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# Wavelet Analysis Applied on EEG Signals for Identification of Preictal States in Epileptic Patients

# Análise wavelet aplicada em sinais de EEG para identificação de estados pré-letais em pacientes epilépticos

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## ABSTRACT

The discrimination of the interictal and preictal states in epilepsy contributes to the construction of an efficient system of seizure prediction. Here, we performed the classification of the interictal and preictal states for EEG signals of the scalp. The energies of the levels obtained by the signal decomposition of the Wavelet Discrete Transform were used as features for classification. The kNN and SVM classifiers were used in the analysis of the individual EEG channels, which gave indications that the occipital lobe region channels are the most relevant to differentiate between the interictal and preictal states. Using these channels, the classification into two states achieved accuracy of 97.29%, sensitivity of 96.25% and specificity of 98.33%. In addition, the different frequency ranges obtained by Wavelet for the classification were analyzed, and it was observed that the range of 32 Hz to 128 Hz presented greater relevance in the task.

**Keywords:** Epilepsy; Electroencephalogram; Wavelet; Prediction; Preictal; Interictal.

Brazilian Applied Science Review

**RESUMO**
A discriminação dos estados interictal e preictal na epilepsia contribui para a construção de um sistema eficiente de previsão de crises. Aqui, realizamos a classificação dos estados interictal e preictal para sinais de EEG do couro cabeludo. As energias dos níveis obtidos pela decomposição do sinal da Transformada Discreta Wavelet foram utilizadas como características para classificação. Os classificadores kNN e SVM foram utilizados na análise dos canais individuais de EEG, o que indicou que os canais da região do lobo occipital são os mais relevantes para diferenciar os estados interictal e preditivo. Usando esses canais, a classificação em dois estados alcançou precisão de 97,29%, sensibilidade de 96,25% e especificidade de 98,33%. Além disso, foram analisadas as diferentes faixas de frequências obtidas pela Wavelet para a classificação, e observou-se que a faixa de 32 Hz a 128 Hz apresentou maior relevância na tarefa.

**Palavras chave:** Epilepsia; Eletroencefalograma; Wavelet; Predição; Preictal; Interictal.

## 1 INTRODUCTION

Epilepsy is a chronic brain disorder characterized by repeated seizures. There are more than 50 million people worldwide who are diagnosed with epilepsy and this neurological disease is considered one of the most common in the world. However, approximately 80% of this population, who live in low and middle-income countries, do not receive adequate treatment (Who, 2019).

Epilepsy should be considered an important, preventable and potentially fatal disease due to social deprivation (Morrish, Duncan and Cock, 2019). Specifically, the inability to reliably detect seizures, track the risk of seizures and monitor the action and effectiveness of the drugs constitute a significant barrier to improve and personalize treatments for epilepsy. The inability to assess the risk and susceptibility of crises are still major clinical challenges and impairs the life quality of patients (Meisel and Loddenkemper, 2019).

Greater attention is lacking to the problem, including to reduce the unnecessary death of people diagnosed with epilepsy in the groups at the greatest risk. Death associated with epilepsy is more evident in the elderly due to the multiple comorbidities that occur in this age group. In addition, the risk is greater in people with lower incomes, as they are commonly less involved in appropriate treatments and less likely to take medications. Improvements in care and new treatments can reduce deaths caused by epilepsy (Morrish, Duncan and Cock, 2019).

People with intractable epilepsy often lack the knowledge of when a seizure will occur. This uncertainty can lead to difficulties in carrying out daily activities such as driving, working, or even socializing, and puts patients at higher risk for injuries. By presenting information about when a seizure is likely to occur, the patient will have some control over the seizures and prevent possible accidents, as well as being very useful in preventing seizures that can be avoided by medication (Williamson et al., 2012; Usman, Usman and Fong, 2017).

Studies on changes in brain dynamics monitored by electroencephalography (EEG) have been promising for predicting seizures (Freestone, Karoly and Cook, 2017). Researches have demonstrated that EEG signals can be used in procedures for detection and prediction of seizures (Sayeid et al., 2016).

The EEG records can be intracranial or scalp. Although intracranial recordings are less susceptible to noise and artifacts (e.g. body motion and electrodes movements), there is a preference for the EEG scalp because it is a non-invasive technique (Tsiouris et al., 2018).

In this study we present an approach to classify the interictal and preictal states of patients with intractable epilepsy as an important step in predicting seizures. The scalp EEG signals from CHB-MIT (2010) were used for this study. This data set has recently been studied for the prediction of epileptic seizures, but its analysis is still quite challenging due to the heterogeneity of patients. Moreover, it is little used to discriminate states. Here, this data set was chosen due to the heterogeneity of patients regarding sex and age, so that the method is generalized among patients.

To perform time-frequency analysis of the signal in each state, the Discrete Wavelet Transform (DWT) was used to extract the characteristics of the signals. In addition, a channel analysis was performed to evaluate the most relevant EEG channels that achieved the highest performance in the classification.

From the pre-selection of the channels it is possible to identify regions of the brain that best represent the differences of the cerebral dynamics between the preictal and interictal states. Identifying regions with more discriminating signals is an important step in developing methods and devices more efficient to predict seizures, as well as cheaper and less visually perceptible.

This work has the following structure: In Section 2 is available information about the neurological disease under study. Section 3 describes some recent works related to the prediction of epileptic seizures. Section 4 describes the methods used in data pre-processing and model validation, the performance measures applied in the experiments and the description of the methodology to classify the interictal and preictal states. Section 5 discusses the results obtained and important observations. Finally, we conclude this paper in Section 6.

## 2 EPILEPSY

Epilepsy is a brain disorder characterized by recurrent and unpredictable disturbances of normal brain function, leading to an excessive neuronal activity or an abnormal synchronous in the brain. This event has a lasting predisposition to generate epileptic seizures (Fisher et al., 2005).

The cerebral cortex is the main element in the generation of epileptic seizures, and can also originate in interactive thalamocortical systems or in the brain stem (Fisher et al., 2005). Elevated levels of cortical excitability are likely to play an important role in the onset and spread of epileptic seizures (Meisel, Loddenkemper, 2019).

Thus, these temporary brain dysfunctions of a set of neurons can occur in a part of the brain and are called focal or partial seizures, or in a more extensive area simultaneously involving the two cerebral hemispheres, which are called generalized seizures (Kanashiro, 2006). The symptoms of the seizure are related to its source, so that it can affect sensory, motor and autonomic function, consciousness, emotional state, memory and behavior. However, depending on the type of seizure, it affects at least one of these factors (Fisher et al., 2005; Kanashiro, 2006).

The EEG directly measures the dynamic and synchronous polarization of pyramidal neurons spatially aligned between the layers of the cortex, which represents 80% of the brain mass and is located under the cranial surface (Michel and Koenig, 2018; Adur, 2008). The excitatory or postsynaptic inhibitory electrical potentials of these cells are able to reach the electrodes connected to the EEG amplifier (Adur, 2008).

The polarity of the surface EEG depends on the location of synaptic activity in the cortex, and the greatest influence is from the local field potential closest to the source (Gomes, 2015), however, an electrode at a given location in the scalp not only detects neuronal activity in areas directly below, but can also simultaneously record activities from potential remote sources resulting in an intrinsic correlation between the signals recorded at the electrodes (Michel and Koenig, 2018).

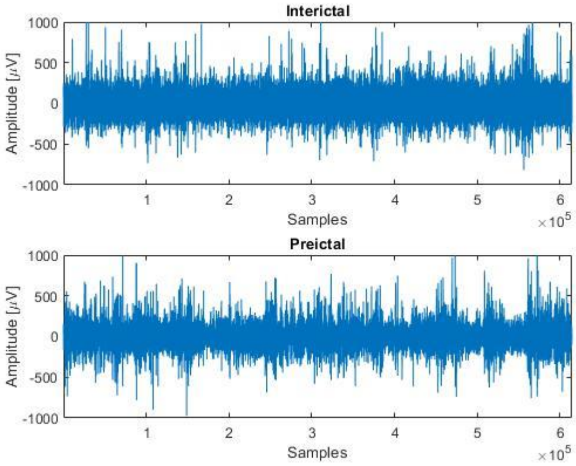
These studies show that changes in the human brain, caused by epileptic seizures, can be captured by EEG records to be analyzed. The physiologic signal captured by EEG can be basically divided in three states: interictal, preictal and ictal. Interictal refers to the period between seizures. For most people with epilepsy, the interictal state comprises more than 99% of their life (Epilepsy Foundation of America, 2019). Preictal refers to the state immediately before the actual seizure and it has variable duration, ranging from a few minutes up to three days (Mula and Monaco, 2011). Ictal refers to the seizure event. In the majority of cases, ictal symptoms are very brief (they last less than 30 seconds) (Mula and Monaco, 2011).

Digital processing of these electroencephalography signals has been popularly used in a wide variety of applications, such as seizure detection and prediction (Alotaiby et al., 2015).

Brazilian Applied Science Review

Figure 1 shows the EEG signals from the CHB-MIT database (2010), of the interictal and preictal states, which are the most studied in predicting epileptic seizures.

Figure 1. Examples of periods referring to EEG signals of only 1 channel, lasting 40 minutes.




Some observations made by Büyükçakır, Elmaz and Mutlu (2020) indicated that some algorithms are able to discern the patterns of patients' interictal EEG signals, even if they have different types of seizures or epilepsy. In addition, the location of the EEG channels also shows relevance in the performance of the classification of brain states (Büyükçakır, Elmaz and Mutlu, 2020).

## 3 RELATED STUDIES

Several seizure prediction methods have been applied in the last years, but many of them still have low sensitivity and high false prediction rate. Moreover, the ideal range of true and false predictions is still not very well defined, as it is related to the amount of convulsions of each patient (Sharif and Jafari, 2017).

Research on prediction of seizures usually study the differences between interictal (period between seizures) and preictal (period immediately preceding a seizure) states. Other approaches have sought the best way to combine characteristics to generate accurate and reliable information about the prediction (Williamson et al., 2012).

The mechanisms generating seizure may be specific to each patient diagnosed with epilepsy. Therefore, it is seldom possible to be sure if these algorithms will work for a given patient when applied prospectively (Freestone, Karoly and Cook, 2017). It has still been challenging to correctly define the problems related to the prediction of seizure and this generates a lack of confidence in machine learning algorithms that have been applied in recent years. This confirms that there is an unmet need for a system that provides early warning of seizure, which can support new approaches to treatment and to improve the patient's quality of life (Kiral-Kornek et al., 2018). More signal analysis is needed to achieve more effective results and methods applied to all patients.

Anyway, machine learning has contributed extensively to the methodologies applied in predicting epileptic seizures due to the complexity of EEG signals. Thus, it has been facilitated the evaluations of the multivariate analyzes and of the feature spaces to differentiate the characteristics between preictal and interictal periods (Tsiouris et al., 2018).

Song and Zhang (2016) assess whether sample entropy can be used to discriminate the interictal and preictal states of 6 intracranial EEG channels recorded at the Epilepsy Center of the University Hospital of Freiburg. For classification using support vector machine (SVM) classifier, they obtained accuracy of approximately 84%, indicating that the method can still be improved.

Previous studies indicate that seizure precursors appear only in certain distinct channels and may facilitate the use of specific devices and early identification of the seizure (Mormann et al., 2005; Chu et al., 2017). Chu et al. (2017) used two EEG databases, with a total of 16 patients. The researchers performed channel selection and gave more relevance to the channel that presented better performance. In the classification of the interictal and preictal states, they reached sensitivity of 86.67%, but with few training data of seizures.

Wavelet Transform (WT) has been used to extract features on the dynamic structure of EEG signals, from the decomposition of EEG signals into levels (Kocadagli and Langari, 2017). Many researchers suggest the detection of epilepsy, or epileptic seizures, using WT of EEG signals. The use of this method to predict epileptic seizures and to discriminate between interictal and preictal states have been very encouraging in recent years (Gadhoumi, Lina and Gotman, 2012; Sayeid et al., 2016).

Gadhoumi, Lina and Gotman (2012) proposed a method based on the analysis of high frequency activity of intracerebral activity. The researchers used wavelet energy and entropy to discriminate between the interictal and preictal states of six patients with temporal lobe epilepsy chosen randomly from a set of patients admitted in the Montreal Neurological Institute between 2004 and 2009. However, for this method to detect the differences effectively, it is necessary that at least one channel in the region where the dynamics of the preictal and interictal state are different.

In addition, this solution has weaknesses, according to the authors. The method did not have high performance for all six patients, with a chance of presenting poor results for other patients.

## 4 METHODS

### 4.1 EEG DATABASE

The CHB-MIT (2010) data set, available online, contains EEG signal records acquired from different regions of the scalp, and it was used in our experiments to discriminate between the interictal and preictal states. This database was collected from 23 pediatric patients with intractable seizures at the Boston Children's Hospital. The times of onset of the seizures for the different registries were annotated previously.

All signals were sampled at 256 sample/s. The signs studied present 23 EEG channels, with recordings of 1, 2 or 4 hours of digitized EEG signals. For these recordings, the International 10-20 system was used for positions and nomenclature of the EEG electrodes. Thus, channels 1 through 23 are respectively: FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, FP2-F4, F4-C4, C4-P4, P4-O2, FP2-F8, F8-T8, T8-P8, P8-O2, Fz-Cz, Cz-Pz, P7-T7, T7-FT9, FT9-FT10, FT10-T8 e T8-P8.

To select the interictal states, 40-minute intervals were selected, approximately 4 hours before or after epileptic seizures (ictal state) (Truong et al., 2018). For the preictal, intervals of 40 min, up to 1 second before the ictal, were selected.

The total recording time used in the analyzes was approximately 19.3 hours of interictal and 19.3 hours of preictal.

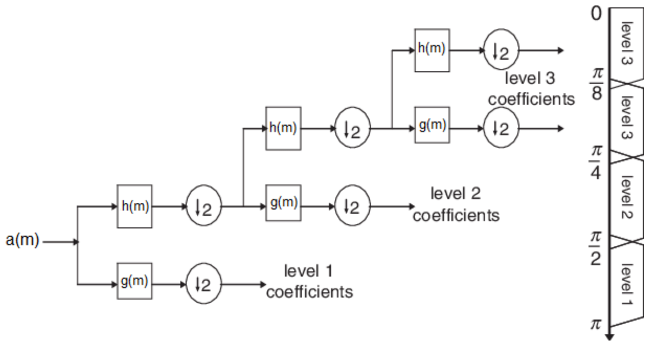
### 4.2 DISCRETE WAVELET TRANSFORM (DWT)

The DWT is used in signal preprocessing to represent frequency characteristics through its coefficients (Faust et al., 2015). This technique is sensitive to changes in EEG signals, which are difficult to detect by analyzing the signal only visually (Faust et al., 2015).

The DWT algorithm decomposes a given signal into approximation and detail coefficients to obtain a first level of decomposition. The approximation coefficients at all levels are further decomposed into the next level in approximation and detail coefficients (Faust et al., 2015). The definition of the discrete transform of periodic signals is described in more detail by Gubner and Chang (1995).

According to Costa et al. (2010) and Gubner and Chang (1995), mathematically, DWT calculations are interpreted as digital filtering processes, followed by decimations (Costa et al., 2010). Figure 2 shows the DWT approximation components at 3 levels (Sun, Shi and Zhou, 2014).

Figure 2. Example of decomposition of the signal by DWT.




Equations 4.1 and 4.2 represent the approximation and detail coefficients, respectively, by applying digital filters:

$$a_j(m) = \sum_n h(n-2m)a_{j-1}(n) \quad 4.1$$

$$d_j(m) = \sum_n g(n-2m)a_{j-1}(n) \quad 4.2$$

where $j = \{1,2,3, \ldots, J\}$, $J$ is the last level of the decomposition; $a_j$ and $d_j$ are the coefficients of approximation and details of the $j$ scale, respectively; $h(m)$ and $g(m)$ are like low-pass and high-pass filters, respectively; in $j = 1$, $a_{j-1} = a_0$ is the original sign (Costa et al., 2010). In this case, therefore, $n$ is the number of coefficients at level $j-1$ and $m$ is the number of coefficients at level $j$. The coefficients of approximation $a_{j+1}$ and of details $d_{j+1}$ are obtained respectively by converting the approximation coefficients $a_j$ with the filters $h$ and $g$ followed by a decimation of two (Costa et al., 2010).

The maximum number of levels $J$ should be established according to Equation 4.3, adapted from Costa et al. (2010):

$$J = \lfloor 1 + log_2(N_t) \rfloor \quad 4.3$$

where $N_t$ is the number of samples of the original signal and $\lfloor\cdot\rfloor$ means to round down.

The shape and frequency of the signal are related to the mother wavelet, which is usually an orthonormal basis function. The choice of the most similar mother wavelet with the analyzed signal is important to obtain a better decomposition. The Daubechies, db4, wavelet is most commonly used in DWT researches on EEG signals, since it has the highest classification accuracy (Khan, Gotman, 2003; Saab, Gotman, 2005; Faust et al., 2015; Li, Chen and Zhang, 2017).

In this paper, the DWT was used to decompose time windows of 10 seconds, using all 23 channels from data set. The Daubechies db4 wavelet was the mother wavelet applied to decompose the signals into 5 levels.

## 4.3 ENERGY

For the Daubechies wavelet, which is an orthogonal basis, the sum of the squares of the coefficients is the signal energy (Khan; Gotman, 2003; Kang et al., 2019). In practice, as the recorded EEG signals are time series in discrete time, the energy for the sub-frequency band obtained by DWT is given as:

$$e_j = \frac{1}{m}\sum_{i=1}^{m} C_j^2 \qquad 4.4$$

where $m$ is the number of coefficients ($C$) obtained by DWT at the level $j$.

## 4.4 CLASSIFICATION METHOD

The classification of EEG signals has been quite challenging in the field of machine learning and signal processing (Richhariya, Tanveer, 2018).

This study consists of preprocessing the data using the DWT on EEG signals and classifying them using kNN (k-nearest neighbors) (Cover, Hart, 1967) and SVM (Burges, 1998). The best value of k obtained in the calibration of the classification algorithm kNN was equal to 3 and the Euclidean distance was used as distance metric. The values tested were only the odd ones, so as not to cause a tie in the classification. The SVM is a powerful EEG signal classification technique capable of obtaining a globally optimal solution (Richhariya, Tanveer, 2018). For the development of the SVM classifier, we fit into a linear model and parameter *c* equals 4.

The wavelet transform is one of the most widely used methods for extracting EEG data features (Richhariya, Tanveer, 2018). Non-overlapping sliding windows of 10 seconds were analyzed using the energy calculated of each level obtained from the DWT. In our approach, we used db4 wavelet with 5 levels of decomposition. The features are used in the classifiers to identify differences between preictal and interictal states.

## 4.5 K-FOLD CROSS VALIDATION

To evaluate the generalization capacity of the classification model, the k-fold cross-validation technique was used, with $k$ equal to 5. The k-fold cross-validation is normally performed to ensure the generalization of a classification model. In this method, the data set is randomly divided into $k$ mutually exclusive, and approximately equal size, subsets (Kohavi, 1995).

For training are used $k-1$ subsets, and the remainder is used as test set. Thus, metrics to performance are calculated iteratively by $k$ times, where in each iteration a different subset is used as test set. After cross-validation, the mean of the results is calculated as final result (Kohavi, 1995).

### 4.6 PERFORMANCE TESTING

The classification performance is evaluated in the test data set in terms of accuracy (Acc), sensitivity (S) and specificity (Sp) which are defined in Equations (4.5), (4.6) and (4.7):

$$Acc = \frac{TP+TN}{TP+FP+TN+FN}100\% \qquad 4.5$$

$$S = \frac{TP}{TP+FN}100\% \qquad 4.6$$

$$Sp = \frac{TN}{FP+TN}100\% \qquad 4.7$$

where TP (True Positive) and TN (True Negative) are the samples correctly classified in positive and negative classes, respectively. The FP (False Positive) and FN (False Negative) are the samples erroneously classified by the model in positive and negative classes, respectively. In this paper, the positive class is the preictal state.

## 5 EXPERIMENTAL DESIGN AND RESULTS

### 5.1 CHANNEL ANALYSIS

The knowledge of the most relevant channels in the classification process gives us the best location on the scalp that discriminates between the interictal and preictal states. The decomposition of the EEG signals by DWT into 5 levels returned 6 frequency ranges, as can be seen in Table 1.

At first, each channel was analyzed individually, in the task of performing the classification of the signal in interictal and preictal. The results of this analysis, in terms of the performance measures, are presented in Table 2, for the kNN and SVM classifiers.

Table 1. Frequency bands of EEG signal using five level decomposition

| Levels | Sub-bands | Frequency range (Hz) |
|---|---|---|
| 1 | D1 | 64–128 |
| 2 | D2 | 32–64 |
| 3 | D3 | 16–32 |
| 4 | D4 | 8–16 |
| 5 | D5 | 4–8 |
| 5 | A5 | 0–4 |

Table 2. Performance of kNN and SVM classifiers in relation to individually analyzed channels

| Channels | Acc kNN (%) | Acc SVM (%) | S kNN (%) | S SVM (%) | Sp kNN (%) | Sp SVM (%) |
|---|---|---|---|---|---|---|
| 1 | 76.25 | 71.04 | 77.50 | 65.41 | 75.00 | 76.67 |
| 2 | 69.79 | 62.71 | 80.00 | 50.42 | 59.58 | 75.00 |
| 3 | 79.17 | 84.38 | 87.08 | 90.00 | 71.25 | 78.75 |
| 4 | 90.42 | 90.83 | 90.00 | 88.33 | **90.83** | 93.33 |
| 5 | 74.38 | 69.58 | 76.25 | 56.25 | 72.50 | 82.92 |
| 6 | 77.29 | 73.33 | 78.33 | 69.17 | 76.25 | 77.50 |
| 7 | 77.50 | 69.17 | 70.42 | 89.58 | 84.58 | 48.75 |
| 8 | 79.17 | 75.00 | 77.92 | 92.50 | 80.42 | 57.50 |
| 9 | 72.71 | 70.21 | 77.08 | 92.50 | 68.33 | 47.92 |
| 10 | 80.00 | 80.42 | 83.33 | 90.00 | 76.67 | 70.83 |
| 11 | 71.46 | 64.79 | 75.42 | 92.92 | 67.50 | 36.67 |
| 12 | 88.12 | 90.42 | 87.08 | 86.25 | 89.17 | **94.58** |
| 13 | 78.33 | 75.00 | 81.25 | 67.92 | 75.42 | 82.08 |
| 14 | 71.25 | 61.25 | 79.58 | 58.75 | 62.92 | 63.75 |
| 15 | 82.71 | 84.38 | 90.83 | 87.08 | 74.58 | 81.67 |
| 16 | **92.92** | **93.75** | **95.42** | **94.58** | 90.42 | 92.92 |
| 17 | 58.75 | 64.58 | 63.33 | 86.67 | 54.17 | 42.50 |
| 18 | 73.75 | 69.37 | 75.83 | 93.33 | 71.67 | 45.42 |
| 19 | 81.25 | 84.58 | 88.33 | 90.83 | 74.17 | 78.33 |
| 20 | 72.92 | 71.04 | 85.00 | 82.08 | 60.83 | 60.00 |
| 21 | 67.92 | 58.54 | 68.75 | 93.75 | 67.08 | 23.33 |
| 22 | 67.92 | 71.25 | 75.42 | 77.08 | 60.42 | 65.42 |
| 23 | 81.46 | 84.67 | 89.58 | 86.67 | 73.33 | 81.67 |

When analyzing the obtained results, it was noticed that the most relevant channels were 4 (P7-O1), 12 (P4-O2) and 16 (P8-O2). By mapping their location on the scalp, was observed to be in the lobe occipital region (4 (P7-O1), 8 (P3- O1), 12 (P4-O2) and 16 (P8-O2)).

Based on this observation, other experiments were done, this time comparing the use of all channels with those of the channels of the occipital lobe region (4, 8, 12 and 16). It was also verified the interference in the classification of the right and left sides: for the channels 12 and 16, which are located further on the right side, and for the channels 4 and 8, which are more on the left side. These results are shown in Table 3.

As we can see in Table 3, the four selected channels achieved the best results, with accuracy of 97.29%, sensitivity 96.25% and specificity with 98.33%, when using the SVM classifier. The SVM classifier that used all channels also resulted in good performances, but for the purpose of creating a seizure alarm device, the use of 23 channels would make it difficult for the patient's daily activities. Besides this information, it was verified that the kNN classifier obtained its best accuracy and specificity when using the channels 4, 12 and 16. When analyzing the effect of the right and left sides in the classification, it was observed, for both classifiers and measures, right side was slightly better than left side.

The results achieved in Table 2 and 3 indicate the occipital lobe region has a great discriminative power to distinguish between the interictal and preictal states.

Table 3. Performance of the kNN and SVM classifiers in relation to the selected channel sets and all channels

| Channels | Acc kNN (%) | Acc SVM (%) | S kNN (%) | S SVM (%) | Sp kNN (%) | Sp SVM (%) |
|---|---|---|---|---|---|---|
| 4,8 | 90.63 | 93.96 | 89.58 | 92.50 | 91.67 | 95.42 |
| 12,16 | 92.71 | 94.58 | 92.08 | 93.75 | **93.33** | 95.42 |
| 4,12,16 | **92.92** | 93.96 | 92.92 | 93.75 | 92.92 | 94.17 |
| 4,8,12,16 | 92.08 | **97.29** | 91.25 | 96.25 | 92.92 | **98.33** |
| All | 90.21 | 97.08 | **94.58** | **97.50** | 85.83 | 96.67 |

It is important to notice about these results, that each EEG channel reports the activity of the brain region where it is located. A focal crisis originating in the occipital lobe has clinical manifestations that reflect this region of the brain (Shoeb, 2009). Occipital crises are usually triggered by visual stimulation, such as induction by television and by the closure of the eyes (Yalçin, Kaymaz and Forta, 2000).

During data collection, in the first study of Shoeb and colleagues (2004), sample included patients with epilepsy who could present focal, lateral or generalized seizures. Therefore, since the most relevant channels to discriminate the interictal and ictal states are in the occipital lobe region in our results, it cannot be said that patients have focal epilepsy. This is likely, because focal seizures can also be spread to other regions of the brain (Shoeb, 2009).

From the results, we can detect the preictal state from the occipital lobe region, with only 4 channels, considering the patient's type of epilepsy.

These findings suggest that it is possible to construct a non-invasive device using 4 channels and allocate it discretely in the posterior region of the head.

## 5.2 ANALYSIS BY SUB-BANDS OBTAINED BY DWT

After the channel analysis step, the classification for each sub-band obtained by DWT, using only channels 4, 8, 12 and 16, was performed to verify the frequency bands that are most important to distinguish between the interictal and preictal states.

The Table 4 shows the results of each sub- band for each classifier.

Table 4. Performance of the kNN and SVM classifiers in relation to the sub-bands

| Sub-bands | Acc kNN (%) | Acc SVM (%) | S kNN (%) | S SVM (%) | Sp kNN (%) | Sp SVM (%) |
|---|---|---|---|---|---|---|
| D1 | 86.25 | 78.13 | 83.75 | 78.33 | **88.75** | 77.92 |
| D2 | 85.42 | 83.75 | 90.00 | 79.17 | 80.83 | 88.33 |
| D3 | **89.58** | **89.79** | **91.67** | **87.50** | 87.50 | 92.08 |
| D4 | 76.25 | 77.50 | 80.83 | 86.25 | 71.67 | 68.75 |
| D5 | 83.33 | 80.42 | 82.92 | 75.00 | 83.75 | 85.83 |
| A5 | 83.75 | 82.29 | 86.67 | 69.17 | 80.83 | **95.42** |

From Table 4 we observed that D1 (64-128 Hz), D2 (32-64 Hz) and D3 (16-32 Hz) presented better relevance in the classification. When the D4 (8-16 Hz), D5 (4-8 Hz) and the approximation (0-4 Hz) levels were removed from the analysis, the classifiers achieved results around 95% for all metrics.

Table 5. Performance of the KNN and SVM classifiers in relation to the sub-bands D1, D2 and D3

| Sub-bands | Acc kNN (%) | Acc SVM (%) | S kNN (%) | S SVM (%) | Sp kNN (%) | Sp SVM (%) |
|---|---|---|---|---|---|---|
| D1, D2, D3 | 94.58 | 95.83 | 95.42 | 95.42 | 93.75 | 96.25 |

Therefore, the range of 32 Hz to 128 Hz presented greater relevance for a classification of the interictal and preictal states. This implies that higher frequencies contribute more to a good classification of the interictal and preictal states and can be analyzed for the precursors of the seizures (Gadhoumi, Lina and Gotman, 2012), despite earlier studies related to the detection of the crisis, that is, to the discrimination of the interictal and ictal state, have considered the bands with lower frequencies as the entry of the classifier (Li, Chen and Zhang, 2017; Kaleem, Guergachi and Krishnan, 2018). Such a focus on lower frequencies was possible due to the fact that most of the convulsive activity occurs in the range of 3 Hz to 29 Hz (Kaleem, Guergachi and Krishnan, 2018).

## 6 CONCLUSION

The understanding of how epileptic seizures are generated and if they are predictable is of paramount importance to research that aim to identify preictal and interictal activities in EEG signals. Thus, discrimination of states between convulsions (interictal) and before the seizures (preictal) contributes to the construction of an efficient prediction and alert system of epileptic seizures (Song, Zhang, 2016).

In this work, we present a methodology of discrimination of the interictal and preictal states from the study of the frequency bands obtained by DWT, and the channels that are most relevant to reach a good classification.

The database used in this work, CHB-MIT (2010) database, has been used in other researches, but few authors have used it for the same purpose presented in this paper. In addition, the high variety of patients and the presence of physiological artifacts present in the data may interfere with the results obtained (Kaleem, Guergachi and Krishnan, 2018). However, our results were favorable for a future application in seizure predictions. The availability of an algorithm, coupled with a device capable of preventing seizures, may avoid the difficulties and concerns associated with the consequences of epilepsy.

Due to the need for an efficient method for all patient types, more research is still needed. These considerations motivate more analyses in order to find out methods that can be generalized among patients of different genders and ages.

As an extension of our work, we intend to use a larger data set with greater diversity among patients. In addition, we intend to apply methods to predict the epileptic seizure.

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