Triangle Simplex Plots for Representing and Classifying Heart Rate Variability

Mateusz Soliński[1], Courtney N. Reed[1], Elaine Chew[1]

[1]Department of Engineering and School of Biomedical Engineering & Imaging Sciences
King's College London, London, UK

Abstract

Simplex plots afford barycentric mapping and visualisation of the ratio of three variables, summed to a constant, as positions in an equilateral triangle (2-simplex); for instance, time distribution in three-interval musical rhythms.

We propose a novel use of simplex plots to visualise the balance of autonomic variables and classification of autonomic states during baseline and music performance.

RR interval series extracted from electrocardiographic (ECG) traces were collected from a musical trio (pianist, violinist, cellist) in a baseline (5 min) and music performance (∼10 min) condition. Schubert's Trio Op. 100, Andante con moto was performed in nine rehearsal sessions over five days. Each RR interval series' very low (VLF), low (LF), and high (HF) frequency component power values, calculated in 30 sec windows (hop size 15 sec), were normalised to 1 and visualised in triangle simplex plots. Spectral clustering was used to cluster data points for baseline and music conditions.

We correlated the accuracy between the clustered and true values. Strong negative correlation was observed for the violinist (r = –0.80, $p \leq .01$, accuracy range: [0.64, 0.94]) and pianist (r = –0.62, p = .073, [0.64, 0.80]), suggesting adaptation of their cardiac response (reduction between baseline and performance) over the performances; a weakly negative, non-significant correlation was observed for the cellist (r = –0.23, p = .545, [0.50, 0.61]), indicating similarity between baseline and performance over time. Using simplex plots, we were able to effectively represent VLF, LF and HF ratios and track changes in autonomic response over a series of music rehearsals to observe autonomic states and changes over time.

1. Introduction

Heart rate variability (HRV) and related beat-to-beat (RR) intervals are important in assessing cardiac health [1]. HRV is related to nervous system response [2] and indicative of how well the heart is able to cope with stress [3, 4]. Power spectrum analysis of HRV (PS/HRV) is particularly relevant to the balance between sympathetic and parasympathetic nervous system response [5]. There are three major frequency components: very low (VLF, 0.0033-0.04 Hz), low (LF, 0.04-0.15 Hz), and high (HF, 0.15-0.40 Hz) [5]. LF, for instance, is linked to vasomotor activity [5] and HF to respiratory-driven vagal efference to the sinus node [6]. The ratios between these components hold special interest for the cardiovascular community.

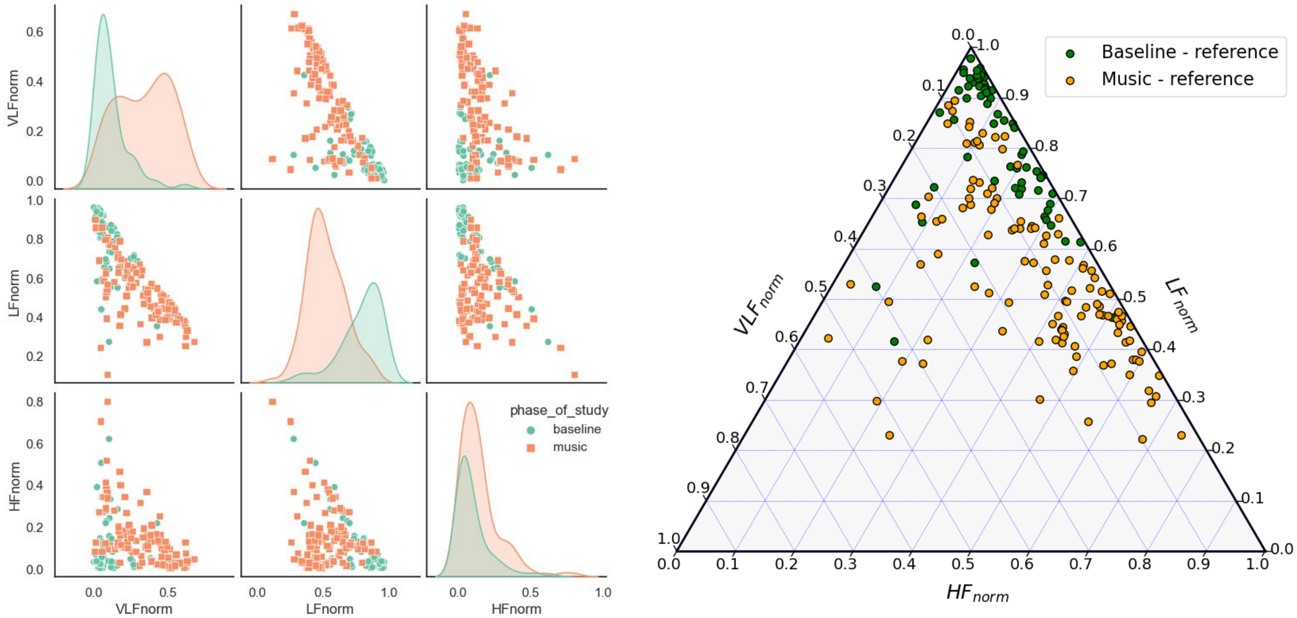
The frequency components in the power spectrum are compositional and do not vary independently [6]. They can be examined by plotting the power spectrum (in the frequency domain), spectrogram (time-frequency plot) or, by comparison, the sum of power within defined frequency ranges. We, therefore, seek an appropriate, and effective visualisation for analysing the three components simultaneously. One such visualisation method is triangle simplex plots, also known as ternary plots or Gibbs triangles. They are 2D plots that depict three variables summed to a constant, typically 1. Simplex plots have been used in physical chemistry and mineralogy to show the compositions of three-piece systems [7] and in game theory to examine evolutionary dynamics [8]. Simplex plots have also been used in musical applications to depict the distribution of time in three-beat patterns [9, 10].

In this paper, we propose the use of simplex plots to depict the PS/HRV distribution of VLF, LF, and HF components. We visualise a real-world example of HRV data gathered from a trio of musicians while performing a music piece during rehearsals over a period of four months. We demonstrate how this visualisation method is useful, for instance as a basis for data clustering, which we use to characterise data collected while playing and during the period of rest before performance. We propose this method as a way to visualise HRV data and future directions, such as applying image classification techniques.

2. Methodology

2.1. Data Collection

RR interval series were collected during performances of Schubert's Trio Op. 100, Andante con moto (from here, "the Schubert"), played by a trio of professional musi-



(a) Scatter plot matrix visualisation of pianist's first rehearsal.

(b) Simplex plot visualisation of pianist's first rehearsal.

Figure 1: Scatterplot matrix vs. simplex data visualisation of normalised VLF, LF, and HF components in the pianist's data from the first rehearsal, examined (a) as pairings in a 2D scatterplot matrix; and, (b) in a triangle simplex plot.

cians (violinist, cellist, and pianist, each with 20+ years of performance experience). The Schubert was selected for its clear musical structures. Twenty-seven RR time series were collected during nine performances of the Schubert in five days between December 2022 and March 2023. Each performance started with a baseline ECG recording during five-minutes' silence. On 3 of the 5 days, the piece was performed 2-3 times; in these cases, a 5+ minute break was taken between each recording, to allow the participants to settle back to the baseline before performing again.

Each musician's ECG signals were collected using a Polar H10 (Polar Electro Oy, Kempele, FI) monitor worn across the sternum with sampling frequency of 130 Hz. QRS complexes were automatically detected and RR interval series calculated within the Polar's firmware. Artefacts and ectopic heartbeats were manually removed. Additionally, music audio signals were collected with a Zoom H5 (Zoom, Tokyo, JP) handheld recorder placed approximately 2 metres from the musicians.

2.2. Data Processing & Plotting

We calculated the power spectrum in the VLF, LF, and HF components from RR intervals in 30-second windows with a hop size of 15 seconds. Then, we calculated relative values in the i^{th} window regarding the sum of components in each window as:

$$
\begin{aligned}
VLF_{norm(i)} &= VLF_i/(VLF_i + LF_i + HF_i) \\
LF_{norm(i)} &= LF_i/(VLF_i + LF_i + HF_i) \\
HF_{norm(i)} &= HF_i/(VLF_i + LF_i + HF_i)
\end{aligned} \tag{1}
$$

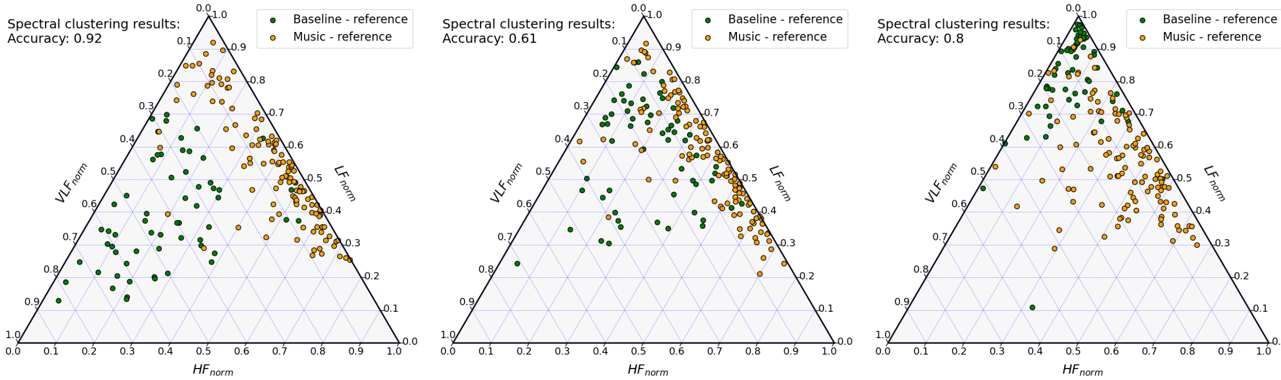
A single point on the simplex plot consists of three coordinates: $[VLF_{norm(i)}, LF_{norm(i)}, HF_{norm(i)}]$.

Triangle simplex plots were created in Python using the `ternary` library. Figure 1 compares the pianist's PS/HRV components in the first performance visualised in a X-Y scatterplot (a) versus in a triangle simplex plot (b).

Additionally, we plotted aggregated performances using point coordinates averaged over all windows. Thus, every rehearsal is represented by one point for baseline and one for music performance in the triangular simplex space.

2.3. Spectral Clustering

One possible analysis using simplex plots is in clustering data points into defined groups. We performed such a spectral clustering method [11] to determine the distinction between baseline and music period data points. We estimated the clustering accuracy in each rehearsal as the number of points correctly classified as baseline or music data divided by the total number of data points. Then, we used linear correlation analysis to check whether the clustering accuracy monotonically increased or decreased with the number of rehearsals for each musician.



(a) Violin PS/HRV components

(b) Cello PS/HRV components

(c) Piano PS/HRV components

Figure 2: Simplex visualisation of performers' heart rate variability during baseline (green) and music (orange) from the trio's second rehearsal. Spectral clustering accuracy reported in top left of each triangle plot.

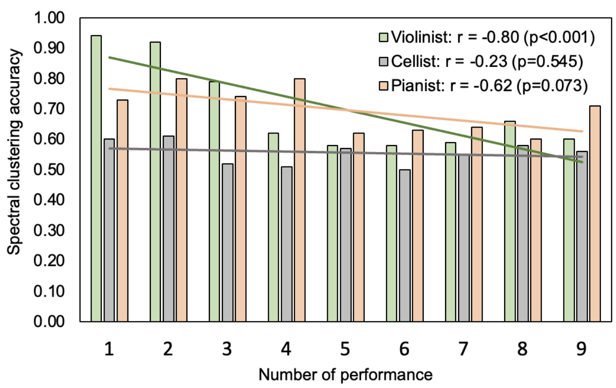


Figure 3: Accuracy of baseline-music categorisation via spectral clustering for each musician together with fitted line and correlation coefficients with the number of the performance.

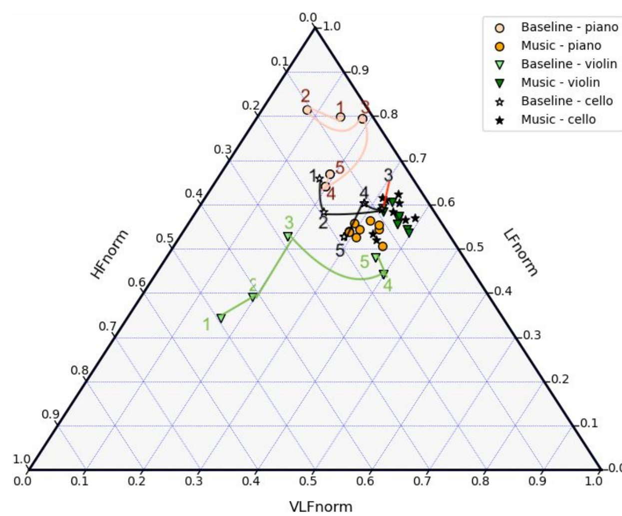


Figure 4: Averaged values (centroids) of data points from each rehearsal and for each performer's heart rate variability during baseline and music: pianist (orange circles), violinist (green triangles) and cellist (blue stars).

3. Results

Accuracy for each performance's clustering can be found in Figure 3. A strong negative correlation with the number of the rehearsal was observed for the violinist (Figure 2a), r = –0.80, $p \leq .01$, accuracy range: [0.64, 0.94], and pianist (Figure 2c), r = –0.62, p = .073, [0.64, 0.80] (non-significant correlation). On the other hand, a weakly negative, non-significant correlation was observed for the cellist (Figure 2b), r = –0.23, p = .545, [0.50, 0.61].

The simplex plot of aggregated performances, visualising the averaged values of the frequency components over all windows, is shown in Figure 4.

4. Discussion

Through visualising PS/HRV with the help of triangle simplex plots, we observed the distribution of the frequency components with respect to their reciprocal relationship. Simplex plots are a novel technique in computational cardiology research. We have demonstrated their usage in visualising and studying three frequency dependencies. In our examples, the simplex plots provided beneficial representations for spectral clustering, which allowed us to group the musicians' HRV data during baseline (silence) and during performance in rehearsal settings. The negative significant correlation between baseline and performance PS/HRV found for the violinist suggests that, over time, the difference between baseline and performance decreased. Figure 4 supports the clustering accuracy in Figure 3. While the centroids of the music periods are relatively similar over performance, the centroids for baseline shift, especially for the violinist, move closer to the performance centroids in later performances. This could be indicative of a learning effect or adaptation to repeating the task. However, this effect was non-significant for the pianist and imperceptible for the cellist, who had low clustering accuracy for all recordings. If learning and adaptation occurred at some parts but the cellist fared worse in others, noticeable effects might have been cancelled out. These results require further investigation.

The 2D plots, therefore, allow for tracking of the proportional changes in linked values between two or more states and for researchers to introduce other analysis methods, such as clustering and other machine learning techniques, for the classification of data points. Further, the ability to express data visually opens up ways to transform HRV classification problems to image recognition and computer vision tasks. Therefore, the visualisation enables alternate ways to efficiently view and analyse cardiac data.

5. Conclusion

We presented triangle simplex plots as a novel data visualisation tool for cardiac data. In an example study, we used simplex plots to inspect the balance of three power frequency components of heart rate variability for a trio of musicians. We examined the relationship between the components and applied spectral clustering to examine the musicians' data. The clustering on the simplex representation showed visible and quantifiable trends in the changes between baseline and performing over nine recordings. We found strong negative correlation in the clustering accuracy with the number of performance for the violinist and pianist. This suggests a reduced distinction in HRV measures between baseline and performance.

Simplex plots can be a useful research tool for assessing autonomic changes. They provide new avenues for utilising image classification techniques in cardiovascular research and exploring musical learning and decreasing stress in real-world tasks.

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Address for correspondence:

Dr. Mateusz Soliński
King's College London
1 Lambeth Palace Road
London, SE1 7EU
United Kingdom
mateusz.solinski@kcl.ac.uk

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