Prevalence of Tresillo Rhythm in Contemporary Popular Music

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ABSTRACT

This paper presents an investigation into the prevalence and significance of the Tresillo rhythm in contemporary popular music. Initially, the Tresillo rhythm is defined and formalized within a computational framework. Subsequently, employing mathematical representations, its presence is traced within the US Billboard Top 20 Charts spanning the last two decades. Detection and quantification of the Tresillo rhythm within musical compositions are achieved through the calculation of similarities between established formalizations of the rhythm and individual songs.

The resulting similarity metrics provide insights into the degree of resemblance between a given pop song's rhythm and the predefined Tresillo pattern. To ensure the robustness of the findings, two distinct formalizations of the Tresillo rhythm are constructed, and multiple methodologies for computing rhythm similarities are systematically assessed and compared. Leveraging these similarity measures, an empirical examination of Tresillo rhythm usage in the US Billboard Top 20 Charts from 1999 to 2019 is conducted. Finally, potential explanations for observed trends are discussed and analyzed.

1. INTRODUCTION

The Tresillo rhythm, a musical motif with roots tracing back to African musical traditions, emerged as a significant cultural artifact during the era of the Atlantic Slave Trade, particularly manifesting in the Caribbean region. Notably, its distinctive cadences and syncopated beats found prominence in Cuba, where it garnered substantial recognition before crossing geographical boundaries to influence musical compositions worldwide [1, 2]. Serving not only as an independent rhythmic framework but also as an integral component within diverse musical genres, the Tresillo rhythm exemplifies remarkable versatility and adaptability [2]. As described by Floyd [2], the fundamental structure of the Tresillo rhythm is characterized by a sequence comprising a dotted eighth note succeeded by a sixteenth note, followed by an eighth rest, and culminating in another eighth note, iterated twice within a standard 4/4 musical measure. Another way to say the same thing is that the *inter-onset intervals* as defined by Toussaint are 3, 3, 2, 3, 3, 2. Slight modifications to this rhythmic template have produced other musical rhythms. By adding a beat on all fours to the rhythm, the Reggaeton rhythm is realised (see Figure 3). By changing the second half of the bar to an eighth rest, two eighth notes and another eighth rest, one creates the basic Clave rhythm pattern (see Figure 2).

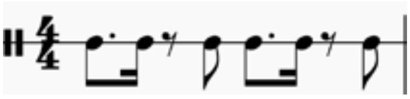

Figure 1. Synthetic Tresillo

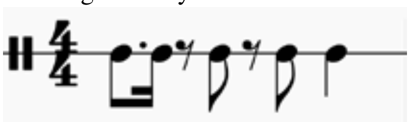

Figure 2. Clave rhythm

Figure 3. Reggaeton Rhythm

These subtle variations in rhythmic configuration underscore the rich dynamism and potential inherent within the Tresillo motif, illustrating its enduring relevance and widespread influence across diverse musical landscapes.

The Tresillo rhythm, notably prevalent in Latin American music, has influence beyond these origins, significantly marking its presence in Western music genres as well. This "danceable Cuban Clave son," as described by Toussaint [3], transcends geographical and cultural boundaries, finding its way into the rhythm sections of Western music compositions [4, 5]. Its popularity in contemporary pop music is evidenced by chart-topping hits such as "Shape of You" by Ed Sheeran and "Cheap Thrills" by Sia. An analysis of Billboard Chart hits, to be presented in Section 5, reveals the Tresillo rhythm's regular incorporation into pop music, underscoring its widespread appeal. While the use, evolution, and popularity of the Tresillo rhythm have been extensively explored in qualitative studies [1, 2, 4–6], a quantitative investigation into its prevalence within the pop music landscape remains to be done. This gap highlights a promising area for further research, potentially offering novel insights into the rhythm's enduring popularity and its impact on global music trends.

In pursuit of a computational approach to analyze the prevalence of the Tresillo rhythm in contemporary pop music, the authors devised a novel computational method. Similar to the case of tonal key detection, we proceed by matching a histogram representing a single piece against a template histogram. Stronger matches indicate more of the Tresillo property. As in the case of tonal key detection, we can either define a binary template a priori [7], or derive a real-valued template from a corpus [8]. This method entails the digital encoding of (1) a pop song's primary rhythm as a histogram of intra-bar onset times and (2) the Tresillo rhythm itself as an analogous "binary histogram". Each of these gives a *rhythm vector*. This enables a direct comparison through various similarity metrics. Utilizing these metrics, our study reveals a discernible trend in the adoption of the Tresillo rhythm within the US Billboard Top 20 Charts over a two-decade period (1999-2019). The methodology's core is based on the premise that rhythmic structures can be quantitatively compared, thus offering a lens through which the evolution of musical tastes and influences can be traced. This computational analysis not only confirms the Tresillo rhythm's growing influence in pop music but also illustrates its role in shaping contemporary musical landscapes.

To answer the research questions, a way of defining the main rhythm of a pop song is necessary. The vast majority of pop songs consist of a simple melodic and rhythmic structure, called a *timeline* by Toussaint [3]. Following Toussaint, we therefore assume that one can identify one dominant rhythm per song. This rhythm is repeatedly played throughout the song and therefore can be characterised by counting the onsets and comparing the onset counts for every position within a bar. To present the music in a usable format, quantification is needed. 16th notes are chosen as the smallest unit. Assuming that all songs used for our analysis are in a 4/4 meter, this gives 16 possible events per bar. All songs in the data which are found not to be in 4/4 are excluded from the analysis. Aggregating all bar onsets of a song to one bar results in a single pseudo-bar which can be described as a 16-dimensional vector, where every value represents the number of onsets on a given bar position. The Tresillo rhythm is used as a rhythm on its own ("clean"), or as part of other more complex rhythms. For our definition of clean Tresillo rhythm, we use the notation in Figure 1.

This paper is organized as follows: First, the literature of several different fields, which are relevant to this paper, will be discussed. Then several assumptions necessary to conduct the presented analysis will be stated in the problem statement section. The Data section discusses the chosen data sources and data format for the analysis. In the Method section, the proposed data representation, rhythm similarity measures, and evaluation metrics are presented and explained. In the Results section, the different rhythm similarity measures are evaluated and compared. The Results section also comprises a description and analysis of the time trend. The paper concludes with a discussion of the chosen methods and obtained results. Furthermore, a possible interpretation of the produced results is presented.

2. RELATED WORK

This paper touches upon different scientific fields such as musicology, audio retrieval and digital musicology.

Prior works have already investigated the evolution and spread of syncopation in American popular music. VanderStel et. al. found that there was a general increase in syncopation over the course of the 20th century [9]. The authors focused on vocal melodies considering one song from each year of the century. Other studies focused on specifically the Tresillo and Clave rhythm patterns and thus provide a clear definition and formalization of those rhythmic patterns from a theoretical viewpoint [1, 2, 6]. We rely on those theoretical accounts to define the Tresillo rhythm used in this project. Music scholars further investigated the diffusion of the Tresillo rhythm from Africa to Latin America and then to United States from a cultural perspective [1, 2]. More generally, there have also been several works discussing the rise in popularity of Latin American music and its influence on U.S. mainstream music [10, 11]. However, the mentioned musicology research is predicated upon qualitative analyses of musicology books, sheet music, recordings and interviews with specialists and practitioners. This paper in contrast chooses to employ computational methods to draw conclusions about the influence and popularity of the Tresillo rhythm in US popular music. Another relevant research area concerns the formalization of rhythm and statistical corpus studies of rhythmic patterns. Previous authors have studied rhythm from a theoretical and generative point of view [12] and from a psychological point of view [13]. Rahn [14] analysed rhythm from a motor (physical movement) point of view [15].

Our paper mainly refers to rhythm representations, which have been used for corpus studies [16], or more generally the study of onset frequency distributions [17]. To represent rhythm in this project we will thus employ rhythm histograms as used and described in prior works [16, 17].

A last field of research that is also relevant for this paper is concerned with computing rhythmic similarity between different pieces. Such techniques are often used for audio retrieval tasks [18] or music genre classification tasks [19, 20]. More generally, this literature is concerned with measuring similarity and dissimilarity of audio signals or signals in general [21]. This literature provides valuable metrics and techniques to compare the rhythmical structure of two songs, however, it is mainly based on using audio files to extract signal features [18–20, 22]. Thus the methods proposed in those papers have been adjusted in our work to work with our symbolic data representation. In addition to this, we employ machine learning-based methods over the rhythm vectors for producing our trends.

3. DATA

In this study, four distinct data sets from different sources were utilized. To assess the effectiveness of our methodology, which is designed to calculate the similarity between the specified Tresillo rhythm and any given song, we compiled two validation data sets. The first data set comprises songs characterized by the Tresillo rhythm, while the second includes songs without this rhythm. Both data sets were carefully curated by the authors through an extensive review of songs available on Spotify to identify relevant examples.

Specifically, for songs featuring the Tresillo rhythm, we examined a pre-existing Spotify playlist purported to include such songs [1]. Following the identification of potential tracks for the validation set, we sought corresponding MIDI files on MIDIdb [2], a MIDI file database, from which the files were subsequently downloaded. This selection process ensured that the data sets accurately represent the presence and absence of the Tresillo rhythm, thereby facilitating an evaluation of the proposed similarity measures.

To trace the Tresillo rhythm in the popular music of the past 20 years a publicly available data set which contains the song names and artist names of the Hot 100 US Billboard Charts (1999-2019) was used [3]. However to reduce the complexity of the data collection, it was decided to only use the US Billboard Top 20 Charts (1999-2019), which consists of in total of 1,447 songs. Given artist and song names, we collected the available songs of the US Billboard Top 20 Charts (1999-2019) from the website MIDIdb. The final Billboard data set on which the analysis was conducted on, consists of 444 distinct Billboard Top 20 weekly songs, which represent around 31% of the US Billboard Top 20 Charts. To assert the representativeness of the collected sample, the sample distribution was compared to the ground truth distribution of the US Billboard Top 20 Charts by evaluating t-test statistics of several features (e.g.: weeks on charts, peak position in charts, date of release). All t-tests indicate that the two distributions are not significantly different. While not conclusive, given the large sample size this may indicate that the subset is indeed representative.

MIDI files offer much broader availability and also their ability to contain multiple voices within a single song. This feature is particularly beneficial for analyzing pop songs, which often are not available in traditional score format. However, to generate onset lists for every musical event – essential for our analysis – MIDI files were converted into the Musescore format. These onset lists, detailing the timing of musical events, serve as the foundation for our data representation and subsequent analysis.

Using these onset lists, we created Figure 4, which illustrates the frequency of musical onsets, relative to the beginning of the bar, notated in 1/128 notes and aggregated into one pseudo-bar. This visual representation aids in understanding the rhythmic structure and frequency of musical events within the songs analyzed. Observing Figure 4, it becomes clear that a granularity of 16th notes is well suited.

[1] https://open.spotify.com/playlist/17Na5AMmlLwY7OTsw6ovsS
[2] https://www.mididb.com/
[3] https://www.kaggle.com/danield2255/data-on-songs-from-billboard-19992019

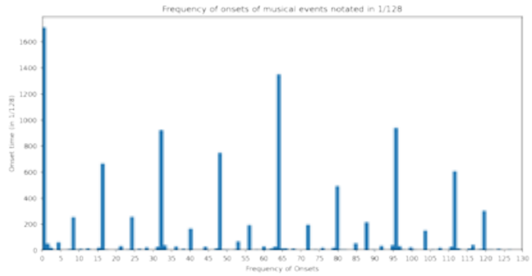

Figure 4. Frequency of onsets of musical events notated in 1/128 aggregated to one bar.

Moreover, Musescore's provision of time signatures for each song enriched our dataset with critical metadata. It is noteworthy that our dataset contained 9 songs with time signatures of 3/4 or 6/8. These songs were excluded from further analysis due to their unique rhythmic structures, which differ significantly from the common 4/4 meter found in most pop music and the focus of our study on the Tresillo rhythm.

The full dataset along with the code is available at the Github repository. [4]

4. METHODS

4.1 Rhythm vectors

To accurately measure the similarity between two rhythms, it is imperative to establish a precise definition of rhythm. Rhythm can generally be defined as "a series of onsets and durations of musical events" [12]. This study focuses on the predominant and recurring rhythm of a song, under the assumption that each musical event is adequately represented by its onset.

In the pursuit of a computational representation of a song's dominant rhythm, we employ a method where all musical onsets within a voice are aggregated into a single pseudo-bar. This approach of collapsing musical onsets into a singular pseudo-bar to generate onset 'histograms' is a well-established technique. It has been employed in various musicological studies, including analyses of Western classical music [17] and American folk music [16]. This methodological framework allows for a concise representation of rhythmic patterns, facilitating the comparative analysis of rhythm similarities across different pieces.

Given prior assessment of the Billboard data (see Figure 4) in conjunction with our choice to work only with songs in a 4/4 meter, we can safely choose to use 16-dimensional vectors for the representation of rhythm.

This method provides for each voice of each song a 16-bin histogram denoting the cumulative number of onsets on a given beat. Here it is important to note that while certain voices within a song may convey more significant informa-

[4] github.com/pushkarjajoria/tresillo

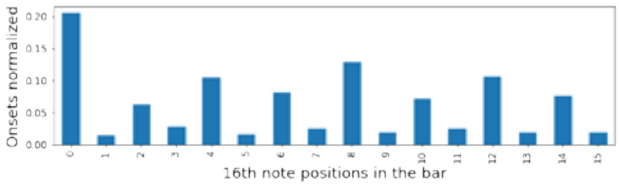

Figure 5. All rhythm vectors of all Billboard songs aggregated to one vector.

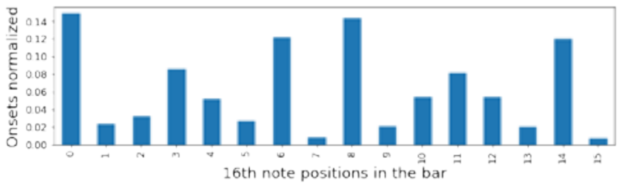

Figure 6. Rhythm vector of the song “Shape of you" by Ed Sheeran.

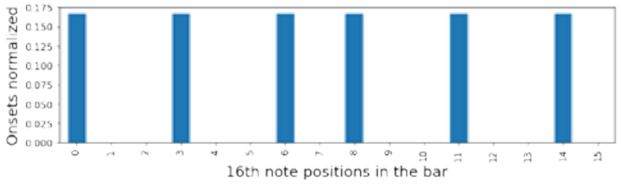

Figure 7. Rhythm vector of the synthetic Tresillo. We use this definition of the Tresillo rhythm computationally. This clean version of the Tresillo is referred to as the Synthetic Tresillo in the following sections.

tion about its main rhythm, distinguishing and quantifying the contribution of each voice to the overall perception of the rhythm requires specialized knowledge. Developing a methodology to ascertain the extent to which each voice influences the perception of the main rhythm falls outside the ambit of this study. Therefore, this paper does not differentiate between the voices, treating them uniformly in the analysis. By aggregating the onsets across all voices onto one single histogram, we obtain a single onset histogram for a given song. The onset histograms are then normalized to transform them into a 16-dimensional vector, which we will refer to as the rhythm vector of a song. This research assumes that the information about the rhythm of the song is captured by these rhythm vectors.

The obtained rhythm vectors can be displayed as bar plots to allow visual inspection. Aggregating all rhythms vectors into one normalized rhythm vector shows the mean rhythm of our Billboard data set, as can be seen in Figure 5. Figure 6 shows a song with high Tresillo similarity.

Next, we introduce in Figure 7 the synthetic Tresillo pattern. Visual inspection and comparison of the compiled rhythm histograms to the synthetic Tresillo pattern reveals similarities and differences. Songs that contain the Tresillo rhythm show a strong visual similarity with the synthetic Tresillo rhythm vector.

4.2 Tresillo similarity measures

Each rhythm vector is a 16-dimensional vector for which similarity compared to another vector in the same space can be computed using a cosine similarity measure. We compare the similarity of rhythm vectors with two different Tresillo vectors which are defined as follows. 1) Template similarity center is the point in this space that corresponds to a plain Tresillo beat. 2) Centroid similarity point is defined as the centroid of all rhythm vectors corresponding to Tresillo songs under the training dataset. Our purpose in defining both methods is to explore and experiment to find the best method.

The Tresillo rhythm is defined by its syncopated pattern. This information is visible in Figure 6 by a sharp peak on the 3rd and 12th beats. Since each rhythm is defined by a pattern of higher and lower values along these 16 dimensions, it is fair to assume that each axis or onset position does not carry equal weight in the identification of this pattern. For example, it is very common in songs to have an onset at the start of a bar. Since the onset on the first beat is so ubiquitous in music, it need not carry a high weight in the identification of a rhythm in this space. To encapsulate this information in a similarity measure, we next learn scaling factors for each dimension of the rhythm space, which are referred to as θ_i. These θ_i are used to increase the gap between “Tresillo similarities” of rhythm vectors which do contain Tresillo and vectors which don't. These θ_i scale the rhythm vector of a song along axis i and in turn scale the similarity measure accordingly. The resulting parameterized cosine similarity is defined in equation 1 where, Θ refers to the set of scaling factors, and A and B are two vectors with the same dimension between which the similarity needs to be computed. The i^{th} dimension of these vectors are denoted by a_i and b_i. A_Θ and B_Θ are the linearly transformed vector after scaling i^{th} dimension by θ_i. 'n' denotes the total number of dimensions in the rhythm space, i.e. 16 in our case. Parameterized distance measures have been successfully used in the past in pattern recognition and machine learning [21].

$$\begin{aligned} \cos_\Theta(\mathbf{A},\mathbf{B}) &= \frac{\mathbf{A}_\Theta \cdot \mathbf{B}_\Theta}{||\mathbf{A}_\Theta||\,||\mathbf{B}_\Theta||} \\ &= \frac{\sum_{i=1}^{n}(\mathbf{a}_i \cdot \theta_i)(\mathbf{b}_i \cdot \theta_i)}{\sqrt{\sum_{i=1}^{n}(\mathbf{a}_i \cdot \theta_i)^2}\sqrt{\sum_{i=1}^{n}(\mathbf{b}_i \cdot \theta_i)^2}} \end{aligned} \tag{1}$$

Equation 1 defines the parameterized cosine similarity used in this research. The parameters for this model are learned by maximizing S^* (defined in the next section), which can also be modeled as a minimization problem as formulated in Equation 2.

$$\underset{\Theta}{\operatorname{argmin}} \frac{cos_\Theta(\mathcal{A}', \mathcal{T})}{cos_\Theta(\mathcal{A}, \mathcal{T})} \tag{2}$$

Where $\mathcal{A}$ is the set of songs with Tresillo present in them, $\mathcal{A}'$ is the set of songs with Tresillo not present in them and $\mathcal{T}$ refers to the reference point for computing the cosine similarity, i.e. either the clean Tresillo rhythm template, or the Tresillo centroid vector.

4.3 Evaluation

To evaluate the proposed similarity methods two different metrics were chosen to assess the variance produced by a given model and to compare the model fits between different models.

To assess the variance in Tresillo similarity estimated by a given model, the bootstrapping method on the validation data sets was used. Thus using the Tresillo and the non-Tresillo validation data sets, we used a given model to calculated the mean Tresillo similarity in a given validation set and its 95% confidence intervals, as obtained by bootstrapping. The bootstrapping was performed with 1000 draws with replacement. The number of samples per draw, correspond to the sample size of a given validation set (i.e either 9 or 10 samples).

To compare different models it was assumed that a good model would have high similarity for all songs which have a Tresillo pattern and a low similarity for songs which do not have such a pattern (see Equation 3). This can be measured by defining 'Similarity Goodness' S^* as the ratio of mean similarity in songs that have Tresillo and mean similarity of songs that do not. A higher value of S^* denotes high similarity for songs with Tresillo and low similarity for songs without Tresillo. Here similarity refers to the similarity computed between the rhythm vector of a song and a Tresillo rhythm vector. This similarity could be computed by using either an unparameterized or a parameterized cosine similarity, depending on the different models defined in the previous section.

$$S^* = \frac{S_{\text{tres}}}{S_{\text{no-tres}}} \tag{3}$$

In Eq. 3, S^* denotes the 'Similarity goodness', a ratio indicating the relative similarity among songs with and without the Tresillo rhythm. Specifically, S_{tres} represents the average similarity score for songs incorporating the Tresillo rhythm, calculated based on the cosine similarity between their rhythm vectors and a defined Tresillo rhythm vector. On the other hand, $S_{no-tres}$ denotes the average similarity score for songs that do not feature the Tresillo rhythm. It is extremely unlikely to get zero in the denominator as the tresillo vector and the song vector would need to be orthogonal, i.e. having zero notes on the first beat of the bar is unlikely. A higher value of S^* suggests that songs with the Tresillo rhythm are, on average, more similar to the Tresillo rhythm vector compared to songs without it, highlighting the distinctive rhythmic pattern associated with the Tresillo rhythm.

5. RESULTS

5.1 Comparing the similarity measures

Figure 8 compares $S*$ using two different Tresillo centers with a parameterized vs unparameterized cosine similarity. The error lines on the bar plot denote the 97.5% confidence interval based on 'leave one out' cross-validation. It can be inferred that the models based on the synthetically defined Tresillo outperform the models based on the centroid methods ($p < 0.001$ in both cases using a t-test). Parameterized models also outperform the un-parameterized models (again, $p < 0.001$ in both cases using a t-test).

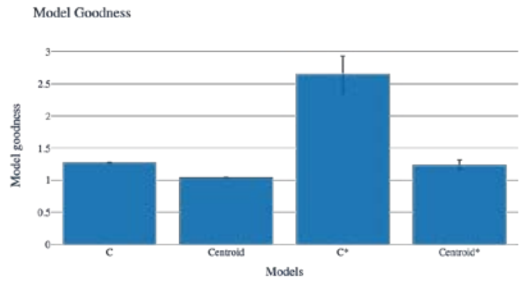

Figure 8. Comparing model goodness. Here, **C** refers to rhythm similarity measured with cosine similarity, using Tresillo template as centre. **Centroid** refers to rhythm similarity measured with cosine similarity, using the centroid of Tresillo songs as centre. **C*** refers to rhythm similarity measured with parameterized cosine similarity, using Tresillo template as centre. **Centroid*** refers to rhythm similarity measured with parameterized cosine similarity, using the centroid of Tresillo songs as centre.

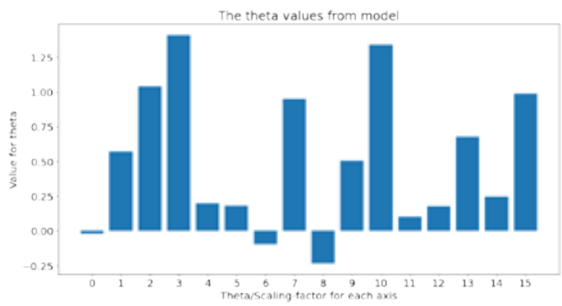

Figure 9. θ_i for each dimension i (i.e. 16th beat).

Figure 9 shows the learned θ_i for each beat after fitting the model. High values here indicate that this location is informative as to *whether* the beat is a Tresillo or not. Low and negative values for the 0^{th} and 8^{th} beats bolster our claim about the ubiquitous 0^{th} beat in popular music. The third beat along with the second beat carry a lot of information about the Tresillo beat and hence have a high value. Other Tresillo beats also share a high peak with the exception of the 6^{th} and the 8^{th} beat. This may be because the onsets for popular rock pop songs coincide here. There is asymmetry across the 8th beat. One of the possible reason for this could be the drum fills, which are often in the latter half of the bar.

5.2 Trend over Time

Considering the evaluation of the proposed models based on our validation data sets, it was inferred that models using the synthetic Tresillo outperformed models using the centroid derived from data. Thus to analyze the Tresillo trend over time, only the two models which are based on the synthetic Tresillo were used. Those two models correspond to the models with best performance on the validation set. However, the parametrized model clearly outperformed the cosine similarity model.

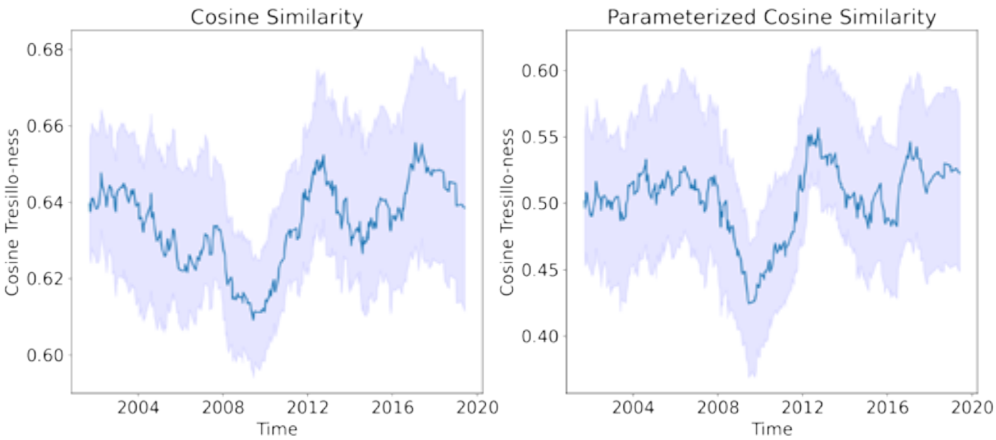

Figure 10. 52 weeks moving average of cosine Tresillo similarity in the US Billboard Top 20 Charts.

Tresillo Songs Names	$\mathcal{C}$	$\mathcal{C}^*$
Cheap Thrills-Sia	0.9089	0.9919
Eastside-benny blanco	0.7112	0.9471
New rules-Dua Lipa	0.8388	0.9431
Non Tresillo Songs Names	$\mathcal{C}$	$\mathcal{C}^*$
Immigrant Song	0.5842	0.5382
Fear of the Dark	0.6894	0.2545
Sweet Child O'Mine	0.7247	0.4840

Table 1. Cosine similarity and parameterized cosine similarity for popular Tresillo songs and Non Tresillo. Here $\mathcal{C}$ denotes cosine similarity and $\mathcal{C}^*$ denotes parameterized cosine similarity.

Given those two models, Tresillo similarity for all songs in the Billboard data set was calculated. By plotting the Tresillo similarity over time, a proxy for the trend in Tresillo use over time was obtained. A rolling yearly mean was applied to the weekly mean value in Tresillo use. The resulting rolling yearly average of Tresillo use can be seen in Figure 10. In both Figures, 95% confidence intervals have been obtained via bootstrapping (1,000 draws with replacement, with the number of samples per draw equal to the sample size) and indicated by light blue coloring.

6. DISCUSSION

This paper shows that, given a clear definition, the intensity of Tresillo rhythm use in a given song can be measured with computational methods. Several methods have been introduced which identify the use of the Tresillo rhythm and its intensity in the collected validation data sets. However, it is still disputable how the proposed models deal with noise which might dilute the Tresillo rhythm. Assessing the uncertainty of our models (e.g.: by looking at outliers as determined by the bootstrapping method), it is notable that not every song which was labeled to contain the Tresillo rhythm, has a very high Tresillo similarity. Although both models in Table 1 give high similarity for a Tresillo song and low similarity for a 'non-Tresillo' song, parameterized model $\mathcal{C}^*$ gives the desired larger gap between the two.

Assessing the trends over time of Tresillo use in the US Billboard Top 20 Charts of the past 20 years, no clear linear trend is observable. However, several interesting peaks and patterns are noticeable. We also found that the results at a granularity of a week are by nature very noisy and there is high variance in Tresillo use from week to week, which is expected and does not offer any meaningful insight.

Using a rolling yearly mean, the trend of Tresillo use over time becomes more visible, as can be seen in Figure 10. Figure 10 offers us some interesting insights. Even though there is considerable yearly variance in the intensity of Tresillo rhythm use (as illustrated by the 95% confidence intervals), there are identifiable peaks and valleys in Tresillo rhythm use. Furthermore, the unparameterised cosine similarity and the parametrized cosine similarity produce consistent results, however on different scales.

Looking at Figure 10, we observe a trend which starts relatively high around the new millennium, stays constant or slightly decreases till around 2008, and collapses to a low in 2010. From 2010 on there is an increase in Tresillo use, with another valley around 2014. Around 2018 the trend in Tresillo rhythm intensity reaches its all time high.

After subjectively evaluating the calculated Tresillo similarity and the corresponding Billboard Charts, we interpret this trend as follows. In the early 2000s it seems that many songs which peaked in the Billboard Charts were either by Latin artists or by artists who used Latin music themes in their songs (e.g.: *Maria Maria*, Santana, 2000; *Be With You*, Enrique Iglesias 2000; *Baby Boy*, Beyoncé, 2003). This trend then decreases steadily, till the Tresillo rhythm seems to reappear in Western dance music after 2010. After 2010 there are several peaks which can be associated to popular dance music songs with particularly high Tresillo similarity (e.g.: *Where Have You Been*, Rihanna, 2012; *Shape Of You*, Ed Sheeran, 2017; *Cheap Thrills*, Sia, 2016). The trend post 2010 agrees with the findings of VanderStel and Temperley [9]. Despite the valleys of 2010 observed in our findings, it is our opinion that the overall trend exhibits an upward trajectory, albeit a modest one. However, to substantiate this interpretation of the trend over time, further empirical research would be needed, which clearly defines and differentiates the use of the Tresillo rhythm in the context of 'Latin American' music and its usage in Western dance music.

7. FUTURE WORK

The channels in a song carry valuable information and could be leveraged upon if a sophisticated algorithm could be developed which is independent to meta data information but rather works on a symbolic level.

The lack of well annotated midi data is also a limiting factor. Annotating more data will result in better parameterized models which in turn, would improve the $\mathcal{S}^*$. The benefits of more data are not limited to this. More sophisticated learning algorithms which could not be used given over-fitting concerns, might become viable. For instance, a non linear transformation of the rhythm vector space may results in better results as this would be better suited at modeling the nuances on, for instance the 3rd beat. Dimension reduction techniques like PCA could also be employed to reduce over-fitting.

Finally, to substantiate our subjective impression that there are two waves in usage of this rhythm, once in Latin American music and once in Western dance music, further empirical research would be needed, which differentiates in which musical context this rhythm is used.

Acknowledgments

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