EEG EMOTION CLASSIFICATION USING 3-DIMENSIONAL CONVOLUTIONAL NEURAL NETWORKS

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Abstract: Classification of electroencephalography (EEG) signals has important applications in the diagnosis and treatment of various neurological disorders. In this paper, we propose a methodology for classifying EEG signals based on signal processing using wavelet transform and superlet transform[3]. The wavelet transform is used to decompose the EEG signal into frequency components, which are then used as features for classification. The proposed approach is evaluated using the publicly available "GAMEEMO" EEG dataset[1], which has been annotated by valence and emotional arousal. We use a Convolutional Neural Network (CNN) for classification at the waveform level. The results of this study suggest that the wavelet transform and its modifications, such as the superlet transform, can be valuable tools for analyzing and classifying EEG signals.

Keywords: biometric signals, electroencephalograms, wavelet transform, convolutional neural networks

INTRODUCTION

The specific features extracted from EEG signals can vary, but they often include power spectral density, coherence, and event-related potentials. These features can be used to train machine learning models that can classify emotions based on patterns of neural activity observed in EEG signals.

Understanding the neural correlates of emotion can be important for the diagnosis and treatment of mental disorders, as emotional disturbances are often associated with these conditions. By developing more accurate and reliable methods for classifying emotions using EEG signals, researchers can work to improve the diagnosis and treatment of these disorders. In addition, EEG-based emotion classification can also be useful in areas such as marketing and advertising, where it can be applied to better understand consumers' emotions and preferences, as well as to develop more effective marketing strategies. Another potential application is in the development of brain-computer interfaces (BCI), which could allow people to control computers and other devices with their thoughts. By classifying emotions based on EEG signals, these interfaces can be designed to respond to the user's emotional state, providing a more personalized and adaptive user experience.

CONTENTS OF THE "GAMEEMO" DATASET

This dataset contains EEG signals collected using a 14-channel Emotiv Epoc+ portable EEG device from 28 subjects playing emotionally charged computer games. Each participant played four different games (boring, calm, scary, and funny) for 5 minutes each, during which EEG data were recorded. Participants also rated the emotional content of each game based on arousal and valence using the Self-Assessment Manikin (SAM) form. The dataset includes both raw and pre-processed EEG data in .csv and .mat formats, as well as each subject's rating and SAM form. The purpose of this dataset is to serve as an alternative data source for emotion recognition research and to demonstrate the performance of wearable EEG devices. The main folder (GAMEEMO) contains 29 subfolders: 28 for each subject and 1 for the game. The folder for each subject contains the corresponding raw EEG data in .csv and .mat formats, as well as SAM ratings in .pdf format. The games are labeled G1, G2, G3, and G4, corresponding to game 1, game 2, and so on.

Table 1.

Attributes of the GAMEEMO dataset

Data type	**Information**
Dataset	"Database for Emotion Recognition System Based on EEG Signals and Various Computer Games - GAMEEMO"
Signal type	Electroencephalogram
Subjects	Number of subjects: 28 individuals selected from the students of Firat University, Faculty of Technology, Department of Software Development. Age of the subjects: 20-27 years old.
Devices	Type of EEG device: 14-channel EMOTIV EPOC+ Mobile EEG device Location of EEG electrodes: 14 different scalp zones Connection type: Wi-Fi Sampling rate: 128 Hz Bandwidth: 0.16 Hz - 43 Hz Operating systems: Windows, Mac, IOS and Android

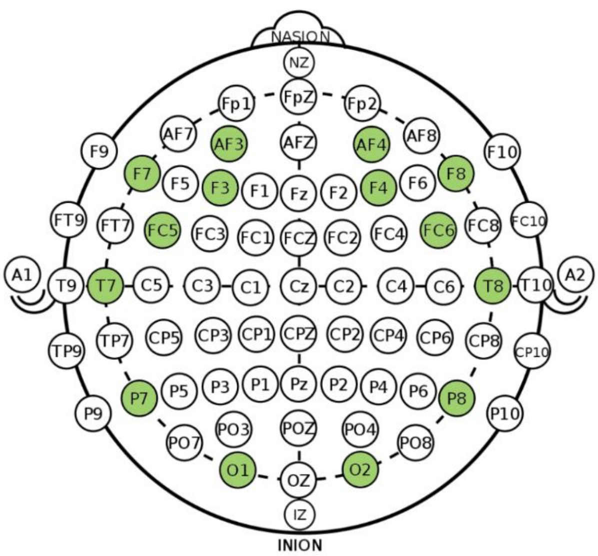

Figure 1. Electrode locations of the EMOTIV Epoc+ EEG headset (AF: anterior-frontal, F: frontal, FC: frontal-central, T: temporal, P: parietal, O: occipital)

WAVELET TRANSFORM APPLICATION FOR EEG SIGNALS

Time series that describe natural phenomena, such as sounds, ground motion, or brain activity, often express bursts of oscillations at different frequencies and with finite durations. In brain signals, these bursts cover a wide range of frequencies (e.g., 0.1-600 Hz) and time intervals $(10^{-2} - 10^{2}\,c)$ [5,6], and it was proposed that these signals have a fractal, scale-free nature, due to which their properties are self-similar at different time scales/frequencies.

Continuous wavelet transform $X_{cwt}(a,b)$ of the signal $x(t)$ is represented by equation (1), where $\psi^{*}_{a,b}(t)$ is a complex conjugation of the scaled and shifted versions of the mother wavelet $\psi(t)$, a - is the scaling parameter b - is the shift parameter.

$$X_{cwt}(a,b) = \int_{-\infty}^{+\infty} x(t)\psi^{*}_{a,b}(t)dt \qquad (1)$$

According to the Heisenberg-Gabor uncertainty principle, finite transient oscillation processes are difficult to localize simultaneously in time and frequency. Higher frequency accuracy requires lower time accuracy, and vice versa. In wavelet analysis, this is usually controlled by the number of cycles used in each wavelet.

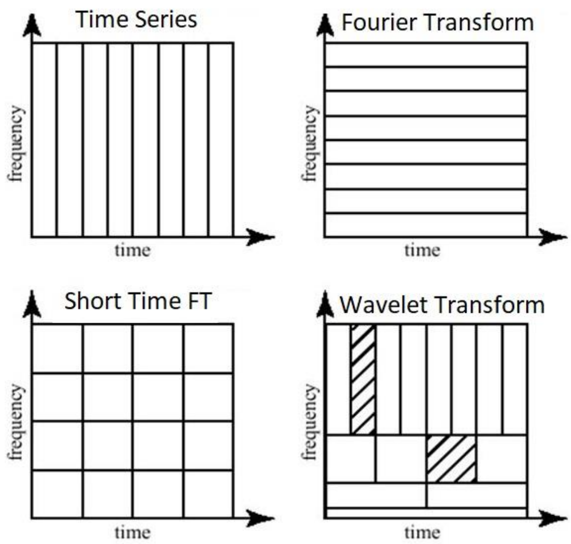

Figure 2. The time- and frequency resolutions of the different methods

Since the EEG power is proportional to $1/f$, the total power between any two frequency points, for $f \neq 0$, can be obtained from the integral, $\int \frac{1}{f} df = \ln|f| + c$. It follows that we can achieve a proportional relationship between frequency and power by adopting a logarithmic scale.

The use of logarithmically distributed frequencies has several advantages[4], namely:

1. Better resolution at low frequencies: Logarithmic spacing provides higher resolution at lower frequencies, which is especially important when analyzing signals such as EEG signals that have many low-frequency components.

2. More efficient use of limited resources: Logarithmic spacing allows for more efficient use of limited resources, such as memory or computing power, as it allows for more points to be allocated to low frequencies where resolution is more critical.

3. Better approximation to the human auditory system: The human auditory system is logarithmically sensitive to changes in frequency, and logarithmic spacing can help provide a better approximation of how the brain processes auditory information.

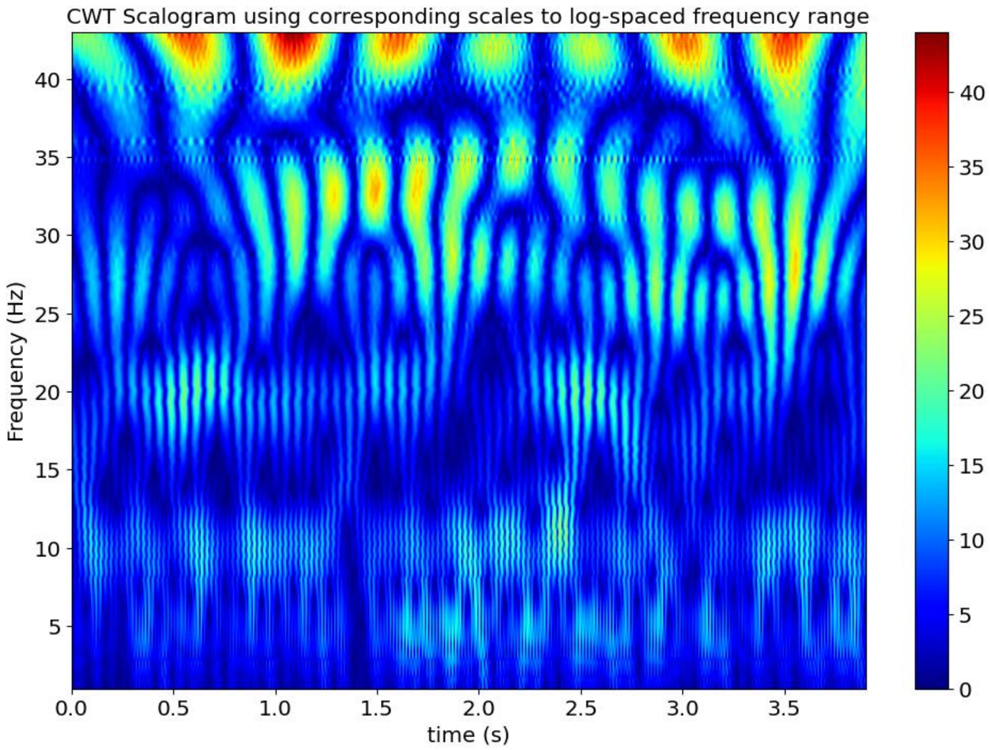

Figure 3. Example of the continuos wavelet transform for logarithmically spaced frequencies

CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE

Two approaches to the implementation of the model were considered:

1. First approach. Data, passed to the neural network was organized in the next form:

Fourteen scalograms were stacked on top of each other and one single image with 42 channels was created, where $42 = 14 * 3$, where 14 is the number of images and 3 is the number of RGB channels. Normally an image has either one channel (grayscale image) or three channels (RGB image), but CNN can handle images with arbitrary number of channels as well.

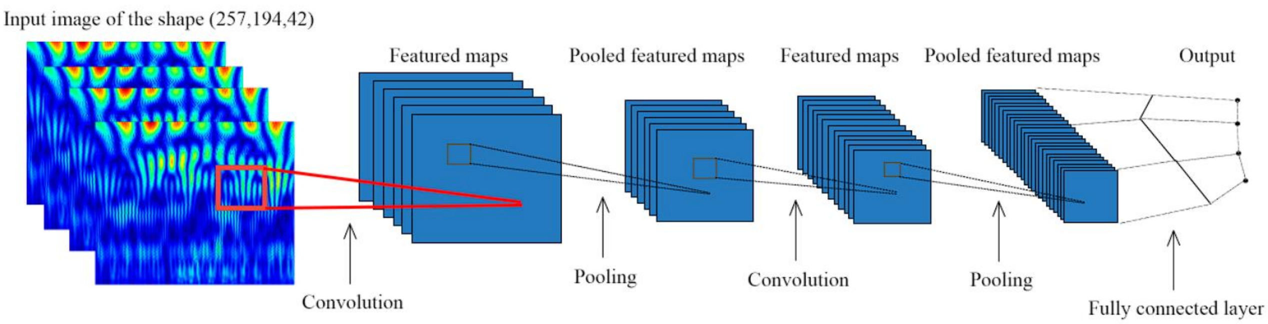

Figure 3. Simplified scheme of a 2-dimensional convolutional neural network

Table 2.

2-dimensional CNN model architecture

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 193, 256, 64)	54528
max_pooling2d_1 (MaxPooling2D)	(None, 96, 128, 64)	0
dropout_1 (Dropout)	(None, 96, 128, 64)	0
conv2d_2 (Conv2D)	(None, 95, 127, 128)	32896
max_pooling2d_2 (MaxPooling2D)	(None, 47, 63, 128)	0
dropout_2 (Dropout)	(None, 47, 63, 128)	0
conv2d_3 (Conv2D)	(None, 46, 62, 128)	65664
max_pooling2d_3 (MaxPooling2D)	(None, 23, 31, 128)	0
dropout_3 (Dropout)	(None, 23, 31, 128)	0
flatten_1 (Flatten)	(None, 90816)	0
dense_1 (Dense)	(None, 256)	23257088
dropout_4 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 128)	32896

2. Second approach. Data, passed to the neural network was organized in the next form

Fourteen scalograms were placed in an array with 14 elements, each of which represents a scalogram, resulting in the shape of the input $(14, 257, 194, 3)$. 3-dimensional CNN was subsequently applied.

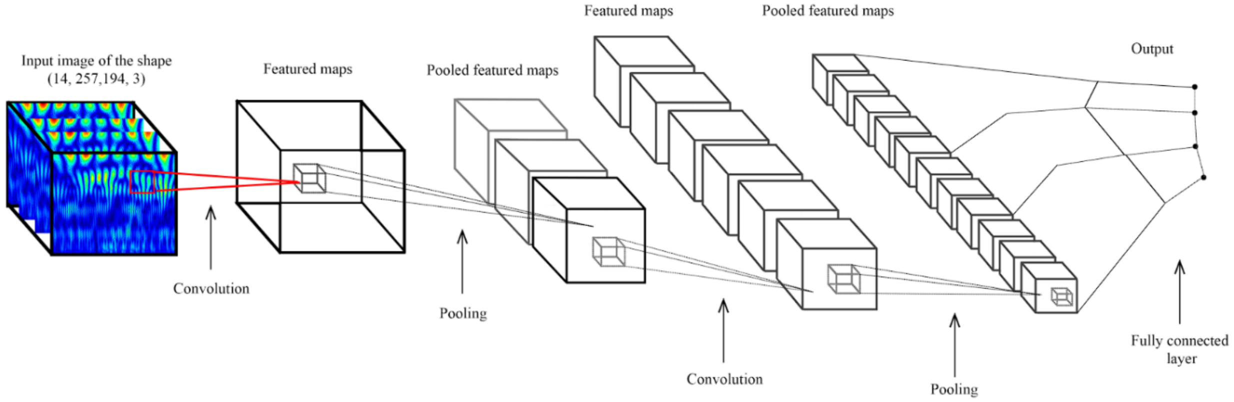

Figure 4. Simplified scheme of a 3-dimensional convolutional neural network

Table 3.

3-dimensional CNN model architecture

Layer (type)	Output Shape	Param #
conv3d_1 (Conv3D)	(None, 12, 192, 255, 32)	896
max_pooling3d_1 (MaxPooling3D)	(None, 6, 96, 127, 32)	0
dropout_1 (Dropout)	(None, 6, 96, 127, 32)	0
conv3d_2 (Conv3D)	(None, 4, 94, 125, 64)	55360
max_pooling3d_2 (MaxPooling3D)	(None, 2, 47, 62, 64)	0
dropout_2 (Dropout)	(None, 2, 47, 62, 64)	0
conv3d_3 (Conv3D)	(None, 2, 45, 60, 64)	36928
max_pooling3d_3 (MaxPooling3D)	(None, 1, 22, 30, 64)	0
dropout_3 (Dropout)	(None, 1, 22, 30, 64)	0
flatten_1 (Flatten)	(None, 42240)	0
dense_1 (Dense)	(None, 128)	5407488
dropout_4 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 64)	8256

RESULTS OF THE ANALYSIS

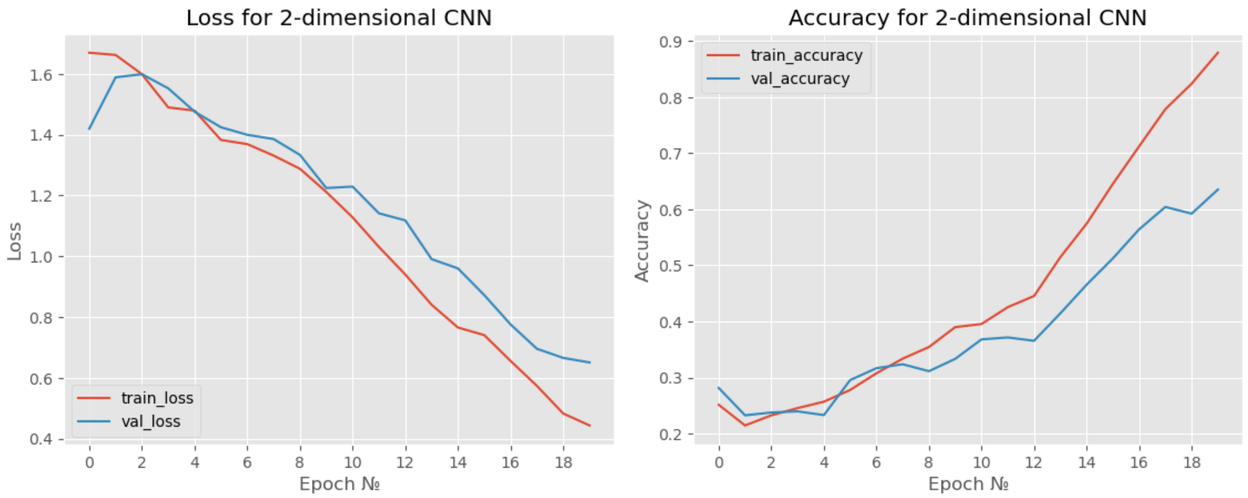

Figure 5. Loss and accuracy for 2-dimensional CNN

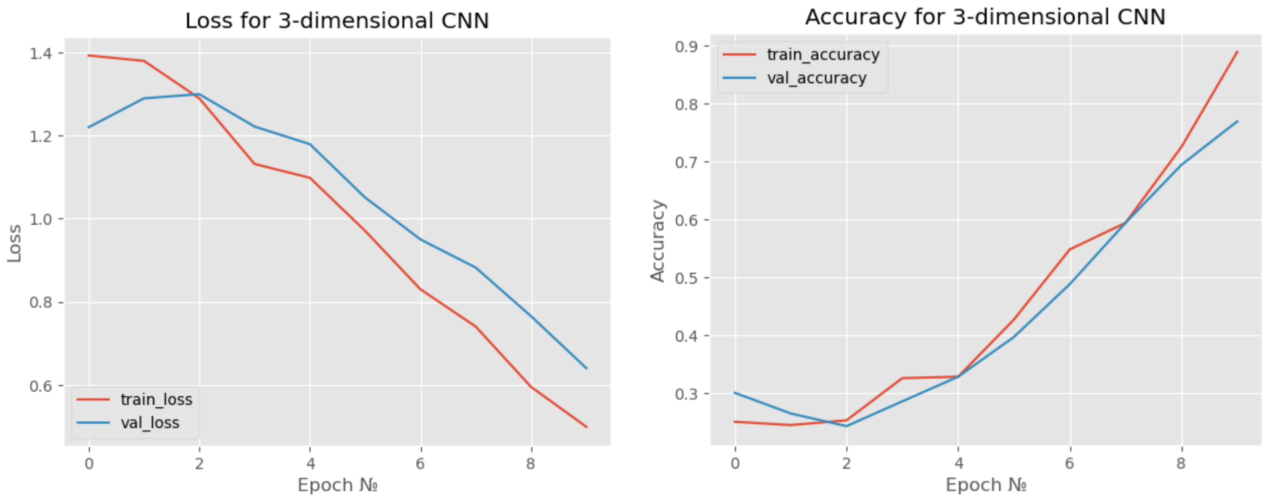

Figure 6. Loss and accuracy for 3-dimensional CNN

As the graphs show, three-dimensional CNN gives us better results even with fewer epochs. Therefore it can be concluded that the use of 3-dimensional convolutional neural networks is justified for solving this type of problems.

CONCLUSIONS

Wavelet transforms, 3-dimensional convolutional neural networks and their modifications can be valuable tools for analyzing and classifying EEG signals. The broader context of the work is the field of biomedical engineering, in particular, the classification of emotions from EEG signals, which has applications in the diagnosis and treatment of mental disorders, as well as in such areas as marketing and the development of brain-computer interfaces.

REFERENCES

1. Alakuş, Talha & Gonen, Murat & Turkoglu, Ibrahim. (2020). Database for an emotion recognition system based on EEG signals and various computer games – GAMEEMO. Biomedical Signal Processing and Control. 60. 101951. 10.1016/j.bspc.2020.101951.
2. Hazarika, Neep & Chen, Jean & Tsoi, Ah & Sergejew, Alex. (1997). Classification of EEG signals using the wavelet transform. Signal Processing. 59. 89-92 vol.1. 10.1109/ICDSP.1997.627975.
3. Moca, Vasile & Nagy-Dabacan, Adriana & Barzan, Harald & Muresan, Raul. (2019). Superlets: time-frequency super-resolution using wavelet sets. 10.1101/583732.
4. Craik A, He Y, Contreras-Vidal JL. Deep learning for electroencephalogram (EEG) classification tasks: a review. J Neural Eng. 2019 Jun;16(3):031001. doi: 10.1088/1741-2552/ab0ab5. Epub 2019 Feb 26. PMID: 30808014.
5. Buzsáki, G. Rhythms of the Brain (Oxford Univ. Press, 2006)
6. Tal, I., Neymotin, S., Bickel, S., Lakatos, P. & Schroeder, C. E. Oscillatory bursting as a mechanism for temporal coupling and information coding. Front. Comput. Neurosci. 14, 82 (2020)
7. Rangayyan, R. M. (2015). *Biomedical signal analysis*. John Wiley & Sons
8. Burgess AP (2019) How Conventional Visual Representations of Time-Frequency Analyses Bias Our Perception of EEG/MEG Signals and What to Do About It. Front. Hum. Neurosci. 13:212. doi: 10.3389/fnhum.2019.00212
9. Rufin VanRullen. Four common conceptual fallacies in mapping the time course of recognition. *Frontiers in Psychology*, 2011. doi:10.3389/fpsyg.2011.00365.