IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received January 29, 2020, accepted February 26, 2020, date of publication March 4, 2020, date of current version March 16, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2978163

EEG-Based Emotion Classification Using Spiking Neural Networks

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This work was supported in part by the National Natural Science Foundation of China under Grant 61976063 and Grant 61762018, in part by the Guangxi Natural Science Foundation under Grant 2017GXNSFAA198180, in part by the Overseas 100 Talents Program of Guangxi Higher Education under Grant F-KA16035 and Grant F-KA16016, in part by the Colleges and Universities Key Laboratory of Intelligent Integrated Automation, Guilin University of Electronic Technology, China, under Grant GXZDSY2016-03, and in part by the Research Fund of Guangxi Key Lab of Multi-Source Information Mining and Security under Grant 18-A-02-02. The work of Guopei Wu was supported in part by the Innovation Project of Guangxi Graduate Education under Grant YCSW2020.

ABSTRACT A novel method of using the spiking neural networks (SNNs) and the electroencephalograph (EEG) processing techniques to recognize emotion states is proposed in this paper. Three algorithms including discrete wavelet transform (DWT), variance and fast Fourier transform (FFT) are employed to extract the EEG signals, which are further taken by the SNN for the emotion classification. Two datasets, i.e., DEAP and SEED, are used to validate the proposed method. For the former dataset, the emotional states include arousal, valence, dominance and liking where each state is denoted as either high or low status. For the latter dataset, the emotional states are divided into three categories (negative, positive and neutral). Experimental results show that by using the variance data processing technique and SNN, the emotion states of arousal, valence, dominance and liking can be classified with accuracies of 74%, 78%, 80% and 86.27% for the DEAP dataset, and an overall accuracy is 96.67% for the SEED dataset, which outperform the FFT and DWT processing methods. In the meantime, this work achieves a better emotion classification performance than the benchmarking approaches, and also demonstrates the advantages of using SNN for the emotion state classifications.

INDEX TERMS Emotion classification, spiking neural network, EEG signal.

I. INTRODUCTION

In the emotion research field, one target is to accurately and quickly detect the emotional states as this can be used to help implementing several applications, e.g. emotional recognition system for mobile application [1]. There are two categories signals used for recognizing emotion: The first category focuses on the analysis of non-physiological signals, e.g., speech and facial expressions [2]–[4]. However sometimes these signals cannot fully reflect the real emotional states. The other category focuses on physiological signals, for instance electrocardiogram (ECG), electroencephalograph (EEG), skin conductance (SC) etc. [5]. Compared to the former, the latter can provide more accurate and detailed information to help estimating emotional states, moreover, the EEG signal is captured non-invasively from the brain, and as a result it is selected for emotion recognitions in this study.

Emotion states for the classification tasks are usually divided into several classes, mainly due to their limited features, high signal noise etc. [6], [7]. Accordingly, to address these problems, the EEG feature selection becomes crucial for the emotion recognition. Many methods are used for feature extraction, where suitable features and electrode location selections are usually on the basis of the outputs of neuro-scientific research [8]. Features can be distinguished into time, frequency, mixed time-frequency domains, and/or by using other nonlinear dynamic methods [9]. In this paper,

The associate editor coordinating the review of this manuscript and approving it for publication was Vivek Kumar Sehgal.

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several different methods are used to pre-process the EEG data, and the accuracy of emotion recognition using these different methods are provided. Once the pretreatment of the EEG data is completed, the pre-processed data can be used to classify emotion. Conventional methods of machine learning, e.g. fuzzy logic [10], multi-layer perceptron (MLP) [11], hidden Markov models [12] and support vector machine (SVM) [13], have also been previously investigated. These classifiers can only process spatial data without considering the temporal relations of the data. However, the EEG data is spatio-temporal, a better performance for emotion recognition can probably be achieved if considering the spatial information and the temporal information of the EEG data during the processing. Most of the current research focuses on the feature extraction of EEG data and the improvement of classifiers [14]. This paper chooses EEG data by calculating variance and identifies it with SNN. The main idea of the paper is to build a sipiking neural network (SNN) and employ the temporal and spatial characteristics of SNN for recognizing the EEG data. Compared to other research works [14], the aim of this paper is to build a spiking neural network (SNN) and employ the temporal and spatial characteristics of SNN for recognizing the EEG data. It allows spatial and temporal neuroinformatic data to be encoded with synapse and neuron locations as well as timing of the spiking activities [15]–[17]. In particular, the SNN considers the sequence order of the EEG data which can greatly help the recognition results. The classification results show that 74∼86% and 96.67% accuracies for different datasets can be achieved by the proposed method, which are superior in effect than the benchmarks.

The remaining part of this paper is organized as follows: The EEG datasets that are used in this study are introduced in Section II which also illustrates the basic principle how the SNN is used to recognize emotions. Section III describes the methods of extracting the EEG features. The emotion classification using the SNN is discoursed in Section IV. Section V provides the experimental results and gives the performance analysis. Section VII provides the discussion, and the conclusion and future work is presented in Section VIII.

II. EEG DATASET AND SPIKING NEURAL NETWORKS

A multimodal dataset using physiological signals for emotion analysis (DEAP) [18] and Shanghai Jiao Tong University emotion EEG dataset (SEED) [19] are used in this paper. These datasets recorded the EEG data at different sampling rates of 512 Hz and 1000 Hz, respectively, and the international 10-20 system was referred to place electrodes on the scalp. Section II-A will give a detailed introduction for these datasets, and Section II-B will discuss the advantages of using SNN for the spatio-temporal EEG data processing.

A. DATASETS

EEG signal is frequently employed for the human emotion assessment. EEG signal is different to other signals, as it is a non-invasive practical method and it is able to accurately reflect the ‘‘inner’’ emotion of human. Thus, the EEG signal can be used for emotion classfication directly from the brain [20].

1) DEAP DATASET

In the DEAP dataset, the movies were used as emotion elicitors in the experiments. Movie is one of the most impactful ways to trigger emotions because it includes dynamic audio and visual stimuli [21]. There are over 32 participants included in the dataset, and the age is between 19 and 37 with an average of 26.9 years. Half of the participants are female [18]. All participants followed the same instructions. Participants are seated one meter from the screen. EEG signals are recorded at 512Hz sampling rates by using the uniform equipment.

The DEAP is a multimodal dataset and it is used for analysis of human affective states. Forty clips of selected music videos were used to trigger emotions. Meanwhile, central nervous system activity, peripheral physiological signals and facial expression were recorded. In the final of each video, experiment asks participants to do self-assessments of arousal, valence, liking and dominance levels. A stimuli selection method was used to collect videos from a set of music video clips followed by a subject test to choose the most suitable test material. According to the description of the dataset, the experiment selected stimuli in several steps. First, 120 initial stimuli were selected by semi-automatically and manually, where 60 of 120 stimuli were chosen manually and the rest semi-automatically. Second, a one-minute highlight was determined for each stimulus. In the end, the final 40 stimuli were selected by a web-based subjective assessment experiment.. A total of 32 active electrodes were selected to collect the EEG data. Other peripheral physiological signals include electromyography, electro-oculogram, blood volume pulse which were gathered based on skin temperature, plethysmograph and galvanic skin responses. The face videos were collected from 22 participants [18], [22].

During the experiment, we use participants' ratings as a baseline to create four binary classifications, namely, classifications of low or high levels for arousal, valence, liking and dominance. The scale ranges of three labels (i.e. arousal, valence and dominance) are from calm (or bored) to stimulated (or excited), unhappy (or sad) to happy (or joyful), submissive (or without control) to dominance (or empowered), respectively. The liking scale is based on the subjects' personal liking of music video, which is different from the valence scale. It is based on the sensing, not feelings. For instance, the participant may like videos that are recorded sad or angry. The self-assessment rating scale ranges are from 1 to 9. Therefore the ratings of subjects are divided into two categories (low or high) by a stable threshold which selected as 4.5. The pre-processed EEG signals in the DEAP dataset are down sampled to 128 Hz. A band pass filter with a cut-off frequency of 4-45 Hz is applied.

2) SEED DATASET

The SEED dataset [19] is also used in this work. The 15 participants' EEG data were collected while they were watching emotional films. With an interval of about one week, three experiments were performed by each participant. The SEED dataset contains totally 45 experiments. An equipment with sampling rate of 1000Hz from 62-channel is used to collected the EEG data according to the international 10-20 system.

For the fair comparison with existing works, the same pre-processed data is used for the performance analysis. The data is down sampled to 200Hz. A filter of band pass frequency from 0-75Hz is applied. The EEG sections are extracted accompanying to the length of each movie. The data file for each subject includes 16 arrays, where 15 arrays include pre-processed segmental 15 test EEG data in one experiment. A label array contains the corresponding emotional labels (1 for positive, 2 for negative and 3 for neutral).

B. SPIKING NEURAL NETWORKS

A brief introduction for the SNNs is given in this subsection. To measure brain responses to external stimuli, the spatial and temporal brain data (STBD) are usually collected. However, current approaches lack of time series data analysis capability and the performance can be further improved, and existing SNN based techniques only use one learning algorithm (supervised or unsupervised) during the training period. In order to learn the EEG data in both supervised and unsupervised ways, the SNN model is used in this work. Therefore, a new scheme to process the STBD is required. This paper argues that the SNNs are suitable for the learning and understanding of EEG data.

An SNN is composed of spiking neurons that substantial amounts of information can be transmitted and received through the relative timing of spikes [23]–[25]. This property of an SNN is particularly suitable for the applications where the timing of input signals carries important information. It has been shown that the SNN can be applied to problems that can be solved by non-spiking neural networks and more importantly, the SNN is more powerful than conventional neural networks [16].

Due to the fact that EEG signals include temporal and spatial information, SNNs are more suitable for processing the spatio-temporal data and time series data compared to conventional methods [16]. For example in the approach of [26], SNN is employed to classify the movement task using electromyography (EMG). The experimental results show that the SNN is more effective for EMG signal recognition than conventionally used machine learning methods. In the approach of [15], an SNN is used to model and recognize complex EEG data that are related to physical and imagined movements. Therefore the SNNs is applicable to perform EEG-based emotion classification, and this paper will explore this potential.

The detailed information of the EEG dataset and the SNN were discussed in this section. The EEG signals include significant temporal and spatial information. However, not all of the information is related to the emotional state. Therefore, it is necessary to pre-process the EEG signals to acquire an accurate measure of emotional state which will be presented in the next section.

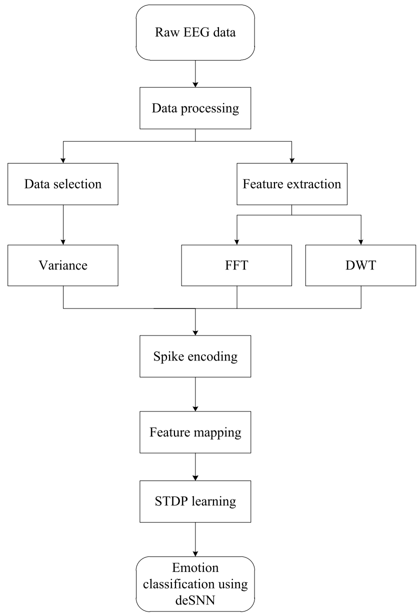

FIGURE 1. Emotion recognition procedure.

III. METHODS OF EEG SIGNAL PROCESSING

The emotion recognition procedure comprises the three stages: data processing, feature extraction and classification, as shown by Fig.1. For the sake of investigating the correlations in the interval of the participants' ratings and the EEG data, the raw DEAP data is down sampled to 128 Hz and band pass filtered with a cut-off frequency of 4-45 Hz using the EEGlab toolbox [27] in data processing step. The approach from Murugappan *et al.*, [28] uses three frequency bands (i.e. alpha, beta and gamma bands) for their work. However, the frequency of 4-45 Hz includes four frequency bands (i.e. theta, alpha, beta and gamma bands) of EEG signal to extract features. In this work, the theta band is also used. Different bands correspond to different physiological states of the participants. For instance, alpha band is the main manifestation of cerebral cortex in awake and quiet state. The theta wave is recorded in the inhibition (or sleepiness) state of central nervous system. Therefore, it can get more effective information by using more frequency bands, which can improve the classification performance. Then pre-processed data are divided into 60-second trails, where a pre-trial baseline of 3 seconds is removed. The rest 60-second data are processed in the third stage. The second stage mainly refers to this process in Fig. 1. The SEED dataset is down sampled to 200Hz and a filter of band pass frequency from 0-75Hz is applied. It also contains four frequency bands.

In the next step, the feature of pre-processed data is extracted. In this section, several methods for the EEG signal feature extraction are proposed. Feature extraction data of DEAP dataset contains 32 participants, where each participant corresponds to a file. The amount of data for each file is $40 \times 32 \times 8064$ ($video/trial \times channel \times data$) bytes. Feature extraction data of the SEED dataset contains 15 participants, where each participant corresponds to three files. The methods of feature extraction is on the basis of time, frequency and time-frequency domains in this study.

The variance is selected for the time domain analysis method in this study. Firstly, the mean of EEG signal needs to be calculated which is given by

$$\mu_\xi = \frac{\xi(t_1) + \xi(t_2) + \ldots + \xi(t_T)}{T} = \frac{\sum_{i=1}^{T} \xi(t_i)}{T}, \quad (1)$$

where t means the time of sample, T means the total time, $\xi(t)$ means the value of EEG signal at time t. The variance method with different sliding windows are used for selecting data. The variance of every row sample and the variance of the different sliding time window are calculated. Finally, the data corresponding to the time window with small variance are selected as the target data. The aim of calculating the variance is to select the signal with a low variance (i.e. a small fluctuation range). Therefore, the variance of the raw EEG signal is calculated. It can be considered that the current moment has been stable in an emotional state, which can make the selected data easy to identify.

Then the variance of the raw EEG signal is defined as

$$\upsilon_\xi = \frac{1}{T} \sum_{t=1}^{T} (\xi(t) - \mu_\xi)^2, \quad (2)$$

The sliding time window is used to select and process the EEG data. Taking into account the amount of data, the lengths of the time windows are selected as 1s, 2s and 3s respectively. We choose these time windows based on the attention mechanism [29]. Studies have shown that the average human attention span is 12s in 2000 and 8s in 2013. In the meantime, we use the sliding time window for the classification where these time windows give fine-grained result and can be used for further decision marking. The data of these time windows is sufficient to reflect the emotional state and make the issues tractable.

The fast Fourier transform (FFT) is selected for the frequency domain processing in this paper. The FFT is used to calculate the discrete Fourier transform (DFT), which is selected as an example method in the frequency domain. The calculation of DFT is given by

$$\xi(k) = DFT[\xi(n)] = \sum_{n=1}^{N-1} \xi(n) W_N^{n\,k}, \quad (3)$$

where $W_N^{n\,k} = e^{-j\frac{2\pi}{N}nk}$. According to the Nyquist theory, the maximum frequency (f_{max}) that can be measured is given by

$$f_{max} = \frac{f_s}{2}, \quad (4)$$

where f_s is the sampling frequency. The frequency composition is continuous, and the exact reproduction of the signal requires all frequency components.

As the EEG signal possesses non-stationary characteristics, a time-frequency domain analysis method can give more information by considering dynamic characteristics. The DWT method is selected to decompose the EEG data into different approximations and the detailed levels (both of them correspond to frequency ranges). The non-stationary characteristic of EEG signals allows them to be expanded onto basis functions created by expanding, contracting and shifting a single prototype function ($\psi_{a,b}$, the mother wavelet) [28]. The filtering methods of signal include low pass filter and high pass filter. The low pass filter can be described by

$$f_l(k) = \sum\nolimits_n s(n)g(2k - n), \quad (5)$$

where $s(n)$ is the input signal. The high pass filter can be described by

$$f_h(k) = \sum\nolimits_n s(n)h(2k - n). \quad (6)$$

The DWT can be calculated by

$$W_x(c, d) = \int s(t)\overline{\frac{1}{\sqrt{2^c}}\psi(\frac{t}{\sqrt{2^c}} - d)}dt, \quad (7)$$

where $c, d \in \mathbb{R}$, $c > 0$, and $\mathbb{R}$ represents the wavelet space. The scaling and shifting factors are presented by parameters c and d, respectively. The only limitation for choosing a prototype function as a mother wavelet is to satisfy the admissibility condition which is given by

$$C_\psi = \int_{-\infty}^{\infty} \frac{|\psi(\omega)|^2}{\omega} d\omega < \infty, \quad (8)$$

where $\psi(\omega)$ is the Fourier transform of $\psi_{c,d}(t)$. In our study, the EEG data uses the ''db4'' wavelet function to decompose into four levels. The ''db4'' wavelet can accurately detect short time information and fast transient signals. Due to the properties of near optimal time-frequency localization, it is used in this work. Therefore, using this method to extract features of the EEG data is far more likely to be successful [28].

Three methods for the EEG signals processing, i.e., variance, FFT and DWT, are explained in this section. They are on the basis of the time, frequency and time-frequency domains, respectively. The post-processed EEG signals are then used as inputs to the SNN for emotion classification, which will be presented in the next section.

IV. EMOTION CLASSIFICATION USING THE SNN

The SNN is employed to classify emotion states for the processed EEG signals. As the EEG signal is a spatial-temporal pattern that needs to be learned, classified and predicted [30], a temporal encoding rule is used for the SNN, which allows to learn the temporal relationships of the input signals.

A model based on SNN architecture named NeuCube [31] is used to classify emotion in this study. The NeuCube SNN architecture is comprised of three principal parts: input module for encoding, the 3D SNNcube and evolving SNN classifier. Temporal coding that considers information as temporally significant is used to encode information

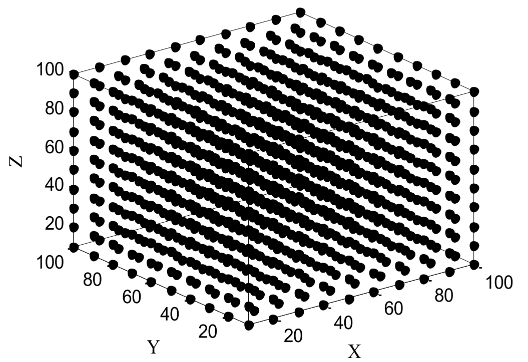

FIGURE 2. An SNN reservoir of 1000 neurons is chosen for the EEG dataset.

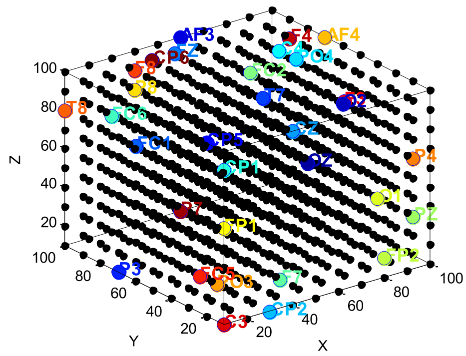

FIGURE 3. The locations of the EEG acquisition sites.The neurons highlighted are used to map the input features.

in NeuCube. Four different rules are included in the NeuCube, i.e., the Ben's spiker rule, temporal contrast encoding rule, step-forward spike rule and moving window spike rule.

Different spike encoding algorithms have distinct characteristics to represent input data. The Ben's spiker rule is appropriate to process the high frequency signals, as it is on the basis of finite spike response technique. The encoded signal can be used to recover the original signal easily. However, the Ben's spiker rule can only generate positive (excitatory) spikes, whereas negative (inhibitory) spikes can be also generated by all other techniques. The hardware in the artificial silicon retina originally implemented the temporal contrast encoding [32]. It identifies significant changes in signal intensity over a specific threshold. However, if the signal intensity changes dramatically, it is too difficult to recover to the original signal by this rule. Therefore, an improved step-forward spike-encoding rule is proposed to establish a mapping of the signal intensities. The advantage of the moving-window encoding rule is that it can be robust to certain types of noises.

The SNNs process discrete spike signals. Therefore, to process data stream expediently in the SNNcube, the continuous data stream is converted into discrete spike trains by encoding module. The SNNcube is a scalable module. The leaky integrate-and-fire (LIF) neurons are used to implement the SNNCube [33], [34]. The parameters of n_x, n_y and n_z are used to control the size of SNNcube, which represent the number of neurons along the x, y and z axes, respectively. $N = n_x n_y n_z$ is the number of neurons in the SNNcube. An SNN reservoir of neurons is used in this study, as shown in Fig.2. The number of neurons in the SNNcube is 1000 ($10 \times 10 \times 10$ neurons).

After the processed EEG data is loaded and the encoding method is chosen, each neuron is allocated to a specific functional and structural area of the neural network, according to its (x, y, z) coordinates. Fig.3 shows the locations of EEG acquisition sites in NeuCube. The neurons highlighted are used to map the input features. These coordinates can be mapped automatically or manually.

After initializing the cube, the unsupervised training of the SNNcube creates connections between the neurons based on the input spikes which is organized as a "small world" connected principle. The principle of "small world" connectivity is chosen based on the biological process. It makes neighbouring neurons interconnected with potentiation to each other. The initialization is a basic process for the learning [30]. To capture the correlations of the encoded data between spatial and temporal relations, an unsupervised learning model of the spike-timing-dependent plasticity (STDP) is employed for the SNNcube [35], [36]. The STDP potentiates the connection between pre-synaptic neurons and post-synaptic neurons if their activation persists and repeats, which follows the Hebbian learning rule. A variant of the STDP model is implemented in this study.

The model is described as

$$w_j(t) = \begin{cases} w_j(t-1) \pm \alpha/\Delta t, & t_j \neq t_i \\ w_j(t-1), & t_j = t_i, \end{cases} \tag{9}$$

where t_i, t_j refer to the firing time of neuron i and j, respectively, α means the STDP learning rate. If $t_i < t_j$, then w_j increases otherwise it decreases with respect to α. In addition, $\Delta t = t_j - t_i + 1$ which is the time elapsed between when a spike is received from pre-synaptic neuron i and when a spike is emitted by post-synaptic neuron j.

There are several hyper-parameters that can be set for the training, such as potential leak rate, STDP rate, firing threshold, training round, refractory time, and the probability of creating a long-distance connection. Once the unsupervised learning finishes, the final state can be analysed and visualized. Fig.4 shows the average one-to-one interaction between the input neurons based on average input interactions for the EEG dataset. Thick lines indicate strong interaction. For instance, FP1, FC2, CZ and O1 refer to the position of left frontal, vertex, central vertex and occipital points, respectively. The interaction of FP1 and FC2 is strong and the interaction of CZ and O1 is weak. It shows that the correlation between FP1 and FC2 is stronger than CZ and O1.

After the training of SNN cube (SNNc), the spatial and temporal connections of neurons can be seen in the form of 2D visualization. Fig.5 shows that the positive connections are represented by blue lines, while negative connections are represented by red lines. The colour code of a node represents the activity strength. The brighter the node, the stronger the

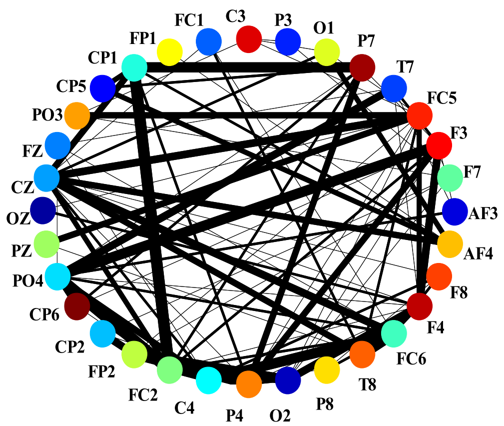

FIGURE 4. Total interactions between the input neurons. Thick lines indicate strong interaction.

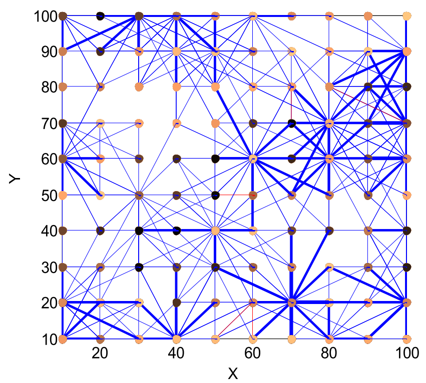

FIGURE 5. Synaptic connections after unsupervised training is completed. The positive connections are represented by blue, while negative connections are represented by red. The colour of a node represents the activity strength. The brighter the node, the stronger the activity is.

activity is. The neuron's connectivity strength can be identified by the thicknesses of lines. The detailed information about the network processes related to emotion classification would be showed by the specific areas of connections in the SNNcube.

The spike activation levels of the neurons are shown in Fig.6. The bright level of a neuron identifies its activation level. Brighter the neuron, more spikes are emitted. The histogram of positive and negative spikes emitted by all neurons can be visualized in NeuCube. Fig.7 shows the spike emission histogram generated for the EEG dataset. All neurons are divided into two categories (excitability and inhibition). Excitability neurons emit positive spikes and inhibition neurons emit negative spikes.

The deSNN classification algorithm [35] is applied to the classifier in a supervised model of learning. Each training instance is corresponded to an output neuron. Neurons are connected with each other in the SNNcube. The synaptic weight between the neuron i and j is calculated on the basis of the rank-order learning algorithm, which is described by

$$w_{i,j}(t) = mod^{\,order(i,j)}, \tag{10}$$

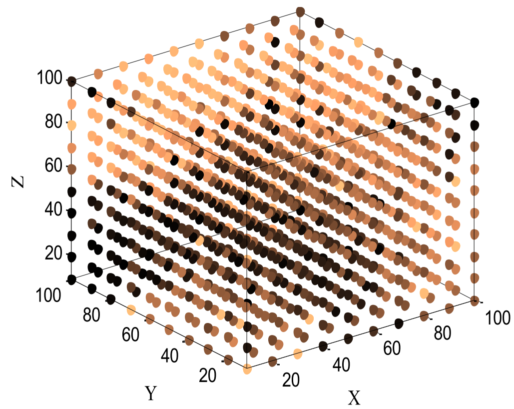

FIGURE 6. Activation levels of the neurons for EEG data in the SNNcube after unsupervised learning. The bright level of a neuron identifies its activation level. Brighter the neuron, more spikes are emitted.

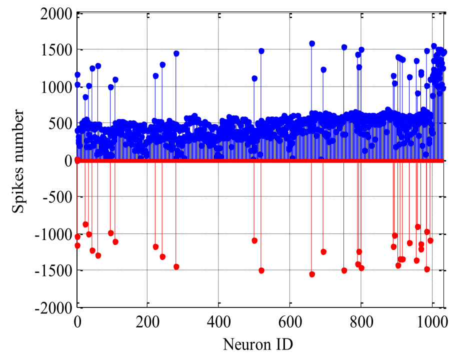

FIGURE 7. Excitative and inhibitive spike firing histogram for EEG data. Excitability neurons emit positive spikes and inhibition neurons emit negative spikes.

where $w_{i,j}$ refers to a connected synapse between neuron i and j, and $order(i,j)$ means the first order of incoming spike. The synaptic weight is updated using a drift parameter on the basis of the spike driven synaptic plasticity learning rule. This is used to update the synaptic weights while taking into account of the natural event of following spikes with respect to time $S_i(t)$. The weights are updated according to

$$w_{i,j}(t) = \begin{cases} w_{i,j}(t-1) + drift, & S_j(t) = 1 \\ w_{i,j}(t-1) - drift, & S_j(t) = 0, \end{cases} \tag{11}$$

where $S_j(t)$ is an spike at time t. If neuron i fires a spike at time t which is after the presynaptic neuron fires, the synaptic weight is potentiated; otherwise, the synaptic weight is depressed.

This section described the process of using NeuCube SNN architecture for emotion recognition. Compared to traditional approaches, the NeuCube-based method has the advantages to analyse the spatio-temporal EEG data and use the history information to help classification. The detailed experimental results will be provided in the next section.

V. EXPERIMENTAL RESULTS

In the recent emotion classification approaches [37], two-dimensional valence-arousal model is widely used [38].

For instance, the positive/low arousal is used to define the ''satisfied'' emotion, the positive/high arousal is used to define the ''happy'' emotion, the negative/low arousal is used to define the ''sad'' emotion, etc. In DEAP dataset, four emotion labels (valence, arousal, dominance and liking) are divided into two categories, i.e. low and high. A label array contains the corresponding emotional labels (1 for low, 2 for high). The SEED dataset is separated into positive, neutral and negative emotional states. Two dataset are used to validate the SNN, i.e. the DEAP and SEED datasets. More datasets will be used to evaluate the proposed method in the future work.

A. EXPERIMENTAL SETTINGS

The DEAP dataset contains 32 participants' data, each participant corresponds to a file. There are 40 music videos, 32 channels, and 128 sampling points per second, i.e. the array shape of $40 \times 32 \times 128$ ($video/trial \times channel \times data$) bytes. The 20 participants are selected as training data, and 12 participants are selected as testing data, randomly. The results are inter-subject. The SNN model has 32 input neurons in the SNN reservoir corresponding to 32 EEG channels. The SEED dataset contains the data for 15 participants, where each participant has three files. There are 62 channels and 200 sampling points per second. The 80% of data are selected as training, and 20% are used for testing. The SNN has 62 input neurons in the reservoir corresponding to 62 EEG channels. The SNN model is a complete network structure, and all participants which are used to train SNN can be represented by one SNN model.

To achieve a reliable classification, a sliding time window is used in this study. To obtain the most suitable length of time window, the variance method is used across all EEG data to compare the classification performance under three different time window lengths which are 1 s, 2 s and 3 s in this approach. The DEAP EEG data is selected from 32 electrodes (e.g. P7, O1, O2 etc.). The SEED EEG data is selected from 62 channels. Due to that the EEG signals contain the time information and the location information, mapping the location information to the input neurons needs to determine the coordinates of the respective electrodes, such as P7 (-60, -60, 0), O1 (-30, -80, 10), O2 (30, -80, 10) etc. The maximum value of the coordinate position is not more than 100, therefore $10 \times 100 \times 100 \times 100$ is selected as the coordinate size of SNNcube and the SNNcube contains $10 \times 10 \times 10$ neurons.

The moving - window spike encoding algorithm is selected to encode the EEG signals. In the encoding section, the threshold is set to 0.3 mV. The training time length, refractory time and STDP rate are set to 1s, 6ms and 0.01 in the training cube section, respectively. In training classifier section, the parameters mod, drift, k, and sigma are set to 1.1, 0.5, 2 and 1.5 respectively. For the experimental parameters, we use multiple experiments to obtain appropriate values. That is, within a certain range, the parameters are adjusted in the same step until the optimal parameter value of the experimental result is obtained. For example, the parameter sigma,in the range of [0,2], it is increased gradually by 0.5 steps, and the best experimental result is obtained at 1.5.

TABLE 1. The classification accuracies under the time window of 1 second using different methods.

Feature extraction methods	Valence	Arousal	Dominance	Liking
Variance method	72%	66%	66%	84.31%
FFT	64%	66%	58%	82.35%
DWT	68%	72%	58%	86.27%

TABLE 2. The classification accuracies under the time window of 2 seconds using different methods.

Feature extraction methods	Valence	Arousal	Dominance	Liking
Variance method	74%	68%	68%	82.35%
FFT	68%	66%	56%	84.31%
DWT	60%	68%	60%	84.31%

TABLE 3. The classification accuracies under the time window of 3 seconds using different methods.

Feature extraction methods	Valence	Arousal	Dominance	Liking
Variance method	78%	74%	80%	86.27%
FFT	70%	66%	68%	84.31%
DWT	68%	66%	64%	82.35%

B. DEAP CLASSIFICATION RESULTS

Three different methods (the variance, FFT and DWT) of EEG feature extractions are used for comparisons. The NeuCube SNN architecture is applied to the proposed data. The classification results under three different time windows are given from Table 1 to Table 3. Variance method chooses data of different periods from original data, and maintains the temporal and location features of metadata. SNN architecture in which both spatial and temporal neuroinformatics data can be encoded as both locations of synapses and neurons, as well as the timing of their spiking activity. It is suitable for representing the EEG characteristic. Therefore the SNN architecture can get a better performance.

Table 1 shows the classfication accuracies under the time window of 1 s. It can be seen that the accuracy of the variance method is much higher than the FFT and DWT for classifying the emotions of valence and dominance. The accuracy of the DWT method is highest to classify arousal and liking.

Table 2 shows the classification accuracies under the time window of 2 s. The recognition accuracy of the variance method is highest to classify valence and dominance. The variance and DWT methods have the same accuracies and are more accurate than the FFT for classifying arousal. The FFT and DWT have the same accuracies and are more accurate than the variance for classifying liking.

Table 3 shows the classification accuracies under the time window of 3s. The accuracy of variance method is the highest for classifying valence, arousal, dominance and liking. In the meantime, Table 3 shows that the accuracy under the

TABLE 4. The classification accuracies under the time window of 3 seconds using different methods.

Feature extraction methods	Valence	Arousal	Dominance	Liking
S. Koelstra et al. [18]	57.6%	62%	/	55.4%
Spectral Features + FLD + naïve Bayes [22]	61.6%	57.1%	53.2%	64.1%
DT-CWPT (12-subbands) [22]	65.3%	66.9%	69.1%	71.2%
DT-CWPT (16-subbands) + SVM [39]	64.3%	66.2%	68.9%	70.2%
Graph features + RVM [40]	67%	69%	65%	65%
SPF + SVM [41]	50%	62%	/	/
SPF + CSP + SVM [42]	59%	56%	/	/
This work (NeuCube + variance)	**78%**	**74%**	**80%**	**86.27%**

time window of 3s using the variance method is higher than the time window of 1s and 2s.

Furthermore, the results of several other approaches using the same dataset are selected for performance comparison. The average accuracies of these approaches are given in Table 4. The results of [18] showed that the EEG signals can be reliably used to classify emotions and report accuracies (55%-62%) by using a Gaussian Bayes classifier. The approach of [22] used different classifiers for classification and experimental results demonstrated that the accuracies of using SVM are higher than naïve Bayes. The same features and classifier in [22] are used in the approach of [39] but with different number of sub-bands, i.e. 12 and 16 sub-bands are used for [22] and [39], respectively. Results show that the approach of [22] has a higher classification accuracy than [39]. The approach of [40] used a relevance vector machine (RVM) classifier and graph feature extraction to classify emotions, which achieves 65%-69% classification accuracies. The approaches of [41] and [42] used the spectral power features (SPF), and SPF with common spatial patterns (CSP) features, respectively. Both of them used SVM for classifications. However, they only classified two emotion states and the accuracies are 50%-62%. In this work, the variance method is used to select the data from pre-processed EEG signals, and then the SNN is used to classify the emotion states. The accuracies of the four emotion states (valence, arousal, dominance and liking) are 78%, 74%, 80% and 86.27%, respectively, which are better than other approaches. This demonstrates that due to the temporal-spatial information processing capability, the SNN can be used to process the tasks in the time series domain such as the EEG-based emotion classifications.

VI. SEED CLASSIFICATION RESULTS

Three different methods (variance, FFT and DWT) of feature extractions are used in SEED dataset for comparisons. The NeuCube SNN architecture is applied to the proposed data. The classification results under three different time windows are given by Table 5 to Table 7. Table 5 shows the accuracies under the time window of 1 s. It can be seen that the accuracy of variance method is much higher than the FFT and DWT, especially the classification accuracies of positive and neutral can reach to 100%.

Table 6 shows the classification accuracies under the time window of 2 s. The overall accuracy of variance method

TABLE 5. The classification accuracies under the time window of 1 second using different methods.

Feature extraction methods	Valence	Arousal	Dominance	Liking
Variance method	100%	100%	66.7%	88.89%
FFT	75%	78%	60%	71%
DWT	33.33%	66.67%	33.33%	44.44%

TABLE 6. The classification accuracies under the time window of 2 seconds using different methods.

Feature extraction methods	Valence	Arousal	Dominance	Liking
Variance method	100%	100%	50%	83.33%
FFT	72.5%	63%	64.5%	66.67%
DWT	75%	50%	62.5%	62.5%

TABLE 7. The classification accuracies under the time window of 2 seconds using different methods.

Feature extraction methods	Valence	Arousal	Dominance	Liking
Variance method	100%	89.99%	100%	96.67%
FFT	66.67%	33.33%	66.67%	55.56%
DWT	70.5%	59.5%	75%	68.3%

is highest, especially for the positive and neutral emotional states. It can be seen that the accuracy using the FFT algorithm is highest for the negative state classification.

Table 7 shows the classification accuracies under the time window of 3 s. The overall accuracy of variance method is higher than others. In the meantime, the individual classification accuracy using the variance method is also highest. It should be noted that the recognition accuracy of 3s time window using the variance method is higher than the time window of 1s and 2s.

The classification results of several other approaches using the SEED dataset for evaluation are also included for performance comparison. These approaches select 62 channels data and four frequency bands. The classification accuracies of these approaches are show in Table 8. The approach of [19] shows that the deep belief network (DBN) model can obtain the overall accuracy of 86.08%. The approach of [43] uses transductive parameter transfer (TPT) method and subject transfer framework, which achieves the overall accuracy of 76.31%. The approach of [44] uses a hierarchical network structure with sub-network nodes for classification, and it can obtain the accuracy of 93.26%. In our work, the variance method and SNN are used to classify emotional states. The overall accuracy shows that a promising result can be obtained (96.67%).

TABLE 8. Classification accuracies of different approaches.

Classification methods	Overall accuracy
DBN [19]	86.08%
TPT [43]	76.31%
Y. Yang et al. [44]	93.26%
This work (NeuCube + variance)	**96.67%**

VII. DISCUSSION

The findings of this study support our hypothesis that the feasibility and advantages of the SNN for the emotional analysis of EEG signals. As an effective tool, the SNN is used with EEG signals. In the previous studies of emotion, many standard machine learning techniques (e.g. naïve Bayes [22], Gaussian Bayes [18], RVM [40] etc.) have been considered. With the comparison of these methods, the SNN is more suitable for spatial and temporal data.

The NeuCube framework can not only learn functional pathways from data, but also predict future states. The model can be developed to learn spatial and temporal data in unsupervised and supervised ways. It includes an input component to encode the input data into spiking sequences, where an SNNcube learns the input data in an unsupervised mode to capture spatial and temporal patterns, and an evolving output part for classification or regression tasks.

This study has demonstrated that the variance is an effective method to process the data. In DEAP dataset, the four emotion states are recognized as low or high classes by SNN. The classification accuracies are 78%, 74%, 80%, and 86.27%, respectively. In SEED dataset, the emotional states are divided into positive, neutral and negative. The overall accuracy of 96.67% can be obtained. The accuracies are much higher than traditional machine learning techniques. Because the SNN exhibits the characteristic of memory to process the time series data, the spatial and temporal information is encoded by synapses locations, neurons locations, and spiking activity times in the SNN. An associative memory and a predictive system can be realized by using the SNN model for classifying the brain emotional states.

VIII. CONCLUSION AND THE FUTURE WORK

Methods for processing EEG signals and classifying emotion states were proposed in this paper. The DEAP and SEED datasets used in this work contains the EEG signals which were collected from a 32-channel and 62-channel brain computer interface (BCI) devices. Three feature extraction methods, including variance, FFT and DWT, were used for processing the EEG data. The SNN was then employed to classify the emotion states. Experimental results showed that compared with other two feature extraction methods, the variance method with a 3-second time window is more suitable to process the raw EEG data. For the emotion state classification, the SNN achieved the highest accuracy than other conventional approaches due to its processing capability for the spatial and temporal data. Future work includes the optimisation of the proposed methods, further exploration of the multi-class classification, and integrations of the SNN-based classifier and the BCI embedded hardware devices.

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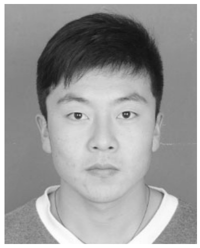

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