Analysis of Cerebral Blood Flow Complexity when Listening Music with Emotional Content

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ABSTRACT

Despite differences in ethnicity, culture, or language, music is a universal stimulus that can evoke intense feelings in people. Studying its effects, however, is challenging because of its emotional nature. This study analyzes the effects of listening different sound stimuli, such as music with emotional content, on cerebral hemodynamics. Cerebral blood flow signals were recorded for 16 subjects while performing five different music tasks. The complexity of each signal was estimated using multiscale Sample Entropy. Significant differences in mean complexity were found between two tasks, which suggests that intense cognitive activities having emotional content yielded a decrease in the complexity of cerebral hemodynamics.

Keywords: Complexity, Multiscale Entropy, Cerebral Blood Flow, Music, Hemodynamics, Sample Entropy.

1. INTRODUCTION

Studying emotions in human beings is both a complex and intriguing field, that includes a wide range of disciplines and several types of researches [1]. Among them, it is particularly interesting to explore different approaches that have been proposed to analyze the physiological contribution of music.

One study [14] analyzed Electroencephalogram (EEG) signals collected from 26 healthy subjects listening to different music using Support Vector Machine (SVM) classification to distinguish four emotions (joy, anger, sadness and pleasure) according to two-dimensional circumplex emotion model comprising valence (positive-negative) and arousal (high-low) axes.

Another study [15] also utilized EEG to compare the levels of signal complexity with the musical complexity that subjects were listening to. They were required to do two tasks: (i) closely track the acoustics (perceptual task) and (ii) think about how the music made them feel (emotional task). Multiscale entropy (MSE) was used to determine complexity matching (effectiveness of the brain to reflect the content of the environment information) between EEG and music signals.

There is another study [16] that examined audible EEG signals (transformation of EEG time series into an acoustic signal) recorded from subjects both in rest state and hearing music stimuli (tanpura drone) to analyze the correlation between both sounds using a microscope called Multifractal Detrended Cross-Correlation Analysis. Results showed there was a rise in correlation as the audio clip progressed and that music stimuli had the ability of activating many brain regions parallelly or in different moments.

There are several complementing investigations. In [3] the researchers asked subjects to listen to consonance and dissonance recordings while measuring their cerebral blood flow (CBF), using a positron emission tomography, to examine correlations between consonance levels and emotions, finding that music might engage neural mechanisms associated with pleasant or unpleasant emotional states. Research in [4] looked at the effects of musical experience on hemispheric lateralization using magnetoencephalography, whose results indicated that musical training changes the hemispheric roles for musical feature processing. Finally, the work in [10] sought changes in CBF velocity (CBFv), by using transcranial Doppler ultrasound, in response to emotional stimuli on healthy subjects.

Despite the above studies, there is a lack of research on the effects of music on cerebral hemodynamics. This is fundamentally due to limitations on the analysis of CBF signals, that usually is limited to the inspection of mean amplitude or spectral density, which have not provided clear results on differentiating emotional states. However, nowadays there are powerful tools that allow signal analysis from a complexity perspective that have found successful applications with biological data.

This study proposes that analyzing the hemodynamic response to different musical stimuli using a complexity estimator derived from MSE will properly differentiate between the emotional reactions they triggered.

2. BACKGROUND

Sample Entropy

Sample Entropy (SampEn) is a method for the estimation of the repeatability or predictability within a time series that has been used to characterize physiological signals from a number of imaging modalities.

SampEn definition considers $A_i^m(r)$ and $B_i^m(r)$ [5, 6]:

$$A_i^m(r) = \frac{1}{N-m-1}\sum_{j=1,j\neq i}^{N-m}\begin{bmatrix} numberof \times that \\ d[|x_{m+1}(j) - x_{m+1}(i)|] < r \end{bmatrix}$$
Eq. (1)

$$B_i^m(r) = \frac{1}{N-m-1}\sum_{j=1,j\neq i}^{N-m}\begin{bmatrix} numberof \times that \\ d[|x_m(j) - x_m(i)|] < r \end{bmatrix}$$
Eq. (2)

In which N specifies the number of observations, r is a tolerance value to filter noise, m is the pattern length, x_i and x_j are two blocks on time series of length N.

Then, the following expressions are presented:

$$A^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} A_i^m(r) \quad \text{Eq. (3)}$$

$$B^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} B_i^m(r) \quad \text{Eq. (4)}$$

Finally, SampEn is defined as:

$$SampEn(m,r) = \lim_{N\to\infty}\left\{-log\left[\frac{A^m(r)}{B^m(r)}\right]\right\} \quad \text{Eq. (5)}$$

The two parameters, namely the length of the segments to be compared (m) and the tolerance for accepting matches (r), are critical to the performance of MSE. As there are no definitive guidelines on how to choose their values [7], all combinations of (m, r) parameters will be analyzed as explained below.

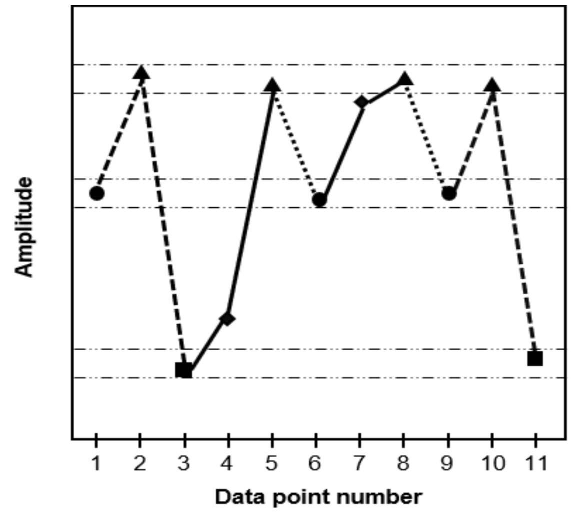

Fig. (1). Simple time series example with representations of the parameters used for SampEn calculation. Using pattern length m = 2, sequences of m and m + 1 (i.e., with length 2 and 3) are collected as templates. r value is represented as horizontal dotted lines around circular, triangular, and squared data points symbolizing points that match each other. Thus, the same sequences of length 2 are found between data points 1-2 and 9-10, 2-3 and 10-11, and 5-6 and 8-9. The same sequences of length 3 are found for data points 1-2-3 and 9-10-11.

The example signal of Fig. (1) will be used as a running example to explain the SampEn calculation.

First, sequences of length m and m + 1 are extracted from the signal. Two sequences are considered to be the same pattern if the values of each of their corresponding data points are within a distance ±r. In Fig. (1), for example, the sequence observed in data points 1-2 matches the sequence formed by data points 9-10. Analogously, sequences 2-3 and 5-6 can be matched to sequences 10-11 and 8-9 respectively. Similarity, the sequence of length 3 composed of data points 1-2-3 can be considered to be the same pattern as the sequence 9-10-11. The degree of repetition of these patterns can be used to assess the predictability or regularity of a signal.

SampEn is the negative natural logarithm of the conditional probability that two different sequences of length m with the same pattern remain similar at length m+1 [6]

Multiscale Entropy

MSE is a method to calculate entropy on complex signals, considering the multiple time scales inherent to biological systems [2].

Although MSE applies to many entropy measures, wherein this study SampEn is utilized.

MSE analysis comprise two steps. In the first step, several coarse-grained time series $\{y(\tau)\}$ are built from the original time series $\{x_1, \ldots, x_i, \ldots, x_n\}$ by averaging τ successive incremental number of points in non-overlapped windows, as shown in Fig. (2).

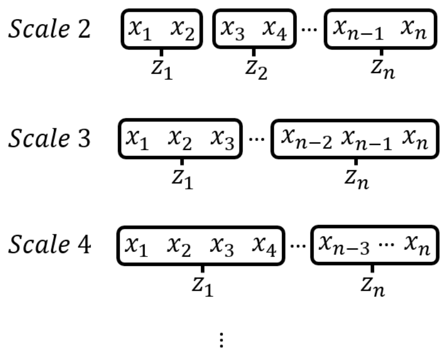

Fig. (2). Construction of coarse-grained time series of scale 2, 3 and 4.

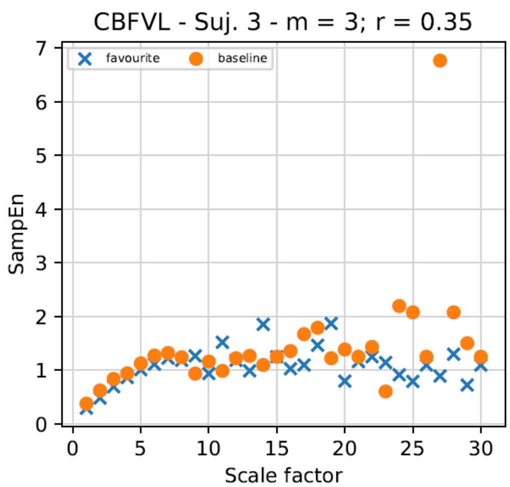

Fig. (3). Entropy signatures obtained using parameters (*m*=3, *r*=0.35) and scale factor $1 \leq \tau \leq 30$, calculated for the CBFv signals of Subject 3 recorded while listening to either baseline sound (blue crosses) and the favorite song. Thus, each element in the coarse-grained time series $y_j^{(\tau)}$ is calculated according to:

$$y_j^{(\tau)} = 1/\tau \sum_{i=(j-1)\tau+1}^{j\tau} x_i \qquad \text{Eq. (6)}$$

where τ corresponds to the scale factor and $1 \leq j \leq N/\tau$. For scale 1, the coarse-grained time series is the original one.

In the second step, an entropy measure is computed for each of the coarse-grained series and then plotted as a function of the scale factor τ to identify regular patterns and quantify its complexity. This plot, as shown in Fig. (3), is named entropy signature.

Complexity

The integral of the scale-dependent entropy values can be used as a complexity measure [9]. For comparison in this study, the area formed between the values 10 and 30 of the scale factor was utilized as the estimation of the complexity of a signal, as represented in Fig. [4]. The integral calculation was made using Simpson's rule.

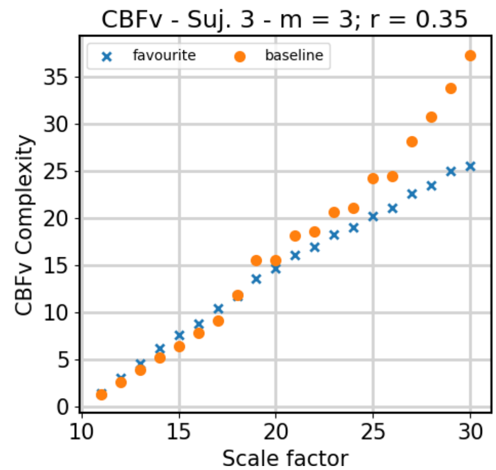

Fig. (4). Complexity estimation of the entropy signatures of Fig. (3) averaging hemispheres. Favorite song and base line tasks are shown.

3. SUBJECTS AND MEASUREMENTS

Subjects

Twenty-five healthy subjects (students, academic and administrative staff) were recruited for the study in the university campus and hospitals. Mean age was 30.2 ± 9.01 years old, ranging from 21 up to 57 years. Research was authorized by the University's Ethics Committee and each participant signed the corresponding written informed consent.

Subjects arrived at the biomedical laboratory of the Universidad de Santiago de Chile at 3:00 PM to do a single session of data capture.

Signals

Non-invasive recordings of CBFv signals were obtained from the bilateral middle cerebral arteries using a DWL Doppler Box system with 2 MHz transducers at a rate of 100 samples per second, while subjects laid supine with their head resting on a pillow at 30 degrees, wearing earphones. Arterial Blood pressure signals were recorded using a Finapres Finometer MIDI in the right middle finger, resampled at a 100 Hz. Preprocessing recommendations of Claassen *et al.* [11] were followed and 5 Hz beat-to-beat data were procured for the analysis.

Music Experiment

Volunteers were exposed to five different tasks:

- **Baseline sound**, in which the subjects listened to ambient noise with their eyes open.
- **Silence**, in which the volunteers wore headphones to block any sound.
- **Noise**, in which the participants heard white noise.
- **Arbitrary song**, in which the subjects listened to a randomly selected song without any meaning to them.
- **Favorite song**, in which the volunteers listened to a special song that had emotional positive content for them.

Except for baseline sound, all other tasks were performed with the subjects keeping their eyes closed and wearing good-quality headphones. Each task lasted 7 minutes and was selected to evaluate different kinds of reactions. Baseline sound is the control stimulus; silence is the simplest task and should not involve much sensory nor emotional brain activity; noise would produce mainly a sensory activation; arbitrary song ought to trigger music-modulated brain activity; and favorite song should add emotion processing. Music tasks were presented to the subjects in one randomly-chosen sequence out of 25 combinations selected from the 120 possible ones.

Parameter Selection

To select the correct range of the scale factor to calculate complexity, two 3-minute-long simulated surrogate time series were created; using 5% noise low-frequency (LF) sinusoidal signals, one medium (LFM) at 0.13 Hz and one high (LFH) at 0.15 Hz, with an amplitude of approximately 48 cm/s and sampled at 5 Hz. These surrogate signals were analyzed applying MSE with scale factor ranging from 1 to 70 and parameters $m = \{2, 3\}$ and $r = \{0.3, 0.35\}$.

Following the procedure described in [8], it was determined that the range of scale factor values that reflected temporal dynamical complexity was [10, 30]. This scale factor range was inspected using the method above to make sure that it complies with the coherence function presented in CARNet's White Paper [11]. Indeed, the coherence function shows noise outside the selected range, confirming the findings.

Statistics

When no significant difference in mean complexity between hemispheres was found (paired comparison), they were averaged for the subsequent analysis.

Repeated-measures ANOVA with Tukey's post-hoc analysis was used to differentiate mean complexity between the different tasks. Afterward, a receiver operating characteristic curve (ROC) was obtained for the pairs of tasks with higher differences. p-values less than 0.05 were considered statistically significant.

Both Python and R scripts were codified, to apply the MSE analysis and to perform the statistical analysis, respectively.

4. EXPERIMENTS AND RESULTS

From the pairs of 25 signals, 16 were selected; the rest had poor quality (due to a wrong installation of the device in a subject's head) and were discarded. Selected CBFv signals were averaged by hemispheres because no statistically differences were found between them.

Repeated measures ANOVA over parameters ($m = 3$, $r = 0.35$) resulted significant ($p = 0.010$) and Tukey's post-hoc analysis found a difference ($p = 0.040$) between favorite song and baseline sound. Fig. (5) summarizes the resulting complexity estimations for the 16 subjects, in which baseline sound exhibited the highest mean complexity value (50.07 ± 16.94) in contrast to favorite song that showed the lowest value (34.12 ± 11.71). Using these complexity values to discriminate between signals recorded in either of these two tasks, a ROC curve with an area under the curve (AUC) of 0.785 could be obtained, represented in Fig. (6). ROC threshold complexity value is 41.32 with both sensitivity and specificity of 0.81.

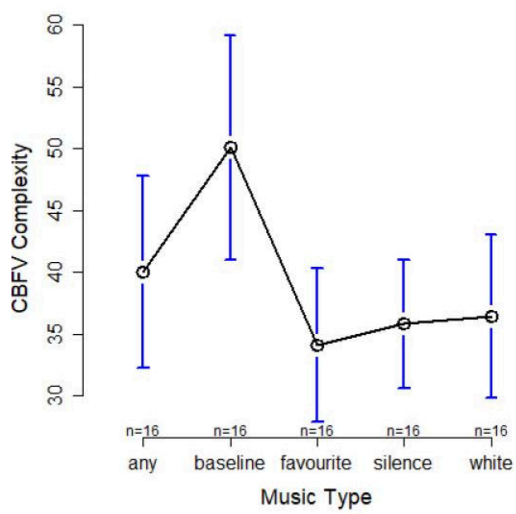

Fig. (5). Mean and confidence intervals of CBFv complexity estimations obtained with parameters ($m = 3$ and $r = 0.35$) in each task: arbitrary song (any), baseline sound (baseline), favorite song (favorite), silence and noise (white).

Inspecting confidence intervals in Fig. (5), shows that the lowest value in the baseline task was 41.03 while the highest value in favorite is 40.36, evidencing no overlapping between those tasks. Post-hoc analysis results are showed in Table 1.

	silence	favourite	any	white
baseline	p=.014	**p=.004**	p=.173	p=.022
white	p>.999	p=.986	p=.933	
any	p=.884	p=.688		
favourite	p=.996			

Table 1. Post-hoc analysis using Tukey alternative from a repeated measures ANOVA on complexity calculation with parameters m = 3 and r = 0.35. Lowest p-value is highlighted in bold.

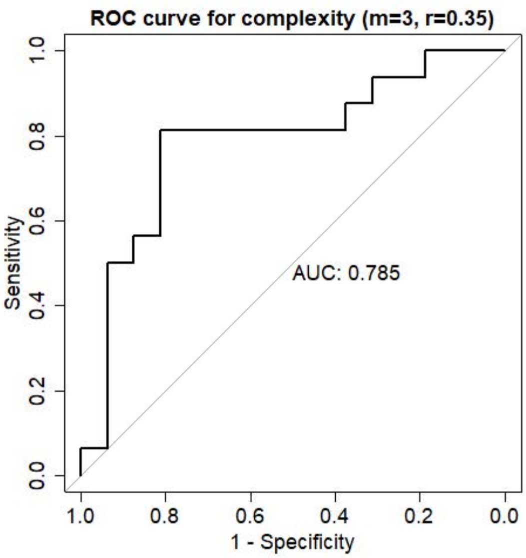

Fig. (6). ROC curve and AUC archived when differentiating baseline sound and favorite song recordings using MSE-derived complexity estimations.

5. DISCUSSIONS

Using the two sinusoidal signals [8] and coherence function [11] whose frequencies are known to be in the range of CBF regulation, between 0.13 Hz and 0.15 Hz, it was possible to determine that they clearly manifested temporal complexity for scale factor valued between 10 and 30. Responses on scale factor values after 30 represented noise. Hence, this range was used to calculate MSE-derived complexity estimations.

Fig. (3) showed an example of an MSE signature for a representative subject, with parameters (m = 3 and r = 0.35), for the (left hemisphere) CBFv signal recorded during baseline sound and when listening to a favorite song. SampEn grows more rapidly for baseline sound than for the favorite song. From this plot, a complexity value was gauged for each series as the area under the multiscale SampEn curve [9] in the higher time scales ($10 \leq \tau \leq 30$), as presented in Fig. (4).

Fig. (4) shows a noticeable difference in complexity between the tasks that registered the lowest and highest complexity values. Although both tasks increased entropy in each scale, baseline rise was faster.

Moreover, it is interesting to observe that higher complexity values are found when the mind is in a base state and subjects' thoughts manifest freely, in contrast to listening to favorite song, which leads to a decrease in the complexity of the CBFv signal.

These results are consistent with studies that link cognitive charge and cerebral hemodynamics (neurovascular coupling) [12, 13]. Works that studied the relation of music and complexity through EEG also showed associations between music with emotional content and signal complexity [14, 15], although the sense of these connections is not as clear as shown in this study.

In Fig. (5), the graphical results of the applied repeated measures ANOVA can be seen for the five tasks showing mean and confidence intervals. It is evident that the largest complexity difference exists between baseline sound and favorite song. This difference could be used effectively to discriminate the responses to those tasks as showed in the ROC curve of Fig. (6) that reached an AUC of 0.79.

Complexity measures derived from MSE signatures showed noticeable classification power when applied to CBFv signals recorded under the different tasks. Larger differences were observed between time series captured at baseline sound and during the playback of a song with emotional content. Moreover, listening to a favorite song yielded the lowest complexity value, which is consistent with the idea that more strenuous cognitive activity might induce some complexity-loss in the cerebral hemodynamics.

6. CONCLUSIONS

Multiscale entropy analysis applied to cerebral hemodynamics is a novel research topic with satisfactory results on signal characterization using different music stimuli and extracting a complexity estimation for each one of them.

This research opens the possibility of undertaking studies on the action of the mechanisms that control CBF when responding to strong emotions in a wide range of applications.

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