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The characterisation of the electroencephalogram (EEG) activity with novel and informative features from has attracted substantial research over the last couple of decades. The article by Ibañez-Molina et al., (2014) in this issue of *Clinical Neurophysiology* represents one of the latest steps in this quest. Ibañez-Molina et al., (2014) propose an elegant modification of a widespread non-linear signal feature – the Lempel-Ziv Complexity (*LZC*, Lempel and Ziv, 1976) – to consider multiple temporal scales related to specific frequencies. The resulting multiscale *LZC*, hereafter *mLZC*, is able to characterise the EEG signals better by capturing the complexity of both fast and slow rhythms (Ibañez-Molina et al., 2014).

The analysis of EEG activity has long been considered as a powerful tool to inspect brain function (Lopes da Silva, 2013; Sanei and Chambers, 2008). Traditionally, the EEG signals have been described in terms of frequency bands with different functional connotations (e.g., θ, α, β) (Lopes da Silva, 2013; Sanei and Chambers, 2008). Thanks to spectral techniques such as the Fourier Transform, it has been possible to quantify these rhythms and how they change in different brain conditions (Sanei and Chambers, 2008).

The emergence of the fields of chaos theory and non-linear dynamics opened up the possibility of using a completely different type of signal features to characterise the EEG brain activity (Hornero et al., 2009; Stam, 2005). Although it soon became clear that claims for "chaos" in the brain activity could not be sustained (Stam, 2005), the field of non-linear EEG analysis has since flourished thanks to the use of new non-linear metrics to detect, characterise and model non-linear dynamics, rather than focusing strictly on finding deterministic chaos (Hornero et al., 2009; Stam, 2005).

Many of these non-linear features, including the traditional *LZC*, are based on estimations of "complexity" (Costa et al., 2002; Escudero et al., 2006; Stam, 2005). *LZC* conceptualises complexity as the information needed to generate the time series under analysis (Lempel and Ziv, 1976). The practical implementation of this idea relies on the binarisation of the signal under analysis. This is done by setting a unique threshold (usually according to the median of the time series) along the whole signal. Samples higher than the threshold are assigned a binary value of "1", whereas points lower than the threshold are assigned "0". Then, this binary sequence is scanned from left to right and parsed into distinct subsequences. A complexity counter is increased each time a new subsequence is encountered (Lempel and Ziv, 1976). The traditional *LZC* can be applied to any type of time series (including short signals), it is easy to compute, and it does depend on input parameters (Aboy et al., 2006; Lempel and Ziv, 1976). Because of these advantages, *LZC* has been used in a wide variety of fields. See, for example, Aboy et al., (2006); Fernández et al., (2012); Hornero et al., (2009); Jouny and Bergey, (2012); Li et al., (2008).

However, the same binarisation process that lies at the heart of those advantages of the traditional *LZC* is also responsible for the limitation discussed by Ibañez-Molina et al., (2014). Ideally, the binary sequence should reflect the non-linear behaviour of the original signal. However, the binarisation may also lead to a relevant loss of information, especially in high frequencies (Ibañez-Molina et al.,

2014). This is because the amplitude of the neural activity is inversely related to its frequency. Slow rhythms have much higher amplitude than faster oscillations (Sanei and Chambers, 2008) and the traditional binarisation of *LZC* will be dominated by slow rhythms, which tend to cause larger excursions around the threshold than the faster frequencies. Therefore, the traditional *LZC* may disregard the behaviour of the faster frequencies in the EEG (Ibañez-Molina et al., 2014).

Overcoming this limitation would enable more insightful evaluations of the non-linear complexity of brain activity. Ibañez-Molina et al., (2014) propose to do so by computing several time-varying thresholds, each of which is associated with a different temporal scale (and thus, frequency) and leads to a different binarisation of the original signal. Then, the rate of appearance of binary subsequences is computed for each of the binarised versions of the signal. This yields a "spectrum" of complexity values, each of which can be interpreted in relation to an approximate frequency rhythm.

Ibañez-Molina et al., (2014) illustrate the *mLZC* by means of simple and short, yet informative, synthetic signals and the publicly available real EEG recordings described by Andrzejak et al., (2001). The traditional *LZC* failed to reveal any difference between the EEGs acquired with eyes closed and open. In contrast, *mLZC* revealed differences in complexity between eyes closed and eyes open, especially for the temporal scales associated with the α rhythm. This suggests that *mLZC* is able to account for the complexity of time series with fast oscillations masked by slower frequencies with higher amplitudes (Ibañez-Molina et al., 2014).

What is more, *mLZC* is considering temporal scales, or temporal information, alongside the non-linear behaviour of the signals. This idea can be traced back to a seminal article by Costa et al., (2002) who proposed the so-called multiscale entropy (*MSE*), which was first applied to EEG signals by Escudero et al., (2006). Since then, *MSE* has provided useful information in different conditions (Catarino et al., 2011; Escudero et al., 2006; Heisz and McIntosh, 2013). It must be noted that there are important differences between the *MSE* by Costa et al., (2002) and the *mLZC* by Ibañez-Molina et al., (2014) but both features fit with the current emergence of non-linear metrics able to bridge the gap between non-linear properties, and frequency- and correlation-based assessments of brain activity (Morabito et al., 2012).

However, work still needs to be done, as it would be important to characterise the behaviour of the non-linear features in terms of other signal parameters to facilitate their interpretation (Aboy et al., 2006; Escudero et al., 2009) and to clarify the extent to which they can provide complementary information to the traditional spectral analyses (Hornero et al., 2009). In the end, this would help us confirm if we can extract more information from EEG signal using this type of approaches.

To sum up, Ibañez-Molina et al., (2014) propose an interesting modification of LZC congruent with the trend in the field to bring temporal and spectral information into the evaluation of non-linear characteristics of biomedical signals. *mLZC* does not replace, but extends, the traditional *LZC*. Moreover, *mLZC* retains the main advantages of the traditional *LZC* and, therefore, I would expect it to achieve similar widespread use in the future. I hope it will help us to increase our knowledge on the dynamical characteristics of brain activity as measured by EEG recordings.

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Conflicts of interest

None of the authors have potential conflicts of interest to be disclosed.

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