Peer-Reviewed Structured Abstract

Emotion Analysis using Spiking Neural Networks

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Summary

Emotion analysis is a prominent research area gaining popularity as more researchers are trying to solve questions in fields that require intensive study of emotions like psychology, human-computer interactions, and affective computing. Music can be used as a tool to identify emotions. NeuCube is a software that considers spatio-temporal data as input and analyzes brain patterns using various encoding, mapping, supervised and unsupervised learning, modelling, network analysis, classification, and optimization techniques. This study used the MUSIN-G dataset to classify the positive emotion 'enjoyment' in healthy participants, employing spiking neural networks with the deSNN classifier and k-fold cross-validation. An accuracy of 83.33% for enjoyment was achieved, with the study identifying stronger connections in brain regions such as AF3, P8, and FC6. Additionally, higher activation levels were observed in the frontal regions, specifically AF3, AF4, and F3. These findings highlight that frontal brain regions process positive emotions.

Background

Emotions are important in daily human communication and are often linked to feelings and moods [1]. Music profoundly impacts human emotions, which can be determined using EEG signals. Traditional machine learning algorithms like fuzzy logic, Random Forest, SVM, etc. use only the spatial data of the EEG signals without taking into consideration the temporal data. In contrast, Spiking Neural Networks (SNN) take into consideration both the spatial and temporal data of the EEG signals. Analyzing spatial data can be used to study localized brain functions or dysfunctions by identifying activity from specific brain regions responsible for particular cognitive or emotional processes. Similarly, analyzing temporal data can be used to understand brain activity in real-time, such as tracking rapid changes in the brain's response to stimuli, cognitive tasks, or emotions. Taking both dimensions into consideration can help understand the different regions that are responsible for the positive emotions occurring in the brain when listening to music and the actions that humans take as a result of it.

Methodology

A) Dataset

The data was acquired from openneuro.org, which is an open-source Music Listening-Genre (MUSIN-G) EEG dataset created by the Indian Institute of Technology, Gandhinagar (IITGN), Gujarat, India [2].

B) Methodology

1) Encoding and Mapping of EEG Data: NeuCube software encodes EEG signals using the threshold representation (TBR) algorithm, where changes in the EEG signals that cross the

threshold are represented by spike trains [3], which are then mapped onto the 3D SNN reservoir.

2) Unsupervised Learning: Spike time-dependent plasticity (STDP), based on Hebbian' s theory, is used for unsupervised learning [4]. Training parameters, including potential leak rate, firing threshold, refractory time, STDP rate, training iterations, and long-distance connectivity (LDC) probability, are set to default values in this study.

3) Supervised Learning: The dynamic evolving SNN (deSNN) is used for supervised learning, with default parameters such as mod, drift, K, and sigma [5]. Classification is performed using k-fold cross-validation.

4) Visualization: Visualization settings include adjusting the visual type, visual content, and threshold. Options like show connection, activation level, spikes emitted, neuron width, spike raster, and spike activity playback can be selected based on analysis needs.

5) Network Analysis: The network analysis tool provides options for clustering, interaction, and information route analysis, with customizable hyper-parameters for each method.

C) Experimental Design

The dataset used in this study comprises EEG data from 12 participants (the first 12 samples), all healthy individuals between the ages of 22 and 28, including both males and females. The emotion classified is enjoyment, a positive emotion, with no negative emotion data present in the dataset. One second of the EEG signal is considered and sampled at 128 Hz. All EEG datasets share the same spatio-temporal dimensions, and the channels selected for analysis are AF3, AF4, F7, F3, F4, F8, FC5, FC6, T7, T8, P9, P8, O1, and O2.

Results and Observations

After unsupervised learning via STDP, the cube was visualized to show spatio-temporal connections between EEG channels and brain regions. Higher connectivity is seen in the AF3 (frontal), P8 (parietal), and FC6 (frontocentral) regions, confirming that positive emotions like enjoyment are concentrated in the frontal area as seen in Fig. 1.

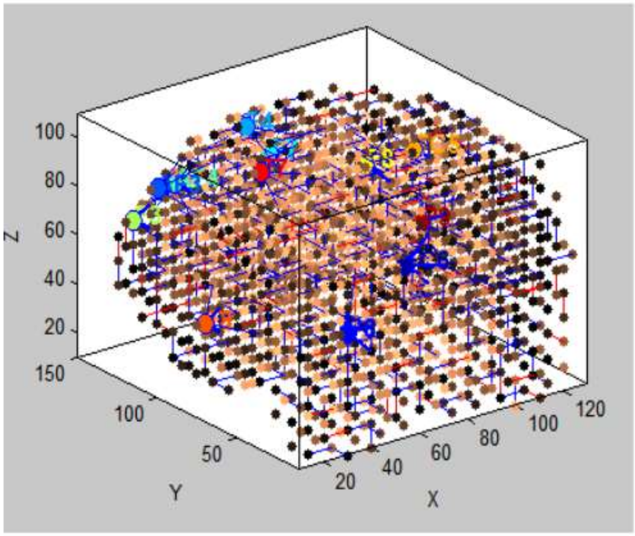

Fig. 1. Connectivity of neurons after STDP learning

Similarly, the activation level begins at AF3, AF4, and F3, further supporting this as shown in Fig. 2.

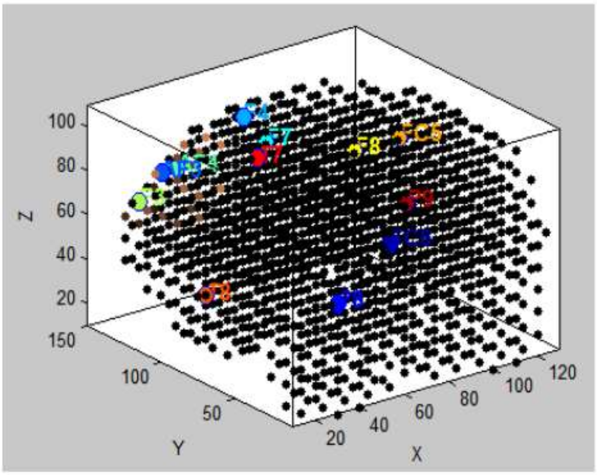

Fig. 2. Activation level

This was also confirmed by [6] and [7], where it was mentioned that positive emotions are concentrated in the frontal regions. In [7], the frontal electrodes were taken into consideration, such as F3, F4, Fp1, and Fp2, for valence emotion, which is a positive emotion. Through information route analysis, which is a Network Analysis feature, AF3, AF4, and F3 are the top neurons for spike gradients, consistent with activation patterns. DeSNN does supervised learning, and classification is carried out by k-fold cross-validation, achieving an accuracy of 83.33% for enjoyment emotion. In [8], the accuracy obtained was 74%, 78%, 80%, and 86.72% for emotions like arousal, valence, dominance, and liking (positive emotions) using the DEAP dataset (which is closer to the proposed method), and for the SEED dataset, the overall accuracy was 96.67% for positive and neutral emotions, whereas in [6], the overall accuracy obtained was 94.83% for positive and negative emotions, and in [7], the overall accuracy was 68.91% for valence emotion. From the varied results, it is understood that it is quite difficult to compare the accuracy results because the methodology, the dataset, and the features used are quite different with each study.

Conclusion

To conclude, the dataset was classified using the deSNN classifier, and cross-fold validation was applied. The SNN cube was visualized using various methodologies, and the results were interpreted. It was found that positive emotions were mainly concentrated in the frontal regions of the brain.

Future research could use music videos and virtual reality (VR) to provide a real-life experience, allowing for brain signal recording and comparative studies, such as how people respond and feel emotionally when they look at a video versus when they experience it through VR. Such findings could enhance music therapy and recommendations, address real-time problems, and improve emotional responses to different scenarios.

Acknowledgement

I want to acknowledge Knowledge Engineering and Discovery Research Innovation (KEDRI at Auckland University of Technology for the NeuCube software and for allowing the students to use this product, as it would help them gain experience in real-world applications.

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