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Transforming Brainwave Signals into Symbolic Strings Towards Academic Emotion Recognition

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Abstract: Students tend to experience varying academic emotions while engaged in learning activities. It is important for affective systems to predict certain emotions, particularly negative emotions, to be able to provide proper remediation and improve the learning experience of students. In this study, patterns of brainwave signals or electroencephalogram (EEG) of academic achiever high school students, such as those formed before the onset of an academic emotion, are analyzed by transforming this data into symbolic strings using a modified Shapelet Transform and SAX and from these strings, determining the emotional state of the students. These strings are shortened to further ease analysis. Results have shown that strings transformed from the same EEG feature and same emotion are significantly different to strings from different features and different emotions.

Keywords: Emotion recognition, Time series analysis, EEG, Affective learning environment, academic emotions, symbolic strings

1. Introduction

The emotions that a student experiences have an impact on the receptiveness of that student to the learning process. Students experiencing positive emotions would most likely have higher engagement and motivation to learn while students who are experiencing negative emotions would likely have lower engagement and motivation and be more susceptible to giving up on assigned tasks (Azcarraga, 2014). These emotions, which are involved in the entirety of the learning process, are referred to as academic emotions (Pekrun et al., 2002). There is an incentive then to identify and understand the emotions of students. This is to better understand the current disposition of the student and be able to adjust the learning program accordingly.

Identifying patterns of EEG readings that correspond to a certain academic emotion could prove useful in quickly identifying the emotions of a student by observing the readings produced. This could give the instructor an idea on the current experience of a student in real time. A student would typically experience a sequence of varying emotions throughout their learning process directly associated to which phase of learning they are in (Kort et al., 2001). Looking into the EEG readings as time series data would allow historical information of the emotions of the student to be considered as well in the classification process. This paper will look into the viability of transforming EEG readings into symbolic strings and from those strings attempt to extract patterns which may help monitor the emotional state of students while engaged in some learning activities.

2. Related Works

2.1 Alternative Representations of EEG data

Transformation of data into a form that can be analyzed more easily or to make it compatible with existing techniques is one of the primary steps of pre-processing. Different approaches of representing EEG and other time series data have been explored with one of these alternative approaches being symbolic representation, which transforms data into strings of symbols. Many researchers have found considerable success with using symbolic transformation for continuous data (Daw, Finney, & Tracy, 2003).

Use of symbolic representation has found relative success with using EEG data. One of these is a research by Muthu et al. (2019) which classifies eye movements through the similarity of strings transformed from windowed EEG data through Symbolic Aggregate Approximation (SAX). Another is a research by Raza and Kramer (2020) where SAX is once again used to transform the EEG data directly and from these strings, discriminating subsequences are extracted and used as features for transformation.

2.2 Emotion Recognition using EEG

Brainwave readings from EEG have been found to be an effective way to determine human emotions and has even been applied in the specific context of learning. The study of Heraz et al. (2007) attempted to train a learning agent which focused on predicting changes in what they call the emomental state of a learner, which they define as the combined mental and emotional state. The research done by Mampusti et al. (2011) attempted to classify a subject's emotions as they perform a learning task, Berg's card sorting task, through EEG data prepared using Butterworth bandpass filter. The research done by Azcarraga (2014) used EEG readings from students as they used computerized learning systems to classify the academic emotions of these students and to also visualize these emotions using structured self-organizing maps (SOM).

Expanding upon the existing literature and particularly the precursor study of this paper, a new method of transforming EEG data which can be used to identify and visualize academic emotions is explored. Although the findings of this research focus on the recognition of academic emotions of students, the techniques explored in this research could potentially br used in other applications which make use of EEG readings or even other types of time series data.

3. Methodology

3.1 Dataset Description

The original EEG dataset used in this study was collected from 52 participants, (only 8 of which were used in this study, 3 are female and 5 are male) consisting mostly of academically gifted science high school students who belong to the top 0.01% of the entire high school students in the Philippines. The brainwave signals of students are captured using the Emotiv EPOC sensor while they are answering mathematical problems using learning systems such as Scooter, a scatterplot tutoring system, and Aplusix, an algebra learning software.

The Emotiv EPOC headset sensor, which is a commercial product typically used for gaming purposes is equipped with 14 channels based on the International standard 10-20 locations. These readings are collected at around 2048 samples per second but the final dataset will contain 128 samples per second after being reduced by the device by performing a moving average.

The experiment involving one student typically lasts for an hour. The student is first briefed about the experiment and given a self-assessment then afterwards, the data collection equipment and the device to be used for the learning system are set up and worn by the student. The EEG of a few minutes of neutral activity, wherein the student simply stares at a blank screen with minimal activity, were collected first. The students were asked to report their level of confusion, boredom, frustration and interest every 2 mins or after each problem. These 4 emotions are some of the academic emotions in the study of Pekrun (2002).

For each of the 14 channels, the frequency bands of EEG signals are extracted using the selected data transformation technique. From the readings recorded from each of these channels, the frequencies and features are extracted. Only the frequency bands alpha, beta, and gamma are considered for this research, as guided by the findings established in Azcarraga (2014). The idea behind the use of these frequencies is that these frequencies are typically observed and associated to states of mind where emotions are expressed.

The class label of each observed instance is defined by the self-assessment of the student's affective state during the time frame that the observation was recorded. The labels consist of a rating of the level of intensity felt by the student for each academic emotion at a specific assessment period and an interpretation of this rating on whether the intensity is considered ”high” or ”low”. The interpretation is considered ”high” if it falls above a certain value and ”low” if it falls below

3.2 Pre-processing

Following what has been established in the basis study of this research (Azcarraga, 2014) and a similar study on EEG and emotion detection done by Dhanani et al. (2018), windowing of the data was guided by the findings established by Scherer and Ekman (1984) wherein emotions are found to usually last for 0.5 to 4 seconds. As such, in this study, the data is segmented into 2-second windows with 1-second overlap between windows.

The data was then transformed into a usable form with time bound information Discrete Wavelet Transform. This algorithm uses wavelets, which are defined us mathematical functions which analyze data as different frequency components with a resolution matching its scale (Graps, 1995). A key distinguishing feature of the wavelet transform is that it can give both the time and frequency information of the input signal. This is an important feature since for non-stationary signals, such as EEG, as certain frequencies do not occur all throughout the signal but rather, only at certain points in time. A transformation algorithm such as wavelet transform will be able to capture this information.

For the analyzing wavelet, Symlet was chosen since it was found to be suitable for decomposing EEG signals into frequency sub-bands. The Symlet wavelet tends to have a comparatively lower mean square error and thus is better for extracting various frequency bands from EEG signals (Shete & Shriram, 2014).

Transformation to the frequency domain by DWT was done for each 2-second window, and from this transformed data, the features that were extracted are peak magnitude and mean spectral power. The peak magnitude is the highest amplitude of the sample data while the mean spectral power is the average power spectrum of the signals in the sample data (Azcarraga, 2014). These two statistical features were computed for each frequency band and sensory location channel resulting in a total of 84 features.

Further pre-processing was done on the dataset after windowing and feature selection. EEG readings collected while the student is in a resting phase served as the baseline of the EEG readings of that student and were subtracted from the extracted features of the main dataset. Finally, the dataset was standardized and all values above 3 and below -3 were clipped to 3 and -3, respectively to manage the outliers.

3.3 Transformation to String Patterns

For the creation of string patterns, the standardized dataset is transformed using two data transformation algorithms: a modified Shapelet Transform and Symbolic Aggregate Approximation (SAX). These two techniques were used to transform windows of the EEG data into symbols which when taken as a dataset, form strings.

3.4 String Pattern Analysis

The resulting transformed strings are evaluated by how representative the strings are to the feature and emotion of the original data which was done by calculating similarity and difference among transformed strings. Difference to strings of different emotion and feature and similarity to strings of the same emotion and feature is indicative of the similar strings having a pattern among themselves. This difference and similarity was computed using Levenshtein edit distance where higher distance means a greater difference and lower distance, lesser difference. Then from the distance, the ratio is calculated where two strings of the exact match will give a ratio of 1.0 while two completely different strings will have a ratio 0.

4. Results and Analysis

A resulting string from the transformation represents only a single feature of one user but is equivalent to the entire data collection session. These strings are comprised of five different symbols, represented in this study by the first five letters of the Latin alphabet in uppercase form (A, B, C, D, and E). Using a different number of symbols retains the general information of the original data but increasing the number increases noises while decreasing the number results in lose of nuance.

The analysis of the transformed strings aim to verify if these strings are representative of the emotion they are labeled as and distinguishable from strings transformed from other features. This would suggest that important information related to the feature was retained even after transformation. This was quantified by calculating the similarity of the transformed strings to other strings of the same emotion and feature using edit distance and statistical significance measures and then inversely, calculating the difference of the same strings to strings of the other emotion labels and features.

4.1 Shapelet Transform Strings

The transformation of Shapelets uses an implementation which follows the original Shapelet Transform paper by Lines et al. (2012). However, in addition. the five most distinguishing shapelets were first selected from all subsequences then for each of these subsequences, the distance to the five shapelets is calculated. The shapelet with the nearest distance is identified and the equivalent symbol of that shapelet is assigned to the subsequence. All subsequences are assigned a symbol which will comprise the final transformed string. The strings transformed in this manner can be seen in Table 1.

Table 1: *Randomly selected sample strings transformed using Shapelet Transform from all emotions.*

Feature	Emotion	Emotion Label	Transformed String
AF3 THETA AP	Bored	L	BEBBABBBBBEEABBBABBBBBEBBBBBEABAB BEBBABBBBBEBBBEEBBBBAEABBBB AEBBBBABABABBBBABBBBAA
		H	BBBBAEBABBBBBEBBE
		L	BBBB
AF4_BETA_AP	Confused	H	DDDDEDDDDEDDE
		L	DDDDCDDDDBDDDD
		H	DEDDDDEDDDDE
F8 THETA PM	Frustrated	H	ECECCCCEEECCCCEECCEECCECCEECCEC CEEEECCEEEBCCECB
		L	CEEEBCECEECEECBEBECBECEEEBCCEEEE CCCEECCBCCCCBECCEECCECCCEEB
O1 BETA AP	Interested	H	BBEEEBBBBEBEBEBBEEEBEBEEEABBBBEE BBEBEDDAEEBBBBEEBBBEBBEBEBBBEEE E
		L	EEEEAEBEBBBBBEDEBBBEEDBE
		H	BDEDDEEEEBBEEAB
		L	ABEBEEEC

4.2 SAX Strings

Among the symbolic representation techniques, SAX is among the more well-known techniques. This technique was used as a baseline of comparison to demonstrate the viability of the novel technique which used Shapelets. The implementation used for this research follows the original paper by J. Lin et al. (2007). The resulting strings that were produced using SAX have a similar visual appearance to the strings produced by the shapelet technique. These transformed strings can be seen below in Table 2.

Table 2: *Randomly selected sample strings transformed using SAX from all emotions.*

Feature	Emotion	Emotion Label	Transformed String
F4 THETA PM	Bored	H	DCDCCCCDDDDCCCDCDCCCDCCCCDCCCCDD CCCCDCDDCDDCDDCCCCD
		L	CCCCDCDDCCCCDCDCCCDDDCCCCDCCDCCCC DCCDCCCCDCCCDCCCCDCDCCCDCCC
		H	CCCC
F8 ALPHA PM	Confused	L	AAAACAAAA
		H	AAAA
		L	AAAAC

AF4 THETA AP	Frustrated	H	CCCCDCCCCDCCCCECC
		L	CCCCDCCCCDCCCCDCCCC
O2 BETA AP	Interested	L	DBBBBCCBBBDBBCCBBBBCBCCBBBB
		H	BBBBCBCCCBBBBCCCCBBBBCDCDDDDBDECCCDEDDB
		L	BBBCC

4.3 Overall comparison

The comparison of edit distances and ratios of the transformed strings can be seen in Table 3. It can be noted that there is a consistent trend of similar strings having higher ratios and different strings having lower ratios for both the shapelet and SAX algorithms. For the distances, there is a similar trend on the difference between the distance of similar strings and different strings: the difference is much higher for shapelet transformed strings compared to SAX transformed strings. Indeed, if measured with these metrics, it can be said that the proposed algorithm which uses shapelet transform can produce an output comparable to or of even better quality than SAX.

Table 3: *Average ratios and distances of the strings transformed using Shapelet compared to the strings transformed using SAX.*

		Compared to Same Feature, Same Emotion		Compared to Same Feature, Diff. Emotion		Compared to Diff. Feature, Same Emotion		Compared to Diff. Feature, Diff. Emotion	
		Shapelet	SAX	Shapelet	SAX	Shapelet	SAX	Shapelet	SAX
Average Ratio	Bored	0.4710	0.4541	0.4102	0.4046	0.2305	0.2706	0.2230	0.2693
	Confused	0.4921	0.4757	0.4222	0.3978	0.2480	0.2787	0.2414	0.2682
	Frustrated	0.4910	0.4772	0.3755	0.3893	0.2390	0.2905	0.2125	0.2750
	Interested	0.6058	0.4875	0.4800	0.4101	0.3636	0.2984	0.3081	0.2799
Average Distance	Bored	35.38	23.80	39.16	25.91	45.75	29.48	46.08	29.22
	Confused	37.63	24.49	43.23	28.08	50.58	31.94	52.12	32.61
	Frustrated	35.42	23.85	46.33	28.31	49.41	31.49	53.39	31.85
	Interested	21.07	20.32	29.30	24.32	30.33	26.27	34.97	27.31

To further support this claim, paired t-tests were conducted on the average ratio when compared to other strings of the same feature and emotion against ratios compared to strings of the same feature but different emotion and strings of different feature but the same emotion. The tests were setup wherein the null hypothesis is that ratios of strings of different feature or emotion have no difference or are greater than the ratios of strings of the same feature and emotion, while the alternative hypothesis is that the ratio of strings of different feature and emotion are less than ratios of strings of the same feature and emotion. These were done on a sample of 30 strings for each emotion and technique.

Table 4: *Resulting p-values of paired t-tests conducted on the average ratios of same emotion and feature against average ratios of other emotion and other feature*

		Against Other Emotion	Against Other Feature
SAX	Bored	0.014800075	1.92E-05
	Confused	4.95E-05	3.21E-08
	Frustrated	0.000407246	0.000150666
	Interested	9.87E-05	3.09E-07
Shapelets	Bored	0.009914672	1.32E-10
	Confused	0.000279542	2.11E-08
	Frustrated	0.000712499	9.66E-10
	Interested	7.32E-05	1.38E-10

From the results shown in Table 4, the alternative hypothesis can be accepted, with very low p-values across all emotions. For the purposes of this research, a confidence level of 0.95 and an alpha of 0.05 is acceptable but almost all the resulting p-values are less than even 0.01 which all the more supports the claim that there is significant difference between strings of the same feature and emotion to strings of a different feature and emotion.

5. Conclusions and Recommendations

In this paper, we explored using different techniques for representing EEG data for identification academic emotions. For transformation to the frequency domain, DWT was used and for transformation to string based representation, SAX and a modified Shapelet Transform was explored. By monitoring the generated emotion strings, affective systems may be able to recognize an academic emotion and provide proper remediation at the right time. The noticeable similarity of strings transformed from similar data shows that such information is retained when EEG data is transformed to strings. This also implies that strings of the same feature and emotions potentially have a common pattern among them. More advanced techniques to verify and analyze the resulting strings could be employed however to possibly provide more information and possibly also allow better recognition of emotions, such those used in natural language processing. Other techniques may be also explored to derive more readable versions of the strings such as Finite State Machines, Regular Expressions, or Hidden Markov Modelling generation which may also be used to extract more informative patterns from the strings.

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