation	Derivative of Standard Deviation of Strongest Beat. Standard Deviation of Strongest Beat. The strongest beat in a signal, in beats per minute, found by finding the strongest bin in the beat histogram. This is the overall standard deviation over all windows.
Beat Sum Overall Standard Deviation	The sum of all entries in the beat histogram. This is a good measure of the importance of regular beats in a signal. This is the overall standard deviation over all windows.
Derivative of Beat Sum Overall Standard Deviation	Derivative of Beat Sum. The sum of all entries in the beat histogram. This is a good measure of

	the importance of regular beats in a signal. This is the overall standard deviation over all windows.
Running Mean of Beat Sum Overall Standard Deviation	Running Mean of Beat Sum. The sum of all entries in the beat histogram. This is a good measure of the importance of regular beats in a signal. This is the overall standard deviation over all windows.
Standard Deviation of Beat Sum Overall Standard Deviation	Standard Deviation of Beat Sum. The sum of all entries in the beat histogram. This is a good measure of the importance of regular beats in a signal. This is the overall standard deviation over all windows.
Derivative of Running Mean of Beat Sum Overall Standard Deviation	Derivative of Running Mean of Beat Sum. Running Mean of Beat Sum. The sum of all entries in the beat histogram. This is a good measure of the importance of regular beats in a signal. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Beat Sum Overall Standard Deviation	Derivative of Standard Deviation of Beat Sum. Standard Deviation of Beat Sum. The sum of all entries in the beat histogram. This is a good measure of the importance of regular beats in a signal. This is the overall standard deviation over all windows.
Strength Of Strongest Beat Overall Standard Deviation	How strong the strongest beat in the beat histogram is compared to other potential beats. This is the overall standard deviation over all windows.
Derivative of Strength Of Strongest Beat Overall Standard Deviation	Derivative of Strength Of Strongest Beat. How strong the strongest beat in the beat histogram is compared to other potential beats. This is the overall standard deviation over all windows.
Running Mean of Strength Of Strongest Beat Overall Standard Deviation	Running Mean of Strength Of Strongest Beat. How strong the strongest beat in the beat histogram is compared to other potential beats. This is the overall standard deviation over all windows.
Standard Deviation of Strength Of Strongest Beat Overall Standard Deviation	Standard Deviation of Strength Of Strongest Beat. How strong the strongest beat in the beat histogram is compared to other potential beats. This is the overall standard deviation over all windows.
Derivative of Running Mean of Strength Of Strongest Beat Overall Standard Deviation	Derivative of Running Mean of Strength Of Strongest Beat. Running Mean of Strength Of Strongest Beat. How strong the strongest beat in the beat histogram is compared to other

	potential beats. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Strength Of Strongest Beat Overall Standard Deviation	Derivative of Standard Deviation of Strength Of Strongest Beat. Standard Deviation of Strength Of Strongest Beat. How strong the strongest beat in the beat histogram is compared to other potential beats. This is the overall standard deviation over all windows.
Strongest Frequency Via Zero Crossings Overall Standard Deviation	The strongest frequency component of a signal, in Hz, found via the number of zero-crossings. This is the overall standard deviation over all windows.
Derivative of Strongest Frequency Via Zero Crossings Overall Standard Deviation	Derivative of Strongest Frequency Via Zero Crossings. The strongest frequency component of a signal, in Hz, found via the number of zero-crossings. This is the overall standard deviation over all windows.
Running Mean of Strongest Frequency Via Zero Crossings Overall Standard Deviation	Running Mean of Strongest Frequency Via Zero Crossings. The strongest frequency component of a signal, in Hz, found via the number of zero-crossings. This is the overall standard deviation over all windows.
Standard Deviation of Strongest Frequency Via Zero Crossings Overall Standard Deviation	Standard Deviation of Strongest Frequency Via Zero Crossings. The strongest frequency component of a signal, in Hz, found via the number of zero-crossings. This is the overall standard deviation over all windows.
Derivative of Running Mean of Strongest Frequency Via Zero Crossings Overall Standard Deviation	Derivative of Running Mean of Strongest Frequency Via Zero Crossings. Running Mean of Strongest Frequency Via Zero Crossings. The strongest frequency component of a signal, in Hz, found via the number of zero-crossings. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Strongest Frequency Via Zero Crossings Overall Standard Deviation	Derivative of Standard Deviation of Strongest Frequency Via Zero Crossings. Standard Deviation of Strongest Frequency Via Zero Crossings. The strongest frequency component of a signal, in Hz, found via the number of zero-crossings. This is the overall standard deviation over all windows.
Strongest Frequency Via Spectral Centroid Overall Standard Deviation	The strongest frequency component of a signal, in Hz, found via the spectral centroid. This is the overall standard deviation over all windows.
Derivative of Strongest Frequency Via Spectral Centroid Overall Standard Deviation	Derivative of Strongest Frequency Via Spectral Centroid. The strongest frequency component of a signal, in Hz, found via the spectral centroid. This is the overall standard deviation over all windows.

Running Mean of Strongest Frequency Via Spectral Centroid Overall Standard Deviation	Running Mean of Strongest Frequency Via Spectral Centroid. The strongest frequency component of a signal, in Hz, found via the spectral centroid. This is the overall standard deviation over all windows.
Standard Deviation of Strongest Frequency Via Spectral Centroid Overall Standard Deviation	Standard Deviation of Strongest Frequency Via Spectral Centroid. The strongest frequency component of a signal, in Hz, found via the spectral centroid. This is the overall standard deviation over all windows.
Derivative of Running Mean of Strongest Frequency Via Spectral Centroid Overall Standard Deviation	Derivative of Running Mean of Strongest Frequency Via Spectral Centroid. Running Mean of Strongest Frequency Via Spectral Centroid. The strongest frequency component of a signal, in Hz, found via the spectral centroid. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Strongest Frequency Via Spectral Centroid Overall Standard Deviation	Derivative of Standard Deviation of Strongest Frequency Via Spectral Centroid. Standard Deviation of Strongest Frequency Via Spectral Centroid. The strongest frequency component of a signal, in Hz, found via the spectral centroid. This is the overall standard deviation over all windows.
Strongest Frequency Via FFT Maximum Overall Standard Deviation	The strongest frequency component of a signal, in Hz, found via finding the FFT bin with the highest power. This is the overall standard deviation over all windows.
Derivative of Strongest Frequency Via FFT Maximum Overall Standard Deviation	Derivative of Strongest Frequency Via FFT Maximum. The strongest frequency component of a signal, in Hz, found via finding the FFT bin with the highest power. This is the overall standard deviation over all windows.
Running Mean of Strongest Frequency Via FFT Maximum Overall Standard Deviation	Running Mean of Strongest Frequency Via FFT Maximum. The strongest frequency component of a signal, in Hz, found via finding the FFT bin with the highest power. This is the overall standard deviation over all windows.
Standard Deviation of Strongest Frequency Via FFT Maximum Overall Standard Deviation	Standard Deviation of Strongest Frequency Via FFT Maximum. The strongest frequency component of a signal, in Hz, found via finding the FFT bin with the highest power. This is the overall standard deviation over all windows.
Derivative of Running Mean of Strongest Frequency Via FFT Maximum Overall Standard Deviation	Derivative of Running Mean of Strongest Frequency Via FFT Maximum. Running Mean of Strongest Frequency Via FFT Maximum. The strongest frequency component of a signal, in Hz, found via finding the FFT bin with the highest

	power. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Strongest Frequency Via FFT Maximum Overall Standard Deviation	Derivative of Standard Deviation of Strongest Frequency Via FFT Maximum. Standard Deviation of Strongest Frequency Via FFT Maximum. The strongest frequency component of a signal, in Hz, found via finding the FFT bin with the highest power. This is the overall standard deviation over all windows.
MFCC Overall Standard Deviation	MFCC calculations based upon Orange Cow codeThis is the overall standard deviation over all windows.
Derivative of MFCC Overall Standard Deviation	Derivative of MFCC. MFCC calculations based upon Orange Cow codeThis is the overall standard deviation over all windows.
Running Mean of MFCC Overall Standard Deviation	Running Mean of MFCC. MFCC calculations based upon Orange Cow codeThis is the overall standard deviation over all windows.
Standard Deviation of MFCC Overall Standard Deviation	Standard Deviation of MFCC. MFCC calculations based upon Orange Cow codeThis is the overall standard deviation over all windows.
Derivative of Running Mean of MFCC Overall Standard Deviation	Derivative of Running Mean of MFCC. Running Mean of MFCC. MFCC calculations based upon Orange Cow codeThis is the overall standard deviation over all windows.
Derivative of Standard Deviation of MFCC Overall Standard Deviation	Derivative of Standard Deviation of MFCC. Standard Deviation of MFCC. MFCC calculations based upon Orange Cow codeThis is the overall standard deviation over all windows.
LPC Overall Standard Deviation	Linear Prediction Coeffecients calculated using autocorrelation and Levinson-Durbin recursion. This is the overall standard deviation over all windows.
Derivative of LPC Overall Standard Deviation	Derivative of LPC. Linear Prediction Coeffecients calculated using autocorrelation and Levinson-Durbin recursion. This is the overall standard deviation over all windows.
Running Mean of LPC Overall Standard Deviation	Running Mean of LPC. Linear Prediction Coeffecients calculated using autocorrelation and Levinson-Durbin recursion. This is the overall standard deviation over all windows.
Standard Deviation of LPC Overall Standard Deviation	Standard Deviation of LPC. Linear Prediction Coeffecients calculated using autocorrelation and Levinson-Durbin recursion. This is the overall standard deviation over all windows.
Derivative of Running Mean of LPC Overall Standard Deviation	Derivative of Running Mean of LPC. Running Mean of LPC. Linear Prediction Coeffecients

	calculated using autocorrelation and Levinson-Durbin recursion. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of LPC Overall Standard Deviation	Derivative of Standard Deviation of LPC. Standard Deviation of LPC. Linear Prediction Coeffecients calculated using autocorrelation and Levinson-Durbin recursion. This is the overall standard deviation over all windows.
Method of Moments Overall Standard Deviation	Statistical Method of Moments of the Magnitude Spectrum. This is the overall standard deviation over all windows.
Derivative of Method of Moments Overall Standard Deviation	Derivative of Method of Moments. Statistical Method of Moments of the Magnitude Spectrum. This is the overall standard deviation over all windows.
Running Mean of Method of Moments Overall Standard Deviation	Running Mean of Method of Moments. Statistical Method of Moments of the Magnitude Spectrum. This is the overall standard deviation over all windows.
Standard Deviation of Method of Moments Overall Standard Deviation	Standard Deviation of Method of Moments. Statistical Method of Moments of the Magnitude Spectrum. This is the overall standard deviation over all windows.
Derivative of Running Mean of Method of Moments Overall Standard Deviation	Derivative of Running Mean of Method of Moments. Running Mean of Method of Moments. Statistical Method of Moments of the Magnitude Spectrum. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Method of Moments Overall Standard Deviation	Derivative of Standard Deviation of Method of Moments. Standard Deviation of Method of Moments. Statistical Method of Moments of the Magnitude Spectrum. This is the overall standard deviation over all windows.
Partial Based Spectral Centroid Overall Standard Deviation	Spectral Centroid calculated based on the center of mass of partials instead of center of mass of bins. This is the overall standard deviation over all windows.
Derivative of Partial Based Spectral Centroid Overall Standard Deviation	Derivative of Partial Based Spectral Centroid. Spectral Centroid calculated based on the center of mass of partials instead of center of mass of bins. This is the overall standard deviation over all windows.
Running Mean of Partial Based Spectral Centroid Overall Standard Deviation	Running Mean of Partial Based Spectral Centroid. Spectral Centroid calculated based on the center of mass of partials instead of center of mass of bins. This is the overall standard deviation over all windows.

Standard Deviation of Partial Based Spectral Centroid Overall Standard Deviation	Standard Deviation of Partial Based Spectral Centroid. Spectral Centroid calculated based on the center of mass of partials instead of center of mass of bins. This is the overall standard deviation over all windows.
Derivative of Running Mean of Partial Based Spectral Centroid Overall Standard Deviation	Derivative of Running Mean of Partial Based Spectral Centroid. Running Mean of Partial Based Spectral Centroid. Spectral Centroid calculated based on the center of mass of partials instead of center of mass of bins. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Partial Based Spectral Centroid Overall Standard Deviation	Derivative of Standard Deviation of Partial Based Spectral Centroid. Standard Deviation of Partial Based Spectral Centroid. Spectral Centroid calculated based on the center of mass of partials instead of center of mass of bins. This is the overall standard deviation over all windows.
Partial Based Spectral Flux Overall Standard Deviation	Cacluate the correlation bettween adjacent frames based peaks instead of spectral bins. Peak tracking is primitive - whe the number of bins changes, the bottom bins are matched sequentially and the extra unmatched bins are ignored. This is the overall standard deviation over all windows.
Derivative of Partial Based Spectral Flux Overall Standard Deviation	Derivative of Partial Based Spectral Flux. Cacluate the correlation bettween adjacent frames based peaks instead of spectral bins. Peak tracking is primitive - whe the number of bins changes, the bottom bins are matched sequentially and the extra unmatched bins are ignored. This is the overall standard deviation over all windows.
Running Mean of Partial Based Spectral Flux Overall Standard Deviation	Running Mean of Partial Based Spectral Flux. Cacluate the correlation bettween adjacent frames based peaks instead of spectral bins. Peak tracking is primitive - whe the number of bins changes, the bottom bins are matched sequentially and the extra unmatched bins are ignored. This is the overall standard deviation over all windows.
Standard Deviation of Partial Based Spectral Flux Overall Standard Deviation	Standard Deviation of Partial Based Spectral Flux. Cacluate the correlation bettween adjacent frames based peaks instead of spectral bins. Peak tracking is primitive - whe the number of bins changes, the bottom bins are matched sequentially and the extra unmatched bins are ignored. This is the overall standard deviation over all windows.

Derivative of Running Mean of Partial Based Spectral Flux Overall Standard Deviation	Derivative of Running Mean of Partial Based Spectral Flux. Running Mean of Partial Based Spectral Flux. Cacluate the correlation bettween adjacent frames based peaks instead of spectral bins. Peak tracking is primitive - whe the number of bins changes, the bottom bins are matched sequentially and the extra unmatched bins are ignored. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Partial Based Spectral Flux Overall Standard Deviation	Derivative of Standard Deviation of Partial Based Spectral Flux. Standard Deviation of Partial Based Spectral Flux. Cacluate the correlation bettween adjacent frames based peaks instead of spectral bins. Peak tracking is primitive - whe the number of bins changes, the bottom bins are matched sequentially and the extra unmatched bins are ignored. This is the overall standard deviation over all windows.
Peak Based Spectral Smoothness Overall Standard Deviation	Peak Based Spectral Smoothness is calculated from partials, not frequency bins. It is implemented accortding to McAdams 99 McAdams, S. 1999. This is the overall standard deviation over all windows.
Derivative of Peak Based Spectral Smoothness Overall Standard Deviation	Derivative of Peak Based Spectral Smoothness. Peak Based Spectral Smoothness is calculated from partials, not frequency bins. It is implemented accortding to McAdams 99 McAdams, S. 1999. This is the overall standard deviation over all windows.
Running Mean of Peak Based Spectral Smoothness Overall Standard Deviation	Running Mean of Peak Based Spectral Smoothness. Peak Based Spectral Smoothness is calculated from partials, not frequency bins. It is implemented accortding to McAdams 99 McAdams, S. 1999. This is the overall standard deviation over all windows.
Standard Deviation of Peak Based Spectral Smoothness Overall Standard Deviation	Standard Deviation of Peak Based Spectral Smoothness. Peak Based Spectral Smoothness is calculated from partials, not frequency bins. It is implemented accortding to McAdams 99 McAdams, S. 1999. This is the overall standard deviation over all windows.
Derivative of Running Mean of Peak Based Spectral Smoothness Overall Standard Deviation	Derivative of Running Mean of Peak Based Spectral Smoothness. Running Mean of Peak Based Spectral Smoothness. Peak Based Spectral Smoothness is calculated from partials, not frequency bins. It is implemented accortding to

	McAdams 99 McAdams, S. 1999. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Peak Based Spectral Smoothness Overall Standard Deviation	Derivative of Standard Deviation of Peak Based Spectral Smoothness. Standard Deviation of Peak Based Spectral Smoothness. Peak Based Spectral Smoothness is calculated from partials, not frequency bins. It is implemented accortding to McAdams 99 McAdams, S. 1999. This is the overall standard deviation over all windows.
Relative Difference Function Overall Standard Deviation	log of the derivative of RMS. Used for onset detection. This is the overall standard deviation over all windows.
Derivative of Relative Difference Function Overall Standard Deviation	Derivative of Relative Difference Function. log of the derivative of RMS. Used for onset detection. This is the overall standard deviation over all windows.
Running Mean of Relative Difference Function Overall Standard Deviation	Running Mean of Relative Difference Function. log of the derivative of RMS. Used for onset detection. This is the overall standard deviation over all windows.
Standard Deviation of Relative Difference Function Overall Standard Deviation	Standard Deviation of Relative Difference Function. log of the derivative of RMS. Used for onset detection. This is the overall standard deviation over all windows.
Derivative of Running Mean of Relative Difference Function Overall Standard Deviation	Derivative of Running Mean of Relative Difference Function. Running Mean of Relative Difference Function. log of the derivative of RMS. Used for onset detection. This is the overall standard deviation over all windows.
Derivative of Standard Deviation of Relative Difference Function Overall Standard Deviation	Derivative of Standard Deviation of Relative Difference Function. Standard Deviation of Relative Difference Function. log of the derivative of RMS. Used for onset detection. This is the overall standard deviation over all windows.
Area Method of Moments Overall Standard Deviation	2D statistical method of momentsThis is the overall standard deviation over all windows.
Derivative of Area Method of Moments Overall Standard Deviation	Derivative of Area Method of Moments. 2D statistical method of momentsThis is the overall standard deviation over all windows.
Running Mean of Area Method of Moments Overall Standard Deviation	Running Mean of Area Method of Moments. 2D statistical method of momentsThis is the overall standard deviation over all windows.
Standard Deviation of Area Method of Moments Overall Standard Deviation	Standard Deviation of Area Method of Moments. 2D statistical method of momentsThis is the overall standard deviation over all windows.
Derivative of Running Mean of Area Method of Moments Overall Standard Deviation	Derivative of Running Mean of Area Method of Moments. Running Mean of Area Method of

	Moments. 2D statistical method of momentsThis is the overall standard deviation over all windows.
Derivative of Standard Deviation of Area Method of Moments Overall Standard Deviation	Derivative of Standard Deviation of Area Method of Moments. Standard Deviation of Area Method of Moments. 2D statistical method of momentsThis is the overall standard deviation over all windows.
Area Method of Moments of MFCCs Overall Standard Deviation	2D statistical method of moments of MFCCsThis is the overall standard deviation over all windows.
Derivative of Area Method of Moments Overall Standard Deviation	Derivative of Area Method of Moments. 2D statistical method of momentsThis is the overall standard deviation over all windows.
Derivative of Running Mean of Area Method of Moments Overall Standard Deviation	Derivative of Running Mean of Area Method of Moments. Running Mean of Area Method of Moments. 2D statistical method of momentsThis is the overall standard deviation over all windows.
Derivative of Standard Deviation of Area Method of Moments Overall Standard Deviation	Derivative of Standard Deviation of Area Method of Moments. Standard Deviation of Area Method of Moments. 2D statistical method of momentsThis is the overall standard deviation over all windows.
Derivative of Area Method of Moments Overall Standard Deviation	Derivative of Area Method of Moments. 2D statistical method of momentsThis is the overall standard deviation over all windows.
Derivative of Running Mean of Area Method of Moments Overall Standard Deviation	Derivative of Running Mean of Area Method of Moments. Running Mean of Area Method of Moments. 2D statistical method of momentsThis is the overall standard deviation over all windows.
Derivative of Standard Deviation of Area Method of Moments Overall Standard Deviation	Derivative of Standard Deviation of Area Method of Moments. Standard Deviation of Area Method of Moments. 2D statistical method of momentsThis is the overall standard deviation over all windows.
Derivative of Area Method of Moments Overall Standard Deviation	Derivative of Area Method of Moments. 2D statistical method of momentsThis is the overall standard deviation over all windows.
Derivative of Running Mean of Area Method of Moments Overall Standard Deviation	Derivative of Running Mean of Area Method of Moments. Running Mean of Area Method of Moments. 2D statistical method of momentsThis is the overall standard deviation over all windows.
Derivative of Standard Deviation of Area Method of Moments Overall Standard Deviation	Derivative of Standard Deviation of Area Method of Moments. Standard Deviation of Area Method

	of Moments. 2D statistical method of momentsThis is the overall standard deviation over all windows.
Area Method of Moments of Log of ConstantQ transform Overall Standard Deviation	2D statistical method of moments of the log of the ConstantQ transformThis is the overall standard deviation over all windows.
Area Method of Moments of ConstantQ-based MFCCs Overall Standard Deviation	2D statistical method of moments of ConstantQ-based MFCCsThis is the overall standard deviation over all windows.
Spectral Centroid Overall Average	The centre of mass of the power spectrum. This is the overall average over all windows.
Derivative of Spectral Centroid Overall Average	Derivative of Spectral Centroid. The centre of mass of the power spectrum. This is the overall average over all windows.
Running Mean of Spectral Centroid Overall Average	Running Mean of Spectral Centroid. The centre of mass of the power spectrum. This is the overall average over all windows.

Appendix D

Symphony Map from Azcarraga & Flores (2016)'s SOMphony

This section contains an image sample of a symphony map

Distance		Classical									19th Century									Romantic									20th Century								
		H1	H2	H3	M1	M2	M3	B1	B2	B3	B1	B2	B3	C1	C2	C2	G1	G2	G3	M1	M1	M3	SM1	SM2	SM3	SB1	SB2	SB3	R1	R2	R3	ST1	ST2	ST3	SH1	SH2	SH3
Classical	Haydn 1		14	7	25	25	30	30	76	31	26	27	31	25	27	30	35	29	27	26	28	28	24	22	22	29	33	31	32	34	32	46	48	65	32	34	33
	Haydn 2			15	29	29	32	37	76	36	29	31	34	30	34	38	36	34	31	27	32	32	30	30	29	34	35	36	33	39	38	47	50	65	34	32	33
	Haydn 3				25	24	28	28	75	30	28	30	31	23	24	28	36	29	29	25	27	27	27	22	24	28	32	30	31	33	29	45	47	64	30	32	32
	Mozart 1					15	27	30	79	41	32	36	35	18	31	30	41	23	25	31	27	25	32	18	28	17	33	24	31	27	23	48	51	66	31	34	34
	Mozart 2						16	32	70	42	22	28	23	14	27	29	33	16	15	23	19	18	23	12	20	10	23	11	20	15	21	36	39	55	21	26	25
	Mozart 3							38	58	43	21	27	19	20	29	31	24	20	16	15	12	11	26	24	27	20	14	15	15	19	22	26	28	45	10	16	15
	Bach 1								84	25	44	47	45	30	32	33	53	34	39	42	38	35	40	29	37	31	43	34	42	36	34	55	56	72	40	44	44
	Bach 2									82	58	57	52	74	77	78	57	74	67	57	63	63	67	74	69	75	50	65	53	63	74	38	41	39	52	50	47
	Bach 3										45	47	48	42	41	43	53	43	44	45	44	41	46	42	45	44	47	46	46	48	46	56	57	70	46	48	46
19th Century	Beethoven 1											10	8	29	35	38	25	29	21	19	25	26	16	25	20	29	19	23	16	24	36	25	29	46	21	23	20
	Beethoven 2												12	34	39	42	27	35	27	22	30	31	16	28	18	35	23	29	20	29	41	28	33	49	26	27	24
	Beethoven 3													29	36	38	25	30	21	18	24	25	18	27	21	30	14	22	11	22	36	19	24	41	18	20	16
	Clementi 1														16	16	35	18	19	23	17	16	27	16	25	13	25	17	25	22	13	41	42	60	23	29	28
	Clementi 2															9	41	30	30	28	26	25	33	26	31	28	32	29	33	33	22	47	44	63	30	36	35
	Clementi 3																42	29	30	31	27	25	36	28	35	27	33	30	35	34	18	48	46	66	32	39	37
	Gossec 1																	30	24	21	21	23	29	36	32	36	24	33	28	35	35	33	36	55	26	28	26
	Gossec 2																		11	27	16	16	26	18	27	12	28	18	28	22	20	41	43	61	27	33	32
	Gossec 3																			21	15	15	21	20	24	17	21	17	20	21	24	33	37	55	22	27	25
Romantic	Mendelssohn 1																				15	17	23	27	25	28	13	24	16	27	28	28	29	48	15	15	14
	Mendelssohn 2																					7	25	23	26	19	18	19	21	23	17	34	35	55	17	22	21
	Mendelssohn 3																						27	22	28	18	17	18	21	22	15	33	35	54	16	23	21
	Schumann 1																							19	10	27	26	23	22	24	35	35	39	57	28	31	29
	Schumann 2																								14	13	29	16	26	17	24	42	45	63	27	32	31
	Schumann 3																									25	28	23	24	23	33	39	42	60	28	31	30
	Schubert 1																										28	13	26	16	17	42	44	62	25	31	31
	Schubert 2																											20	9	22	28	19	22	41	11	14	9
	Schubert 3																												18	6	22	31	34	51	17	24	23

Appendix E

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