Nonlinear Methodologies Applied to Automatic Recognition of Emotions: An EEG Review

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Abstract. Development of algorithms for automatic detection of emotions is essential to improve affective skills of human-computer interfaces. In the literature, a wide variety of linear methodologies have been applied with the aim of defining the brain's performance under different emotional states. Nevertheless, recent findings have demonstrated the nonlinear and dynamic behavior of the brain. Thus, the use of nonlinear analysis techniques has notably increased, reporting promising results with respect to traditional linear methods. In this sense, this work presents a review of the latest advances in the field, exploring the main nonlinear metrics used for emotion recognition from EEG recordings.

Keywords: Emotion recognition · Complexity · Regularity · Predictability · Connectivity patterns

1 Introduction

Emotions are essential in human experiences since they influence in cognition, perception and daily tasks like learning, communication and rational decision-making [11]. Although emotions are basic in human interaction processes, human-machine interfaces (HMIs) are still not able to properly identify human emotional states and execute actions according to those feelings [56]. In a technological society in which HMIs are being increasingly applied in countless fields like medicine [45], computer games [9] or digital society [62], there is an urgent need of developing automatic systems able to correctly interpret human emotions. In this sense, the affective computing science [50] is mainly focused on the development and improvement of algorithms for emotions recognition, thus endowing affective systems of emotional intelligence [17,41].

In any case, quantifying an emotion is not a simple task. One of the main reasons is the fact that there are no standard models for the definition of emotional states [63]. Hence, in the literature there is a wide variety of theories for discrete emotion classification. Those emotional models vary from Ekman's six

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basic emotions (happiness, sadness, surprise, disgust, anger and fear) [14], to those in which dozens of emotional states are defined (a total of fifty-five different emotional states were defined by the HUMAINE project) [59]. Nonetheless, the model presented by Russell is nowadays one of the most extended [57]. This two-dimensional model distributes all emotions in two dimensions called valence (pleasantness or unpleasantness) and arousal (calmness or excitement). Locations of emotions within this model are according to their level of these two dimensions.

Emotions have been traditionally identified by means of facial gestures and vocal expressions [7,38]. Nevertheless, those physical features are not universally accepted since social and cultural aspects may influence on the way emotions are expressed in each part of the world [58]. For this reason, emotion recognition studies have focused on the assessment of physiological signals, which present different levels of activation for distinct emotional states [40]. Furthermore, physiological variables have demonstrated to follow a similar behavior independently of social and environmental factors, thus they can be universally accepted [63]. In this sense, electrocardiogram (ECG), electromyogram (EMG) or electro-dermal activity (EDA) have been widely studied under different emotional conditions. However, the most promising physiological variable is the electroencephalogram (EEG), since it reflects the first response to an external stimulus while the rest of variables are secondary effects of the brain's processes [26].

Traditionally, EEG recordings have been studied from a linear point of view, using linear algorithms based on statistical parameters and frequency characteristics of the signals [26]. However, some works have recently demonstrated a complex performance of the brain dynamics, suggesting that nonlinear analysis methodologies are more suitable than linear techniques for a better assessment of the underlying processes contained within EEG time series [8]. For this reason, the application of nonlinear metrics for EEG signals analysis has notably increased in the last years for the study of diseases like Alzheimer, Parkinson, epilepsy, depression or schizophrenia, among others [54].

In the present paper, nonlinear metrics are classified according to the algorithm used for the characterization of the nonlinearity of a temporal signal [2]. In this sense, indexes of evaluation of dimensional complexity (see Sect. 2.1) are based on the analysis of the evolution of correlation and temporal properties of a signal. Other metrics focus on the quantification of regularity and degree of chaos of finite time series (see Sect. 2.2). On the other hand, measurements of predictability can be provided with different symbolic metrics (see Sect. 2.3). Finally, it is also possible to detect functional connectivity patterns between different brain regions (as described in Sect. 2.4).

2 Nonlinear Feature Extraction from EEG Recordings

The basic principle of nonlinear techniques for time series analysis is the quantification of the intrinsic patterns generated by the chaotic dynamics of a complex system [16]. Currently, a wide number of algorithms for nonlinear signal assessment can be found in literature. Those metrics can be classified into four different groups, depending on their computation methods for nonlinearity evaluation.

2.1 Correlation and Dimensional Complexity Metrics

These methodologies allow to evaluate nonlinearity features of a time series by a thorough study of correlation properties directly in the time domain, where the signal is considered a geometric object [15]. It is the case of fractal algorithms, which focus on the time-evolutionary features and correlation properties for dynamic temporal signal characterization. Fractal dimension (FD) metrics analyze temporal ordering of time series by means of the quantification of the non-integer or fractional dimension that a geometric object occupies in the Euclidean space [16].

In the emotion recognition field, FD algorithms have been extensively used. For instance, Hatamikia and Nasrabadi [20] computed Katz and Petrosian's algorithms to detect four emotions corresponding to the four quadrants of the valence-arousal space (HAHV - high arousal, high valence; HALV - high arousal, low valence; LAHV - low arousal, high valence; LALV - low arousal, low valence). The combination of these two FD methods with other nonlinear metrics reported a classification accuracy around 70%. In another work, Sourina and Liu reported similar accuracy results using Higuchi and box-counting FD methods to discern between positive, negative and neutral feelings [60]. In the case of Lan *et al.* [31], Higuchi's FD was combined with spectral and statistical parameters to distinguish between happiness, pleasantness, fear and fright. Furthermore, multifractal FD algorithms have also been considered given the strong complexity and multiscalar nature of the brain. Hence, Lui and Sourina [37] demonstrated the effectiveness of multifractal Higuchi FD for discerning between more than two emotional states. In this sense, they achieved a maximum accuracy of 85.83% for two emotions, and 54.58% for eight emotions (happy, surprised, satisfied, protected, angry, frightened, unconcerned and sad) [37].

Detrended fluctuation analysis (DFA) has also been applied in emotion recognition processes. DFA is based on the quantification and evaluation of fluctuations in a non-stationary temporal signal to distinguish between internal and external causes of fluctuations of a complex system [47]. For this purpose, a scaling factor α is used as a self-similarity parameter that represents the main correlation features of the signal. In the literature, DFA has been used in combination with linear and nonlinear indexes for emotional states detection with EEG recordings. For example, Yuvaraj *et al.* [65] combined DFA with FD and spectral features to study the brain's performance of subjects with Parkinson's disease under six different emotional states (the six Ekman's basic emotions). However, results of DFA and FD were slightly lower than those reported by some linear metrics. Nevertheless, given the high complexity of the neural system, DFA has also been computed in its multifractal form with the aim of improving the results reported by single DFA. In this sense, Paul *et al.* [48] applied several multifractal DFA algorithms and different classifiers to recognize positive and negative feelings, reporting a classification rate of 84.5% for positive emotions and 82.5% for negative emotions.

All FD and DFA metrics previously described can be computed directly from time series, thus reducing the computational complexity of those indexes. Nevertheless, other methodologies require a reconstruction of the phase space of the time series to be analyzed, being a reconstructed phase space valid if any state of the dynamical system under study can be defined at any point [28]. Hence, a temporal signal is transformed into a geometric object or *attractor* in a state. The reconstruction of the phase space is made according to the Taken's delay embedding theorem, which asserts that an attractor can be reconstructed from a time delayed embedded space preserving the topological properties of the original time series [16].

One of the most used methods for reconstructed phase spaces characterization and measurement of dimensional complexity of a dynamic system is the correlation dimension (CD). This index is based on the assessment of the attractor's dimensionality by means of the quantification of the self-similarity of its points in the phase space [28]. To calculate the CD of a signal, the correlation sum of the temporal sequence (i.e., the number of points in the reconstructed space closer than a threshold r) is firstly computed [28]. Then, CD value corresponds to the line fitting slope in the log-log plot of the correlation sum as a function of r.

Numerous recent works have reported interesting results of the application of CD on EEG recordings for discerning between a group of emotional states. For instance, Peng *et al.* [49] combined CD with other linear and nonlinear features to assess chronic stress of mothers of children with mental retardation and mothers of healthy children. Apart from demonstrating the considerable effectiveness of nonlinear methods with respect to linear techniques, results reported an increase of CD for stress group in comparison with controls [49]. In addition, Khalili and Moradi [29] computed the CD of EEG signals and other physiological parameters to discern between positive, negative and rest states. Results highlighted the reliability and efficiency of EEG over other peripheral signals to detect emotions [29]. Furthermore, Hoseingholizade *et al.* [21] claimed that positive and negative stimuli produced a decrease of CD in frontal, temporal and parietal brain regions with respect to rest states. That could be translated into a more active implication of those areas when facing emotional situations, either positive or negative [21].

Finally, Hurst exponent (HE) has been also widely used to extract correlation properties of temporal signals. HE is based on the estimation of statistical self-similarity and correlation features of fractal time series by evaluating the asymptotic behavior and the recurrence rate of similar patterns at different scales in the reconstructed phase space [6,16]. In emotions recognition research field, Wang *et al.* [64] applied HE together with spectral, wavelet, and nonlinear features to discern between positive and negative states. Nevertheless, results derived from nonlinear methods were slightly lower in this case than those extracted from linear analysis techniques.

2.2 Regularity Metrics

Regularity of a time series can be defined as the degree of stability or chaos of the corresponding geometric attractor. More repetitiveness of patterns in a time series derives in a high level of regularity, while non-repetitive and disordered signals are considered strongly irregular. A well-known measure of regularity of a time series is entropy, which quantifies the disorder or rate of information contained within a temporal signal [28]. There is a wide variety of algorithms for entropy computation. For instance, approximate entropy (ApEn) assigns a non-negative number with higher values for completely irregular signals and lower levels for time series with many repetitive patterns [51]. ApEn is computed as the logarithmic likelihood that two sequences that match for m points (within a tolerance r) will also match for $m + 1$ points with the same tolerance r. Nevertheless, this algorithm considers each pattern matches itself, which influences on the entropy result obtained. As a solution, an improvement of ApEn called sample entropy (SampEn) was introduced [53]. SampEn excludes self-matches from the calculations so that the final entropy result is independent of the selected pattern length [53]. Furthermore, a new improvement called quadratic SampEn (QSampEn) estimates the regularity of a time series with an algorithm insensitive to the selection of threshold r by adding the term $\ln(2r)$ to SampEn equation [30].

In the literature, many works have studied the suitability of these regularity-based entropy metrics for emotions recognition. Indeed, most of these works have outperformed the results previously obtained for identification of emotional states with other linear and nonlinear indexes. It is the case of García-Martínez *et al.* [19], who demonstrated that QSampEn was the first single metric to correctly discern between calm and negative stress states. Furthermore, only two EEG channels from left frontal and right parietal areas were necessary to reach a classification accuracy over 75% [19]. In the same work, SampEn was also calculated, although it reported a slightly lower discriminant ability than QSampEn [19]. ApEn and SampEn have also been calculated to detect depression [52], positive and negative states [23], high and low levels of arousal and valence [27], and emotions in the four quadrants of the arousal-valence space [55].

However, it has been previously commented on the multiscale nature of physiological signals. In this sense, multiscale entropy (MEn) can be a useful tool to calculate the regularity of time series in multiple time scales. This method consists of computing and averaging independent entropy values for each time scale, commonly considering consecutive and non-overlapped samples [12]. With this algorithm, Li *et al.* [35] reported an accuracy of 70% when discerning between different emotional states. Nevertheless, an improvement of 12% was obtained by means of the empirical mode decomposition (EMD) of the original time series [35]. EMD is a time-frequency technique based on the Hilbert-Huang transformation used for non-stationary signals analysis [66]. Hence, all EEG channels were decomposed into intrinsic mode functions (IMF) on which SampEn was then computed. In this sense, Zhang *et al.* [66] applied EMD to discern between the four quadrants of the arousal-valence space with a discriminant power around

95%. Similarly, Mert and Akan [43] used multivariate EMD with SampEn and Shannon entropy (ShEn) from IMFs to identify emotions with high and low levels of valence and arousal.

2.3 Predictability and Symbolic Metrics

Predictability of nonlinear systems depends on the stability and deterministic temporal evolution of the time series dynamics. To this respect, Lyapunov exponents (LE) are well-known indexes for predictability quantification by means of the characterization of the trajectories in the reconstructed phase space [28]. In this sense, the exponential convergence or divergence of the trajectories with respect to the initial point informs about the degree of predictability or chaos of the system. An exponentially fast increase of divergence of the trajectories corresponds to a higher level of unpredictability, and it is represented with positive exponents. A multidimensional system presents one LE for each scale, but in many occasions only the largest Lyapunov exponent (LLE) is enough to characterize the system.

This metric has been applied in a variety of studies reporting interesting results in emotional states detection with EEG signals. With a combination of LLE and other nonlinear methods, Hosseini *et al.* [22] showed an accuracy over 80% to discern between calm and stress states. Furthermore, EEG signals reported better results than the rest of peripheral recordings in this work [22]. Similarly, Hosseinifard *et al.* [24] combined LLE and other nonlinear features with machine learning algorithms, reaching a discriminant ability around 90%. On the other hand, Acar *et al.* [1] reported the existence of considerable differences in LLE values for subjects under three emotional states, namely happiness, sadness and fear.

Symbolic methodologies base their performance in a transformation of the original time series into discrete symbols that are grouped in sequences or words according to their temporal order [47]. Hence, the word length template has to be previously defined and it has to be moved along the signal one step each time to form new sequences. A thorough analysis of these symbolic patterns with different techniques is the key to obtain valuable information of the underlying dynamic processes in those time series.

In addition, symbolic time series can also be analyzed with entropy metrics able to assess temporal relationships among samples contained within a sequence. For example, common Shannon entropy (ShEn) has been computed in emotions recognition context to detect excitement, happiness, sadness and hatred [3]. Murugappan *et al.* [46] also compared the performance of ShEn with linear techniques to discern between five emotions (disgust, happy, surprise, fear and neutral). Results of ShEn were around 83% of accuracy, outperforming those reported by linear methods [46]. Another interesting symbolic metric is permutation entropy (PerEn), which evaluates the ordering of the data of a sequence in a fast and noise-robust manner [5]. This metric was used by Li *et al.* [34] to detect states of excitement and fear with a discriminant ability around 80%. However, PerEn only considers the order of the data in a pattern, ignoring the amplitudes of the samples in the sequence. Thus, a new approach called amplitude-aware permutation entropy (AAPE) was developed as an improvement of PerEn's algorithm [4]. García-Martínez *et al.* [18] has recently computed the predictability-based metrics PerEn and AAPE with the regularity-based QSampEn to discern between calm and distress emotional states. The combination of only two channels (left parietal P3 from AAPE and right parietal P4 from QSampEn) showed a classification accuracy over 80%, also demonstrating the complementarity of regularity and predictability-based entropy measures [18].

Furthermore, Lempel and Ziv proposed a symbolic algorithm for evaluation of time series randomness called Lempel-Ziv complexity (LZC) [33]. This technique converts a time series into a binary sequence and quantifies the different patterns in the signal and their temporal occurrence rate. High values of LZC represent high levels of complexity of a word sequence. The effectiveness of this technique has been demonstrated by Chen *et al.* [10], reporting a discriminatory ability of about 80% for identification of different emotions only using a single index in a simple classification model. On the other hand, Akar *et al.* [2] studied the EEG processes of patients with major depression under different emotional conditions. In this sense, LZC and other nonlinear methodologies were computed, demonstrating a highlighting ability of LZC when discerning between depression patients and healthy controls [2].

2.4 Functional Connectivity Metrics

Dynamic systems, such as the brain, are characterized by a strong stochasticity and complex coordinated interconnections of all areas contained within the whole system. Hence, it is also necessary to study the possible connections among brain lobes instead of just developing algorithms for single-electrode level assessment. In this sense, functional connectivity evaluates the relation between brain regions in the search of functional patterns, ignoring the existence of anatomical corticocortical connections between those areas [61]. Functional connectivity can be measured by means of a variety of algorithms mainly based on the quantification of correlation, coherence, and phase and magnitude synchronization [32]. Correlation gives information about the similarity of two time series, with high levels of correlation corresponding to higher similarity. On the other hand, coherence measures the similarity of two signals (exactly as correlation does) as a function of frequency. One of the most used algorithms for coherence estimation is the magnitude squared coherence (MSC), which evaluates and compares the power spectral density of two different EEG channels [25]. Finally, phase and magnitude synchronization metrics assess the differences in phase and magnitude between two EEG electrodes.

In the literature, several works have searched for precise functional patterns associated with specific emotional states. In this context, Lee and Hsieh [32] studied correlation, coherence and phase synchronization to discern between positive, negative and neutral emotional states. Their study reported a better performance of phase synchronization over the rest of metrics, and a higher amount of synchronization for positive emotions [32]. Martini *et al.* [42] also studied synchronization features of EEG signals under unpleasant and neutral emotional states. In addition, Miskovic and Schmidt [44] evaluated coherence and synchronization patterns to discern between pleasant, unpleasant and neutral stimuli. Jadhav *et al.* [25] applied MSC to identify four emotions (happy, sad, angry and relax) in a group of students before and after 8 weeks of meditation. In that work, the power of meditation for regulating the level of arousal triggered by each emotional state was demonstrated [25]. MSC was also applied by Daly *et al.* [13] to assess the effects of musical stimuli with emotional content. A very recent EEG-based work has also studied the influence of musical parameter timing on brain areas [39]. Finally, Li *et al.* [36] measured coherence patterns of subjects under different emotional conditions, reporting a higher coherence in the case of negative emotions.

3 Conclusions

This state-of-the-art review has demonstrated the suitability of nonlinear analysis methodologies for emotion recognition with brain activity recordings. Indeed, most of the research works which apply those nonlinear techniques have reported results that notably outperform the discriminant power of traditional linear metrics. All the aforementioned analysis methodologies evaluate the complexity of temporal signals from different perspectives. Hence, their combination would lead to an improvement of the results. Nevertheless, in the literature there are dozens of nonlinear metrics that have not been applied yet in emotions recognition context. For this reason, it would be interesting to study other techniques that could provide new insights about the dynamics of the underlying processes developed in the brain under different emotions. In this sense, it would be possible to endow affective computing systems with emotional intelligence and capability for properly interacting with humans from an emotional point of view.

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