AUTOMATIC ACOUSTIC ANALYSES QUANTIFY PITCH DISCRETENESS WITHIN AND BETWEEN HUMAN MUSIC, SPEECH, AND BIRDSONG

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ABSTRACT

Scientists studying music and evolution often discuss similarities and differences between music, language, and bird song, but few studies have simultaneously compared these three domains quantitatively. One of the striking features often considered to distinguish music from speech is pitch discreteness. Here we devised two approaches for quantifying pitch discreteness and measured its correlation to human ratings. We utilized a small subset of 9 recordings of human music, human speech, and bird song selected to maximize variation within and between these three domains. Our quantitative analyses confirmed that both methods achieved substantial correlations with subjective ratings of pitch discreteness ($r = -0.6$). However, both methods suggest that human judgment of pitch discreteness does not necessarily correlate to the “flatness” of fundamental frequency (F0) contours potentially due to some non-linear or cognitive factors involved in pitch perception. Our study suggests that it could be useful to distinguish between acoustic and perceptual pitch discreteness, analogous to the distinction between acoustic F0 and perceived pitch. We also identify areas in need of future development such as automated note segmentation.

1. INTRODUCTION

Music and language are both found universally in all human societies, yet vary greatly within and between cultures [3, 4, 10, 22, 23, 25]. To understand the origins of music and language, scientists have tried to compare music, language, and non-human vocalization [11, 13]. Language is found in all known societies but appears to be unique to humans, while music has potential parallels in non-human species, particularly songbirds and other vocal learning animals [11, 13]. However, the degree of similarity and difference between language, music, and animal song remains actively debated [13, 17, 24].

While many studies have compared music with speech, human song with bird song, or human speech with bird song [1, 13, 16, 24, 27, 28], there remain few quantitative attempts to characterize the degree of variation within and between language, music, and birdsong using standardized methods that can be objectively applied to all three domains. One such comparison found similarities in all three domains for contour and interval size across a sample of music from 5 countries, speech from 4 languages, and songs from 56 bird species [28]. These similarities were argued to reflect motor constraints on production. However, this study’s analysis of music was based on notation rather than audio recordings, and the music analyzed was instrumental rather than vocal music, making it impossible to compare speech against song using consistent methods. It also did not compare pitch discreteness, an aspect speculated to distinguish music from language [11].

Another study used a sample of 96 audio recordings (vocal and instrumental music from 30 cultures, speech from 26 languages, and songs from 30 bird species), to compare average scale tunings for all three domains [18]. The authors found consistent scale tunings predominated only in human music, and appeared at simple-integer ratio tunings (e.g., 3:2 ratio [perfect 5th]), which they speculated was related to the evolution of synchronized group performance. However, this study also did not compare pitch discreteness, and did not quantify variation *within* each domain. Thus, it is possible that the general lack of clear scale structure observed in averaged data for human speech or bird song may have obscured possible scale structure in a more “musical” subset of these recordings that used more discrete pitches (cf. [9]).

Comparing the pitch discreteness of acoustic communication signals among different domains and species could provide important insights into their biological and cultural connections. Therefore, our goal for this study was to develop methods for quantifying pitch discreteness using a reduced sample. By doing a case study analysis using a small set of recordings chosen to vary along a continuum from most to least “musical” examples for each domain, we aimed to explore the validity of methods for automatic comparison when used on particularly diverse samples, and to characterize variation within and between these three domains using quantitative methods.

2. METHODS

2.1 Corpus

Three short excerpts each of recordings of human music (“M”), human speech (“S”), and birdsong (“B”) were selected in order to highlight the degree of variation in pitch discreteness within and between these categories (Fig. 1). For example, the recording of instrumental music (M1; top left) displays mostly discrete pitches, while the song of the Canyon wren (bottom right) and American English speech (middle right) display almost no discrete pitches. Other recordings display intermediate levels of pitch structure. Please refer to the supplementary materials for the details of each recording.

2.2 Analysis

We propose two novel methods for the evaluating pitch discreteness: the first method fit a horizontal line (i.e. 0th order polynomial) to each algorithmically segmented F0 contour and measured the error, and the second method evaluated the narrowness of F0 distribution per segment by information complexity (i.e. entropy) using the manual onset and break annotations to determine the segment.

Before the computation of pitch discreteness, we extracted F0 as in our previous study [18] using the YIN pitch estimation algorithm [20] as implemented in Tarsos

[26]. Note that previous versions of this manuscript included additional analyses of pitch structure involving manual correction of Tarsos and Tony automated outputs, but the current manuscript focuses only on pitch discreteness, which do not involve these post-processing steps.

2.2.1 Pitch Discreteness: mean percentage error

Human music is generally thought to use discrete pitches, which enables the study of intervals between notes, here defined as segments of continuous pitch. If we want to use the same type of analysis for human music, speech and bird song, we ought to quantify how discrete these segments are. To this end, we selected our samples based on an estimation of pitch discreteness. However, this selection was based on our subjective judgments, so to better understand this concept we investigated human and algorithmic measures of pitch-discreteness for each of our samples. To calculate the pitch-discreteness of a sample we must first segment the pitch trace into distinct units (Figure 1A).

We tried to segment, respectively, human music into notes, speech into syllables, and to treat bird song in a similar way; this goal motivated the following algorithm and parameter choices. We first used a clustering algorithm that groups pitches based on temporal proximity and pitch change: pitches are grouped if they are within 0.07 seconds (i.e. if $dt < 0.07$) and 5% frequency differ-

Figure 1. A: Segmented pitch traces for the 9 recordings. Segments are determined by the method 2.2.1. and delimited by colour; black indicates too few pitches for a segment. **B:** Results of the pitch discreteness evaluation by human rating, the method 2.2.1. and the method 2.2.2. Please also see 3.2. for how entropy values were averaged. The x-axis is ordered to the decreasing pitch discreteness by human rating. **C:** Pearson’s correlation coefficients and those p-values (one-tailed) among the pairs of the evaluation methods.

ence (i.e. if $|1 - (f_1 - f_2/f_1)| < 0.05$). (For two speech recordings we increased the frequency difference threshold to avoid multiple segments per syllable; S2, 5.5%; S3, 8%.) We only count clusters of more than 2 pitches. For two recordings, M2 and M3, this algorithm was insufficient because the singers continue to vocalize in between notes, which blurs the segments. For these two recordings we additionally segmented pitches if the gradient of the pitch trace changed sharply, i.e. if $df/dt < 10$. We calculated the gradient by fitting a cubic spline to the entire sample. This constraint was too strong as it segmented pitches due to small oscillations, so a final step was added. We amalgamated adjacent segments if the difference in the mean pitch was less than 10% (5% for sample M3), i.e. if $|1 - (f_A - f_B/f_A)| < 0.1$, where f_A is the average frequency of segment A. Then, for our measure of pitch-discreteness we calculated the mean percentage error obtained from fitting a 0th order polynomial to each segment.

2.2.2 Pitch Discreteness: IOI (inter-onset interval)-based

We also tried a second approach that is simpler and does not require manual tuning of parameters for each data. This analysis has regarded discrete pitch as a perception of representative pitch within a sound unit and hypothesized that the flatter F0 contour within a unit, the more likely to induce people to perceive a representative pitch in that segment. Here we manually add onset annotations to the recordings and consider an IOI as a natural acoustic unit (e.g., note, syllable). The acoustic signals we deal with in this study are various (i.e. human song, human speech, instrumental music and birdsong). Therefore, though prominent amplitude modulation would be a dominant factor, our perception of sound onset is also likely to be influenced by domain-unique acoustic features (e.g. phonemes in the case of human vocalizations), which leads the definition of acoustic unit ambiguous. How to measure the unit of sound consistently in a cross-domain way will be investigated in future work.

Like phrase-nPVI [6, 29], we also annotate breaks if there is a pause between two sounds to avoid measuring IOI at non-consecutive sound sequences (e.g., between phrases or sentences). In such cases, an onset-break interval was used instead. The onset annotation was put to the beginning of the notes for singing and instrumental playing, vowels for speech, and the syllables for birdsong, though we admit the identification of each of the beginnings and the breaks is somewhat subjective. We calculated the entropy of F0 per IOI (or onset-break interval) as a quantity of the flatness (i.e. how narrowly F0 distributes) using the Kozachenko–Leonenko fixed k-nearest neighbor estimator [15], which was shown to provide consistent estimation of differential entropy [8, 19]. Tarsos estimated F0 per around 0.006 seconds, so if the duration of an F0 contour is 1 second, we would measure around 170 F0 values (i.e. 170 data points) and the entropy of that F0 segment is measured from those 170 samples. Entropy is also known as the information complexity, so this quantification allows us to use less-complex F0 as a proxy for flatter F0. However, the complexity of F0 contours could also be quantified by other techniques such as shape complexity

metrics developed in the fields of computer vision and image processing [5, 7].

2.2.3 Pitch Discreteness: Human Ratings

We collected ratings of pitch discreteness to compare with the automated methods used in the present study. Eight raters participated in the study who served as undergraduate research assistants in author PQP’s lab. These raters were musically trained individuals with expertise in auditory processing. They were familiar with the general goals of this research but were blind to specific hypotheses regarding classification of stimuli. Participants rated each stimulus with respect to whether they perceived discrete pitch events characterized by periods of pitch stability on a Likert Scale, with “7” reflecting maximal agreement and “1” reflecting maximal disagreement. In order to remove cues that may bias participants toward assumptions about stimulus domains, all speech and music stimuli were converted to a neutralized timbre without any phonetic cues, by extracting the f0 contour and re-synthesizing as a voice-like timbre using the “hum” command in Praat [2]. Bird-song data were slowed and frequency-shifted so that pitch/time properties would be comparable to those of speech and music; the original timbre of B1 and B2 were retained because conversion led to frequent octave errors in F0 extraction; the timbre of B3 was converted as done for speech and music.

3. RESULTS

3.1 Pitch Discreteness: mean percentage error

Figure 1A shows the results of the pitch segmentation algorithm, which we used to calculate our algorithmic measure of pitch discreteness (the mean percentage error obtained when fitting a zeroth order polynomial to the segments). Mean participant ratings are shown in Figure 1B. As can be seen, ratings of discreteness were significantly lower for speech stimuli than either human music or birdsong. An Analysis of Variance (ANOVA) with the factors domain (music, speech, bird song) and discreteness category (1-3) yielded a significant main effect of domain ($F_{2,14} = 55.11$, $p < .001$, $\eta^2p = .73$), whereas the main effect of discreteness category and the 2-way interaction were not significant ($p > .50$ for each).

We compare the algorithmic measurement of pitch discreteness (mean percentage error) with human ratings of pitch discreteness (mean pitch-discreteness ratings given by participants) in Figure 1B and C. The human and algorithmic measures of pitch discreteness are correlated ($r = -0.60$, one-sided $p = 0.04$, Figure 1C; note the correlation is negative due to our algorithmic operationalization), indicating that the human judgments are approximated by the algorithm. Some notable discrepancies exist: B3 is rated as very discrete by humans but is labelled the least discrete by the algorithm; M2 is ranked 1st by humans, while ranked 4th by the algorithm. Human judgment of B3 may be impaired due to the fast rate of pitch change and the difficulty of discriminating pitches at high frequencies, despite our attempts to mitigate these features by slowing/octave shifting the recordings. For M2, the algorithm returns a higher fitting error due to the sharp, yet continuous

changes of vocal pitch in between the stable pitches. Instead, humans might focus disproportionately on the longest periods of stable pitch in M2, and ignore the regions in between. Furthermore, the fact that humans judge M2 more discrete than M1 may be partially explained by the “vocal generosity effect”, whereby vocal music is perceived as more in-tune than comparably tuned instrumental music [16]. However, this is unlikely to fully explain this discrepancy because the recordings played to listeners were re-synthesized to a consistent timbre so vocal timbre alone could not fully account for this discrepancy.

3.2 Pitch Discreteness: IOI-based

The Pearson’s correlation coefficient between subjective pitch discreteness judgment and the weighted average of the entropy of F0 per IOI was -0.57, which is similar (though slightly weaker) to the value of -0.60 measured by the method of 2.2.1. Weights are proportional to the duration of the segment where the entropy was measured. This weighting is applied by assuming that a longer segment would be more influential for the perception of discreteness. The results of both automated methods are similar, as indicated by the strong correlation ($r = 0.9$) depicted by figure 1C. For instance, B3 has the highest F0 information complexity though human rating ranked it as the fourth discrete stimuli. Likewise, as obvious from the F0 contour, M1 achieved the lowest entropy but this recording is considered less discrete than M2, which is rated as most discrete while ranked third by the proposed method.

In general, both our automated and human ratings tend to agree that human music is the most discrete. The bird songs that were selected for discreteness (B1-2) are comparable in this regard to human music, while B3 shows mixed results. However there appears to be surprisingly little difference between the three speech samples, which are unanimously ranked less discrete. We speculate that humans may judge discreteness as some non-linear function of the length of periods of stable pitch and there are cognitive or psychological factors making particular F0 patterns easy to identify.

4. DISCUSSION & FUTURE WORK

We have proposed methods for establishing empirical comparisons of vocalizations across cultures, species, and domains (music vs. language) using standardized and objective methods. The audio samples used are similar to a previous study [18], but the current study explores and extends these methods through a case study of 9 audio examples varying along a continuum from pieces/songs with very discrete pitches and clear scale structure to those without. Pitch discreteness/precision varies both within and between domains. For both human music and bird song, some examples (e.g., instrumental *guqin* music with fixed tunings, Kauai O’o bird song) show very discrete pitches, while some do not (e.g., poor-pitch singing, Canyon Wren song). For speech, however, even the most “musical” examples (speech-to-song illusion, tonal language) do not score high on pitch discreteness. It is difficult to draw strong conclusions on the mechanisms underlying

any similarities or differences given the small sample size of this case study.

These case studies show that our basic methods of objectively calculating pitch discreteness match subjective ratings by humans as indicated by a substantial correlation ($r = -0.6$). However, the study also demonstrated the challenges of technical issues with the automated algorithms even for samples with relatively discrete pitches and clear pitch structures. Pitch estimation and note segmentation all presented challenges in consistently applying algorithms to the diverse samples, in some cases requiring manual adjustment of some parameters or relying on manual annotations. For example, our analyses identified octave errors in fundamental pitch estimation that required manual lowering of maximum pitch values to overcome. Interestingly, such octave errors appeared to affect human music (M1 and M2) more than bird song, probably because both human instrumental music and vocal music tend to have more complex harmonic structures than bird song, which tends to use pure tones with little harmonic structure. While cross-species comparison of vocal communication is a promising research area, automated pitch analysis for such study requires methods that overcome challenges to accommodate the diverse acoustic characteristics of non-human vocalizations.

Although the proposed methods both approached the quantification of pitch discreteness by evaluating the flatness of F0 contours while employing rather different techniques, the obtained conclusions are quite similar. One interpretation of such a similar result is that the simple levelness of F0 contours would not fully account for the rating of discrete pitch. For example, if the perception of pitch discreteness is about the perception of the representative pitch within a sound unit, then what cues people use to segment sound into a unit may influence the rating of pitch discreteness.

Another factor could be the ease of processing. It would be easier for people to follow the pitch conforming to the familiar scale structure, which may relate to the readiness of finding a representative pitch. A recent study [12] showcased that a pitch contour consisting of discrete pitches enhances pitch contour memorization compared to a pitch contour consisting of gliding tones, which is more frequently encountered in daily life through speaking. This suggests that the notion of pitch discreteness could relate to pitch memorability, which could be slightly different from a recognition of the physically dominant frequency. This memorability effect may be consistent with a transmission chain experiment of melody reproduction by [30], which found that participants began to use more specific frequency ranges (i.e. discrete pitches) as the generation in each chain progressed. Since the transmission chain experiment requires participants to memorize the melody to reproduce it, this experimental result also suggests our cognition of discrete pitch could relate to pitch memorability. From this viewpoint, we propose distinguishing between acoustic pitch discreteness and perceptual pitch discreteness, like the distinction between F0 and pitch. The former is a quantity measuring the levelness of F0 contours, but the latter is a quality perceived by a listener. We have shown that acoustic and perceptual pitch discreteness are

correlated, but this distinction may help people identify the gap between the perception of pitch discreteness and the acoustic characteristics of F0 trajectories. Findings from music psychology and auditory cognition (e.g. [21]) may help fill the gap between acoustic features and cognition. This study focused on a small case study approach to test and validate methods of automatic comparison of pitch discreteness within and between the domains of human music, human speech, and bird songs. The knowledge obtained here can be used for comparative studies using larger corpus in the future. This study focused only on pitch, but automatic methods of objectively comparing other features including rhythm and timbre will also be important to develop in future research. Overall, our case study suggests that the methods developed here are appropriate for automatic comparison of pitch discreteness in human music, human speech, and bird song. These methods could help future larger-scale comparative analysis across diverse domains and species, shedding light on the evolution of acoustic communication.

5. DATA/CODE AVAILABILITY

Data and analysis code are available at https://github.com/comp-music-lab/musi-lang-bird_added

6. AUTHOR CONTRIBUTIONS

Conceptualization: PES, SS, JMM, PQP, ATT, SF, JS, YO; Methodology/ Analysis/ Investigation/ Visualization: YO, JMM, PQP, SS, PES (YO and JMM led the automated pitch discreteness analyses and PQP led the human rating collection); Project administration/ supervision/ funding acquisition: PES; Writing – original draft: SS, PES, JMM, PQP, YO. Writing – review & editing: ATT, SF, JS.

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Supplementary Material

1. DETAILS OF THE RECORDINGS

1.1 Human Music

The three samples of human music selected are shown in the top row of Figure 1. H1 and H2 were selected from the companion recordings to the Garland Encyclopedia of World Music [5] that has been used in previous cross-cultural music corpus studies [2, 8, 9, 10]. H1 is “Yangguan Sandie”, an instrumental piece played on the Chinese guqin (zither). H2 is an Irish old-style song that also uses a pentatonic scale, but with less precise pitches. H3 was selected from one of the “poor-pitch singing” subjects singing “Happy Birthday” from a study of vocal precision [7]. It was intended to be sung to a diatonic major scale, but was performed highly imprecisely.

1.2 Human Speech

The three samples of human speech are shown in the middle row of Figure 1. S1 is the phrase “but they sometime behave so strangely”, the classic example used in the “song-to-speech” illusion in which listeners tend to hear the words as a sung melody after repeated listening [1]. Both S2 (Vietnamese) and S3 (American English;) speech excerpts were selected from the Linguistic Data Consortium [3], the cross-cultural database of speech primarily recorded from telephone conversations that we previously used to create a cross-cultural speech corpus [2]. We chose samples in which only one person’s voice was recorded. Vietnamese was chosen because it is a tonal language, and so pitch structure plays a more important role in Vietnamese than in non-tonal languages such as English [6].

1.3 Bird Songs

The three samples of bird song selected are shown in the bottom row of Figure 1. All three samples were selected from the corpus of global bird songs used in previous studies [2, 9, 11]. B1, sung by the extinct Kauai O’o, contains mostly discrete pitches. B2, sung by the Firecrest, has intermediate levels of discrete pitches, and B3, sung by the Canyon Wren, mostly features non-discrete, continuously varying pitches.

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