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# STFT Spectrogram for Epilepsy Seizure Detection and Channel Selection

**Sukjoo Chang** Department of Biomedical Engineering, Georgian Technical University, Georgia, 0160, Tbilisi, 77, M. Kostava str.
E-mail: Elijah.s.chang@gtu.ge

**Irine Gotsiridze** Department of Biomedical Engineering, Georgian Technical University, Georgia, 0160, Tbilisi, 77, M. Kostava str.
E-mail: i.gotsiridze@gtu.ge

**Reviewers:**
**Z. Gurtskaia,** Professor, Faculty of Informatics and Management systems, GTU
E-mail: Elijah.s.chang@gtu.ge
**P. Kervalishvili,** Professor, Faculty of Informatics and Mnagement systems, GTU
E-mail: i.gotsiridze@gtu.ge

**Abstract.** Epilepsy is the chronic neurological disorder which affects more than 1% of the population in the world. More than 50 million individuals have been suffered and living under the condition, among them, approximately 30% of patients were suffer from intractable epilepsy which is hard to control with convulsant medication. (Fisher et al, 2005). Various factors induce epilepsy such as trauma, postoperative brain damage, acquired condition, or genetic factors but nothing may not be confirmed for sure to its reason. The main problem and challenging factor of epilepsy is unprovoked seizures which are unpredictable and challenging to detect.

The research aims to visualize enhance the detection of seizure events to conduct prediction systems. 24 patients Scalpe EEG (Electroencephalogram) set from CHP-MIT(Children's Hospital and MIT university in Boston) and 30 patients Scalpe EEG from MCG (Mediclub in Georgia) have been collected and used to conduct STFT (Shor Time Fourier Transform) Spectrogram to visualize EEG signal to be identified easily even for the non-professional doctors. Conducted STFT from raw EEG data will be able to use deep learning processing for future research to improve accuracy and efficiency.

**Keywords:** Epilepsy; Spectrogram; STFT.

## Introduction

EEG (Electroencephalography) is the most effective and accurate method to detect epilepsy through electric signals in certain parts of the brain. The normal amplitude of brainwaves are between -1 μV and 100μV and normal frequency is between 0Hz and 100Hz which consists of Delta, Theta, Alpha, Beta, Gamma frequency from the low to high. Alpha and Beta frequency could be involved to major role in abnormal brain function. Seizure signal often divided three stages, Pre-ictal, Ictal, and Post-ictal and normal stage as a epilepsy are called Inter-ictal. Fig 1 shows the difference of EEG signal that Inter-ictal(a) and Ictal stage. (Alma 2019)

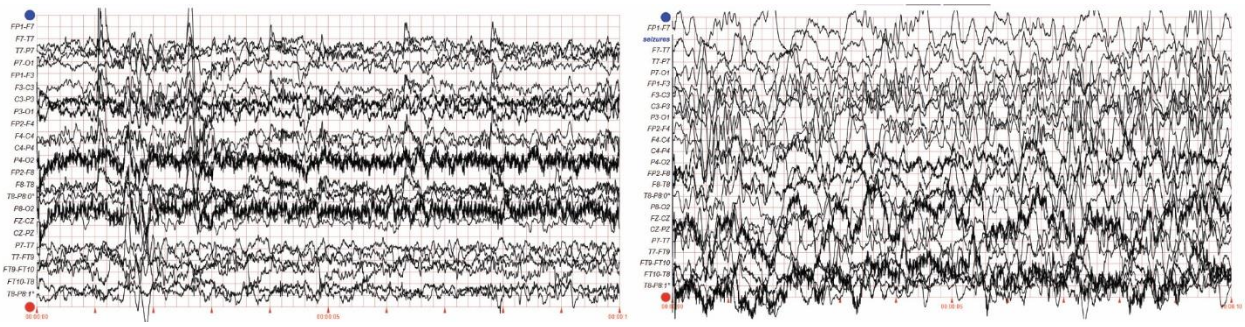

**Fig 1. Inter-Ictal stage: left (a) and Ictal stage: right (b)**

Electrodermal activity (EDA) and accelerometers (Onorati et al, 2018), as well as methods for detecting focal seizures using electroencephalogram (EEG) signals are developed and studied, recently(Khan H, 2017). Also, Koatas et al in 2018, developed PSM (Patient-Specific Method) by conducting STFT and classified CNN model with 81.2% sensitivity and FPR (False positive rate) of 0.16.

In this study, scalp EEG data, collected via non-invasive EEG tests using electrodes placed on the scalp, were employed. EEG has been used for one of the important biomarker to identify and characterize the type of abnormal neurological disorder. In 2020, Zhang et al used CHP-MIT scalp EEG dataset to transform raw EEG to visualize image with SFTF spectrogram to improve accuracy which could be used with deep learning to detect and predict chronic seizure prediction. With deep learning technology and methods, Explanation Artificial Intelligence(XAi) developed to model behavior and interpret Ai generated results.

Resnet learning process was used for Most CNN based deep learning algorithms have gradient vanishing problem as processing of the layers are deepen in its learning. Resnet provide short cut to bypass this problem through the residual block that those gradient can be skipped the connection. In this study, Resnet was used and it may not only explains the rationale behind model predictions but also helps identify biases in datasets and clarify how models reach at their results.

## Main Part

Each patient have variation of locating of electrodes but followed by most common EEG locating method by Roger, 2018, the experiment was conducted using 20 commonly available channels among many channels. FP1, F7, T3, T5, O1, FP2, F8, T4, T6, O2, F3, C3, P3, F4, C4, P4, Fz, Cz, and Pz

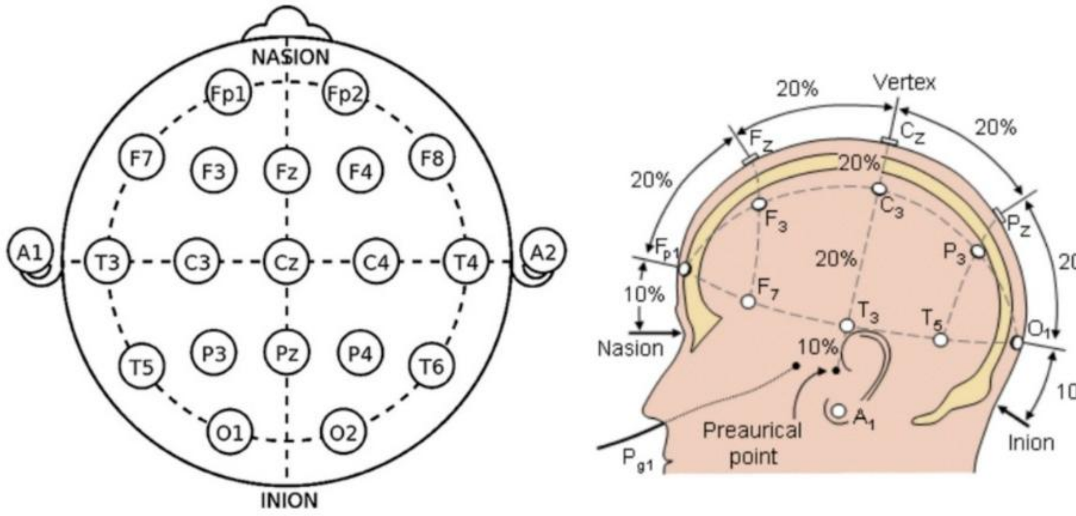


Fig 2 is the measurement type of brain waves is Scalp EEG in this study(Rogers, 2018, Seeck, 2017).

Scalp EEG is a method of measuring by attaching electrodes to the scalp. The positions of the electrodes are determined according to the 10-20 electrode system. It is decided depending on Place the electrodes as shown in [Figure 1] and measure the distance between the frontal and occipital lobes. 10-20 electrodes system are used for this research which arrange equal amount of 10-20% of electrodes. MHG data can be divided according to the reference electrode selection method. It is converted into a digital signal using each adjacent electrode as ground by using the bipolar reference method.

Two sets of scalp EEG data used in this study collected at CHB-MIT (Children's Hospital and MIT university in Boston) in 24 patients and Mediclub Hospital in Georgia(MHG) data scalp EEG in 30 pediatric patients(table 1). Composed recorded signal with sampling rate was 256Hz and 196, 20 common channels were used for electrodes among 72.

Table 1.

**EEG dataset information**

| Dataset | CHB-MIT | MCG |
|---|---|---|
| EEG type | Scalp EEG | Scalp EEG |
| Number of Patients | 24 | 30 |
| Number of channels | 20 among 72 channels | 20 selected channels among over 40 channels |
| Number of seizures | 245 | 192 |
| Sampling rate | 256 | 240 |

Collected signals transformed by STFT method which can maintain time information axis. STFT is an algorithm that converts EEG signals(raw eeg EEG data) into frequency power spectrograms. The power value of the corresponding time specific frequent band is calculated with the original signal input. In order


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words, correlated with time and signal frequency, the power value can be identified by STFT.

$$STFT(m,w)=\int_{-INF}^{+INF}x(t)h(t-m)e^{-jwm}dt$$

Short Time Fourier Transform (STFT)

X(t) indicates raw EEG signal and t indicates time axis. h(t) indicates window function and m indicates windows location according to the time axis. 0-50Hz frequency wave length used as Ictal and inter-ictal stage were able to clearly divided compared to other frequency channels in these frequency. Metlab STFT used for transformation.


Fig 3. Raw signal and Seizure onset panel point


Fig 4. STFT spectrogram: Left, Seizure(Ictal): Right, normal(Inter-ictal)

Window size was 10 sec in both Ictal and Inter-ictal stage to design the preprocessing. Overlap space was 0.12 sec for Ictal and 10 sec for Inter-ictal. In Ictal design, seizure onset was set in 5 sec before the seizure starts while Inter-ictal preprocessing ended 5 sec before seizure onset. Both Ictal and Inter-Ictal data ratio was 1:1.

## Conclusion

54 patient EEG data with 20 channel can be converted with STFT method in Metlab. Total of 20 channels, one channel(F7-T3) was selected for machine learning (Renset-18) and 3 channels were identified with significant sensitive scores in each single channels with Renset-18 learning model. Channel 2, 5, and 19 were collected as their sensitivity and specificity were relatively significant than other channels (Table 2 ).

Table 2.

**20 channel scores of sensitivity, specificity, and accuracy**

| Channel | Specificity | Sensitivity | Accuracy | Channel | Specificity | Sensitivity | Accuracy |
|---|---|---|---|---|---|---|---|
| 1 | 77.3 | 78.3 | 78.1 | 11 | 81.9 | 78.1 | 81.0 |
| 2 | 84.1 | 80.2 | 83.45 | 12 | 79.3 | 75.3 | 77.1 |
| 3 | 80.2 | 78.4 | 79.1 | 13 | 80.1 | 75.2 | 76.1 |
| 4 | 78.3 | 79.2 | 78.2 | 14 | 73.1 | 75.2 | 75.0 |
| 5 | 82.9 | 79.3 | 82.9 | 15 | 80.1 | 76.3 | 77.2 |
| 6 | 66.8 | 70.9 | 70.1 | 16 | 76.1 | 75.1 | 77.8 |
| 7 | 80.1 | 78.3 | 79.3 | 17 | 77.4 | 78.9 | 80.3 |
| 8 | 79.1 | 80.1 | 79.2 | 18 | 71.1 | 78.2 | 75.3 |
| 9 | 77.9 | 76.2 | 77.5 | 19 | 81.1 | 80.1 | 80.9 |
| 10 | 80.3 | 75.1 | 76.2 | 20 | 81.1 | 76.2 | 75.1 |

Overall satisfied sensitivity and specificity score can be obtained with combined two sets of EEG data in various channels and patients. Overall scores were over 80 in Channel 2, 5, 19 with range of 1.5-2 FPR range.

In this study, from raw EEG data, it was able to be shown that time-frequency power factor characterized by STFT was able to used for machine learning in EEG analysis to detect seizure. For future research, the constructed STFT factor spectrum will be considered for use in other CNN machine learning methods and models for EEG analysis. Additionally, multiple-channel learning models utilizing multiple STFT spectrograms will be designed to correlate with the single-channel design model.

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## STFT სპექტროგრამა ეპილეფსიის კრუნჩხვის გამოვლენისა და არხის შერჩევისთვის

**სუკჯუ ჩანგ** ბიოსამედიცინო ინჟინერიის დეპარტამენტი, საქართველოს ტექნიკური უნივერსიტეტი, საქართველო, 0160, თბილისი, მ. კოსტავას 77
E-mail: Elijah.s.chang@gtu.ge

**ირინე გოცირიძე** ბიოსამედიცინო ინჟინერიის დეპარტამენტი, საქართველოს ტექნიკური უნივერსიტეტი, საქართველო, 0160, თბილისი, მ. კოსტავას 77
E-mail: i.gotsiridze@gtu.ge

**რეცენზენტები:**
**ზ. ღურწკაია,** სტუ-ის ინფორმატიკისა და მართვის სისტემების ფაკულტეტის პროფესორი
E-mail: z.gurtskaia@gtu.ge
**პ. კერვალიშვილი,** სტუ-ის ინფორმატიკისა და მართვის სისტემების ფაკულტეტის პროფესორი
E-mail: paata.kervalishvili@gtu.ge

**ანოტაცია.** ეპილეფსია არის ქრონიკული ნეიროლოგიური აშლილობა, რომელიც მსოფლიოში მოსახლეობის 1%-ზე მეტს ემართება. 50 მილიონზე მეტი ადამიანი იტანჯება და ცხოვრობს ეპილეფსიური კრუნჩხვის მოლოდინის სტრესის ქვეშ. მათ შორის, დაახლოებით 30%-ს აქვს ე.წ. დაუმორჩილებელი ეპილეფსია, რომელიც რთულად ემორჩილება მედიკამენტურ კონტროლს (ფიშერი და სხვ. 2005). ეპილეფსიის

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**საკვანძო სიტყვები:** ეპილეფსია; სპექტროგრამა; STFT.

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