TIPTEKNO'24 MEDICAL TECHNOLOGIES CONGRESS
10-12 October 2024
Yasmin Bodrum Resort, Muğla, Türkiye

Classification of Epileptic EEG Signals Using Time-Frequency Analysis and Deep Learning

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***Abstract*— Diagnosing and tracing of neurological disorders using Electrencephalography (EEG) signals is a promising and popular approach. For analyzing the EEG signals, time-frequency (TF) analysis is effective and useful method because of the stochastic behavior of the signals. Wavelet Transform (WT) was used broadly for analyzing the EEG signals and successful results were reported for various neurological disorders. As a new and promising TF method, concentration of frequency and time (ConceFT) was preferred to use in this study. This new TF method improves the TF resolution obtained using WT. ConceFT combines the multitaper technique and the synchrosqueezing transform (SST). This approach increases the TF resolution and the accuracy of the energy representation. In this paper, an algorithm designed for distinguishing the stages of epileptic seizure using ConceFT was presented. TF images of EEG signals were produced using ConceFT and these images were fed into SqueezeNet. The aim of this approach is to show the success of ConceFT in analyzing the non-stationary signals. Classifications of epileptic EEG signals were performed according to different scenarios. Classification accuracies were obtained between 91,18% and 100%, which showed the promising performance of ConceFT.**

Keywords—Electroencephalography, ConceFT, Epilepsy, Deep Learning.

I. INTRODUCTION

Epilepsy is a common and serious neurological problem that effects nearly 70 million people throughout the world. Epileptic seizures occur because of the electrical activity anomalies in brain cells. These anomalies can be observed in various locations of the brain [1]. EEG recordings are used to identify epileptic seizures. Monitoring the brain activity makes possible to distinguish stages of epilepsy [2-4]. EEG signals are recorded from the patient's scalp using electrodes. Thus, electrical activity of the brain is saved. This EEG signals can be investigated to detect spikes. Spike detections are the informer of epileptic seizures and important in the detection of epileptic attacks [5,6]. Specialists of these kind of disorders lose time and give high effort while investigating the EEG signals for possible epileptic seizures. These decisions might be inaccurate because of the experience lack, difficulties of analyzing enormous EEG data and the interpretation differences among neurologists [7-9]. Because of these reasons, number of the scientific studies on the automated epileptic seizure detection is increasing rapidly.

Last decades, machine learning (ML) and deep learning (DL) methods used in a lot of research to classify epileptic EEG signals. With the help of fast computers and efficient algorithms, time and effort of neurologists can be used more efficiently.

In this study, we proposed to use the ConceFT [10] method for analyzing the EEG signals in TF domain. ConceFT employes the SST and multitapering together to obtain a sharp and stable TF representation. Images of TF representations were used to feed DL structure and classification results were obtained. Epileptic EEG signals were segmented and short non-overlapping signals were obtained. By this way, the data used in DL stage was increased. Thus, more effective training of the DL structure becomes possible because of the high number of samples.

There are two main contributions in our study: Firstly, ConceFT was used to obtain the TF images and it was employed in the classification of EEG signals; Secondly, the SqueezeNet architecture was used for classifying the TF images and for seizure detection. The proposed approach was employed for various stages of epileptic seizure. Classification results were reported in Section III. Accuracy results show that, our algorithm achieves high classification accuracies while using a ratherly small data set.

II. MATERIALS AND METHODS

A. Experimental Dataset

In this study, epilepsy dataset of Bonn University [9] was used. This public dataset includes the records of EEG signals. These signals were recorded by using the 10-20 placement technique [9]. The value and importance of the Bonn University's dataset is come from the number of EEG signals and classes of epileptic stages it includes. Figure 1 shows the EEG signals recorded and classified in five groups depending on the stages of epilepsy.

Classes A and B were recorded while subjects are conscious with both eyes open and closed. Classes C and D were formed using the EEG signal records of subjects with epilepsy. Records of class C are from the pre-ictal state and includes the EEG

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signals obtained from Hippocampus. EEG signals in class D are called as inter-ictal state and they belong to the epileptogenic zone. EEG signals in class E were recorded during the epileptic seizure. They are called as ictal state. Each classes contains one-channel EEG signals with one hundred parts. Sampling frequencies of EEG signals are 173.61 Hz. Each signal has 23.6 seconds duration, 4097 samples [9].

In the presented study, each signals were segmented into 23 non-overlapped parts. Thus, the number of signal segments in learning stage were increased. Each of the segments includes 178 samples, i.e. 1 second part of the signal. At the end, number of the EEG data were increased for classification and 2300 signal parts were added to each class.

B. Time-Frequency Analysis Using ConceFT

Traditional Fourier analysis is used to obtain the frequency spectrum of a signal. However, it does not give the time information of frequency content. Therefore, it is not a sufficient tool for understanding the frequency spectrums of the stochastic signals. TF analysis methods are useful and effective signal processing techniques for analyzing the signals which have time-varying spectrums. Especially, these methods are useful for the nonstationary signals because their frequency spectrums change with time randomly and they are very common in real life signals.

EEG signals are non-stationary and they can be analyzed effectively using TF methods. In this study, we used ConceFT to classify epileptic EEG signals. ConceFT is a combined and improved version of SST and Multitaper (MT) technique. It increases the resolutions of TF representations. ConceFT takes SST as a base and advances it with help of MT. SST is an advanced and concentrated TF method. It is also useful and successful especially at the analysis of non-stationary signals. While using SST, algorithm calculates the Instantaneous Frequency (IF) of the signal continuous wavelet transform (CWT) first of all. After that, the method squeezes the frequency bins of TF representation through IF. This method looks simple theoretically, but its algorithm needs very long nonlinear calculations. So, the number of computations increases rapidly. Same disadvantage is valid for ConceFT too. It is shown that the SST effective and concentrated method for nonstationary signals [10,11].

In this study, we aim to show the usefulness and success of ConceFT while analyzing the non-stationary signals like EEG. Moreover, results show that it is an effective tool for the diagnosis of neurological disorders. At the training and testing stages of the Convolutional Neural Networks (CNN), we employed the TF images of EEG segments.

For understanding the ConceFT algorithm, we should describe the MT part of it firstly. In ConceFT, $h_j, j = 1,2,\dots,J$, shows the orthonormal window functions, J, with finite energies. We must specify random vectors which have unit norms. Let r_n, $n = 1,2,\dots,N$, be the random vectors. In vector notation, it is shown as; $r_n = \left[(r_n)_1, (r_n)_2, \dots, (r_n)_J\right]^T$. We obtain a modified window function for each r_n [10]:

$$h_{[n]} = \sum_{j=1}^{J} (r_n)_j h_j. \quad (1)$$

After that, different TF representations can be obtained for each of these new windows. We show them as, $R^{h_{[n]}}$. At last, the ConceFT representation of the signal is obtained as the average of the TF representations:

$$CFTR = \frac{1}{N}\sum_{n=1}^{N} R^{h_{[n]}}. \quad (2)$$

In [10], the authors say that J must be smaller than N. So, we took J as 2 and N as 10. An important improvement in ConceFT method according to the MT technique is the usage of many orthonormal windows.

Many different TF analysis methods can be used in MT technique. However, only SST is used to obtain TF representations in ConceFT approach. In this stage, we briefly describe the calculation of SST.

The CWT of a signal $f(t)$ is calculated as equation (3). Here, $a \in \mathbb{R}^+$ is scale and $b \in \mathbb{R}$ is the shifting value.

$$W_f^{(\psi)}(a,b) = \frac{1}{|a|^{\frac{1}{2}}}\int_{-\infty}^{\infty} f(t)\psi^*\left(\frac{t-b}{a}\right) dt. \quad (3)$$

$W_f^{(\psi)}(a,b)$ shows the CWT coefficients obtained with the mother wavelet $\psi(t)$. Mother wavelet is a continuous function.

The reassignment law is written as [10]:

$$\Omega_f^{(\psi,\Gamma)}(a,b) = \frac{1}{2\pi i}\frac{\partial_b W_f^{\psi}(a,b)}{W_f^{\psi}(a,b)}, \text{ if } \left|W_f^{\psi}\right| > \Gamma, \quad (4)$$

and

$$\Omega_f^{(\psi,\Gamma)}(a,b) = -\infty, \text{ if } \left|W_f^{\psi}\right| \le \Gamma. \quad (5)$$

Γ represents the threshold and it is always positive. By changing it, the numerical error and the noise can be decreased. ∂_b shows the partial derivation. The wavelet coefficients, W_f^{ψ}, are concentrated around the IF of the signal with the help of the reassignment expression, $\Omega_f^{(\psi,\Gamma)}(a,b)$, and SST representation is obtained as [10]:

$$S_f^{(\psi,\Gamma,\alpha)}(b,\xi) = \int_{\{a:\left|W_f^{\psi}(a,b)\right|>\Gamma\}} W_f^{\psi}(a,b)\frac{1}{\alpha}g_\alpha\left(\xi - \Omega_f^{(\psi,\Gamma)}(a,b)\right)a^{\frac{-3}{2}}da. \quad (6)$$

Here, α is selected between $0 < \alpha \le 1$. Let g be a smoothing function i.e. $g_\alpha(\cdot) = \frac{1}{\alpha}g\left(\frac{1}{\alpha}\right) \to \delta$ while $\alpha \to 0$.

Mother wavelets directly affect the result of SST. In ConceFT, different orthonormal mother wavelets can be obtained with the help of unit norm vectors. By using different wavelets, many different SST results and TF representations can be obtained. Thus, multitapering technique is applied to SST with the help of orthonormal wavelets.

Let ψ_j shows dissimilar orthonormal wavelets while $j = 1,2,\dots,J$. Similarly, r_n represents the unit norm vectors while $n = 1,2,\dots,N$. We can form many different linear mother wavelet combinations using unit norm vectors, $\psi_{[n]} = \sum_{j=1}^{J}(r_n)_j\psi_j$. By employing the linear combinations, N various CWT matrices are calculated as:

$$W_f^{\psi_{[n]}} = \sum_{j=1}^{J}(r_n)_j W_f^{\psi_j}. \quad (7)$$

Then, SSTs are obtained for every different CWT matrices separately. Thus, N dissimilar SST matrices, $S_f^{(\psi_{[n]},\Gamma,\alpha)}(b,\xi)$, for the signal f are formed. At the end, the mean of SST matrices is calculated and used as the ConceFT matrix of the signal:

$$C_f^{(\Gamma,\alpha)}(b,\xi) = \frac{1}{N}\sum_{n=1}^{N} S_f^{(\psi_{[n],\Gamma,\alpha})}(b,\xi). \quad (8)$$

The power spectrum of the signal is calculated from ConceFT matrix like below:

$$P_f(b,\xi) = \left|C_f^{(\Gamma,\alpha)}(b,\xi)\right|^2. \quad (9)$$

C. Classification Using Deep Learning

In this study, we used the images obtained using ConceFT of EEG signals in classification stage. TF representations were obtained using ConceFT and they were converted to RGB images. These RGB images of epileptic EEG signals were used to feed deep learning architecture. At this stage, we preferred to use SqueezeNet for classifying the TF images. SqueezeNet was introduced as a pre-trained deep learning model in 2016. The developers of it aimed to design a dynamical neural network model with less parameters. They achieved to decrease the memory requirements and obtain faster transmissions over the networks [12]. For reducing the parameters, SqueezeNet employes fire modules which squeeze the parameters through 1x1 convolutions. It includes 18 layers, and its pre-trained version distinguishes images into many categories [13]. The SqueezeNet reduces the communication costs during the training stage and improves the availability to use in memory-constrained systems like Field-Programmable Gate Arrays (FPGAs).

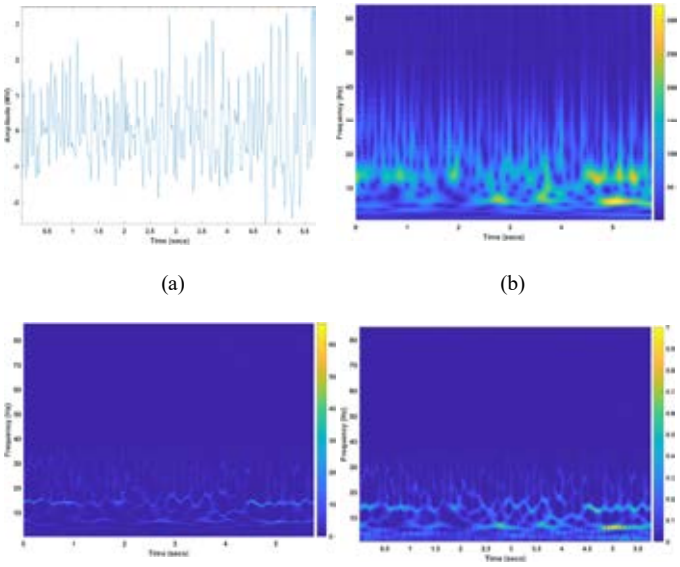
III. Results

In this study, TF representations of epileptic EEG signals were formed using ConceFT. In classification stage SqueezeNet was employed as the deep learning structure. For minimizing the loss function, we used the gradient descent algorithm. We chose 0.0001 as the initial learning rate, 20 as the minimum batch size, and 30 as the maximum epochs.

Figure 1 shows the TF representations, obtained with different techniques, of same EEG signal. The TF resolution is lower in CWT. As it can be seen in figure 1(c), SST has sharper time and frequency resolutions, but its power representation is not enough distinguishable. Figure 1(d) shows that, ConceFT represents the signal with a high TF resolution and improved power distribution. When compared to other methods, ConceFT produces sharper and cleaner results.

In table 1, classification results for various classification scenarios can be seen. The least accuracy result is 98.06% in two-class classification tasks obtained at (AD vs. E) and (BD vs. E) tasks. The highest one is 100% obtained at (C vs. E) task. In three-class classification scenarios, the least accuracy is 95.28% obtained at (A vs. D vs. E) task. The highest accuracy is 97.22% obtained at (B vs. C vs. E) task. Classification accuracy in five-class classification task is 79.33%. Classification results are high in all scenarios and differences between them are not enough to make meaningful interpretations about the classification scenarios. As it can be seen in references [14] and [15], ConceFT based approach was tried by employing GoogleNet [14] and SqueezeNet with the help of Kruskal-Wallis test [15] for different signal sets and classification tasks. By comparing the results, it can be said that there are no meaningful and important difference between these various trials.

The classification results are quietly enough for classifying the epileptic EEG signals. Results are also show that the presented model can be applied to all classification tasks of the Bonn University's dataset. Our approach was tested for the different classification tasks. The calculated accuracies show that our approach gives high results for all classification tasks. Classification accuracies reveal that ConceFT is very promising as a TF analysis technique for non-stationary signals.



(a) (b) (c) (d)

Figure 1. (a) EEG signal, (b) CWT, (c) SST, (d) ConceFT.

Table 1: ConceFT-based epileptic EEG signal classification results.

Classification Tasks	Accuracy	Sensitivity	Precision	F1-Score
A vs. E	99.58%	99.58%	99.59%	99.59%
B vs. E	98.75%	98.75%	98.84%	98.83%
C vs. E	100.00%	100.00%	100.00%	100.00%
D vs. E	98.75%	98.75%	98.75%	98.75%
AB vs. E	99.17%	98.75%	99.38%	99.07%
AC vs. E	98.89%	98.33%	99.18%	98.76%
AD vs. E	98.06%	97.08%	98.58%	97.83%
BC vs. E	98.33%	97.50%	98.78%	98.14%
BD vs. E	98.06%	97.08%	98.58%	97.83%
CD vs. E	98.61%	97.92%	98.98%	98.45%
ABC vs. E	99.79%	99.58%	99.86%	99.72%
ABD vs. E	99.58%	99.44%	99.44%	99.44%
BCD vs. E	98.96%	98.19%	99.02%	98.61%
$ABCD$ vs. E	99.17%	98.23%	99.16%	98.69%
A vs. C vs. E	95.56%	95.56%	95.68%	95.62%
A vs. D vs. E	95.28%	95.28%	95.42%	95.35%
B vs. C vs. E	97.22%	97.22%	97.32%	97.27%
B vs. D vs. E	96.39%	96.39%	96.51%	96.45%
AB vs. CD vs. E	97.00%	96.67%	97.37%	97.02%
A vs. B vs. C vs. D vs. E	79.33%	79.33%	80.57%	79.95%

IV. Conclusions

In this research, a promising approach was proposed for the classification of epileptic seizure stages using EEG signals. These signals belong to the University of Bonn. TF images of the EEG signals were obtained using ConceFT, and they were used to feed SqueezeNet at classification stage. High classification scores were obtained for all classification scenarios. Classification results show the representation accuracy and sensitivity of ConceFT. ConceFT shows outstanding performance while concentrating the signals to obtain high level frequency and time resolutions.

Our classification results are successful and quite enough to separate the epileptic EEG signals. However, for improving the classification accuracies, we can increase the number of epochs and decrease the learning rate. In this case, training time will be longer. ConceFT and DL are already time consuming methods. Therefore, the enormous computational load and the long time necessary for computations are the main disadvantage of the method presented in this paper.

Acknowledgments

This work was supported by Scientific Research Projects Coordination Unit of Istanbul University – Cerrahpasa with project number FBA-2021-36160. Mosab A. A. Yousif would like to thank to the Turkish Presidency for Turks Abroad and the University of Gezira in Sudan for their funding of this project.

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