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DOI
10.1145/3570991.3571029

Publication date
2023

Document Version
Final published version

Published in
CODS-COMAD 2023 - Proceedings of the 6th Joint International Conference on Data Science and Management of Data (10th ACM IKDD CODS and 28th COMAD

Predicting drum beats from high-density Brain Rhythms

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ABSTRACT

Entrainment is a phenomenon of phase or temporal matching of one system with that of another system. Human neural activity has been shown to resonate with external auditory stimuli. When we enjoy a piece of music, there is a resonance of brain responses with auditory signals. The crux of music cognition is based on this resonance of musical frequencies with intrinsic neural frequencies. It has also been demonstrated that the neural activities are synchronized across participants while listening to music, shown by high inter-subject correlation. In this work, we use this fact to predict the drumbeat a participant listens to based on their EEG response to the drumbeat. We also tested whether we could train on a smaller dataset and test with the rest of the dataset. We generated a frequency * channel plot and fed it to a CNN model to predict drumbeat with a classification accuracy of 97% for 60-20-20 (train-dev-test) data split protocol and 94% accuracy for 20-20-60 data split. We also got 100% classification accuracy for predicting participants for both the data split protocols.

CCS CONCEPTS

• **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

KEYWORDS

Music, Drumbeats, CNN, Classification, Music Information Retrieval, EEG

ACM Reference Format:

Shivam Chaudhary, Krishna Prasad Miyapuram, and Derek Lomas. 2023. Predicting drum beats from high-density Brain Rhythms. In *6th Joint International Conference on Data Science & Management of Data (10th ACM IKDD CODS and 28th COMAD) (CODS-COMAD 2023), January 4–7, 2023, Mumbai, India.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3570991.3571029

1 INTRODUCTION

It is not uncommon for us to tap our fingers or foot and swivel our heads to the beats of our favorite music. This is due to the phenomenon known as resonance. *Resonance* is defined as the temporal matching of processes of one system with that of the other system [6]. Past research has shown that human neural activity resonates with external auditory stimuli [7]. Human behavioral cues of resonance are finger tapping, head moving, etc., which tells us there is a synchronization between the auditory stimulus and neural response. Music is a complex stimulus, and it is characterized by features such as melody, pitch, harmony, etc. Music Information Retrieval (MIR) as a field has been able to extract such features and see the effect of these features on these neural responses [4].

The scientific literature has well documented that when we are familiar with the music we listen to, our brain entrains or resonates with the beats of the music. This work contributes to the increasing research on naturalistic stimuli, in our case, drum beats. To the best of our knowledge, this is a novel study where brain responses to different drum beats are analyzed.

2 RELATED WORKS

Many researchers are working on finding the relationship between musical beats/rhythms and the corresponding response of the brain activity, increasing the body of work in Music Information Retrieval (MIR). In an EEG study conducted by Kaneshiro et al. [2], they played naturalistic and distorted music to the participants. Even though the pleasantness rating was high for natural music, measure-shuffled versions of the music have higher time-domain correlations with the brain response.

Pandey et al. [4] observed that each song had various beats but had one dominant beat. They then divided the 12 songs into three groups of beats. They then applied spatial filtering techniques: mean across electrodes and principal components. They passed these features through machine learning classifiers. They achieved accuracies of 70% and 56% for binary and ternary classification, respectively.

In another research by Sonawane et al. [5], they used various convolutional neural network (CNN) architectures to classify what song the person was listening to (out of 12) using EEG signals. They obtained 94.2% classification accuracy on the data of 20 participants.

3 METHODOLOGY

3.1 Stimuli Selection and Experimental Design

The drumbeats are based on Shamanic beats that were electronically modified, having varied tempos and base beats. We trimmed 30-second excerpts from drum beats since the smallest drum beat was of 30 seconds totaling 13 beats. As a control, we created a beat with an average of all beats. We made a second control beat which was the reverse of the average of all beats, giving us 15 beats.

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CODS-COMAD 2023, January 4–7, 2023, Mumbai, India

ACM ISBN 978-1-4503-9797-1/23/01.
https://doi.org/10.1145/3570991.3571029

We asked the participants to listen to 15 drum beats twice in a dimly lit room. They were asked to focus on a white cross for 10 seconds followed by drum beat listening for 30 seconds. This was followed by a behavioral rating where they responded to how pleasant they found the drumbeat to be on a scale of 1 to 9.

3.2 Experimental Setup

We used a combination of open-source softwares to create a data collection pipeline that synchronizes the EEG data with events such as drumbeat start time, end time, beat name, and behavioral rating. We presented the songs on stimulus presentation software PsychoPy, sent and synchronized event markers using LabStreamingLayer (LSL) [3], and visually inspected and collected data using NeuroPype. We used the 64-channel Hydrocel Geodesic Sensor Net (HCGSN) by EGI to capture EEG signals. The stimuli were played through Kardon Harman speakers. The data pipeline is shown in figure 1.

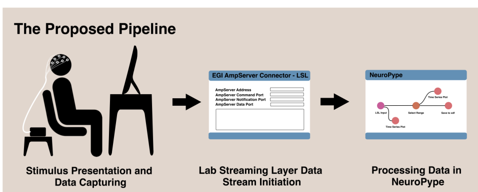

Figure 1: Data flow pipeline.

3.3 Dataset Description

The dataset consists of EEG data collected from 17 participants (8 Males and 9 Females) in the range of 20 to 27 years of age (mean 23) at the Indian Institute of Technology Gandhinagar. The EEG data were collected using Hydrocel Geodesic Sensor Net (HCGSN) by EGIs 64-channel EEG caps. The data is sampled at 1000Hz. Each participant listened to each of the 15 drumbeats twice. The raw data file has a marker stream denoting each event's time. The raw data in extensible data format (xdf) is available publicly on OSF.

3.4 Data cleaning and analysis

We used EEGLAB [1] to pre-process the data which included a band-pass filter from 0.1 Hz to 45 Hz. After the pre-processing step, we split the data according to the trials and subjects to get the EEG data of different beats. We used the *spectopo* function of EEGLAB to get the spectrogram of different channels for 65 samples at a time. Using this method, we got approximately 238000 examples of training the classifier. We split the samples into train-dev-test sets to perform the classification. We then passed these samples (238156, 64, 65, 1) through a convolutional neural network (CNN) to classify drum beats from neural responses, as shown in figure 2.

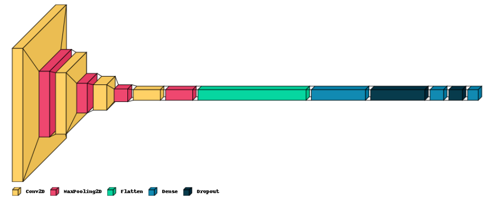

Figure 2: Convolutional Neural Network (CNN) architecture.

Table 1: Classification results

Classification	Data Split (train-dev-test)	Accuracy
Participant	60-20-20	100%
Participant	20-20-60	100%
Drumbeat	60-20-20	97%
Drumbeat	20-20-60	94%

4 RESULTS

We analyzed the dataset by classifying the drumbeats and participants from the neural responses for two data split protocols. In the first split, our data is divided as 60-20-20 for the train-dev-test. We classified the drumbeats the participants were listening to with an accuracy of 97%, and we recognized the participants with an accuracy of 100%. In the second split, our data was divided as 20-20-60 for the train-dev-test. We achieved a classification accuracy of 100% for participant classification and an accuracy of 94% for drumbeat classification.

5 DISCUSSION AND CONCLUSION

It is fascinating to note that the neural responses of different participants are different for the same drum beat. Nevertheless, our model successfully generalized the neural responses to the drumbeats of various participants and classified which drum beat was being listened to with high classification accuracy—indicating that there are latent features in brain responses common to all participants. Accuracy serves as a quantitative measure of the similarity and differences in participants' responses to repetitive naturalistic stimuli. In the future, we plan on quantifying the correlation of music with EEG signals and checking whether we get a high correlation with beats with a high pleasantness rating.

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