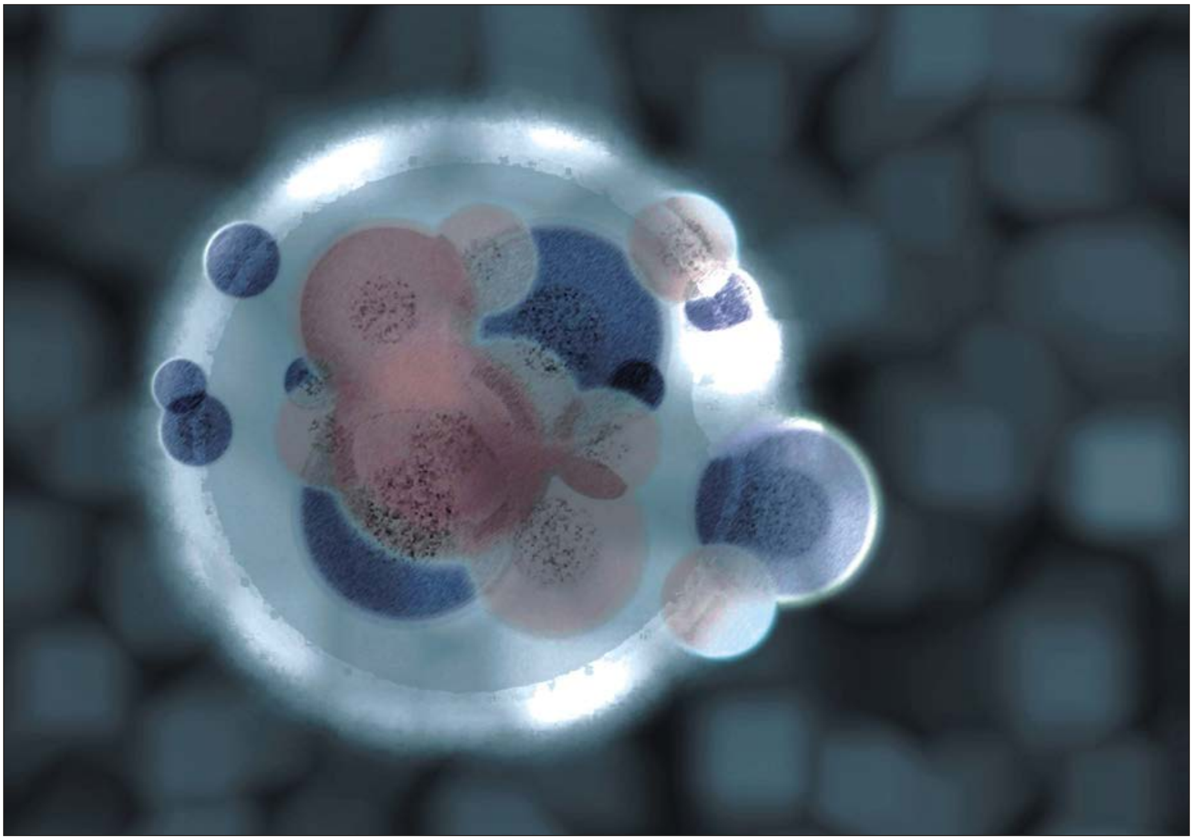

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Research Article
Classification of Eeg Signals Based on Different Motor Movement Using Multi-layer Perceptron Artificial Neural Network

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Abstract
Brain Computer Interface (BCI) is becoming more common now a days as a platform used to support communication between the human brain and external hardware, such as a computer or other electronic peripherals. The communication between these two realms are based on reading the EEG signals produced by the brain. Electroencephalography or EEG is a neuroimaging technique through which the brain signals are measured by using an electrode cap. Every action, movement and thought by an individual in known to produce different patterns of EEG signals, which are generated due to electromagnetic activity inside the brain. In this study, a method used to analyze and classify different EEG patterns based on different motor movements performed by an individual. Useful features are extracted from the pre-processed EEG data by using the Power Spectral Density (PSD) function. These features are then fed as inputs to the neural network classifier for classification process. From the conducted experiments, a high accuracy value was obtained by the classifier in correctly distinguishing the different motor movements by the subject.

Key words: Brain computer interface, EEG, PSD, ANN, MLP

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Competing Interest: The authors have declared that no competing interest exists.

Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Communication is the act of transferring information whether through speaking, writing, sign language or other medium. Communication is the most important thing in our daily life but some people are unfortunate, where they do not have the privilege to communicate like other normal individuals[1]. Understanding the way a person initiates communication, one fact is that the message is always constructed in the brain first. Can we tap our brain to interpret such thoughts? This question provides a context for our research in analyzing the electroencephalography (EEG) signals especially to interpret the brain activities. Human brain is the most important part in human body, where it controls all activities of our body including motor and muscle movement[2]. Human brain contains more than 100 billion of neurons that communicate with each other. The EEG signals are produced by neurons when there are communicate with each other. Different thoughts will produce different pattern of EEG signals, which are generated due to electromagnetic activity inside the brain[3]. Scoping down into a more specific area, our aim is to decode the EEG signals, especially to capture and understand the brain activities with the occurrence of motor movement.

The EEG technology has grown faster and gains many attentions from researchers especially those from the domain of biomedical engineering. Many studies have been carried out and published on EEG. The EEG signals can be grouped by frequency range or bands. Each band carries different type of information about the individual's mental state, e.g., dominant alpha waves denotes calm or relax mind.

As we know, EEG signals carry a lot of information about activities that are going on in the brain. To interpret this information, EEG signals need to be collected for analysis. The EEG signals are highly recognized as complex signals. Before the actual analysis can be performed on the signals, some preprocessing on the raw data need to conducted. Raw EEG signal is contaminated with artifacts and noises and it is almost impossible to see any Event Related Potential (ERP)[4-6]. Event Related Potential (ERP) is reflect of cerebral activity which is associated to the external or internal stimulus[7] e.g., motor movements. The Event Related Potential (ERP) is recorded either in positive (P) or negative (N) polarity[8]. Most of the neuroscientists visualize the Event Related Potential (ERP) to occur at N200 (negative peak around 200 m) and P300 (positive peak around 300 m) after the excitation of stimuli.

Raw EEG signals need to go through preprocessing to remove all unwanted artifacts and noises. There are a number of methods that can be used for preprocessing of EEG signals e.g., signal filtering, Blind Source Separation (BSS) and Independent Component Analysis (ICA). Some researchers rely on ICA to remove artifacts, however the process using ICA is lengthy, time consuming and not pruned to human errors[6]. After the collected EEG signals are preprocessed with appropriate method, the signals will then go through the feature extraction process.

Feature extraction is a process that aims to identify common patterns occurring in the signals. Such patterns, when correctly identified will represent the best data for a particular expression, movement or thought. In this study, the Power Spectral Density (PSD) function will be employed for feature extraction process. The output of this function are in the form of PSD coefficient values, which will be used as inputs for the neural network classifier. In this study, we are using the multi-layer perceptron artificial neural network as the classifier.

MATERIALS AND METHODS

Figure 1 shows the overall methodology of this study. In general, there are five steps that we follow in decoding the EEG signals.

Collection of EEG data using Emotiv Epoc and data-export to MATLAB: The first and most crucial step is to record the EEG signals from the subject by using the Emotiv Epoc Neuroheadset. Emotiv Epoc Neuroheadset is a device with 14 electrodes (plus CMS/DRL as reference electrodes) with gold-plated connectors and connects wirelessly with the PC. Figure 2 shows the electrode placement for Emotiv Epoc (P1-P14). This electrode placement is according to international 10-20 electrode placement system.

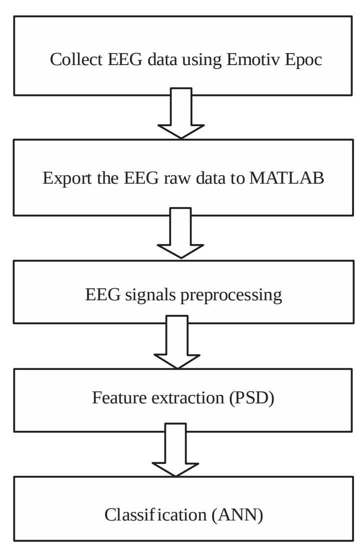

Fig. 1: General methodology

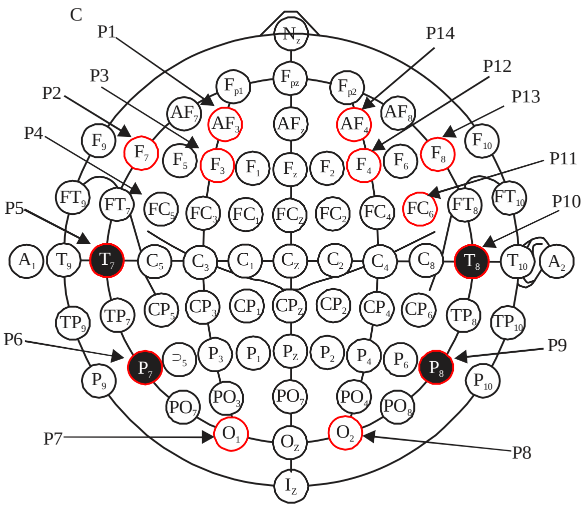

Fig. 2: Emotiv Epoc with 14 electrodes placements (P1-P14)

Emotiv Epoc Neuroheadset is a low cost and non-invasive BCI device with a sampling frequency of 2048 Hz. We have chosen this device as the recording device since it has been shown that the information retrieved is reliable and sufficient for most applications and compares well with high level research equipment[9]. In this particular experiment, 14 sets of data are expected for one recording session; where each data set is recorded by one of the 14 electrodes (AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1 and O2).

In the experiment, two instructors will conduct each EEG recording session. The first instructor is in charged of assisting and guiding the subject on what to be done. While, the second instructor is in charged of handling the Emotiv device and EEG recording. Each experiment session is conducted in a room equipped with air conditioning and the lamp is moderately lit. Every subject is recommended to focus during the experiment. But, if the subject is tired, they are allowed to take a break and the experiment session will be postponed. The subject chosen for this experiment should be within a normal condition i.e., not too tired and stressed because such condition would influence the quality EEG signals being recorded.

Firstly, the subject is requested to sit on a chair and will be equipped with Emotiv Epoc by both instructors. Then some instructions and tips are given to the subject in order to ensure good EEG recording. Some of the tips are as follow:

- Subject must keep their body still to lessen EMG (muscle movement) artifact
- Subject must keep their eye shut to avoid EOG (eye movement) artifact

Once the subject is ready to proceed with the experiment, the second instructor will then start recording the EEG signals of the subject. For the first 5 sec, the subject is asked to relax but focus. After 5 sec, the first instructor will verbally instruct the subject to lift the right hand. Then the subject is asked to relax again for the next 5 sec. Then in the following 5 sec, the subject is again verbally instruct to lift the left hand.

EEG signal preprocessing (Signal filtering): Raw EEG data (recorded data) are contaminated with noises and artifacts (EMG, EOG and ECG)[10]. To clean these raw EEG data, the signals need to go through preprocessing. Preprocessing is a process to remove artifacts and noises. This step is very important since we want to have a clean data for further processing but without losing any crucial data. The EEG signals are recorded in microvolt range and normally artifacts and noises can generate 10 or 100 times larger in amplitude[11]. Due to this fact, rtifacts and noises are removed from the raw EEG signals in the preprocessing by cutting off the signals with amplitude beyond the 100 to -100 range[12,13]. The clean data are regarded as ones within this 100 to -100 amplitude range. The signals with amplitude outside this range are regarded as artifacts or noises due to the fact that the higher the frequency values means the lower its value of amplitude. Delta band have the highest amplitude (about 300 μV) and slowest frequency. Based on this rationale, amplitude that exceed the 100 to -100 ranges is considered as noises or artifacts[14].

After removal of artifacts and noises, the signal is passed through a band-pass filter with an impulse response to produce four bands alpha (8-12 Hz), beta (13-24 Hz), theta (4-8 Hz) and delta (2-4 Hz)[15]. For the convolution between EEG signal and impulse response, hamming windowing function is used and the filter can be describe in Eq. 1 as follow:

$$g\,(n) = y\,(n) \times h_H\,(n) \tag{1}$$

where, g (n) is the output of the filter, y (n) is the EEG signal and h_H (n) is the impulse response, n = 1, 2, 3,......, N.

The impulse response of the actual hamming filter is as in Eq. 2 as follow:

$$h_H\,(n) = h_D\,(n) \times w\,(n) \tag{2}$$

where, w (n) is the hamming windowing function and h_D (n) denotes as ideal impulse response, where, $0 \leq n \leq N-1$.

Once the signal is divided into four bands, the filtered EEG signals, which are in time- domain, are then converted into frequency-domain signals by applying Fast Fourier Transform or FFT. This conversion is implemented by using FFT function in MATLAB. This step is crucial as the frequency-domain data is required to get the Power Spectral Density (PSD) value, which willlater be computed by utilizing the PSD function in MATLAB.

Feature extraction based on Power Spectral Density (PSD): In this study, the Power Spectral Density (PSD) function is used to extract the important features of the EEG signals. PSD shows the strength of variations (energy) as the function of frequency. In other words, PSD shows at which part of the frequency, variation are stronger or weaker[16]. By integrating PSD within some frequency range, we can obtain the energy with that frequency range. Power spectral density generalizes in a straight manner to finite time series with $1 \leq n \leq N$:

$$S(e^{jw}) = \frac{1}{2\pi N}\left|\sum_{n=1}^{N} x_n e^{-jwn}\right| \tag{3}$$

The PSD can be computed by using a Fast Fourier Transform (FFT) or by computing the autocorrelation function and then transforming function. The coefficient values obtained from such feature extraction process based on PSD will then be fed into the classifier[17] to classify the EEG to determine whether the subject is lifting the right or left hand.

Classification based on Artificial Neural Network (ANN): Artificial Neural Network (ANN) is a computational or mathematical model that is inspired from the structure of neurons cell[7]. The ANN is used to perform pattern classification, function approximation, recognition and optimization. The ANN can be divided into two groups, specifically the Single-Layer Perceptron (SLP) and Multi-Layer Perceptron (MLP). The SLP is the simplest form of neural network, where SLP is used to classify linearly separable cases. Linear separable cases denote that the data can be divided into two groups by straight line (Fig. 3a). However, there are many non-linear cases in this world. Because of the limitation of SLP, researchers have found that by combining the single perceptron it can form a much larger neural network, i.e., to become the Multi-Layer Peceptron (MLP). This design offers a better solution to non-linear cases, where MLP is known to solve non-linear cases better than SLP (Fig. 3b). Neural network non-linear classifier is regarded as a popular method used to solve brain computer interface application, especially in pattern classification and function approximation[18]. Most researchers opt to use neural network as the classifier because of its generalization capabilities and simplicity[19].

The MLP can be used for either as a function approximation or a pattern classification. For this study, MLP is employed as the pattern classifier, especially to determine the EEG signal patterns being produced when a subject is lifting either the right or left hand. The MLP contains one or more layer of hidden units. The hidden units allow the MLP to learn complex tasks and relationships between input and output. Figure 4 shows the structure of neural network for one hidden layer.

The pattern classification process has tan-sigmoid (Tansig) as the activation function. Tansig activation function is usually used in hidden and output layer. Figure 5 shows Tansig activation function graph. The graph shows that the input is between -1 and +1 and all other values outside this range will be pushed inward within these limits:

$$\text{Tansig}\,(n) = \frac{e^{cn} - e^{-cn}}{e^{cn} + e^{-cn}} \tag{4}$$

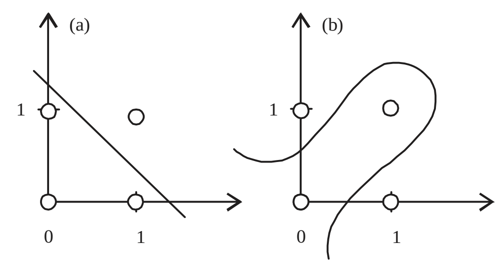

Fig. 3(a-b): Example for (a) Linearly separable case and (b) Non-linear separable case

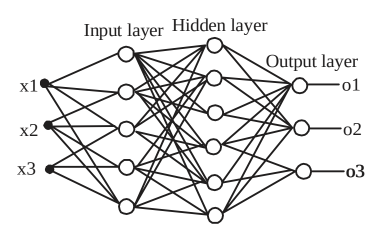

Fig. 4: Structure of a neural network model with one hidden layer

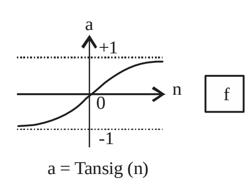

Fig. 5: Tan-sigmoid transfer function graph

Equation 4 shows the Tansig equation where c is the constant and n as the input.

RESULTS AND DISCUSSION

This section presents the results obtained from the analysis based on the recorded EEG signals when a subject is lifting his/her right and left hand. In this initial experiment, we are focusing on one individual's EEG recording and thus the data being analyzed are recorded from a single subject. From the experiment conducted based on a single subject, EEG signals are recorded for the activity of lifting right and left hand, where each physical activity has been repeated for 18 times to obtain 18 data samples.

Preprocessing (signal filtering): Figure 6 shows the sample of raw EEG signals recorded from channel 1 (electrode AF3). The amplitude of the recorded signals are very high because they are transmitted as unsigned integer by the Emotiv device. Due to the high unsigned integer values, the DC offset-correction will need to be removed first by using the first-order highpass-filter. The amplitude of EEG signals after the removal of DC offset-correction is found to be much smaller than before. Figure 7 shows the EEG signal after the DC offset-correction removal. The amplitude of EEG signal is much smaller than before.

After the DC offset-correction removal process, the EEG signal will then be cut off to remove the unwanted artifacts and noises because all signals with amplitude more than 100 or less than -100 are most probably noises. Below is the MATLAB code used to cut off the signal into the range of -100<EEG<100 (Fig. 8):

```
a = EFG signal
for a = 1:1:14;
find a>100
a = [ ];
find a<-100
a = [ ]
```

Feature extraction (power spectral density): From the filtered EEG signals, their PSD coefficients will then be calculated. For each data set, four PSD coefficients were obtained. This is due to the fact that the EEG signal was divided into four bands (alpha, beta, theta and delta) and thus the PSD coefficient is calculated for every band. Table 1 shows the coefficient for two data set of lifting left and right hand. From Table 1, the coefficient value for lifting left hand is slightly higher than lifting right hand. Such coefficient values will then be fed into the neural network classifier to differentiate whether the subject is lifting the right or left hand.

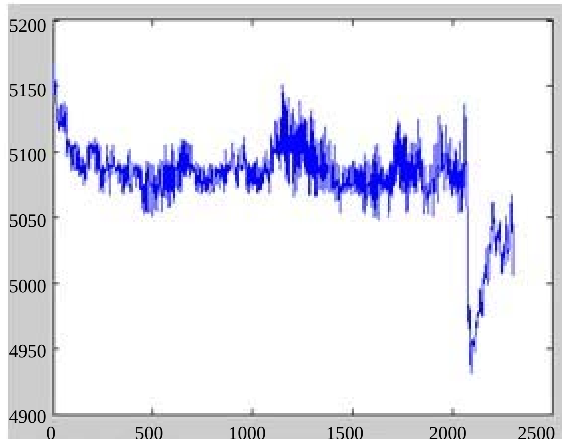

Fig. 6: Channel 1 raw EEG signal

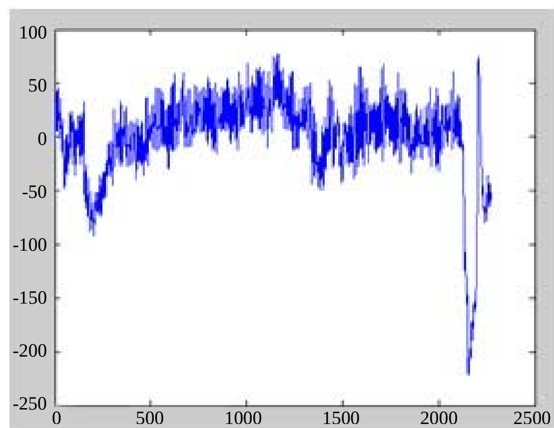

Fig. 7: EEG signal after DC offset-correction

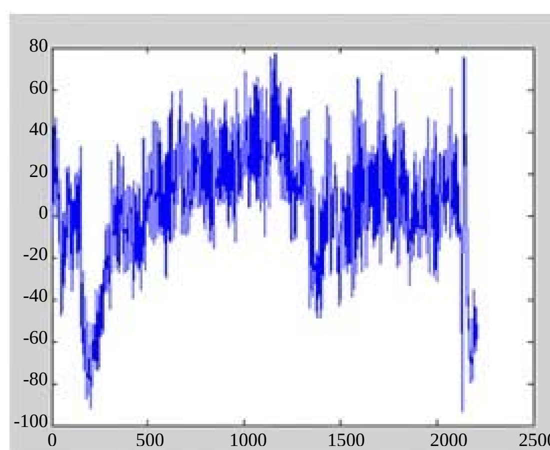

Fig. 8: Channel 1 data after removal of noises and artifacts

Table 1: PSD coefficient

Lifting hands (dataset)	PSD coefficient Alpha	Beta	Theta	Delta
Left 1	10.7725	18.7083	5.7935	1.7773
Left 2	10.7784	18.7040	5.8409	1.8009
Right 1	10.3221	18.3129	6.0650	1.5640
Right 2	10.4084	18.3924	6.0498	1.7207

Table 2: Neural network pattern classification performance based on all 4 bands (alpha, beta, theta and delta)

	Neural network performance			
No. of hidden unit	Threshold	TPR	FPR	Accuracy (%)
10	0.3	0.7368	0.1875	83
11	0.5	0.8333	0.1176	86
12	0.5	0.8000	0.0666	86
13	0.3	0.600	0.3043	77

TPR: True positive rate, FPR: False positive rate

Table 3: Neural network pattern classification performance based on alpha and beta bands

	Neural network performance			
No. of hidden unit	Threshold	TPR	FPR	Accuracy (%)
10	0.5	0.68182	0.1538	74
11	0.4	0.7222	0.2353	77
12	0.4	0.7778	0.1764	83
13	0.9	0.2500	0.8000	51

TPR: True positive rate, FPR: False positive rate

Classification (neural network): Table 2 shows the performance of the neural network classifier by considering all the 4 bands and all 14 electrodes. The parameters used and configured in the neural network include the number of hidden layer, hidden unit and threshold value. The neural network is trained starting from the smallest no of layer, which is one. Based on this one layer, different numbers of hidden unit are then configured for analysis. From the analysis conducted on a single hidden layer, the accuracy value obtained is acceptable and thus there is no need to go further on adding more hidden layer. From the Table 2, it can see that when the total of hidden units are 11 and 12, the accuracy of the classifier in correctly distinguishing the different actions (of lifting right and left hand) is 86% at threshold 0.5. Table 3 shows the performance of the neural network classifier when only alpha and beta bands are being considered. From the Table, it can see that the highest accuracy value that can be achieved by the classifier is 83% at 0.4 thresholds by using the total of 12 hidden units. By comparing both Table 2 and 3 and looking at the different accuracy values, it can say that by using features from all bands (alpha, beta, theta and delta), higher classification accuracy can be obtained rather than just relying on classification based on only features from alpha and beta bands.

This study presents an analysis and results for an experiment designed to distinguish the different physical actions (involving motor movement) performed by an individual based on the recorded EEG signals. For this initial experiment, the EEG signals were recorded from a single subject where the subject was first asked to lift right hand and then to lift left hand. The same activities were repeated for a number of recording sessions and the resulting EEG data were later analyzed and classified. Prior to the main processing, raw EEG data was first preprocessed to remove the artifacts and to filter the EEG signals into different frequency bands. The filtered data will then undergo further processing that is to extract important features from the signals based on PSD, which are later used for feature classification purpose by using the ANN classifier. The purpose of classification process is mainly to differentiate different EEG patterns based on the two different actions, i.e., lifting right hand and lifting left hand. Two classification attempts were performed, where the first attempt was to classify features based on all four bands. Whereas the second attempt was to classify features based on only two bands, specifically alpha and beta bands. Our finding has shown that the ANN classifier can classify more accurately in the first attempt when compared to the second one. Based on this finding, it can safely assume that the ANN classifier can perform better in classifying the different EEG patterns based on different motor execution when the inputs are covering all bands i.e., alpha, beta, delta and theta.

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