Time Warping Solutions for Classifying Artifacts in EEG

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***Abstract*— The most common brain-computer interface (BCI) devices use electroencephalography (EEG). EEG signals are noisy owing to the presence of many artifacts, namely head movement, and facial movements like eye blinks or jaw movements. Removal of these artifacts from EEG signals is essential for the success of any downstream BCI application. These artifacts influence different sensors of the EEG. In this paper, we devise algorithms for detection and classification of artifacts. Classification of artifacts into head nod, jaw movement and eye-blink is performed using two different varieties of time warping; namely, linear time warping, and dynamic time warping. The average accuracy of 85% and 90% is obtained using the former, and the later, respectively.**

I. INTRODUCTION

Electroencephalogram (EEG) measures the electrical activity on the scalp triggered by millions of neurons. EEG signals contain useful information corresponding to the state of the brain [1]. In addition to this useful information, EEG also captures artifacts, which are undesirable electrical potentials that come from non-cerebral sources. Typical artifacts are caused by eye blink, eyeball movement, muscle movement, movement of the head, and so on. Such artifacts overwhelm the EEG signal and make EEG analysis challenging. This issue is addressed by first locating the artifacts, and excluding the EEG segment from analysis [2]. This could lead to a loss of useful information. An alternative approach would be to reduce the effect of the artifact on the EEG signal. Occasionally, artifacts are used to build BCIs [3], [4], Prof. Hawking used cheek twitch to communicate [5]. This paper aims to classify the different types of artifacts, namely eye blink, head nod, head turn and jaw movements in the EEG signal. We devise a novel thresholding technique to detect the artifacts. After detecting the artifacts, time warping algorithm such as Linear Time Warping (LTW) and Dynamic Time Warping (DTW) are used to classify the artifacts.

The remainder of the paper is organized in the following manner. Section II focuses on related works in artifact detection. Data collection and preprocessing techniques are discussed in Section III. Section IV briefly discuss LTW and DTW approaches. We present our observations and results in Section V followed by conclusion in Section VI.

II. RELATED WORK

In contrast to brain signatures, the artifacts show high amplitude in EEG signals. In [6], an automated threshold on the amplitude of the signal based artifacts rejection approach was proposed. Wavelet, Kurtosis and Renyi's entropy based investigation to detect artifacts was introduced in [7]. In [8], methods for EEG artifacts detection based on Kalman filter autoregressive model and radial basis function Neural Networks was proposed. All the above approaches are agnostic to the type of artifact. Our work not only determines the presence of artifact but also identifies the type of artifact.

Independent Component Analysis (ICA) in EEG signals has been extensively used for artifact removal and can be found in [9], [10], [11]. An attempt has been made to detect and exclude eyeball movement and blink artifacts from EEG data using blind component separation in [12]. In [13], detection and removal of heartbeat artifacts from EEG signals using wavelet analysis were proposed. In [14], spectral analysis based muscular artifacts detection in EEG was introduced. It is observed that the artifacts have temporal signatures. In this paper, we take advantage of these temporal signatures and propose the use of LTW and DTW algorithms for classifying different artifacts from signals.

III. DATA COLLECTION

The dataset used in this study was acquired using a 128 electrode EEG setup provided by Electrical Geodesics, Inc (EGI). EEG signals were recorded at the sampling rate of 250 Hertz. The impedances of the electrodes were monitored throughout the experiment. The subjects were instructed to generate artifacts using a controlled experiment protocol. During the experiment, the subjects were requested to close their eyes unless stated in the instruction. Instructions were presented to the subject using a loudspeaker to make an appropriate muscular movement, namely eye open and close, mouth open and close, head nod, and head left to right turn. The instructions were given randomly to prevent the subject from being able to predict the movement apriori. Before every trial, the subject was provided two seconds to relax. Subjects were requested to listen to the instruction completely and make a muscular movement. Three seconds was provided to the subjects to perform the muscular movements after the instruction playback. After making a muscular move, the subjects were asked to perform a mouse click. This is to ensure that they indeed performed the movement. Illustrative timeline for data collection during a trial is shown in Figure 1. EEG artifacts of two different subjects are shown in Figure 2 and from the Figure it can be seen that the temporal signatures of different artifacts are distinct even across subjects. This study was approved by the Ethics Committee of the Indian Institute of Technology Madras. All the subjects were informed about the aim and scope of the experiment, and written consent was also obtained to collect the data. Data was collected from nine subjects. Out

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Fig. 1: Time-line diagram illustrating the data collection protocol.

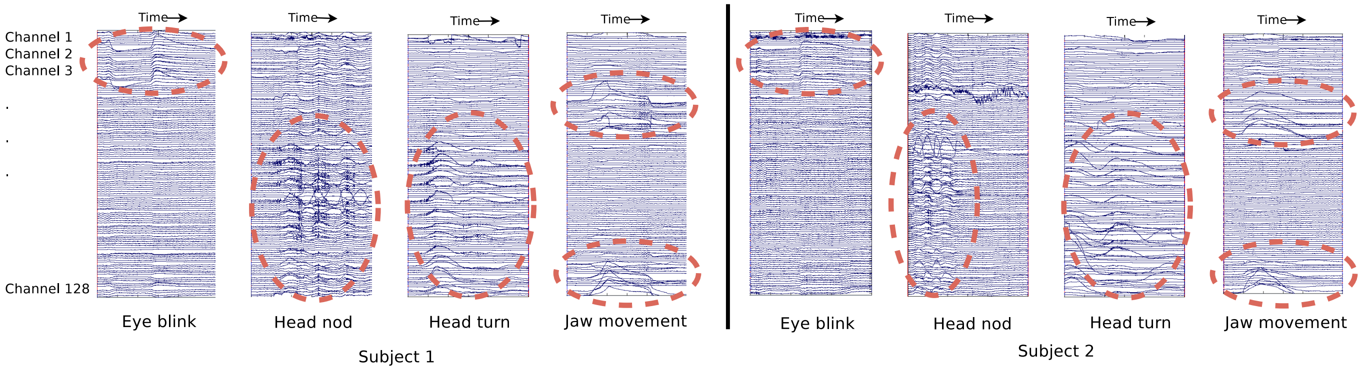

Fig. 2: EEG signals of different artifacts of two subjects

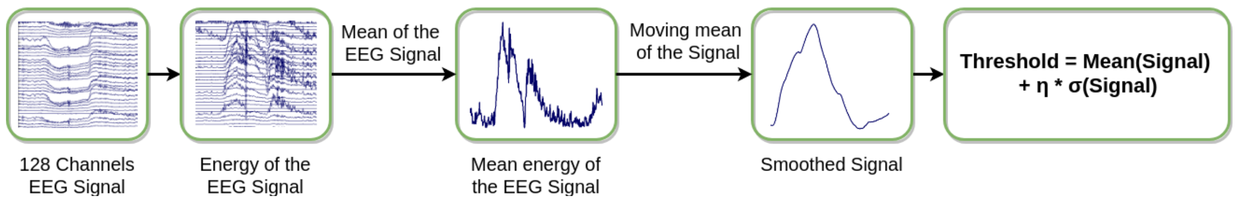

Fig. 3: Illustration of artifact detection using 128 channel EEG

of these nine subjects, four subjects came for the second session after 6 months. An average of 22 trials was acquired during each session. Acquired EEG signals were filtered with 0.3 to 60 Hertz bandpass filter, and a notch of 50 Hertz applied to reduce line noise. Three seconds interval provided for artifact generation were extracted from the mean-centered EEG signal. Assuming that all the channels are independent, the raw signal results in a 128x750 dimension vector with a sampling rate of 250Hz.

IV. Methods

A. Threshold Based Detection

Artifacts influence and show high amplitudes in the sensors. Using this knowledge, we design a threshold based technique to detect the artifacts. The mean of energy signal obtained from all the 128 channels is first computed. This energy signal is then smoothed using a moving average filter of length 100 samples (0.4 seconds).

This signal gives a signature of the artifact and will be referred henceforth as “artifact-signal”. Using a threshold on the energy value of this smoothed signal the artifacts can be reliably detected. The onset and decay of the artifacts can be found by the following threshold method,

$$Threshold = mean\,(\text{“artifact-signal”}) + \eta * \sigma\,(\text{“artifact-signal”})$$

where σ is the standard deviation of “artifact-signal”, and η is a hyper-parameter. The span of signal crosses the threshold defines the onset and decay of the artifacts. This process is illustrated with an example in Figure 3. Once the onset and decay of the artifacts have been detected, the type of artifact can reliably be identified using time warping techniques. The time warping is essential because the duration of each artifact can vary from trial to trial and person to person. Figure 2 shows the variation in the duration of the artifacts for different subjects[1].

B. Linear Time Warping algorithm

Linear Time Warping (LTW) algorithm is a technique in sequential pattern recognition where both sequences are interpolated to the same length and classified based on Euclidean distance of the sequences. The onset and the decay of an artifact are first detected using IV-A. However, the duration of the artifacts can vary from time to time. Hence, we first interpolate the test and the reference templates to the same length and then compare using Euclidean distance. To account for the variability in the amplitude of artifact signatures, the signals are normalized to zero mean and unit variance of energy before comparing. This LTW distance is then used as a score to classify or detect an artifact of a particular type.

C. Dynamic Time Warping algorithm

In contrast to LTW, Dynamic Time Warping algorithm tries to match a non-linear warp between the test and the reference [15]. This warping between two time series can be used to determine the similarities and distinctions between the two time series. The following equation estimates DTW

[1]Supplementary plots for artifacts, and DTW matrices of various subjects are available in http://bit.ly/EEGPlot.

distance of two signals.

$$r_{i,j} = dist\left(\bar{x}_i, \bar{y}_j\right) + min\left(r_{i-1,j-1}, r_{i-1,j}, r_{i,j-1}\right) \quad (1)$$

where $\bar{x}_i$ and $\bar{y}_j$ are features of the two signals compared, $dist\left(\bar{x}_i, \bar{y}_j\right)$ is the Euclidean distance between $\bar{x}_i$ and $\bar{y}_j$. $r_{0,0}$ is initialized with 0 and remaining $r_{i,j}$ are initialized with infinity. The final DTW distances are normalized by the warping path length. Similar to Section IV-B, the signals are normalized to zero mean and unit variance before comparing.

TABLE I: Number of Subjects and Trials used

	No. of Subjects		No. of Trials	
	Train	**Test**	**Train**	**Test**
Single Session	9	9	103	103
Inter Sessions	4	4	50	55
Inter Subjects	5	4	75	60

V. Results

A. Classification

During data collection (Section III) the subjects were instructed to perform artifacts in a 3s time window. In this section, we take the 3s windows in which we expect to see an artifact and try to classify them using LTW and DTW. We attempt the harder problem of detecting the artifacts in the continuous EEG signal without this 3s ground truth window information in Section V-B. The start and end of the artifact within the 3 window is detected using the threshold technique given in Section IV-A. Empirically, we found that the hyper-parameter $\eta = -1$ performs well for this task. After detecting the artifacts within the ground truth windows, they are classified using LTW and DTW distance based k-Nearest Neighbour classifiers. Three different experiments are designed to detect and classify the artifacts. The entries in the tables indicate the individual accuracy of each artifact, achieved by the four class classification models, along with the total accuracy of the classification model. The number of subjects and trials used for training and testing in different conditions is summarized in Table I.

TABLE II: Classification Results for Intra-Session

	K	Eye Blink	Head Nod	Head Turn	Jaw Movement	Model Accuracy
LTW	**1**	100%	74.8%	85.4%	90.3%	***87.6%***
	3	100%	70.9%	86.4%	88.3%	***86.4%***
	5	99.0%	70.9%	83.5%	88.3%	***85.4%***
	7	99.0%	68.9%	81.6%	92.2%	***85.4%***
DTW	**1**	100%	83.5%	92.2%	87.4%	***90.8%***
	3	100%	80.6%	88.3%	84.5%	***88.3%***
	5	100%	81.6%	86.4%	88.3%	***89.1%***
	7	99.0%	78.6%	85.4%	89.3%	***88.1%***

1) Intra-Session: In this experiment, single session data from all nine subjects is used. From each session, arbitrary 50% of the trials were used as the reference sequences, and the remaining are used for the test sequences. The result of this classification for various values of k is given in Table II.

TABLE III: Classification Results for Inter-Session

	K	Eye Blink	Head Nod	Head Turn	Jaw Movement	Model Accuracy
LTW	**1**	94.5%	45.4%	81.8%	78.2%	***75.0%***
	3	98.2%	52.7%	78.2%	74.5%	***75.9%***
	5	96.4%	49.1%	80.0%	69.1%	***73.6%***
	7	90.9%	45.5%	80.0%	70.9%	***71.8%***
DTW	**1**	98.1%	49.1%	67.3%	47.3%	***65.5%***
	3	100%	47.3%	67.3%	40.0%	***63.6%***
	5	100%	40.0%	70.9%	38.2%	***62.3%***
	7	100%	40.0%	70.9%	43.6%	***63.6%***

TABLE IV: Classification Results for Inter-Subject

	K	Eye Blink	Head Nod	Head Turn	Jaw Movement	Model Accuracy
LTW	**1**	95.0%	11.7%	61.7%	86.7%	***63.8%***
	3	98.3%	11.7%	61.7%	88.3%	***65.0%***
	5	98.3%	10.0%	61.7%	90.0%	***65.0%***
	7	98.3%	1.7%	61.7%	88.3%	***62.5%***
DTW	**1**	93.3%	5.0%	48.3%	80.0%	***56.7%***
	3	93.3%	6.7%	51.7%	75.0%	***56.7%***
	5	93.3%	8.3%	53.3%	76.7%	***56.1%***
	7	93.3%	1.6%	51.6%	76.6%	***55.8%***

2) Inter-Session: In this section, the four subjects data with multiple sessions have been used. The arbitrarily chosen session data of each subject was used as reference sequences, and another session data was used as test sequences. The result of this experiment is shown in Table III.

3) Inter-Subject: In this section, artifact signatures were tested across subjects. From all the nine subjects, four subjects' EEG data were randomly chosen as the reference sequences, and the remaining five subjects data were used as the test sequences. The result of this experiment is shown in Table IV.

From Tables II, III and IV, it can be observed that the proposed technique classifies the artifacts with highest accuracy of 90.8% when all sessions are used for both training and testing. The accuracy falls to 75.9% when tested across session and further reduces to 63.8% when tested across subjects. It is important to note that only the "Head Nod" class is identified with poor accuracy. The primary reason for this is both head nod and head turn influence the same set of channels (in Figure 2) and hence their signatures are not classifiable across session and subjects. Also, LTW is observed to give slightly better accuracy in inter-session and inter-subject setting. This result explains that the time warping in artifacts are more linear than non-linear.

B. Detection

In this section, the ground truth information of 3s where the subject was instructed to perform the artifacts was not used. The whole EEG data was taken, and the onset and decay of all the artifacts were detected using the threshold method as discussed in Section IV-A. The detected artifacts were assumed to be correct if the time span between detected onset and decay of the artifacts overlap 60% or more with the 3s ground truth window. The hyper-parameter η was tuned, and it was observed that a value of 0.8 and 0.9 works best, and this has been shown in the Table V. In the

TABLE V: Detection scores for all EEG subjects

η	-0.4	-0.2	0	0.2	0.4	0.6	0.7	**0.8**	**0.9**	1	1.2	1.4
F1 Score	72.31%	76.57%	81.23%	87.10%	91.60%	93.88%	94.44%	**94.94%**	**94.94%**	92.74%	89.34%	83.19%

TABLE VI: Classification Results for Intra-Session after Detection

	K	Eye Blink	Head Nod	Head Turn	Jaw Movement	Model Accuracy
LTW	**1**	75.7%	52.4%	79.6%	74.8%	***70.6%***
	3	78.6%	36.9%	79.6%	71.8%	***66.8%***
	5	78.6%	37.9%	83.5%	71.8%	***68.0%***
	7	78.6%	34.9%	83.5%	72.8%	***67.5%***
DTW	**1**	91.3%	92.2%	91.3%	88.4%	***90.8%***
	3	90.3%	90.3%	93.2%	87.4%	***90.3%***
	5	90.3%	90.3%	93.2%	84.5%	***89.3%***
	7	90.3%	88.4%	92.2%	79.6%	***87.6%***

TABLE VII: Classification Results for Inter-Session after Detection

	K	Eye Blink	Head Nod	Head Turn	Jaw Movement	Model Accuracy
LTW	**1**	89.1%	18.2%	78.2%	63.6%	***62.3%***
	3	89.1%	23.6%	80.0%	74.6%	***66.8%***
	5	89.1%	16.4%	74.6%	72.7%	***68.2%***
	7	89.1%	14.6%	74.6%	72.7%	***68.2%***
DTW	**1**	89.1%	38.2%	74.6%	36.4%	***59.6%***
	3	90.9%	32.7%	76.4%	32.7%	***58.2%***
	5	90.9%	20.0%	78.2%	29.1%	***55.0%***
	7	90.9%	14.6%	78.2%	29.1%	***53.2%***

remainder of the section, $\eta = 0.8$ was chosen. Similar to Section V-A, the results are shown for *Intra-Session*, *Inter-Session* and *Inter-Subject* conditions in Tables VI, VII and VIII, respectively. From the Table VI, it is evident that the proposed model performs well for seen subjects with accuracy around 80%. The performance of *inter-sessions* and *inter-subjects* are shown in the Tables VII and VIII. From the results, it is observed that in spite of the performance degradation in *inter-sessions* and *inter-subjects*, the pattern of artifacts is consistent. Moreover, given that the accuracy for *intra-subject*, the artifacts can be gainfully used for building communication interfaces.

VI. Conclusion and Future Work

This paper proposes an intelligent threshold based detection technique to detect onset & decay of the artifacts, LTW and DTW distance-based techniques for classifying artifacts accurately. The proposed models were determined to be robust to classify the EEG artifacts of unseen subjects for three classes. The future work would be designing a method to reduce the number of required channels for detecting and classifying artifacts and building a feasible interface for motor and speech challenged.

ACKNOWLEDGMENT

We thank Dr. Sriram Ganapathy, Indian Institute of Science, Bangalore for igniting the thought during NeuroCom Workshop 2018.

TABLE VIII: Classification Results for Inter-Subject after Detection

	K	Eye Blink	Head Nod	Head Turn	Jaw Movement	Model Accuracy
LTW	**1**	87.7%	12.3%	40.0%	87.7%	***56.9%***
	3	89.2%	20.0%	41.5%	76.9%	***56.9%***
	5	87.7%	15.4%	53.9%	69.2%	***56.5%***
	7	89.2%	4.6%	53.9%	67.7%	***53.9%***
DTW	**1**	86.2%	9.2%	40.0%	81.5%	***54.2%***
	3	86.2%	7.7%	47.7%	81.5%	***55.8%***
	5	87.7%	9.2%	49.2%	81.5%	***56.9%***
	7	87.7%	10.8%	49.2%	80.0%	***56.9%***

References

[1] C. W. Anderson, S. V. Devulapalli, and E. A. Stolz, "Determining mental state from EEG signals using parallel implementations of neural networks," *Scientific programming*, vol. 4, no. 3, pp. 171–183, 1995.

[2] J. L. Whitton, F. Lue, and H. Moldofsky, "A spectral method for removing eye movement artifacts from the EEG," *Electroencephalography and clinical neurophysiology*, vol. 44, no. 6, pp. 735–741, 1978.

[3] S. Maruthachalam, S. Aggarwal, M. G. Kumar, M. Sur, and H. A. Murthy, "Brain-computer interface using electroencephalogram signatures of eye blinks," *Proc. Interspeech 2018*, pp. 1059–1060, 2018.

[4] W. Ma, D. Tran, T. Le, H. Lin, and S.-M. Zhou, "Using EEG artifacts for BCI applications." in *IJCNN*, 2014, pp. 3628–3635.

[5] "Attempts to convert prof hawking's brainwaves into speech," 2012, [Online; accessed 28-September-2018]. [Online]. Available: https://www.bbc.com/news/technology-18749963

[6] H. Nolan, R. Whelan, and R. Reilly, "Faster: fully automated statistical thresholding for EEG artifact rejection," *Journal of neuroscience methods*, vol. 192, no. 1, pp. 152–162, 2010.

[7] G. Inuso, F. La Foresta, N. Mammone, and F. C. Morabito, "Brain activity investigation by EEG processing: wavelet analysis, kurtosis and renyi's entropy for artifact detection," in *Information Acquisition, 2007. ICIA'07. International Conference On.* IEEE, 2007, pp. 195–200.

[8] M. Rohál'ová, P. Sykacek, M. Koskaand, and G. Dorffner, "Detection of the EEG artifacts by the means of the (extended) kalman filter," *Meas. Sci. Rev*, vol. 1, no. 1, pp. 59–62, 2001.

[9] T.-P. Jung, C. Humphries, T.-W. Lee, S. Makeig, M. J. McKeown, V. Iragui, and T. J. Sejnowski, "Extended ICA removes artifacts from electroencephalographic recordings," in *Advances in neural information processing systems*, 1998, pp. 894–900.

[10] N. Mammone, F. La Foresta, and F. C. Morabito, "Automatic artifact rejection from multichannel scalp EEG by wavelet ica," *IEEE Sensors Journal*, vol. 12, no. 3, pp. 533–542, 2012.

[11] I. Winkler, S. Haufe, and M. Tangermann, "Automatic classification of artifactual ica-components for artifact removal in EEG signals," *Behavioral and Brain Functions*, vol. 7, no. 1, p. 30, 2011.

[12] C. A. Joyce, I. F. Gorodnitsky, and M. Kutas, "Automatic removal of eye movement and blink artifacts from EEG data using blind component separation," *Psychophysiology*, vol. 41, no. 2, pp. 313–325, 2004.

[13] J.-A. Jiang, C.-F. Chao, M.-J. Chiu, R.-G. Lee, C.-L. Tseng, and R. Lin, "An automatic analysis method for detecting and eliminating ECG artifacts in EEG," *Computers in biology and medicine*, vol. 37, no. 11, pp. 1660–1671, 2007.

[14] D. Brunner, R. Vasko, C. Detka, J. Monahan, C. Reynolds III, and D. Kupfer, "Muscle artifacts in the sleep EEG: Automated detection and effect on all-night EEG power spectra," *Journal of sleep research*, vol. 5, no. 3, pp. 155–164, 1996.

[15] H. Sakoe and S. Chiba, "Dynamic programming algorithm optimization for spoken word recognition," *IEEE transactions on acoustics, speech, and signal processing*, vol. 26, no. 1, pp. 43–49, 1978.