Absence Seizure Detection Using Ramanujan Filter Banks

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***Abstract*—Absence seizures are a type of generalized seizures characterized by a 3 Hz periodic spike and wave discharge pattern in the Electroencephalogram (EEG). The most common way to diagnose them is by detecting such periodic patterns in a patient's EEG. Recently, a new method known as Ramanujan Filter Bank (RFB) was proposed for identifying, estimating and localizing periodicities in data. The RFB was shown to offer important advantages over traditional period estimation techniques in DSP. In this work, we demonstrate that the RFB offers very useful diagnostic information when applied to EEG signals from absence-seizure patients[1].**

I. Introduction

A seizure is defined as a sudden uncontrolled surge in the electrical activity of the brain. It is usually accompanied by physical symptoms such as alterations in behavior, loss of consciousness, uncontrolled muscle spasms and so on. Seizures are generally caused when a large number of neurons get excited simultaneously, leading to a sudden surge in the electrical activity of the brain. While some seizures are hardly noticeable, others can be severely disabling. In both cases, it is important to note the occurrence of a seizure, since the chances of a second seizure is ofter greater than 50% after the first [2]. Since a seizure is essentially an electrical phenomenon, the most common way to identify them is using electroencephalography (EEG). Seizures produce characteristic EEG patterns, which can be used by doctors for diagnosis.

Absence seizures, the subject of this paper, are a type of seizures more commonly occurring in children (ages 4 - 14). They derive their name from a "lack of consciousness" state that occurs during this seizure. Typical symptoms include sudden unresponsiveness, staring, fluttering of the eyelids, mild clonic jerks and possible automatisms. They typically last for 5 to 20 seconds, and are often confused with day dreaming or not paying attention. Currently, the only diagnostic test for these seizures is EEG [8]. Typical absence seizures show a prominent 3 Hz periodic spike and wave discharge pattern in the EEG [4], as shown in Fig. 1.

At present, the criterion standard for the diagnosis of absence seizures is EEG video monitoring, which involves monitoring a continuous recording of the EEG, along with a simultaneous video recording of the patient for observing the clinical manifestations of the seizure [17]. Visual inspection of EEG records for seizures is tedious and time consuming, especially when patients are monitored over hours at a stretch. So a number of methods have been proposed in the past few years for automatic detection of seizures from EEG signals.

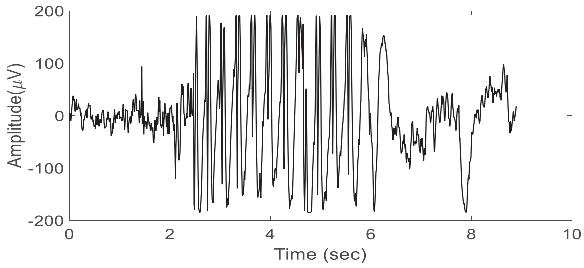

Fig. 1: An example of the 3Hz spike and wave discharge pattern in the EEG during an absence seizure.

An important class of such methods is based on the traditional spectral estimation techniques from DSP, such as the Short Time Fourier Transform (STFT) [5] and wavelets [1], [16]. These methods were originally designed for estimating the spectrum of a signal. By identifying the fundamental frequency of a periodic signal from among its harmonics in the spectrum, one can estimate the period. Apart from these methods, there are others based on metrics such as the EEG signal's amplitude [3], or more complex statistical features of the signal such as its average entropy and multi-scale variance [7].

A. This Paper's Contribution

The Ramanujan Filter Bank (RFB) was proposed in [9] and [13] as a new method to identify periodic components in data. While the traditional spectral estimation techniques of DSP such as STFT and wavelets tile the *time vs frequency* plane, the RFB directly tiles the *time vs period* plane, giving the instantaneous period of the signal as a function of time. Apart from being computationally simple due to small integer coefficients, the RFB was shown to offer some important advantages over the spectral techniques [9], [13]. For example, in a spectral estimation technique, one needs to find the fundamental frequency from among all the harmonics in the spectrum. This can sometimes be tricky. For example, a large number of periodic signals have a weak or missing fundamental frequency. The RFB, on the other hand, automatically decodes the spectrum to give us the period of the signal directly in all cases. So far, the RFB has been shown to offer promising results in applications such as DNA microsatellites [10] and protein repeats [11]. Since the EEG waveform during an absence seizure is essentially periodic, the RFB is a suitable technique to be applied here as well. In this paper, we demonstrate that the RFB indeed offers very useful diagnostic information by being able to detect the occurrence of these seizures in the EEG.

Outline: In Sec. II, we provide a brief introduction to period

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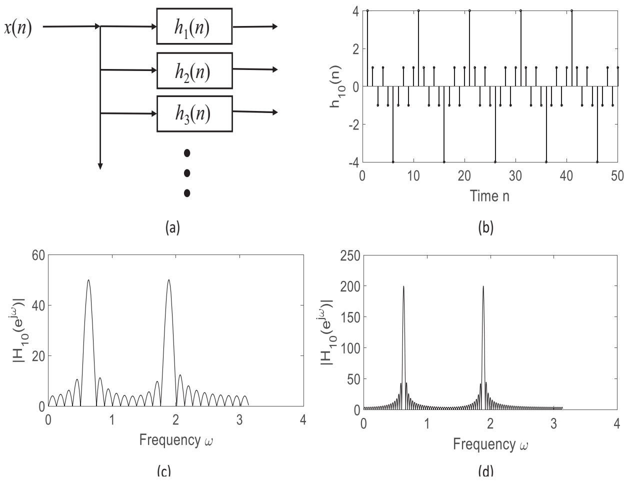


Fig. 2: Part(a) - Block diagram of the Ramanujan Filter Bank. Part (b) - An example of the impulse response of an RFB filter, $h_{10}(n)$. Parts (c) and (d) - Frequency responses of $h_{10}(n)$ for $K = 5$ and $K = 20$ respectively.

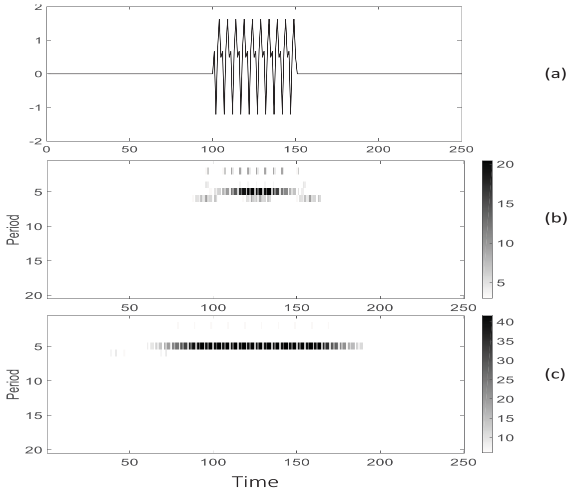


Fig. 3: An example of Time vs Period plots using RFB. See Sec. II for details.

estimation using the RFB. In Sec. III, we apply the RFB to EEG signals from absence-epilepsy patients, and discuss the results. Finally, concluding remarks are given in Sec. IV.

II. The Ramanujan Filter Bank: An Overview

In 1918, the Indian mathematician Ramanujan proposed the following sequences known as Ramanujan sums:

$$c_q(n) = \sum_{\substack{k=1 \\ \gcd(k,q)=1}}^{q} e^{j2\pi kn/q} \tag{1}$$

It can be shown that $c_q(n)$ has period q, and is integer valued for all n [14], [6]. Following are some examples of Ramanujan sums, with one period shown in each case:

$$c_1(n) = 1,\ c_2(n) = \{1, -1\},\ c_3(n) = \{2, -1, -1\},$$
$$c_4(n) = \{2, 0, -2, 0\},\ c_5(n) = \{4, -1, -1, -1, -1\} \tag{2}$$

Ramanujan originally proposed these sequences to show that several arithmetic functions in number theory, such as the Euler Totient function, Von Mangoldt function etc. can be expanded in terms of the Ramanujan sums. In a recent series of works [14], [15], [12], these sequences were shown to have many useful properties in the context of periodicity analysis. The Ramanujan Filter Bank, proposed in [9] and [13], is one such application based on Ramanujan sums.

The Ramanujan Filter Bank is a collection of filters as shown in Fig. 2(a). It has P_{max} filters, where P_{max} is the largest expected period in the signal. For every P in $1 \leq P \leq P_{max}$, the P^{th} filter's impulse response is given by:

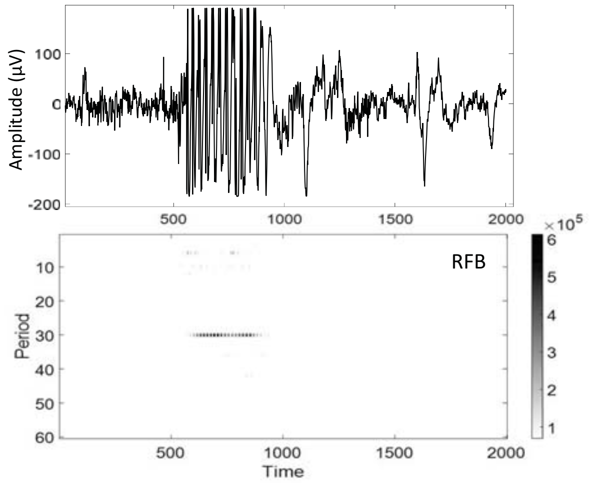
$$h_P(n) = \begin{cases} c_P(n) & 0 \leq n \leq KP - 1 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

That is, $h_P(n)$ consists of K periods of the P^{th} Ramanujan sum $c_P(n)$, where K is an integer parameter. The choice of K will be addressed below. An example of an RFB filter, $h_{10}(n)$, is shown in Fig. 2(b) for $K = 5$. Notice that each RFB filter has multiple passbands. The passband centers are at $2\pi m/P$ where m are coprime to P. These are called coprime frequencies.

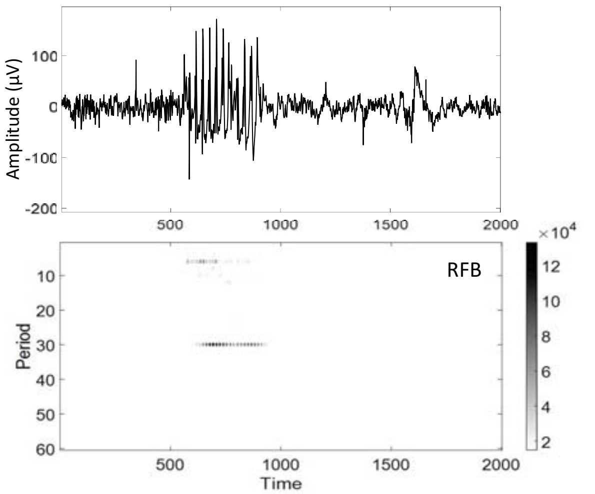
The RFB can be used to identify periodic components in a signal in the following way. Consider, for now, the case when $h_P(n) = c_P(n)\ \forall n$. That is, the filters in the RFB are of infinite length. Suppose that the input signal was a periodic signal with period P. Let $\{h_{i_1}(n), h_{i_2}(n), \ldots, h_{i_N}(n)\}$ be the set of all those filters in the RFB that have non-zero outputs. Then, it can be shown that the least common multiple (lcm) of the filter indices $\{i_1, i_2, \ldots i_N\}$ must be equal to the period P of the signal (follows from Theorem 3 in [13]). So, by taking the lcm of the indices of filters with non-zero outputs, we can estimate the period of the input signal.

To a good approximation, this result also holds true for finite length filters, as we will demonstrate in the following example. Fig. 3(a) shows a signal $x(n)$ that is zero for $n < 100$ and $n > 150$. In the range $100 \leq n \leq 150$, it has a periodic segment with period 5. Fig. 3(b) shows a time vs period plane produced using an RFB with $K = 7$. For every period P on the vertical axis, the horizontal line shows the output power of the P^{th} RFB filter as a function of time. Ideally, since the periodic segment had period 5, from our argument in the previous paragraph, we should have seen bands only at periods 5 and its divisor 1. However, we see bands at other periods such as 2, because the filter lengths are quite small in this case. If we increase K to 25, we get the time vs period plot shown in Fig. 3(c). Notice that the period estimate is much cleaner in this case. This is because, larger filter lengths have sharper frequency responses (for example, compare Fig. 2(c) and (d)). Nevertheless, smaller filter lengths are better in localizing the time duration of the periodic segment. This is because of smaller transients. This can be observed in Fig. 3, where the localization in time of the periodic segment is much better for the $K = 7$ case than for $K = 15$. For detecting absence seizures in the following section, we observed that $K = 5$ gave the best trade-off between both these phenomena.

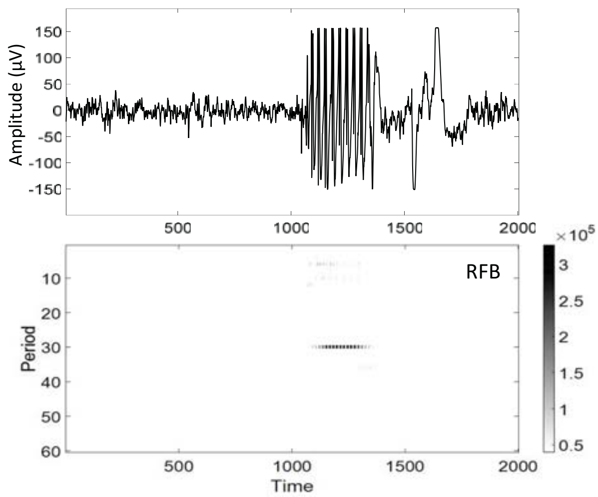
The RFB has some important advantages over period estimation via spectral estimation methods, as was mentioned in Sec. I-A. In Sec. III-B3, we will show one such comparison. We refer the reader to [9], [13] for more details about the RFB.



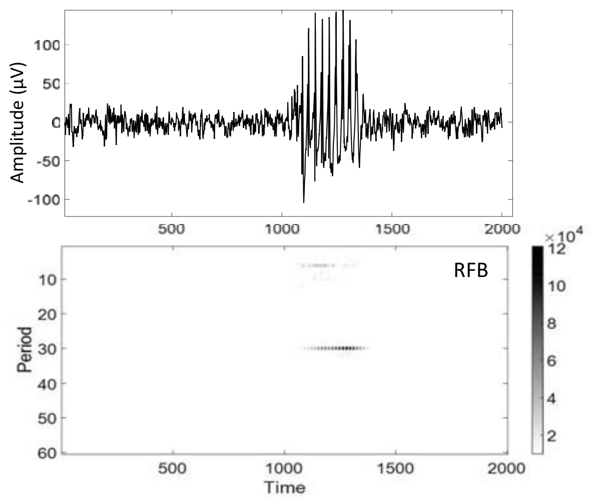
(a) (Top) Sampled EEG showing Seizure 1 in Patient 1 as measured across the F8-C4 channel. (Bottom) The RFB's time vs period plane.



(b) (Top) Sampled EEG showing Seizure 1 in Patient 1 as measured across the T5-O1 channel. (Bottom) The RFB's time vs period plane.



(c) (Top) Sampled EEG showing Seizure 2 in Patient 1 as measured across the F8-C4 channel. (Bottom) The RFB's time vs period plane.



(d) (Top) Sampled EEG showing Seizure 2 in Patient 1 as measured across the T5-O1 channel. (Bottom) The RFB's time vs period plane.

Fig. 4: RFB's test of sensitivity. See Sec. III-B1 for details.

III. Analyzing Epileptic EEG Signals Using RFB

A. Data

The source for the EEG data in this work is the public FTP site of the Sleep and Sensory Signal Analysis Group from Tampere University of Technology (ftp://sigftp.cs.tut.fi/pub/eeg-data/). This data has been used in popular seizure detection papers such as [1], but is annotated to a limited extent only. So our verification of the RFB's detection of seizures in the following experiments is based on (a) results from previously published works that used the same data, such as [1], and or or (b) the information provided with the data itself. Inspired by the RFB's performance on this data set, we are working to acquire completely annotated data from experts for further analysis. The EEG signals used in the following examples were sampled at 100 Hz (we downsampled the original files by 2 for convenience). This means that the 3 Hz spike and wave discharges associated with absence seizures would appear as periodic patterns with period around 33 samples.

B. Experiments

In the following, we have divided our examples into three categories. In Sec. III-B1, we test the sensitivity of the RFB in detecting absence seizures. That is, we apply the RFB to multiple instances of absence seizures to see if we are able to detect them in all cases. In Sec. III-B2, we test for the

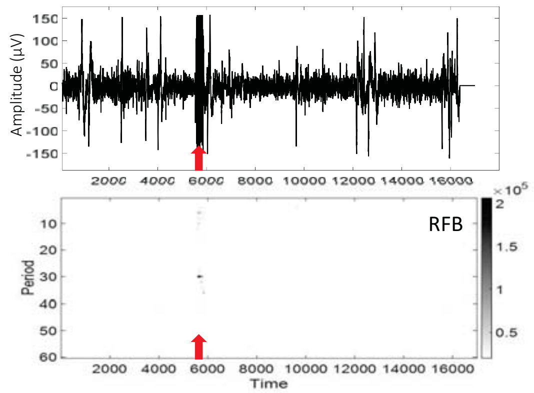


Fig. 5: (Top) The entire record of sampled EEG containing Seizure 2 in Patient 1, as measured across the F8-C4 channel. (Bottom) The RFB's time vs period plane.

specificity of detection. That is, whether the RFB is able to distinguish absence seizures from normal background EEG in a precise manner. Finally, in Sec. III-B3, we compare the RFB to an STFT based method to illustrate its advantages over the traditional spectral methods. In all the following examples, we chose $K = 5$ for the RFB.

1) Testing Sensitivity: Fig. 4a and Fig. 4b show the (sampled) EEG signals of Patient 1, measured between channels F8-C4 and T5-O1 respectively during a seizure. These two channels are located on opposite sides of the scalp, so the seizure waveform appears different in shape in each case. Fig. 4c and Fig. 4d show EEG signals from the same patient, but during a different episode of absence seizure. In each of these figures (and also in all the other examples in this work), a Time vs Period plane was produced by an RFB with 60 filters. As shown in Fig. 4, in each case, the RFB was able to identify a periodic segment with period around 30, which matches with what we would expect during an absence seizure. For clearer plots, the color-bar in these plots was chosen such that all the outputs below 10-15% of the maximum output appear white.

2) Testing Specificity: The seizures shown in Fig. 4 occurred as short segments of much longer data records, which, for most part, contained normal EEG measured during non-seizure intervals. In Fig. 5, the red arrow indicates the instance at which the seizure of Fig. 4c occurred in its complete data record. As shown in the time vs period plane in Fig. 5, the RFB was able to identify this seizure event very precisely.

3) Comparison with STFT: Fig. 6(a) shows an EEG recording from Patient 2, with three epileptic seizures shown by the red arrows. Fig. 6(a) shows the time vs period plane obtained using an RFB, and the three seizures can be easily identified. However, notice that the three seizures manifest as a band of periods around period 30. This is because the spike and wave discharges during an absence seizure need not always have a precise periodicity of 3Hz [8]. Fig. 6(c) shows the time vs frequency plane obtained by using STFT with a length 128 window. 3Hz in continuous time would correspond to a frequency of around 0.03 on the shown (discrete time normalized) frequency scale. Notice that apart from the seizure features (indicated by the red arrows), there are many other

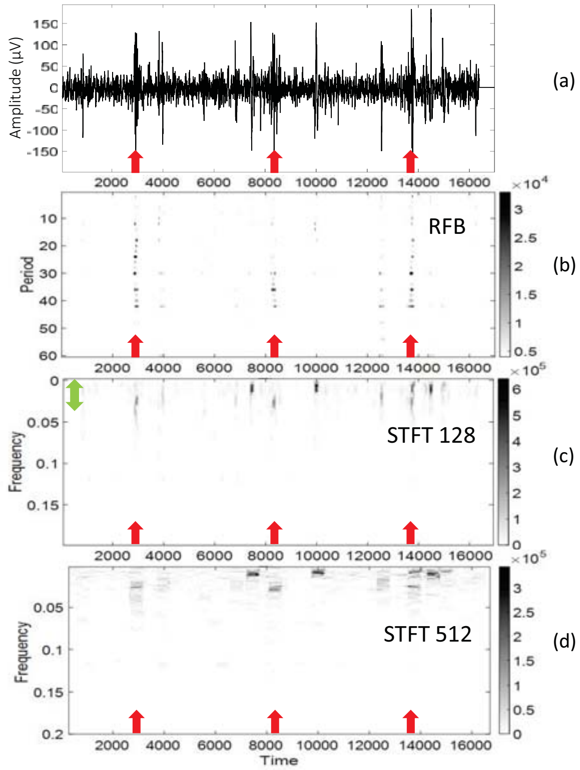


Fig. 6: Comparison of the RFB with STFT. See Sec. III-B3 for details.

strong features in the time vs frequency plane. This is because the range of frequencies represented by the green band in Fig. 6(c) correspond to periods 30 and above in the signal. Hence, most of the low frequency noise is being captured in this narrow region of the time vs frequency plane, producing those other features. The only way to increase the resolution in this region of frequencies is to use larger window lengths. Fig. 6(d) shows that we only get a slight improvement when we use length 512 STFT. Further increase in the window lengths produce a bad resolution along the time axis. This is an example of a case where the RFB offers clearer results than STFT.

IV. Conclusion

In this work, we showed that the Ramanujan Filter Bank is a good method for detecting absence seizures from EEG data. The RFB can be interpreted as being an automatic decoder of the spectrum to give a time vs period plot directly. Since the annotation available to us was limited for this data set, we only intend to use these results as a demonstration of RFB's suitability for this application. One of our next goals is to work with an EEG expert on a more formally annotated data set, to demonstrate further the applicability of the RFB.

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