Temporal epilepsy seizures monitoring and prediction using cross-correlation and chaos theory

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Temporal seizures due to hippocampal origins are very common among epileptic patients. Presented is a novel seizure prediction approach employing correlation and chaos theories. The early identification of seizure signature allows for various preventive measures to be undertaken. Electro-encephalography signals are spectrally broken down into the following sub-bands: delta; theta; alpha; beta; and gamma. The proposed approach consists of observing a high correlation level between any pair of electrodes for the lower frequencies and a decrease in the Lyapunov index (chaos or entropy) for the higher frequencies. Power spectral density and statistical analysis tools were used to determine threshold levels for the lower frequencies. After studying all five sub-bands, the analysis has revealed that the seizure signature can be extracted from the delta band and the high frequencies. High frequencies are defined as both the gamma band and the ripples occurring within the 60–120 Hz sub-band. To validate the proposed approach, six patients from both sexes and various age groups with temporal epilepsies originating from the hippocampal area were studied using the Freiburg database. An average seizure prediction of 30 min, an anticipation accuracy of 72%, and a false-positive rate of 0% were accomplished throughout 200 h of recording time.

1. Introduction: Epilepsy is a neurological pathology originating from a serious nervous disorder, causing recurrent seizures to its victims. Seizure triggering can be because of either physiological or environmental causes and their repetition can occur in several week intervals or even several hours. Loss of conscience and equilibrium happening during seizures can lead to serious injuries, fractures or even burns. Health costs linked to these accidents are also very important.

In this Letter, a novel procedure for anticipating seizures in temporal epilepsy is described. The methodology uses dual channel cross-correlation and chaos theory to predict upcoming seizures. The Letter is divided as follows: the next section highlights the state-of-the-art in seizure prediction and discusses the signal processing techniques used for seizure prediction as well as the anticipation methodology. Signal processing for seizure prediction is briefly explained in Section 3. Experimental results using electro-encephalography (EEG) recordings from the Freiburg database [1] are presented in Section 4. Finally, results are analysed and a discussion comparing the proposed technique with similar works is presented in Section 5.

2. State-of-the-art and background: EEG is the summation of neuronal electrical activities and is widely used in diagnosing epileptic disorders and seizure onsets. During a seizure, brain waves differ considerably from the normal state. Differences in amplitude, phase, correlation, spectral density and chaos rate are observable due to the abnormal neuronal firing. Brain activity in the ictal, interictal and healthy states are significantly different. Such variations are monitored through the use of non-linear dynamical techniques. Isamendis and Sackellares [2] were the pioneers in anticipating seizures through this approach in the 1980s. They first started using the principal Lyapunov exponent, then the short-term Lyapunov exponent (STL).

In the last decade, non-linear approaches were used by several researchers to obtain better sensitivity, lower False-Positive (FP) and higher anticipation time [3–6].

Other combined techniques were used as well and obtained similar results. Netoff et al. [7] experimented a patient specific classification algorithm on nine patients from the Freiburg database. Shiau et al. [8] proposed an automated seizure prediction algorithm (ASPA) based on non-linear techniques (STL) and adaptive transition thresholds according to the current state of dynamical interactions among brain sites. More recently, Senger et al. [9] used cellular non-linear networks (CNN) or ‘brain like computing’ to work on two patients having ten seizures. Duman et al. [10] used the Hilbert-Huang transform. Zandi et al. [11] used a patient specific variational Bayesian–Gaussian mixture model of zero-crossing intervals and, finally, Zheng et al. [12] developed a seizure prediction model based on a method of common spatial patterns and support vector machine (CSSVM) to establish a support vector machine classifier.

This Letter combines statistical and non-linear approaches to form an integral technique aiming to define a unique seizure signature for each patient. This signature will be used to ‘train’ the implant to anticipate seizures with an acceptable anticipation rate and a reliable FP. EEG signals are initially filtered into the five conventional sub-bands: delta (0–4 Hz); theta (4–8 Hz); alpha (8–15 Hz); beta (15–30 Hz); and gamma (30–120 Hz). The gamma sub-band was extended from 60 to 120 Hz to include the ripple effects noted in such seizures.

Seizure detection, such as for [13], takes place after the seizure electrical onset whereas seizure anticipation and prediction take place before the onset arrival. Comparing the two latter techniques in the literature reveals that the closer the onset, the greater the accuracy. On the other hand, precious time where proactive actions might be taken by both the patient and the neurologist is lost. Although there are several predicting/anticipation methods in the literature, there are two main parameters to validate each method: sensitivity and specificity. Sensitivity is the parameter able to detect the epilepsy seizure. In most cases, it is expressed in percentage. Specificity is the parameter by which false alerts or FPs are avoided.

Although the aforementioned techniques may have similar performances to ours in terms of anticipation time and sensitivity, only the proposed method and [7] offer a 0% FP. However, the latter has an anticipation window of 10 min while this work realizes 30 min. In addition, in all the other published papers, complexity is
much higher since all five sub-bands are needed and numerous subsequent features are required to process EEG data. This makes the learning and anticipation process tedious. To overcome this complexity, the presented approach relies on two sub-bands and only three features, as will be shown in the following Sections. Both software and hardware implementation costs will thus be alleviated.

3. Signal processing for seizure prediction: In this Section, the signal processing techniques used for the proposed seizure prediction algorithm are presented. A thorough monitoring of the preictal signals has revealed an increase in the Delta amplitudes compared with the interictal phase. This change in voltage generally occurs several tens of minutes before the seizure onset. Fig. 1 shows the interictal voltage histogram whereas Fig. 2 depicts it for the preictal phase. The difference in voltage thresholds between both phases is visible. Indeed, by setting the preictal threshold voltage to 8 mV, a seizure warning can be observed in the distribution at around 15 mV.

A typical spectral repartition in a given EEG channel during the preictal phase is shown in Fig. 3. This Figure shows little impact on the mid-frequency portions of the EEG signal compared with the boundary sub-bands, i.e. delta and gamma. Use of histograms for the gamma frequencies shows little efficiency in determining voltage thresholds because of the overlap between maximum voltage levels in interictal phase and minimum voltage thresholds in the preictal phase. An increase in the delta voltages is notable at different times announcing a seizure approach, as shown in Fig. 3.

Voltage thresholds were used as an initial classification parameter for low frequencies. The cross-correlation between different channels (Fig. 4) and the Chaos level of high-frequency channels are also considered in this study. These techniques are described in the following paragraphs:

3.1. Cross-correlation definition: For each channel, the choice of delay giving best cross-correlation is shown in the following equations:

\[
C_{a,b}(\tau) = \begin{cases}
\frac{1}{N-\tau} \sum_{t=\tau+1}^{N} x_a(t) x_b(t), & \tau \geq 0 \\
C_{b,a}(-\tau), & \tau < 0
\end{cases}
\]  

(1)

Maximum cross-correlation for delays \(|\tau| < 10\) s

\[
C_{a,b} = \max_{-0.5s < \tau < 0.5s} \left\{ \frac{C_{a,b}(\tau)}{\sqrt{C_{a,a}(0) C_{b,b}(0)}} \right\}
\]  

(2)

Applying cross-correlation and taking into consideration potential delays between different waves is more observable in the delta frequency range than in the gamma.

\[K\] nearest neighbours of \(x_a(t)\)

\[\{t'_1, t'_2, \ldots, t'_K\}\]

(3)

Distance of neighbours of \(x_a(t)\) to \(x_a(t'_j)\)

\[
R(t, x_a) = \frac{1}{K} \sum_{k=1}^{K} \|X_a(t) - X_a(t'_k)\|^2
\]  

(4)

Figure 1 Delta histogram during an interictal phase recording. Patient#2, file#82, EEG channel #1. The highest voltage is around 7.5 mV.

Figure 2 Delta histogram during preictal phase recording. Patient#2, file#17, EEG channel #1. The highest voltage is around 15.5 mV which exceeds the interictal maximum voltage.

Figure 3 EEG voltage at the approach of a seizure (preictal phase). Peak noted around sample # 700 000 in a given channel.
K nearest neighbours of \( x_d(t) \)

\[
\{ t_1, t_2, \ldots, t_K \}
\]  

Distance of neighbours of \( x_d(t) \) to \( x_d(t) \)

\[
R(t, x_d | y) = \frac{1}{K} \sum_{i=1}^{K} \| x_d(t) - x_d(t_i) \| ^2
\]  

Similarity of trajectory of \( x_d(t) \) to the trajectory of \( x_b(t) \)

\[
S(x_d | x_b) = \frac{1}{N} \sum_{n=1}^{N} \frac{R(t, x_d)}{R(t, x_b)}
\]  

Symmetric measure of similarity of trajectories

\[
S_{ab} = \frac{S(x_a | x_b) + S(x_b | x_a)}{2}
\]  

3.2. Lyapunov exponent theory: The use of the Lyapunov exponent is a powerful measure to detect and characterise the behaviour of a dynamic system (either chaotic or regular). This measure is intensively used to determine the behaviour state of oscillating systems that can be described through total non-linear differential equations. The Lyapunov exponent is mainly used for in depth analysis of local stability for stationary states in different wave trajectories.

A coupled model is considered in order to trace the Lyapunov index. A perturbation to the described model will lead to the following differential system

\[
\begin{align*}
\ddot{x}_1 - e_1 (1 - x_1^2) \dot{x}_1 + (\omega^2 + 2 e_2 x_1) x_1 &= c_1 \dot{y}_1 + c_2 \dot{x}_1 \\
\ddot{y}_1 + e_2 \dot{y}_1 + (-\omega^2 + 3 c_0 x_1^2) y_1 &= c_1 x_1 + c_2 \dot{x}_1
\end{align*}
\]  

From which \( (x_1, y_1, \dot{x}_1, \dot{y}_1) \) computing will lead to deduce the Lyapunov exponent defined by

\[
\lambda = \frac{1}{t} \ln \left( |x_1| + |\dot{x}_1| + |y_1| + |\dot{y}_1| \right)
\]  

Two figure cases may exist:

- \( \lambda < 0 \): In this case regular oscillations are present.
- \( \lambda = 0 \): In this case we have a Taurus orbit built from an assembly of multi-period waves.
- \( \lambda > 0 \): This figure case expresses a chaotic state.

At this level, the chaos can be described as a temporal evolution with sensitive dependencies to the initial conditions that are hard to predict and made from an infinity of frequency components.

In a dynamic system, sensitivity to initial conditions can be expressed by a distance separating two trajectories that can increase exponentially in time up to equalling the attractor diameter. In this case, the obtained waveforms, qualified as external attractors, are far from having a smooth surface and look rather like Fractals illustrating the external perturbations. Considering a system described by the following state model equation

\[
\dot{X}(t) = A(t) \cdot X(t)
\]  

where \( X(t) \in \mathbb{C}^n \) and \( A(t) \) is a \( n \times n \) matrix with complex entries depending on \( t \in \mathbb{R} \) and assuming that the matrix \( A(t) \) is bounded:

\[
\operatorname{Sup}_{t \in \mathbb{R}} \| A(t) \| < \infty
\]

Consequently, for each \( X_0 \in \mathbb{C}^n \), there exists a unique solution

\[
X(t) = X(t, X_0)
\]  

for (12) satisfying the initial condition

\[
X(0, X_0) = X_0
\]  

Let us consider the trivial solution \( X(t) = 0 \) where \( t \geq 0 \). If matrix \( A(t) \) is constant, i.e., \( A(t) = A \) for \( t \geq 0 \), then the trivial solution is asymptotically (indeed exponentially) stable if, and only if, the real part of every eigenvalue of the matrix \( A \) is negative. A similar result holds in the case when the matrix \( A(t) \) is periodic. To characterise the stability of the trivial solution in the general case, the Lyapunov exponent is introduced: \( \lambda^+ : \mathbb{C}^n \to \mathbb{R} \cup \{-\infty\} \) of (11) by the formula

\[
\lambda^+ = \lim_{t \to \infty} \frac{1}{t} \ln \| X(t) \|
\]  

Estimate of the largest Lyapunov exponent of \( x_d(t) \), i.e. exponential

\[
\text{Figure 4 Delta cross-correlation at the approach of a seizure (preictal phase).}
\]  

Total correlation around sample # 680 000

\[
\text{doi: 10.1049/htl.2013.0010}
\]  

\( \lambda \leq 0 \) in this figure case, two sub-cases are distinguished where the oscillatory states are stable:

- Case \( \lambda < 0 \): In this case regular oscillations are present.
- Case \( \lambda = 0 \): In this case we have a Taurus orbit built from an assembly of multi-period waves.

- Case \( \lambda > 0 \): This figure case expresses a chaotic state.

\begin{figure}
\centering
\includegraphics[width=\textwidth]{delta_cross-correlation_patients2_file17}
\caption{Delta cross-correlation at the approach of a seizure (preictal phase).}
\end{figure}
rate of growth of a perturbation in \( x_a(t) \)

\[
\text{STL}(x_a) = \frac{1}{N} \sum_{t=1}^{N} \log_2 \left( \frac{\delta x_a(t + \Delta t)}{\delta x_a(t)} \right)
\]

Measure of convergence of chaotic behaviour of EEG channels \( x_a \) and \( x_b \):

\[
\text{DSTL}_{a,b} = |\text{STL}(x_a) - \text{STL}(x_b)|
\]

### 3.3. Anticipation methodology

Because of the possible overlap observed in the previous figures (Figs 1 and 2) in the voltage thresholds, another parameter was required to have a better tuning in determining seizure signatures. Observations revealed a high cross-correlation level in the delta sub-band along with the increase in voltage at the approach of a seizure. Studying EEG signals from six patients showed high levels of cross-correlation occurring in several inter-channels. It is worth mentioning that many low frequency waves correlate across channels with a certain delay between them. The current technique studied cross-correlations between channels on a one-on-one basis with a delay going up to 2560 samples (where the sampling frequency is 256 samples per second). This delay was applied alternatively on each of the two compared waves since there is no symmetry in this case. In other words, since there is data for six channels, this results in 15 cross-correlation combinations.

The anticipation methodology consisted of two major parts: the learning process, as is depicted in Fig. 5; and the anticipation process. A learning process should be performed for every patient in whom the interictal and ictal phases are monitored.

- **Learning process**: The algorithm establishes delta voltage thresholds for both preictal and interictal states then establishes a discriminating threshold between both. It then computes the highest cross-correlation level between different electrodes. At the same time, the algorithm calculates the entropy level in the gamma sub-band and determines the current values and the derivative for the Lyapunov index. All these values are stored in the memory as a seizure approach signature.
- **Anticipation process**: EEG signals are filtered and continuously compared against the signature. Any match happening for a specific sub-band will raise a flag. Having three flags at the same time would be considered as a seizure anticipation.

A graph model can be used to represent the six electrodes as if there are \( n = 6 \) nodes and all the inter-channel dependencies are represented as edges. A threshold of a minimum number of edges per patient had to be established along with the voltage thresholds to determine a flag, or a possible warning, emerging from the delta sub-band.

### 3.4. Delta behavior study

The algorithm has clearly revealed that the same nodes involved in the delta frequencies activities (high voltage and high cross-correlation) will also be involved in the gamma frequencies occurring after a certain delay. This observation formalises the anticipation algorithm and makes the anticipation effort easier since we know where to expect the gamma frequency activities (decrease in chaotic behaviour).

Values for voltages and cross-correlation for the same patient in preictal phase are bigger than those in the interictal phase, which makes it a potential anticipation tool in this frequency range. Figs 3 and 4 deal with seizure anticipation for patient #2. In the file #18 of the Freiburg database, there is a seizure at the sample 252 098 which is clearly predicted in file # 17 at samples 100 000 and 680 000. The complete graph (15 edges meaning total correlation between all channels) occurring in these two cases is clearly shown in Fig. 4. The anticipation time here is around 31.4 min. Detailed results for all seizures will follow later in Table 1.

The analysis was repeated to all sub-bands and showed both the inter-channel correlations and the peak-to-peak voltages reached for different frequency ranges. The three following sub-bands (theta, alpha and beta) showed little voltage and little correlation. The latter often takes place after the seizure onset which does not represent any use in the anticipation process.

From this experience, the following observations can be drawn:

- Delta and gamma sub-bands are highly linked in temporal seizures. Actually, gamma bursts or spikes seem to originate from the same electrodes/nodes a certain time after the appearance of the delta high voltages along with high cross-correlations.
- The other sub-bands did not show any significance in the anticipation process. Either the cross-correlation was too low or it appeared after the seizure onset; or the voltages were too low and could not be distinguished in preictal or interictal phases. Consequently, it was decided to discard the theta, alpha and beta frequencies from the current technique.

### 3.5. Gamma behaviour study

This Section will deal with the gamma behaviour during the preictal phase. The previous Section showed that gamma activity follows the delta-band high voltage and high correlation. Gamma cross-correlation may contribute in the seizure anticipation, however the proximity to the onset time (<10 min) makes it less efficient and requires investigating other techniques. The chaos theory described earlier along with the Lyapunov index has the potential to overcome this issue.

In the interictal phase, brain waves tend to have a totally random activity, meaning a Lyapunov index \( \lambda \) higher than zero. Moving toward a seizure means gradually leaving the chaotic state and converging to zero (see (15)). Since it is impossible to have an infinite...
The limit to compute $\lambda$, smaller windows of 300 s are used. This scheme was applied to the gamma frequencies. $\lambda_{\text{Gamma}}$ results are summarized in Fig. 6. For each patient, $\lambda_{\text{Gamma}}$ had specific value ranges and it was important to determine the two main parameters below: (i) the value for $\lambda$ and its derivative at a given time for a specific channel. (ii) The number of channels decreasing at the same time representing a convergence of the system towards the zero value.

Having $\lambda_{\text{Gamma}}$ simultaneously decrease in several channels would raise a flag of a seizure warning emerging from the Gamma frequency range. The Lyapunov index method showed significant differences between interictal and preictal phases. The first being more chaotic and having bigger positive values with less or no convergence toward zero whereas the latter had smaller positive values and a more distinct tendency to converge to zero and even reach negative values (stable system) prior to a seizure as can be seen by the multiple transitions from the yellow/orange colours to the blue strips in Fig. 6.

### 4. Results

The Freiburg database includes six patients with temporal epilepsy because of hippocampal origin (patients #2-4-7-10-12 and 16). In this work, all six patients have been studied. However, the electrode number 3 for patient #16 had a lot of artifacts during both interictal and preictal phases. Consequently, no significant information could be extracted from this electrode as EEG signal seems to be buried in noise. This electrode was thus suppressed from the measurements. Experimental results are shown in Table 1 which reflects considerable differences in the delta peak-to-peak value reaching sometimes a ratio of 36:1 between different patients. This may be related to several factors such as the location of focal zones, the age and sex of the patient, and finally the type and location of the electrodes. In the current database, neurologists decided in some cases to put all electrodes in the same hemisphere whereas different configurations were chosen in other cases. Electrode configuration has a direct influence on EEG channel voltages and correlations.

In this study, we deliberately decided to minimise false alerts at the expense of the sensitivity, 72% here. However, the algorithm sensitivity can potentially be tuned to increase the prediction accuracy at the cost of a slight increase of false alerts. This tradeoff is shown in Fig. 7 where moving the sensitivity threshold bar level up decreases the number of false alerts while lowering the anticipation sensitivity rate; conversely, moving it down increases both the false alerts and the anticipation sensitivity.

### 5. Conclusion

This study revealed that temporal seizures can be anticipated by analysing three features in two-frequency sub-bands (delta and gamma). It showed that delta high voltages and inter-electrode correlations are followed by high-frequency signal bursts or ripples along with a drop in entropy (increase in order or stability). It was demonstrated that the mid-frequencies do not present any significant or useful information in the

![Figure 6](image1.png)

**Figure 6** $\lambda_{\text{Gamma}}$ simultaneous decrease is visible at several times in this figure

![Table 1](image2.png)

**Table 1** Experimental results based on the Freiburg epilepsy database.

<table>
<thead>
<tr>
<th>Patient ID</th>
<th>Seizure type</th>
<th>Electrodes</th>
<th>Detection time, s</th>
<th>Interictal hours</th>
<th>False alerts</th>
</tr>
</thead>
<tbody>
<tr>
<td>#2 male, 38</td>
<td>SP,CP,GTC</td>
<td>D</td>
<td>1884</td>
<td>24</td>
<td>0</td>
</tr>
<tr>
<td>#4 female, 26</td>
<td>SP,CP,GTC</td>
<td>d,g,s</td>
<td>2201</td>
<td>24</td>
<td>0</td>
</tr>
<tr>
<td>#7 female, 42</td>
<td>SP,CP,GTC</td>
<td>D</td>
<td>1027</td>
<td>25</td>
<td>0</td>
</tr>
<tr>
<td>#10 male, 47</td>
<td>SP,CP,GTC</td>
<td>D</td>
<td>1019</td>
<td>25</td>
<td>0</td>
</tr>
<tr>
<td>#12 female, 42</td>
<td>SP,CP,GTC</td>
<td>d,g,s</td>
<td>3004</td>
<td>26</td>
<td>0</td>
</tr>
<tr>
<td>#16 female, 50</td>
<td>SP,CP,GTC</td>
<td>d,s</td>
<td>2349</td>
<td>24</td>
<td>0</td>
</tr>
<tr>
<td>Average results</td>
<td></td>
<td></td>
<td>1817.83 sec (30.29 min)</td>
<td>147</td>
<td>0</td>
</tr>
</tbody>
</table>

SP = simple partial, CP = complex partial, GTC = generalised tonic-clonic; d = depth electrode, g = grid electrode and s = strip electrode.

![Figure 7](image3.png)

**Figure 7** Statistical power threshold adjustment showing tradeoff between sensitivity and false alerts, where TP is true positive and FN is false negative.

The obtained prediction accuracy is 72% with a 0% false alert rate. Table 2 shows better anticipation for this kind of seizures. The obtained prediction algorithm based on the dynamics of intracranial EEG, *Epilepsy Res.*, 2005, **64**, pp. 93–113


6. Acknowledgments: We would like to thank Mr V. Fono for the fruitful discussions about non-linear techniques.

7 References


<table>
<thead>
<tr>
<th>Ref.</th>
<th>Number of patients</th>
<th>Total months, h</th>
<th>Total number of seizures</th>
<th>Number of sub-bands</th>
<th>Sens. (%)</th>
<th>FP/HR</th>
<th>Prediction time, min</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>D’Alessandro et al. [5]</td>
<td>4</td>
<td>160 (baseline)</td>
<td>ND</td>
<td>5</td>
<td>62.5</td>
<td>0.27</td>
<td>10</td>
<td>non-linear</td>
</tr>
<tr>
<td>Maiwald et al. [3]</td>
<td>21</td>
<td>582</td>
<td>88</td>
<td>5</td>
<td>21–42</td>
<td>0.04–0.15</td>
<td>less than 30</td>
<td>non-linear</td>
</tr>
<tr>
<td>Chaovalitwongse et al. [4]</td>
<td>10</td>
<td>ND</td>
<td>ND</td>
<td>5</td>
<td>68–76</td>
<td>0.15–0.17</td>
<td>22.4–135</td>
<td>STL, non-linear</td>
</tr>
<tr>
<td>Iasemidis et al. [2]</td>
<td>2</td>
<td>ND</td>
<td>15</td>
<td>3</td>
<td>81.82</td>
<td>0.12</td>
<td>89 ± 15</td>
<td>STL, non-linear</td>
</tr>
<tr>
<td>Shiau et al. [7]</td>
<td>10</td>
<td>2100</td>
<td>120</td>
<td>5</td>
<td>85</td>
<td>0.159</td>
<td>63 ± 45</td>
<td>ASPA</td>
</tr>
<tr>
<td>Netoff et al. 2009 [6]</td>
<td>7</td>
<td>219</td>
<td>45</td>
<td>5</td>
<td>77.8</td>
<td>0</td>
<td>10</td>
<td>CSSVM</td>
</tr>
<tr>
<td>Senger et al. [8]</td>
<td>2</td>
<td>201.1</td>
<td>10</td>
<td>5</td>
<td>0.59–0.63</td>
<td>ND</td>
<td>30</td>
<td>CNN</td>
</tr>
<tr>
<td>Duman et al. [9]</td>
<td>21</td>
<td>582</td>
<td>87</td>
<td>5</td>
<td>89.66</td>
<td>0.49</td>
<td>ND</td>
<td>2–20</td>
</tr>
<tr>
<td>Zheng et al. [11]</td>
<td>7</td>
<td>ND</td>
<td>51</td>
<td>5</td>
<td>57%</td>
<td>ND</td>
<td>2–20</td>
<td>variational Bayesian-Gaussian mixture model</td>
</tr>
<tr>
<td>Zandi et al. [10]</td>
<td>20</td>
<td>561</td>
<td>86</td>
<td>5</td>
<td>88.34</td>
<td>0.155</td>
<td>22.5</td>
<td>zero-crossing intervals</td>
</tr>
<tr>
<td>this work</td>
<td>6</td>
<td>200</td>
<td>25</td>
<td>2</td>
<td>72</td>
<td>0</td>
<td>30.29</td>
<td>statistical and non-linear</td>
</tr>
</tbody>
</table>

Table 2 Anticipation algorithm performances in the literature for intra-cranial EEG signals. Some data is not defined (ND)