Emotion Classifier using EEG Signal Analysis

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Abstract - It is difficult to look at the EEG signal and identify the state of the human mind. In this project, the SVM classifier is trained with the DEAP dataset to predict the state of mind. the state of mind is predicted in terms of valence, arousal. which can further be used to predict the state of mind in terms of expression.

I. INTRODUCTION

Emotion is an important aspect of mankind. Humans interact using expressions and emotions, emotions play a huge role in critical decision making consciously and subconsciously. Their emotional recognition can have major applications in the growth of various fields such as medical, education, intelligent system, psychology, human-computer interaction, etc, hence emotion detection has been highly valued by researchers as one of the most important issues. Emotional recognition can be performed using facial expression or voice modulation study or internal factors such as analysis of electroencephalogram signals. The internal signals always provide a much more accurate result as the human has much less control over the same.

Emotion recognition is actually a pattern recognition task, and one among the key steps is extracting the emotion-related features from the multichannel EEG signals. Time domain, frequency domain, and time-frequency domain features have been proposed in the past.

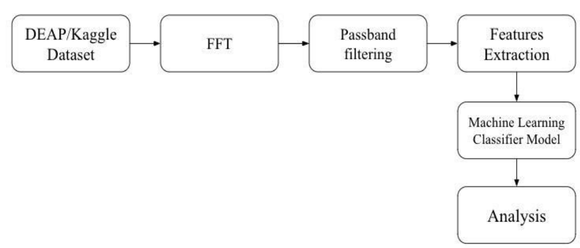
A Brain-Computer Interface (BCI) is a system that makes persons communicate with the external world only by thinking without relying on muscular or nervous activity. The mapping of brain signals processed to obtain features grouped into vectors results in commands to be executed by the system that displays feedback to the user in order to fine-tune or modulate his brain activity. Technologies such as Functional Magnetic Resonance Imaging (FMRI), Positron Emission Tomography (PET), and Functional Near-Infrared Brain Monitoring (FNIBM) are used to measure brain manifestation.

II. METHODOLOGY

In this project, the preprocessed data is used for training the classifier. Steps involved in training the dataset:-

1. Extracting the dataset
2. Finding the features
3. Reducing the dimension
4. Training the vector

The workflow of the project is given below



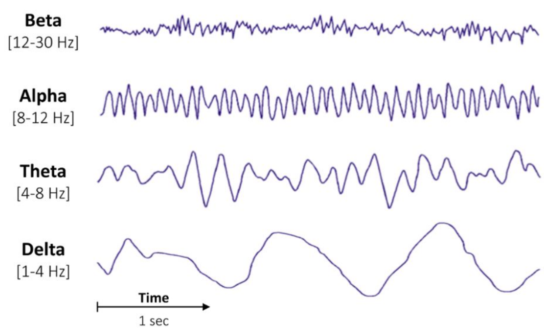
A. Extracting the Dataset

The DEAP dataset consists of two parts:
The ratings from an online self-assessment where 120 one-minute extracts of music videos were each rated by 14-16 volunteers based on arousal, valence, and dominance.

The participant ratings, physiological recordings, and face video of an experiment where 32 volunteers watched a subset of 40 of the above music videos. EEG and physiological signals were recorded and each participant also rated the videos as above. In this project, labels are extracted into separate files, and data of each channel are extracted into separate files. data from each channel is stored row-wise versus time in the column for each trail, per person.

B. Finding the Features

In this project, Wavelet transform is used to decompose each channel data into the five feature i.e • Delta (< 4 Hz) • Theta (4-7 Hz) • Alpha (8-15 Hz) • Beta (16-31 Hz) • Gamma (> 32 Hz) In this project, obtained the 7 decomposed values but we neglected the frequency whose range is in 0-0.5 Hz so that the artifacts are removed. The frequency whose range is near 50 Hz is removed to reduce the effect of the power line on signals. finally, the EEG band is obtained for each channel.



C. Reducing the Dimension

The dimension can be reduced using one of the below mention methods:-

Standard Deviation

Mean

Variance

Median

But for EEG signals we are using Standard Deviation

In order to compute the typical band power within the delta band, we first got to compute an estimate of the facility spectral density. the foremost widely-used method to try to do that's the Welch's periodogram, which consists of averaging consecutive Fourier transform of small windows of the signal, with or without overlapping.

Welch's method improves the accuracy of the classic periodogram. the rationale is simple: EEG data are always time-varying, meaning that if you check out 30 seconds of EEG data, it's very (very) unlikely that the signal will seem like an ideal sum of pure sines. Rather, the spectral content of the EEG changes over time, constantly modified by the neuronal activity at play under the scalp. Problem is, to return a real spectral estimate, a classic periodogram requires the spectral content of the signal to be stationary (i.e. time-unvarying) over the period of time considered. Because it's never the case, the periodogram is usually biased and contains way an excessive amount of variance (see the top of this tutorial). By averaging the periodograms obtained over short segments of the windows, Welch's method allows us to drastically reduce this variance. This comes at the value, however, of a lower frequency resolution. Indeed, the frequency resolution is defined by:

$$F_{res} = \frac{F_s}{N} = \frac{F_s}{F_s t} = \frac{1}{t}$$

where

Fs is the sampling frequency of the signal,

N is the total number of samples and t the duration, in seconds, of the signal. In other words, if we were to use the full length of our data (30 seconds), our final frequency resolution would be 1/30 =0.033Hz, which is 30 frequency bins per Hertz. By using a 4-second sliding window, we reduce this frequency resolution to 4 frequency bins per Hertz, i.e. each step represents 0.25 Hz.

How do we define the optimal window duration then? A commonly used approach is to take a window sufficiently long to encompasses at least two full cycles of the lowest frequency of interest. In our case, our lowest frequency of interest is 0.5 Hz so we will choose a window of 2/0.5=4 seconds.

D. Training the Vector

In this project, we have used an SVM Classifier to train our model and classify the emotions into Valence and Arousal.

The objective of the support vector machine algorithm is to find a hyperplane in N-dimensional space(N-the number of features) that distinctly classify the data points.

To separate the two classes of data points, there are many possible hyperplanes that could be chosen. Our objective is to find a plane that has the maximum margin, i.e the maximum distance between data points of both classes. Maximizing the margin distance provides some reinforcement so that future data points can be classified with more confidence.

III. RESULTS

In this project, we successfully implemented the above methodology and were able to get the desired output. We were able to extract the data from the DEAP dataset and convert the raw data into processed data, we were able to reduce the Dimensions of the Data and remove the outliers present.

The Data we will be using for training purposes is stored in CSV format which contains 1279 rows and 160 columns.

```
[ ]  df = pd.read_csv("train.csv")
```

```
[ ]  df.shape

     (1279, 160)
```

```
df.head()
```

	4.188588095907905	6.647708727092416	7.897348573759797	3.1290524997942493	1.1571803918930776
0	4.207449	7.303605	9.135929	4.380094	2.983259
1	4.345065	7.666760	8.825792	3.508968	1.296291
2	4.072856	6.752900	8.435405	3.833372	2.686686
3	3.904540	6.179935	6.595278	2.653142	0.737726
4	4.067055	6.933025	7.831297	3.323372	0.972481

5 rows × 160 columns

We were able to classify the test Data into Valence and arousal and check the efficiency of the SVM classifier

```
# classifier efficiency
'''
predicted valence 98.046875 percentage
predicted arousal 97.890625 percentage
predicted valence 95.0
predicted arousal 96.09375
'''
# output
'''
predicted valence 17.9166666667
predicted arousal 13.3333333333
'''
```

The output is stored in a 1-D array named as predic_al and predict_val for outputs of arousal and valence respectively. These outputs are then compared with the given ideal output of the data and the count is stored, with the help of this count we were able to find the frequency of the valence and arousal emotions in the data using the formula.

(Val_count / length of data) * 100.

The output is given below.

```
predicted valence 23.515625
predicted arousal 26.640625
[5 5 5 ... 6 6 6]
[7 7 7 ... 4 4 4]
'\npredicted valence 17.9166666667\npredicted arousal 13.3333333333\n'
```

IV. CONCLUSION

The results proved sufficient in providing evidence that electroencephalography may be a viable method of recognizing human emotion. There are various factors that affect the efficacy of EEG readings for emotion recognition, chiefly being the positions on the scalp from which the readings are taken, and thus the exact features of the readings that are taken. As this field remains relatively new, the complete extent of the capabilities of this technology isn't fully known. However, ascertaining its viability is that the initiative to any future development and is crucial to reach the betterment of the many other fields.

Further exploration is often wiped out in the areas of signal processing and data analysis. The performance of the models is very hooked into both the info being operated on and therefore the statistical model used. Further research is often done to determine the simplest methods to process and filter the EEG data, also on identify the simplest statistical model to use for emotion analysis.

V. ACKNOWLEDGEMENT

We would like to thank our project guide for his enormous co-operation and guidance. We have no words to express our gratitude for a person who wholeheartedly supported the project and gave freely of his valuable time while making this project. All the inputs given by him have found a place in the project. The technical guidance provided by him was more than useful and made the project successful. He has always been a source of inspiration for us. It was a memorable experience learning under such a highly innovative, enthusiastic, and hardworking professor.

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