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Dynamic Time Warping based connectivity classification of Event-Related Potentials

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Abstract*—Human brain electrical responses measured as Electroencephalogram epochs have different characteristics by means of amplitude and frequency content depending on the conditions and stimuli. Event-related potentials are the responses given to the stimuli and can be measured using the EEG. The average of these epochs are computed to remove the background activity and helps to exhibit the response to stimuli solely. In the concept of this study, dynamic time warping based connectivity features are used to classify the single-trial ERP epochs. Color Stroop test was implemented and ERP data are collected from 10 subjects. Support vector machine and K-NN classifiers are used and accurate classification results are achieved with the use of DTW metrics.

***Keywords*— DTW, SVM, KNN, ERP**

I. INTRODUCTION

The human brain is the most complicated organ of the human body that contains approximately 10 billion nerves and it is responsible for controlling various body functions such as controlling all-important human actions that keep him alive. To monitor the activity originated from the brain tissue help researchers to make decisions about mental health and status. The functional changes of the brain tissue can be determined from the electrical signals measured from the scalp surface (Electroencephalogram, EEG) or as the change of the blood oxygenation using functional Magnetic Resonance Imaging (fMRI). The former technique has the ability to measure the cognitive neurodynamics on order of milliseconds whereas the temporal resolution of the latter one is limited with the hemodynamic response of the brain. Thus, EEG signals are widely used in the classification of the mental status of the subjects [1]. Several researchers have been conducted in the analysis of the EEG classification [2] and relevant features were obtained for different states of the brain. When the subjects are presented with a repetitive stimulus, the average of the time-locked brain responses to these stimuli is called event-related potential (ERP). The ERP is constructed of the average of many trials (10 to 50) [3]. By averaging process, it is likely that we lose information. However, as a result of this process, the background activity is eliminated and only the response to the given stimuli is obtained. This process causes trimming the time information of the presented stimuli.

In a recent study, electrical activity due to local synchronization and connectivity computed by synchronization between electrodes are extracted by phase-amplitude coupling, power spectrum, and phase-locking metrics to classify cognitive tasks [9]. Deep learning was also adopted in the classification of the scalp topographies of the Stroop task [10]. In the concept of this paper, we aimed to classify the single-trial ERP measurements using dynamic time warping (DTW) as a feature extraction technique. Connectivity between EEG time-series is computed using DTW. For each epoch having a duration of 1 second, the connectivity value is computed between each possible pair of 16 electrodes. Thus, 120 undirected features are obtained for the classification purpose. Machine learning classification techniques have been adopted to identify the stimulus type that the participant has seen. ERP is measured using the Color Stroop task. The features of the time series are analyzed in 1-sec length epochs to determine if the stimulus is congruent or incongruent.

II. METHODOLOGY

A. Data collection and experimental design

The data collected from 10 volunteers. The mean age of the volunteers was 25. The volunteers have been subjected to the Color Stroop test. In Stroop test visual stimuli were used with color names. If the color of the stimulus was matching with the written text (congruent), the right arrow key of the keyboard is pressed otherwise (incongruent) the left arrow key was pressed. Data preprocessing is an important stage in any machine learning study. It is used to reduce the noise and variance in data. In the concept of this study, connectivity metrics are used as features and these features are computed with the use of dynamic time warping techniques. Prior to feature computation, time series are normalized [4] using the z-normalizing technique.

B. Classifiers

In this work, we used two machine learning classifiers that proportional to our numeric dataset to classify it into two classes congruent and incongruent. The first classification algorithm used was the support vector machine it is a supervised classification technique evaluated by Vapnik[5]. The main idea of SVM is to detect alignment hyperplane or decision boundary that can sperate the data into two classes this can be done by looking for maximum marginal hyperplane. SVM has many parameters that can influence on classification approach most common parametres (which we used also in this work)are. The second classification technique that used in this work was the K-nearest neighbor algorithm KNN it is a non-parametric supervised classification technique that works well with large datasets [11]it is appropriate with data that contain noises and when there is absent prior knowledge about the distribution of data. it is put all the dataset tuples in n-dimensional space ,every point in this space represent a training tuples, to classify the new unknown tuple(test data tuple) the KNN algorithm search for k-nearest training tuples to this new unknown tuple and uses the majority voting to choose the test tuple class by its k-nearest neighbors of training tuples [6]. the mechanism that the KNN used to determine the closest tuples is the euclidean distance(Equ 1) between the test tuple and its k-nearest training tuples.

$$dist(A,B) = \sqrt{(A2-A1)^2 + (B2-B1)^2} \quad (1)$$

so if the new unknown tuple is close to its k-nearest training tuples of class A that means the new unknown tuple belongs to this class(class A) and if it is close to its k-nearest tuples of class B it's mean this new test tuple belongs to class B. the k is integer number that determines the number of training tuples that we want to compare the test tuple with them. it preferred to set it as an odd number to avoid the confusion. Figure 2.1 illustrates the KNN classification algorithm working mechanism.

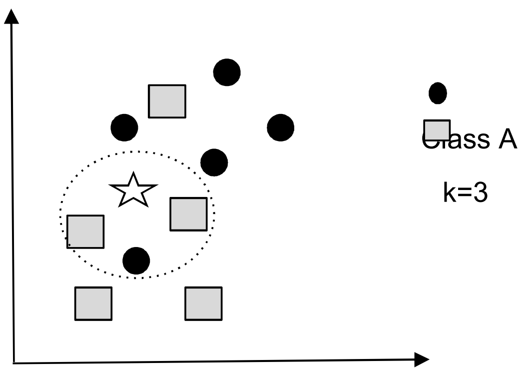

Figure 2.1: Data classification using KNN, the star shape represents new test tuple and the circle and square shapes represent training data tuples whereas the dashed circle refers to the rang of k-nearest to compare the test tuple with.

C. Feature extraction: DTW

Dynamic Time Warping is a similarity metric for measuring connectivity to find the similarity between two-time series by using an optimal warped path between two series [7]. This technique is widely used in speech recognition and data mining to solving time series classification. In this work, we use this technique to find similarities between all possible pairs of EEG channels to extract features from single-trial data. A sample implementation of the DTW is given in Fig. 2.1.

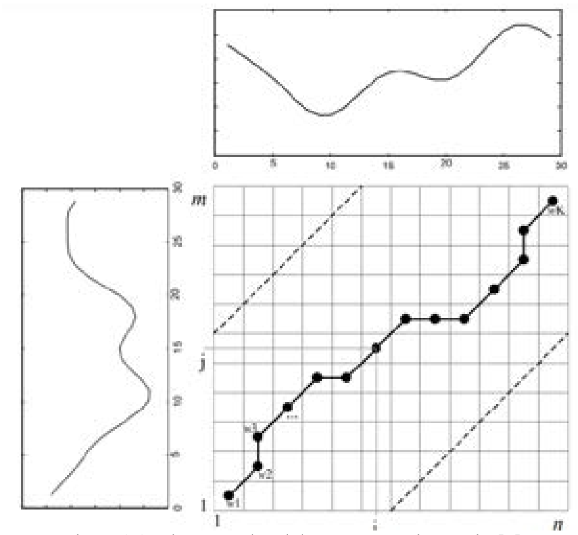

Figure 2.2: The warped path between two-time series[7]

Dynamic time warping is an algorithm used to measure the similarity between two sequences which may vary in time or speed. It works as follows:

The time series of an electrode pair is set as two series having an equal number of points. Then Euclidean distance between the first entry of the first time series and all points in the second series are computed. The minimum of the distance is selected and called as a time warp. This process is repeatedly implemented for the other points of the first time series.
The whole process is implemented once more by changing the order of time series. Finally, the minimum distance values are added to form the similarity measures between the time series.

III. RESULTS

The sample results are illustrated from the DTW algorithm and are shown in Fig.2.2 and Fig. 2.3. The electrodes are plotted with red circles and the lines between electrodes are used to represent the connectivity between electrodes. The red and yellow colors of the lines show higher connectivity values than the blue lines.

The DTW values are used for connectivity features. 120 features are used to represent the response regarding the congruent and incongruent stimuli. The classification procedures were implemented using the connectivity features.

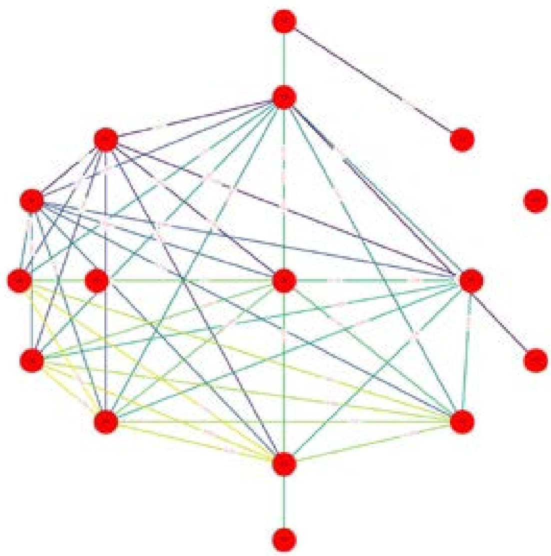

Figure 2.2: Connectivity between channels deduced from DTW from one subject's one second (congruent) EEG data.

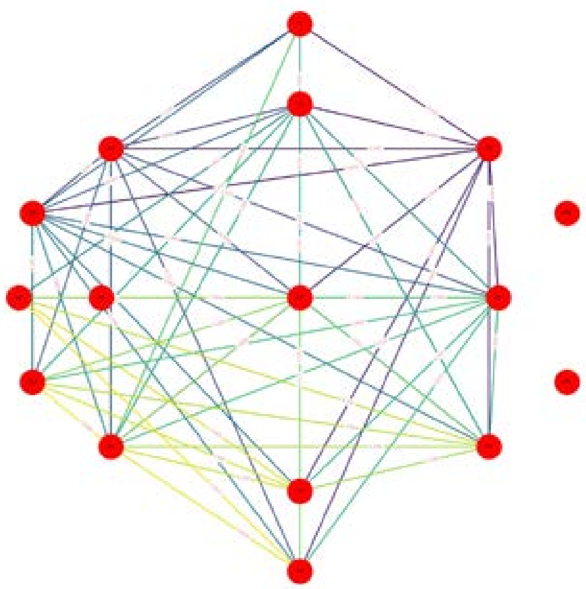

Figure 2.3: Connectivity between channels deduced from DTW from one subject's one second (incongruent) EEG data.

The normalization of ERP data enhances to achieve higher classification accuracy for both classification techniques that are used in this work as shown in tables 3.1 and 3.2. The use of both techniques are in agreement and it has been observed that the congruent and incongruent cases can be successfully separated with the use of the connectivity values between the electrodes.

TABLE 3. 1: SUPPORT VECTOR MACHINE CLASSIFICATION REPORT

Class label	precision	Recall	F1-score	support
1 (congruent)	0.99	1.00	0.99	1932
2 (incongruent)	1.00	0.99	0.99	2005
avg	0.99	0.99	0.99	3937

TABLE 3. 2: KNN CLASSIFICATION REPORT

Class label	precision	Recall	F1-score	support
1 (congruent)	1.00	1.00	1.00	1932
2 (incongruent)	1.00	1.00	1.00	2005
avg	1.00	1.00	1.00	3937

IV. DISCUSSION

ERP classification can be performed using well-known attributes such as P200, P300, N400, and late positive potentials. However, the average of all responses should be used to obtain the ERP waveform to obtain a high contrast between the responses. In the concept of this study, similar to our previous work, single-trial EEG epochs were taken into account [8]. A similar approach based on epoched data classification was performed with the muscle oxygen saturation measurements [12] and using motor imagery dataset [13]. Using the epoched data enable us to train classifiers efficiently.

The novelty of this study was the usage of DTW based connectivity features in the Stroop task rather than using the conventional markers of the ERP. There are several techniques for the computation of connectivity. For instance, coherence values between the channels were commonly used to determine the connectivity. The limitation of the coherence technique is the problem of the frequency selection. As an enhancement, wavelet coherence enables researchers to use the time-frequency contrast for coherence, but still, there is a need for frequency selection. However, DTW can be used on raw time-series and in this study, high accuracy values are obtained when they were used to classify two states of the measured ERP.

The connectivity metrics are deduced from the raw single trial ERP epochs without performing any filtering. Generally, the ERP components are thought to occur in the low frequency bands of the EEG. But in this study, in the absence of frequency filtering, we successfully classify congruent and incongruent waveforms by the DTW based connectivity metrics.

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