Armonique: a framework for Web audio archiving, searching, and metadata extraction

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Abstract

Armonique is a Web2 framework for the management of audio material, including searching, archiving, and metadata extraction. It allows users to navigate large audio collections based solely on the similarity of the audio content itself, as opposed to metadata generated from human beings (e.g., musicologists and listener preferences). This framework allows new material to be added easily into an existing archive as it automatically extracts metadata. This is accomplished through hundreds of metrics based on power laws. Results from experiments with human subjects indicate that power-law metrics correlate with aspects of human emotion and aesthetics. The main advantages of this approach are that (a) it requires no human pre-processing, and (b) it allows discovery of similar songs that musicologists may miss (e.g., cross-style) or that are rarely listened to (i.e., no listener ratings). These results are by no means complete, but they suggest a powerful, automated alternative (or complement) to existing practices involving humans.

1. Introduction

The cultural legacy of our society is being captured and increasingly preserved in digital transcriptions of audio, text, images, and video. Organizations ranging from national archives, to libraries, to museums, to Internet repositories all have to deal with massive amounts of digital material. This digital growth demands innovative ways of processing archival data; it also requires usable management tools, which can help users navigate through large data collections to discover items of interest.

This paper (originally given at the 40th IASA conference in Athens, Greece) reports on results from many years of research in artificial intelligence, cognitive neuroscience, computer science, and psychology of music. We have developed hundreds of metrics involving the extraction of power-law features from MIDI and MP3 audio, which capture statistical proportions of music-theoretic and other attributes (e.g., Pitch, Duration, Pitch Distance, Duration Distance, Melodic Intervals, Harmonic Intervals, Melodic Bigrams, etc.). These metrics have been incorporated into Armonique, a Web2 framework for the management of audio material, including searching, archiving, and metadata extraction.

Armonique (http://armonique.org) allows users to navigate large audio collections based solely on the similarity of the audio content itself. The majority of online music similarity engines (50+) are based on context/meta-data (i.e., social networking, or users' listening habits). This includes systems such as iTunes Genius, Last.fm, and Pandora, which involve either musicologists listening and carefully tagging every new song across numerous dimensions (e.g., Pandora), or collaborative filtering techniques based on user preferences and ratings (e.g., Genius). The main advantages of our approach are that (a) it requires no human pre-processing, and (b) it allows discovery of similar songs that musicologists may miss (e.g., cross-style) or that are rarely listened to (i.e., no listener ratings). We have also developed an iPhone client application, called Armonique Lite, which uses the Armonique engine as its server.

Results from various experiments, some with human subjects, indicate that our approach models essential aspects of music aesthetics. This research is potentially transformative to the Internet music economy and functionality.

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Section 2 discusses the history of and some issues related to quantifying music aesthetics. Section 3 introduces Zipf's law and related power laws. Section 4 provides an overview of our power-law metrics for music. Section 5 describes automated classification tasks used to validate these metrics. Sections 6 and 7 present the Armonique search engine and its iPhone client. Section 8 presents results from psychological experiments with human subjects assessing how well Armonique's similarity model corresponds with human music aesthetics. Conclusion, acknowledgements, and references follow.

2. How can numbers describe aesthetics?

Webster's defines *aesthetics* as "the study or theory of beauty and of the psychological responses to it; specif., the branch of philosophy dealing with art, its creative sources, its forms, and its effects" (Guralnik 1980). Aesthetics originates from the Greek "αίσθηση – αισθάνομαι", which means to *perceive*, *feel*, *sense* (all three notions combined). These notions span the artifact (external), the emotional response (internal), and the sensory organs (interface between external and internal). Over the centuries, use of the term has become less philosophical (i.e., the *nature* of beauty, art, and taste), and more functional (the analysis, synthesis, and evaluation of *artifacts*), perhaps reflecting our society's evolution. Schoenberg, among others, promoted this transition in his 1911 "Theory of Harmony" (Dahlhaus 1982, pp. 1-3).

Figure 1. J.S. Bach and the Canon Triplex a 6 Voc. by E.G. Haussmann (1746)

What is the nature of beauty? Where can we find beauty in music? Is it culturally independent (objective) or does it rely on cultural conditioning (subjective)? These are old questions, which are unavoidably raised in the context of this work.

Kahlil Gibran asks: "Where shall you seek beauty, and how shall you find her unless she herself be your way and your guide? And how shall you speak of her except she be the weaver of your speech?" (1973, pp. 74). Gibran's perspective raises the intriguing possibility that any potential answers about quantifying aspects of music aesthetics will inevitably also reflect related aspects of human physiology/psychology.

To begin, let's consider two musical pieces, *Song1* and *Song2*, i.e., http://tiny.cc/song1 and http://tiny.cc/song2. (It is recommended that you listen to them before reading on. Also, see figure 1 for a hint about their origin.) Assuming you find the pieces at least aesthetically agreeable, then what aspects of these pieces make you feel this way?

This, actually, is a very old exploration. It begins at least 2,500 years ago with the Pythagoreans, who were the first to connect numbers with aesthetics. Aristotle states that "the Pythagoreans were the first to take up mathematics, and ... thought its principles were the principles of all things" (1992, pp. 70-71). They observed that strings exhibit harmonic proportions, i.e., they resonate at integer ratios of their length (i.e., 1/1, 1/2, 1/3/, 1/4, 1/5, etc.). They also observed that these proportions are aesthetically pleasing to the human ear. Accordingly, they developed musical modes based on these ratios, which formed the basis of our modern-era musical scales.

Aristotle supported the Pythagorean view that "[the interplay] between opposites is the beginning of all beings" (1992, pp. 72-73). Plato, Euclid and others provided a more precise description of this interplay in the form of proportional analogies (e.g., "A is to B as C is to D"). The apex of this exploration may have been the discovery of the golden mean, or 1.61803399… This special proportion, which humans find aesthetically very pleasing, is found in natural or human-made artifacts (Beer 2008; Calter 2008, pp. 46-57; Hemenway 2005, pp. 91-132; Livio 2002; May 1996; Pickover 1991, pp. 203-205). It is also found in the human body (e.g., the bones of our hands, the cochlea in our ears, etc.). The golden ratio reflects a place of balance in the structural interplay of opposites.

Considering again our Song1 and Song2, what makes a musical piece aesthetically appealing? Given the Aristotelian/Pythagorean view of opposites, perhaps it is the interplay between silence (rests) and sound (notes). Also, it is the interplay among different sound frequencies occurring concurrently (harmony) and sequentially (melody). Of course, some forms of interplay are more aesthetically pleasing than others. Music theory, which originated with the Pythagorean modes, was developed precisely to codify the aesthetics of this interplay (e.g., scales and modes, chords and inversions, cadences, counterpoint, etc.).

Arnheim (1971) discusses another kind of interplay — between chaos and monotony — which creates aesthetically pleasing artifacts. In other words, if the proportions are too chaotic or unpredictable, the artifact will be difficult to comprehend or appreciate (e.g., 12-tone or aleatory music). At the other extreme, if the proportions are too monotonous or too predictable, the artifact will be uninteresting or boring.

This theory was experimentally validated by Voss and Clarke (1975, 1978). Music was generated through a computer program, which used various random-number generators to control the pitch and duration of successive notes. One piece was created with chaotic (aka *white-noise*) statistical proportions, a piece with monotonous (aka *brown-noise*) statistical proportions, and a piece with statistical proportions between chaos and monotony (aka *pink noise* or *1/f proportions*). As predicted by Arnheim, they observed that the *1/f* music was much more pleasing to most listeners. The chaotic music was "too random," whereas the brown-noise music was "too correlated." They concluded, "the sophistication of this *1/f* music (which was 'just right') extends far beyond what one might expect from such a simple algorithm, suggesting that *1/f* noise (perhaps that in nerve membranes?) may have an essential role in the creative process" (1975, p.318). It should be noted that the harmonic proportions observed by the Pythagoreans on strings (i.e., 1/1, 1/2, 1/3/, 1/4, 1/5, etc.) are statistically equivalent to *1/f* proportions.

In our case, both Song1 and Song2 exhibit near *1/f* proportions in terms of notes (pitches, durations), melodic intervals, harmonic intervals, etc. Song2 is J.S. Bach's "Invention #13 in A minor" (BWV784). Song1 was "composed" by a computer program, called NEvMuse, which recombined Song2 notes, while aiming to preserve its *1/f* proportions. One goal of this experiment was to demonstrate the relationship between music aesthetics and proportions (Manaris, et al. 2007). For comparison, also consider Song3 (i.e., http://tiny.cc/song3), which was created to "counterbalance" the original's *1/f* proportions by aiming towards chaotic (white-noise) proportions.

Schroeder (1990) explains that the basilar membrane found in the cochlea of the human ear is attuned to sounds with *1/f* proportions. Since the cochlea is a logarithmic spiral (see figures 2 and 3), such sounds stimulate "a constant density of the acoustic nerve endings that report sounds to the brain" (ibid. p. 122). Logarithmic spirals exhibit golden ratio proportions (see figure 3). This demonstrates a physiological connection between *1/f* proportions and the golden ratio, and both to music aesthetics.

Figure 2. Cochlea in human ear (courtesy of Widex APS)

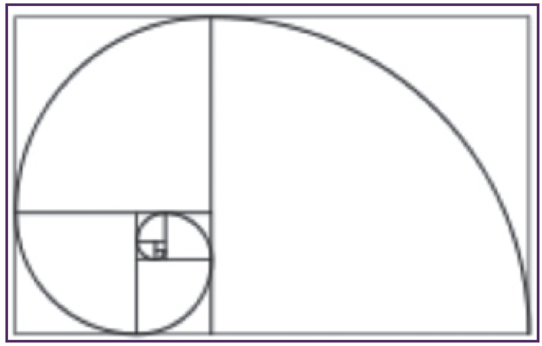

Figure 3. A logarithmic spiral (sides of consecutive boxes approximate the golden ratio)

3. Zipf's Law and Power Laws

George Kingsley Zipf (1902-1950) was a linguistics professor at Harvard University. His seminal book, "Human Behavior and the Principle of Least Effort", contained results from various fields demonstrating the presence of *1/f* (harmonic) proportions in natural and human-made phenomena (Zipf 1949). Zipf was the first one (with the possible exception of Johannes Kepler and his 1619 "Harmonices Mundi" work) to hypothesize that there is a universal principle at play, and to propose a mathematical formula to describe it.

Informally, Zipf's law describes phenomena where certain types of events are frequent, whereas other types of events are rare. For example, in English, short words (e.g., "a", "the") are very frequent, whereas long words (e.g., "anthropomorphologically") are quite rare. If we compare a word's frequency of occurrence with its statistical rank, we notice an inverse relationship: successive word counts are roughly proportional to 1/1, 1/2, 1/3, 1/4, 1/5, and so on (Bogomolny 2010). In other words, books contain the **same** type of harmonic proportions as those observed by the Pythagoreans on strings 2,500 years ago.

Zipf generalized this observation to other types of harmonic proportions (ibid., pp.130-131). This is captured by the *Generalized Harmonic Series* equation:

$$F \cdot Sn = \frac{F}{1^p} + \frac{F}{2^p} + \frac{F}{3^p} + \mathrm{L} + \frac{F}{n^p}$$

where *F* is a constant, *n* is a positive integer, and *p* may range from 0 to infinity, with 1 corresponding to Zipf's law.

This equation may be best understood by plotting the data (e.g., see figure 4). This produces a near straight line whose slope corresponds to the exponent *p* above. The slope may range from 0 to negative infinity, with –1.0 denoting Zipf's ideal (aka *pink-noise*, harmonic, or *1/f* proportions). A slope near 0 indicates a random probability of occurrence (i.e., chaotic of *white-noise* proportions). A slope of –2.0 denotes *brown-noise* proportions. A slope tending towards negative infinity indicates a very monotonous phenomenon, e.g., a musical piece consisting mostly of one note (aka *black-noise* proportions).

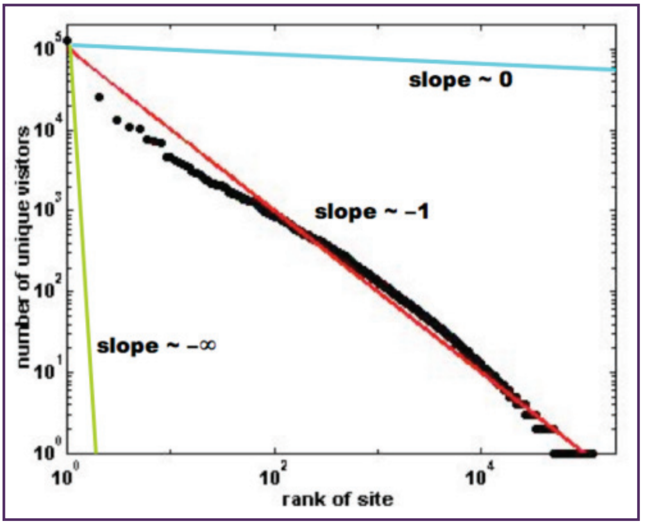

Figure 4. Number of unique website visits (y-axis) ordered by website's statistical rank (x-axis) on log scale [9]

In physics, white-noise, pink-noise, brown-noise, and black-noise proportions are known as *power laws*. Zipf (pink-noise) proportions have been discovered in a wide range of human and naturally occurring phenomena, including music, city sizes, peoples' incomes, subroutine calls, earthquake magnitudes, thickness of sediment depositions, clouds, trees, extinctions of species, traffic jams, visits to websites, and opening chess moves (Blasius, B. & Tönjes 2009; Mandelbrot 1977; Schroeder 1991; Voss & Clarke 1975, 1978; Zipf 1949).

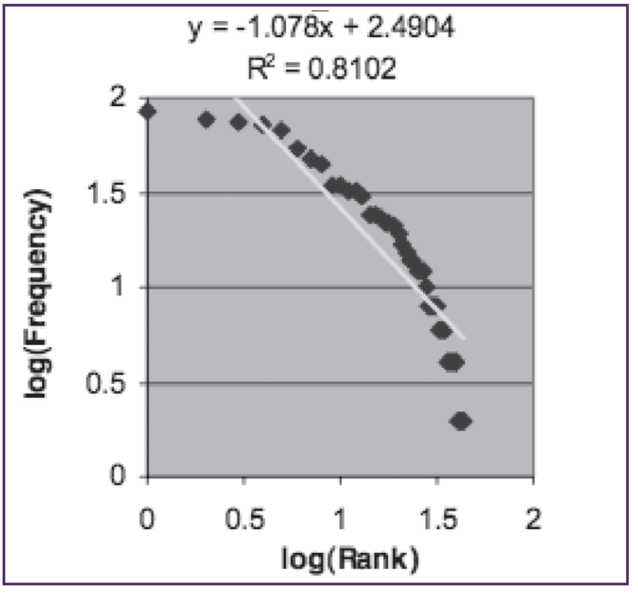

Figure 5. Pitch proportions for J.S. Bach's Overture No. 3 in D, "2. Air on the G string" (BWV1068)

4. Music and Zipf's law

Zipf reports results from four musical pieces: Mozart's *Bassoon Concerto in Bb*, Chopin's *Etude in F minor, Op. 25, No. 2*, Irving Berlin's *Doing What Comes Naturally*, and Jerome Kern's *Who* (1949, pp. 336-7). Since Zipf and his students did not have access to computers, they manually counted notes in music scores. They focused on notes and distances between repeated notes. In both cases, they demonstrated that the above songs exhibit *1/f* proportions similar to the ones observed in natural language.

With the use of a computer and the proper algorithms, this arduous effort may be performed in a few seconds. We have developed hundreds of metrics based on Zipf's law. These metrics capture proportions of music-theoretical and other attributes, such as pitch, duration, melodic intervals, chords, and various proportions of timbre in the frequency domain.

For example, using a note (pitch) metric, J.S. Bach's *Air on The G String* exhibits a slope of –1.08 and an R^2 of 0.81 (see figure 5). Again, a slope near –1 indicates a Zipf distribution. The R^2 value indicates how well the data points fit the trendline — it may range from 0 (no fit) to 1 (perfect fit). Anything above 0.7 is considered a good fit. We have studied thousands of musical pieces from the public music culture. Our results indicate that most socially-sanctioned music, across styles, exhibits near Zipfian distributions across various attributes (e.g., (Manaris et al. 2005)). Moreover, deviations from ideal Zipfian proportions tend to correlate with composer and style, as we discuss in the next section.

Our approach allows us to generate thousands of measurements from a single musical piece. However, we have discovered that 250 or so metrics are sufficient for estimating music similarity.

5. Automated classification tasks

Our experiments demonstrate that extracting a large number of power-law metrics serves as a statistical "signature" mechanism, which can help to identify musical pieces and even to automatically classify them in terms of composer or style. We have trained numerous artificial neural networks (ANNs) on hundreds of values derived from applying our metrics to many music corpora. These ANNs were trained to perform various classification tasks in order to assess our metrics. These tasks included:

- Composer classification: (J.S. Bach, Beethoven, Chopin, Debussy, Purcell, D. Scarlatti) with 93.6% - 95% accuracy (Machado et al. 2004);
- Style identification: (Medieval, Renaissance, Baroque, Classical, Romantic, Modern, Jazz, Country, Rock) with 71.5% - 96.6% accuracy (Manaris et al. 2008);
- Popularity (pleasantness?) prediction: We used a corpus of 14,695 classical pieces from the Classical Music Archives and a web access log for one month (1,034,355 downloads). Using this log, we extracted from the corpus the 1,000 most-popular (most downloaded) pieces and the 1,000 least-popular (least-downloaded) pieces. Trained on a subset of the data, the ANN managed to classify pieces into the proper category (popular vs. non-popular) with 90.7% accuracy (Roos & Manaris 2007).

6. Armonique — a music similarity engine

Several applications have been developed to expose a much greater audience to this innovative approach for searching music collections based on aesthetic similarity. One of these is the server application that powers the Armonique website.

For example, see the latest Armonique portal to the Magnatune corpus of 6,045 songs (available at http://armonique.org). These songs span Ambient, Classical (Baroque, Renaissance, Medieval, Contemporary, Minimalism), Electronica, Jazz and Blues, Metal & Punk Rock, New Age, Rock and Pop, and World (Indian, Celtic, Arabic, Tango, Eastern-European, Native-American) music, and are available under a Creative Commons License.

The design of this site follows a minimalist approach that is consistent with existing popular search engines (see figure 6). This approach was chosen to maximize usability through familiarity even for new visitors. When a user first visits the site, it is populated with a set of random songs for the user to explore. The user can then select a song and request songs similar to it. This generates a playlist sorted in descending order of similarity with regards to the original song.

The majority of online music similarity engines (50+) are based on *context/meta-data* (i.e., social networking, or users' listening habits). This includes systems such as iTunes Genius, Last.fm, and Pandora, which involve either musicologists listening and carefully tagging every new song across numerous dimensions (e.g., Pandora), or capturing listening preferences and ratings of users, also known as collaborative filtering (e.g., Genius). To the best of our knowledge, there are only two *content-based* music similarity engines in full implementation, i.e., Mufin (http://mufin.com), and ours. Both techniques are related in that they measure musical information entropy along many dimensions. Mufin uses 40+ metrics related to MP3 compression (that company owns the MP3 patent).

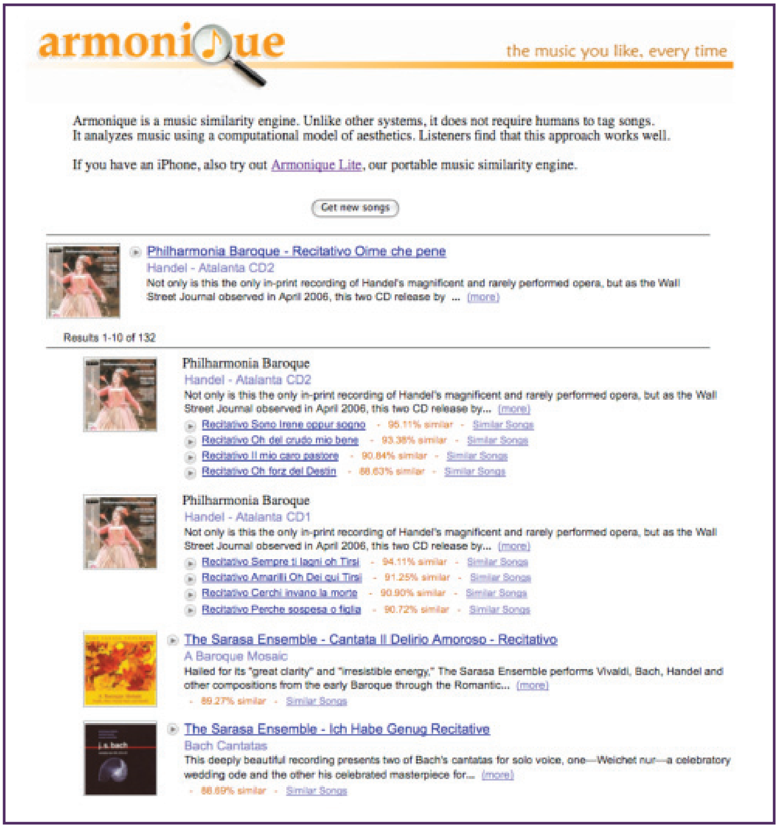

Figure 6. The Armonique search engine's user interface

Our approach uses 250+ metrics based on power laws, which have been shown to correlate with aspects of human aesthetics (see section 8). Through these metrics, we are able to automatically create our own metadata (e.g., artist, style, or timbre data) by analyzing the song content and finding patterns within the music. Since this extraction does not require interaction by humans (musicologists or listeners) it is capable of scaling with rapidly increasing data sets.

We plan to deploy Armonique to larger music collections. In preparation for this step, we implemented the Armonique server application with performance in mind. The search method currently in use employs a binary reduction technique to minimize the time required to complete a search request. This search method has been found to provide very accurate search results at a fraction of the time or computational expense of a more traditional approach.

The main advantages of using Armonique with large music collections are that (a) it requires no human pre-processing, and (b) it allows users to discover songs of interest that are rarely listened to and are hard to find otherwise. This framework may be used in a variety of music information retrieval (MIR) applications, including music recommenders and Internet radio applications (as discussed in the next section).

7. Armonique Lite — an iPhone music discovery app

We have developed *Armonique Lite*, a free iPhone application for exploring online music archives (available through the Apple AppStore). The application submits queries to the Armonique server and reads the server's responses. This keeps the burden of performing the search computations with the server, rather than a less powerful mobile device. Through efficient use of cache techniques, the server can handle thousands of simultaneous requests.

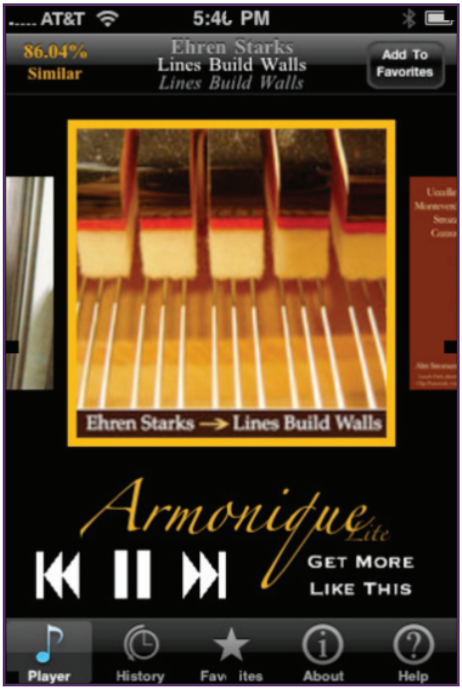

Figure 7. The Armonique iPhone user interface

Armonique Lite provides a number of additional features not supported by the current version of the Armonique website. These features include state preservation between user sessions; a history of the most recently played songs; and the ability to store a list of favorite songs. In addition, the Armonique Lite application presents search results in a much more interactive, intuitive way, allowing the user to scroll through and interact with the album art for each song in the search results. Future versions of the website could be expanded to support user accounts, which would allow many of these features to be available on the web application.

Relying on the server application for the bulk of search processing, although born of necessity, allows for a variety of other implementations. We are also working on a client for the Android platform.

8. Assessment with human listeners

We have conducted several experiments with human subjects. Our main goal was to evaluate Armonique's similarity model in comparison to human aesthetic judgments. Due to space limitations, we only summarize the major findings (more detailed reports are forthcoming).

Methodology: We asked participants to listen to musical pieces that Armonique considers similar. For comparison, we also asked participants to listen to pieces that Armonique considers dissimilar. All experiments involved five to seven pieces. The pieces were presented to each participant in random order.

For each experiment, we measured various psychological and physiological responses. In particular, we asked participants to judge (on a 1 to 10 scale) how *similar* each Armonique-recommended piece was to the original one. Then, we asked participants to rate (a) how *pleasant* and (b) how *active* all pieces were (original and Armonique-recommended), using a standard instrument known as the Self-Assessment Manikin (Bradley and Lang, 1994). In some experiments, we asked participants to rate (a) how much they *liked* and (b) how *familiar* they were with the pieces. Finally, in some experiments, we recorded *heart rate*, *skin conductance*, and up to 32 channels of *brain electrical activity* (EEG). These were recorded before, during, and after each piece.

Psychological results: In terms of psychological measurements, our findings are clear and unequivocal: Human listeners agree with Armonique's similarity recommendations.

In one large-scale experiment, 40 participants listened to a piece chosen by the experimenters, three *similar* pieces recommended by Armonique, and three *dissimilar* pieces recommended by Armonique. Participants strongly agreed with Armonique's recommendations, i.e., their ratings exhibited large and reliable differences between similar and dissimilar pieces.

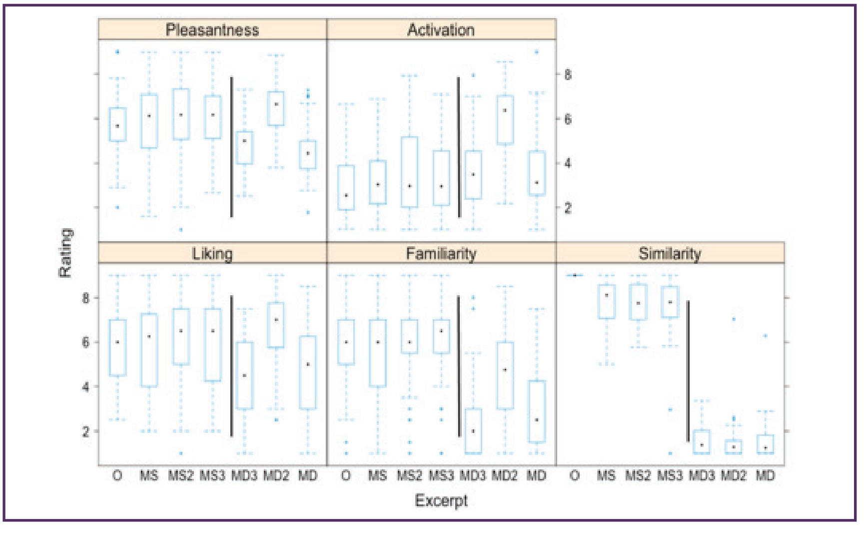

Figure 8. Responses (self-ratings) from 40 subjects to music recommended by Armonique (O = original piece; MS, MS2, MS3 = 1st, 2nd, 3rd most similar piece; MD3, MD2, MD = 3rd, 2nd, 1st most dissimilar piece)

Figure 8 (right panel) shows the 40 participants' *similarity* ratings for these pieces (O, the original piece, denotes perfect similarity; MS, MS2, MS3 are the similar pieces; MD, MD2, MD3 are the dissimilar pieces). These box plots summarize ratings (numeric responses) across all 40 participants. The black dot in each box indicates the median response for that piece. Each box indicates the spread of the ratings for that piece (i.e., it encloses 50% of the values around the median). The dotted lines (whiskers), beyond each end of the box, extend to the value that is a maximum of 1.5 times the box length. Finally, the blue dots beyond the whiskers indicate outlier values.

In other experiments, we had each participant select their own original piece, or identify a musical style from which we selected a piece. Then, we had Armonique recommend similar and dissimilar pieces. Overall, listeners agreed with Armonique, i.e., *similarity* ratings exhibited substantial differences between similar and dissimilar pieces. However, these differences were less pronounced (compared to figure 8).

In terms of *liking* and *pleasantness* measurements, in the large-scale experiment, all 40 participants gave high ratings to pieces that Armonique considered similar (see figure 8, left panels). In other words, if a listener likes a piece, Armonique may recommend other pieces that the listener likes.

It should be noted that listeners also gave high *liking* and *pleasantness* ratings to the MD2 piece (2nd most dissimilar). Since listeners did consider MD2 to be dissimilar (see figure 8, right panel), this suggests that *liking* and *pleasantness* are more general dimensions than *similarity*. In other words, a listener may like various dissimilar pieces (e.g., baroque, jazz, and ambient pieces).

Across several experiments, however, ratings for *liking* and *pleasantness* tended to differentiate similar from dissimilar pieces. Ratings for *activation* did not.

Physiological results: Physiological dimensions (i.e., *heart rate*, *skin conductance*, and *EEG*) differentiated similar from dissimilar responses in some experiments.
For instance, asymmetry of cortical activity between brain hemispheres (derived from EEG (Allen, Coan, and Nazarian, 2004)) was reliably greater for similar pieces than for dissimilar ones. However, this difference was only found in the large-scale experiment where 40 participants listened to the same music.

Another dimension, *heart rate* responses, differentiated similar from dissimilar music in some experiments. Specifically, when listening to similar pieces, participants exhibited higher heart rates.

Discussion: We have found correspondences between Armonique's computational aesthetic model and human psychological & physiological responses, across several experiments. Given the multiple dimensions of human response involved (as described above), this suggests that power-law metrics (as incorporated in Armonique's model) may capture essential aspects of human aesthetics. This is a significant finding as it corroborates Voss & Clarke's results on the aesthetic relevance of Zipf's and related power laws (1975, 1978). This computational aesthetic model is obviously not complete, as some degree of individualized response is also present.

We would encourage the reader to assess Armonique's similarity model independently (via the web, http://armonique.org, or the Armonique Lite iPhone application). This is the exact same model used in "composing" Song1 as a variation of Song2 (see section 2).

9. Conclusion

We present Armonique, a content-based music similarity engine, which utilizes a computational model of aesthetics. This engine applies years of research in the development and evaluation of power law metrics related to music aesthetics. This model has been specifically validated through various psychological experiments with human listeners. We also present Armonique Lite, an iPhone music discovery application. Currently, Armonique has been deployed on two music corpora — the Classical Music Archives corpus (14,659 pieces) and the Magnatune corpus (6,045) pieces.

We hope this article will attract interest to our approach and allow us to deploy Armonique to larger-scale audio archives.

Acknowledgements

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References

Allen, J.J.B., Coan, J.A. and Nazarian. M. (2004), "Issues and Assumptions on the Road from Raw Signals to Metrics of Frontal EEG Asymmetry in Emotion", *Biological Psychology* 67: 183-218.

Arnheim, R. (1971), *Entropy and Art: An Essay on Disorder and Order*, University of California Press, Berkeley, CA.

Aristotle (1992), *Compete Works*, vol. 10, "Metaphysics I", Hatzopoulos, O., (ed), Kaktos, Athens, Greece (in Greek).

Bogomolny, A. (online). "Benford's Law and Zipf's Law", accessed April 7, 2010.

Beer, M. (2008), "Mathematics and Music: Relating Science to Arts?", *Mathematical Spectrum* 41(1), pp. 36-42.

Blasius, B. and Tönjes, R (2009), "Zipf's Law in the Popularity Distribution of Chess Openings", *Physics Review Letters* 103(21), American Physical Society, pp. 218701-1 - 218701-4.

Bradley, M.M. and Lang, P.J. (1994), "Measuring Emotion: The Self-Assessment Manikin and the Semantic Differential", *Journal of Behavioral Therapy and Experimental Psychiatry* 25(1): 49-59.

Calter, P.A. (2008), *Squaring the Circle: Geometry in Art and Architecture*, John Wiley & Sons, New York.

Dahlhaus, C. (1982), *Esthetics of Music*, Austin, W.W. (trans.), Cambridge Univ. Press, Cambridge.

Gibran, K. (1973), *The Prophet*, 91st ed., Alfred A. Knopf, New York.

Guralnik, D.B., ed. (1979), *Webster's New World Dictionary*, 2nd College Ed., William Collins, Ohio.

Hemenway, P. (2005), *Divine Proportion: Φ (Phi) in Art, Nature, and Science*, Sterling Publishing, New York.

Livio, M. (2002), *The Golden Ratio*, Broadway Books, New York.

Machado, P., Romero, J., Santos, M.L., Cardoso, A., and Manaris, B. (2004), "Adaptive Critics for Evolutionary Artists", 2nd European Workshop on Evolutionary Music and Art, Coimbra, Portugal, *Lecture Notes in Computer Science, Applications of Evolutionary Computing, LNCS 3005*, Springer-Verlag, pp. 437-446.

Manaris, B., Romero, J., Machado, P., Krehbiel, D., Hirzel, T., Pharr, W., and Davis, R.B. (2005), "Zipf's Law, Music Classification and Aesthetics", *Computer Music Journal* 29(1), pp. 55-69.

Manaris, B., Roos, P., Machado, P., Krehbiel, D., Pellicoro, L., and Romero, J. (2007). "A Corpus-based Hybrid Approach to Music Analysis and Composition", in *Proceedings of the 22nd Conference on Artificial Intelligence (AAAI-07)*, Vancouver, BC, pp. 839-845.

Manaris, B. , Krehbiel, D., Roos, P., Zalonis, T. (2008), "Armonique: Experiments in Content-Based Similarity Retrieval Using Power-Law Melodic and Timbre Metrics", in *Proceedings of the Ninth International Conference on Music Information Retrieval (ISMIR 2008)*, Philadelphia, PA, pp. 343-348.

Mandelbrot, B. (1977), *Fractal Geometry of Nature*, W.H. Freeman and Company, New York.

May, M. (1996), "Did Mozart Use the Golden Section?", *American Scientist* 84(1): 118-119.

Pickover, C.A. (1991), *Computers and the Imagination*, St. Martin's Press, New York.

Roos, P. and Manaris, B. (2007), "A Music Information Retrieval Approach Based on Power Laws", in *Proceedings of 19th IEEE International Conference on Tools with Artificial Intelligence (ICTAI-07)*, Patras, Greece, vol. 2, pp. 27-31, Oct. 2007.

Schroeder, M. (1991), *Fractals, Chaos, Power Laws: Minutes from an Infinite Paradise*, W. H. Freeman and Co., New York.

Voss, R.F., and J. Clarke (1975), "1/f Noise in Music and Speech", *Nature* 258: 317–318.

Voss, R.F., and J. Clarke (1978), "1/f Noise in Music: Music from 1/f Noise", *Journal of the Acoustical Society of America* 63(1): 258–263.

Zipf, G.K. (1949), *Human Behavior and the Principle of Least Effort*, Hafner Publishing Co., New York.