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# Evidence of self-organization in brain electrical activity using wavelet-based informational tools

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**Abstract**

In the present work, we show that appropriate information-theory tools based on the wavelet transform (relative wavelet energy; normalized total wavelet entropy, $H$; generalized wavelet complexity, $C_W$), when applied to tonic–clonic epileptic EEG data, provide one with valuable insights into the dynamics of neural activity. Twenty tonic–clonic secondary generalized epileptic records pertaining to eight patients have been analyzed. If the electromyographic activity is excluded the difference between the ictal and pre-ictal mean entropic values ($\Delta H = \langle H^{(ictal)}\rangle - \langle H^{(pre\text{-}ictal)}\rangle$) is negative in 95% of the cases ($p<0.0001$), and the mean complexity variation ($\Delta C_W = \langle C_W^{(ictal)}\rangle - \langle C_W^{(pre\text{-}ictal)}\rangle$) is positive in 85% of the cases ($p = 0.0002$). Thus during the seizure entropy diminishes while complexity grows. This is construed as evidence supporting the conjecture that an epileptic focus in this kind of seizures triggers a self-organized brain state characterized by *both* order and maximal complexity.


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*Keywords:* EEG; Epileptic seizures; Time–frequency signal analysis; Wavelet analysis; Signal entropy; Complexity

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## 1. Introduction

In the characterization of the time evolution of the complex EEG dynamics, quantifiers based on nonlinear dynamics have been applied by investigating: (i) the temporal evolution of the EEG signal's correlation dimension $D_2$ and, (ii) the associated degree of chaoticity (largest Lyapunov exponent, $\Lambda_{max}$). A transition from a rather complex behavior (of the neural network) to a much simpler one can be detected at (or just before) epileptic seizure onset [1,2]. Despite the obvious physiological relevance of such findings, serious doubts arise concerning the applicability of nonlinear metric tools to this endeavor. EEG-time series should be representative of a unique and stable attractor (i.e., be stationary) for nonlinear dynamic metric tools to be applicable. This is *not* the case with EEGs. Application of deterministic chaos' ideas to EEG data remains highly controversial. The concomitant interpretation of data is still under discussion [3]. An alternative, natural approach for quantifying the degree of order of a complex signal is provided by its spectral entropy (SE), as defined from the Fourier power spectrum [4]. The SE measures just how "concentrated" the Fourier power spectrum of a signal is. However, the Fourier transform (FT) requires stationarity of the concomitant signal and EEGs are highly nonstationary. The terms "nonstationary" and "time varying" mean that the statistical properties, which are the statistical moments, change with time. Statistical tests of stationarity EEG time series have revealed a variety of results depending on conditions, which estimate the amount of time during which the EEG is stationary, ranging from several seconds to several minutes [5–8]. In the case of tonic–clonic EEG records stationarity of the time series can be assumed for intervals of 30 s [9,10]. However, as a practical matter, whether or not a data segment is considered stationary depends on the problem being studied, the type of analysis being performed, and the measure used to characterize the data. Moreover, the FT does not yield the time evolution of the frequency patterns associated to the traditional EEG bands ($\delta$ : 0.5–3.5 Hz; $\theta$ : 3.5–7.5 Hz; $\alpha$ : 7.5–12.5 Hz; $\beta$ : 12.5–30.0 Hz; $\gamma$ : > 30.0 Hz) [11,12]. As a consequence, the spectral entropy does not get defined as a function of time.

All the above difficulties can be overcome by using the wavelet transform [13–15], an efficient time–frequency decomposition method. In particular, the orthogonal discrete wavelet transform (ODWT) makes no assumptions about a record's stationarity. The only input needed is the time series itself. If the Shannon entropy is computed via the wavelet transform, the time evolution of frequency patterns can be followed with an optimal time–frequency resolution. The ensuing entropy-form, i.e., the "normalized total wavelet entropy" (NTWS), carries information about the degree of order/disorder associated with a multi-frequency signal response [14]. Consequently, the time evolution of the NTWS would yield information concerning the dynamics associated with the EEG records [9,16–18].

Our goal here is to introduce the notion of *complexity* within such a wavelet scenario so as to gather new insight into the dynamical transition from epileptic tonic and clonic stages. Definitions of complexity can be classified into three groups, according to the calculational procedure one employs [19–21]: (i) computational