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A Review on Nonlinear Methods Using Electroencephalographic Recordings for Emotion Recognition

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***Abstract*—Electroencephalographic (EEG) recordings are receiving growing attention in the field of emotion recognition, since they monitor the brain's first response to an external stimulus. Traditionally, EEG signals have been studied from a linear viewpoint by means of statistical and frequency features. Nevertheless, given that the brain follows a completely nonlinear and nonstationary behavior, linear metrics present certain important limitations. In this sense, the use of nonlinear methods has recently revealed new information that may help to understand how the brain works under a series of emotional states. Hence, this paper summarizes the most recent works that have applied nonlinear methods in EEG signal analysis for emotion recognition. This paper also identifies some nonlinear indices that have not been employed yet in this research area.**

***Index Terms*—Electroencephalogram, emotion recognition, nonlinear metrics, survey.**

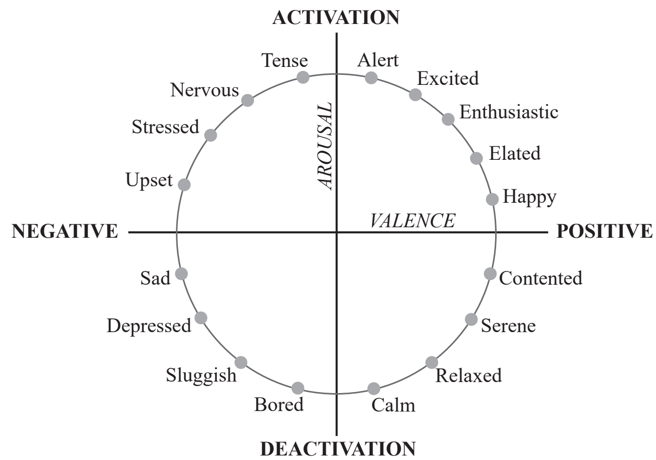

Fig. 1. Circumplex model of Russell for emotions classification according to valence and arousal levels (figure inspired in [4]).

I. Introduction

EMOTIONS play a key role in a great number of human daily experiences, influencing cognition, perception, and rational decision-making [1]. Given their relevance, emotions have been studied in areas like Psychology, Philosophy and Neurobiology, thus conforming the basis of Affective Neuroscience [1]. In the literature, many different emotional states have been defined, ranging from a few basic emotions [2] to dozens of complex states derived from combining basic feelings [3]. All of them can be classified by using different approaches, being Russell's circumplex model of affect one of the most widely used [4]. In this bidimensional model, all emotions are distributed according to their level of valence (pleasantness or unpleasantness degree) and arousal (activation or deactivation degree), as shown in Fig. 1.

Although emotions are essential in human communication and interaction, automatic systems for emotion recognition are still an unreached objective in our society. Given the lack of emotional intelligence in current and increasingly used human-machine interfaces, it becomes crucial to develop and implement new algorithms for automatic recognition of emotions. In this way it would be possible to improve and humanize the interaction between humans and machines [5]. Many works have focused on detecting emotions by means of the analysis of bodily reactions under emotional conditions. For this purpose, many researches have assessed the influence of emotions on different physiological variables, making special efforts in the evaluation of electroencephalographic (EEG) recordings [6]. Whilst the rest of physiological variables are secondary effects of mental activity, the brain is considered the source of all reactions to any external stimulus. In this regard, the number of works in literature focused on EEG signal analysis for emotion recognition has increased in the last few years [6]–[8].

Traditionally, EEG recordings have been studied from a linear point of view [9]. Thus, many indices considering EEG as the output of a linear system, i.e. governed by the superposition principle, have been proposed for their characterization. To this respect, algorithms based on frequency features, such as power spectral density or asymmetry of brain hemispheres in different frequency bands, have been widely used [8]. Nevertheless, linear metrics can only provide limited information from the EEG signal, since neural processes, far from being linear and therefore from meeting the superposition principle, present a highly heterogeneous and nonstationary behavior, even at cellular level [10]. In this sense, nonlinear techniques have

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recently demonstrated to reveal new insights that outperform the results of traditional linear methods [11]. For this reason, the use of nonlinear analyses becomes essential for an improved understanding of the brain's performance in a variety of mental processes, including automatic recognition of emotional states [10], [11].

Hence, the present paper's aim is to review the last few years' scientific literature in studies focused on emotion detection with EEG signals and nonlinear metrics. To the best of our knowledge, this is the first work that surveys the recent literature exclusively related to emotion recognition using nonlinear techniques for analysis of EEG signals. Thus, the present work aims to be a starting point for researchers who want to initiate their studies in this field.

The remainder of the paper is organized as follows. Section II describes the main characteristics of EEG signals. Section III defines the different types of nonlinear indices used for emotion recognition with EEG recordings. Section IV contains information about the survey procedure followed in this review and includes all papers focused on the detection of emotional states from EEG signals with different nonlinear techniques. Section V discusses several aspects related to the studies reviewed, and, finally Section VI presents some conclusions derived from this survey.

II. Electroencephalographic Recordings for Emotion Recognition

EEG signals represent the electrical activity derived from synaptic connections of neurons in the cerebral cortex. Although electrical signals are generated under the skull and other tissues that attenuate them considerably, most of them are strong enough to pierce those layers and present amplitudes between 10 and 100 μV on the scalp [9]. Hence, those electrical impulses are measured in a non-invasive manner by means of electrodes directly placed on the scalp. There exist some standard electrode positioning systems that determine the locations of EEG channels according to the patients' head dimensions. This fact guarantees the reproducibility of experiments and a posterior comparison of the results from different subjects. The most widely used arrangement is the international standard 10–20 system, which locates up to 128 electrodes [12]. In terms of nomenclature, each channel is represented with a letter and a number. Letters indicate the brain lobe over which an electrode is located: Fp (frontopolar), F (frontal), C (central), T (temporal), P (parietal) and O (occipital). Electrodes between two areas are represented with the two corresponding letters. On the other hand, numbers represent the brain hemisphere where an electrode is located, being even numbers used for the right hemisphere and odd ones for the left.

The EEG spectrum ranges from 0.5 to 45 Hz, and is divided into different frequency bands [9]. The *delta* (δ) band, ranging from 0.5 to 4 Hz, is related to deep sleep. The *theta* (θ) waves, ranging from 4 to 7.5 Hz, appear in meditation and light sleep phases. The *alpha* (α) band, going from 8 to 13 Hz, appears in relaxed states of conscious subjects. On the contrary, *beta* (β) waves, ranging from 14 to 26 Hz, appear when the subject is thinking actively or solving complex problems. Finally, the *gamma* (γ) band, spanning from 30 to 45 Hz, is related to attention, cognition and learning processes [9], [13].

Nevertheless, these frequency bands are not exclusive of EEG signals. Some other electrophysiological recordings such as electrocardiogram (ECG) and electromyogram (EMG) signals present part of their spectrum in these frequencies [14]. In addition, noise and interferences can appear during the signal acquisition process. Hence, raw EEG recordings usually contain extra information that may hide brain dynamics. For this reason, it is necessary to preprocess EEG signals before any kind of analysis, such that only the neural information is maintained. In this sense, digital high-pass and low-pass filters are used to reject all frequencies out of the brain signals' bands of interest. Notch filters are also used to eliminate the effect of power line at 50 or 60 Hz [9]. In addition, artifacts derived from physiological (e.g. ECG or eye blinks) and technical or instrumental sources (e.g. electrode-pops) are usually removed by means of blind-source separation techniques like independent component analysis [15]. On the other hand, low-frequency noise and EMG artifacts are eliminated with methods including the interpolation of adjacent electrodes [16]. Once EEG signals are preprocessed, they are ready for further characterization.

III. Nonlinear Analysis Methods

Complexity of nonlinear and nonstationary signals can be quantified from different perspectives [17]. In this respect, dimensional complexity algorithms estimate the evolution of temporal and correlation properties of a nonstationary signal. Other indices are based on quantifying the regularity as well as the degree of chaos of a nonlinear system. On the other hand, some symbolic metrics report information about the predictability of a finite time series. Furthermore, new multiscale approaches have been introduced to evaluate the time structure of a nonstationary signal at different scales. All these types of metrics have been successfully employed in the study of different physical and mental disorders such as Alzheimer [18], epilepsy [19], schizophrenia [20], depression [21] or Parkinson [22]. This is the reason why the application of nonlinear indices to EEG for automatic recognition of emotions is receiving growing attention in recent years.

Therefore, nonlinear metrics can be classified according to the algorithm used for the analysis of the complexity of a nonstationary time series. In this sense, works reviewed in the present manuscript apply indices of either dimensional complexity, regularity or predictability assessment (see Fig. 2).

A. Correlation and Dimensional Complexity Indices

Dimensional complexity measures are based on nonlinear features extraction from dynamic time series by studying correlation properties of the samples contained within a signal [23].

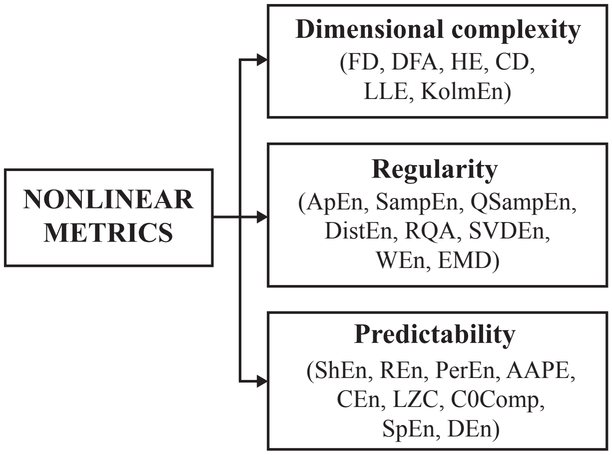

Fig. 2. Three groups of different nonlinear metrics.

1) Characterization in Time Domain: Some of these metrics have been designed to assess temporal sequences directly in time domain, considering a signal as a geometric figure. That is the case of fractal dimension (FD) indices which evaluate the correlation and evolutionary features of dynamic signals by quantifying the fractional space occupied by its associated geometric object [24]. This quantification is computed through a wide variety of algorithms, being the three most widely used in EEG signal characterization those proposed by Katz [25], Petrosian [26] and Higuchi [27].

Katz's algorithm is based on the calculation of FD of a planar curve or waveform [25]:

$$D = \frac{\log(L)}{\log(d)}, \tag{1}$$

where d is the diameter of the curve, computed as the maximum distance between two points, and L is the total length of the curve. Furthermore, an average value of Katz's FD is obtained as:

$$D = \frac{\log(L/a)}{\log(d/a)} = \frac{\log(m)}{\log(m) + \log(d/L)}, \tag{2}$$

where a is the average distance between successive points, and $m = \frac{L}{a}$ represents the number of samples in a segment.

On the other hand, Petrosian developed different methods for FD computation [26]. In all cases, time series are converted into binary sequences before computing their FD. The five methods of Petrosian's FD calculation correspond to five manners of transforming the data into binary series [26]. After that, fractal dimension D is computed as:

$$D = \frac{\log(m)}{\log(m) + \log(\frac{m}{m+0.4N_\delta})}, \tag{3}$$

being N_δ the number of dissimilar segment pairs in the binary sequence.

Lastly, Higuchi's FD converts the original signal $x(n)$ of N samples in length into k new time series [27], such that

$$x_k(n) = \left\{x(n), x(n+k), x(n+2k), ..., x(n + \left\lfloor \frac{N-n}{k} \right\rfloor k)\right\}, \tag{4}$$

being $n = 1, 2, ..., k$ the initial time values and k the delay between the points. Then, the average length of each $x_k(n)$ constructed is calculated as:

$$L_n(k) = \frac{1}{k}\left\{\frac{N-1}{\lfloor\frac{N-n}{k}\rfloor k}\sum_{i=1}^{\lfloor\frac{N-n}{k}\rfloor}|x(n+ik) - x(n+(i-1)k)|\right\}, \tag{5}$$

being $\frac{N-1}{\lfloor\frac{N-n}{k}\rfloor k}$ a normalization factor. After that, an average length $\langle L(k)\rangle$ is obtained for k sets of $L_n(k)$ as:

$$\langle L(k)\rangle = \frac{1}{k}\sum_{n=1}^{k} L_n(k). \tag{6}$$

Finally, $\langle L(k)\rangle$ is proportional to k^{-D}, being D the Higuchi's FD, i.e.

$$D = \frac{\log\langle L(k)\rangle}{-\log k}. \tag{7}$$

However, as brain signals are considered multifractal, modified algorithms for this kind of analysis have also been introduced. For instance, the Higuchi FD spectrum (GHFDS) [28] is based on the identification of the q-order average length scaling $L_q(k)$ (note that the original Higuchi FD corresponds to $q = 1$):

$$L_q(k) = \left(\frac{1}{k}\sum_{i=1}^{k}[L_n(k)]^q\right)^{\frac{1}{q}}. \tag{8}$$

Finally, GHFDS of order q is calculated as:

$$\text{GHFDS}_q = \frac{\log L_q(k)}{-\log k}. \tag{9}$$

On the other hand, detrended fluctuation analysis (DFA) also evaluates nonlinear characteristics of temporal signals directly in time domain [29]. In brief, this method is based on the quantification of fluctuations in an integrated and detrended nonstationary signal by calculating its root-mean square. First of all, the original time series $x(n)$ is integrated as:

$$y(n) = \sum_{i=1}^{n}\{x(i) - \langle x\rangle\}, \tag{10}$$

being $\langle x\rangle$ the average of all sequences contained within the data. Then, the integrated signal is divided into boxes of length m. Each box presents a least-squares line that fits the signal and represents the trend of the corresponding box. After that, the integrated time series $y(n)$ are detrended by subtracting $y_n(n)$, which is the local trend of each box and corresponds to y coordinate of the straight line segments. Then, root-mean-square fluctuation $F(m)$ is calculated as:

$$F(m) = \sqrt{\frac{1}{m}\sum_{i=1}^{m}[y(i) - y_n(i)]^2}. \tag{11}$$

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Finally, self-similarity is detected with a scaling factor α, which corresponds to the slope of the line interrelating $\log\Big(F(m)\Big)$ and $\log(m)$, and represents the correlation properties of the time series [29]. However, this index is only able to remove constant trends in the original data and, indeed, it is usually named α_1. Nonetheless, trends of higher order can also be removed by replacing the linear fit by a polynomial one. In general, with a polynomial fit of order i, trends of order $i-1$ can be analyzed. Index α_2 has been widely analyzed to remove linear trends from the mean of the original signal $x(n)$ in a variety of scenarios, including the analysis of EEG signals [30].

It is worth noting that α_1 can also be considered a generalization of the Hurst exponent (HE) [31]. HE is also a relevant and well-known metric for the analysis of time series correlation properties. HE estimates correlation and self-similarity properties of a signal according to its asymptotic behavior and the recurrence rate of similar data sequences at different scales [24], [32]. Although, there exist several alternatives to estimate HE, DFA is one of the most used for nonstationary time series [31]. Contrarily, the well-known R/S estimation is mainly used for computing the HE from stationary data. In this case the index is defined as [24]:

$$\text{HE} = \frac{\log\frac{R}{S}}{\log N}, \tag{12}$$

being N the length of the time series, and $\frac{R}{S}$ the value of the rescaled range. R is the difference between maximum and minimum deviation from the mean, and S is the standard deviation.

2) Characterization in State Space: As previously mentioned, both fractal and DFA algorithms allow to characterize nonlinearity of dynamic signals directly in time domain, thus presenting a fast performance and a low computational complexity. On the contrary, a wide variety of nonlinear metrics need to previously reconstruct the phase or state space of the time series before its assessment [33]. With this respect, temporal signals are considered as geometric structures, also called attractors, in a state space. One of the most widely used algorithms for the reconstruction of the space is the Taken's delay embedding theorem, affirming that attractors are reconstructed from a time delayed embedded space maintaining the topological features of the initial signal [24]. Hence, that reconstructed space is considered valid only if a state of the dynamical system can be unequivocally described at any point of the space.

In this sense, correlation dimension (CD) is one of the most well-known techniques for assessment of reconstructed state spaces and evaluation of dimensional complexity of a nonlinear system. For this purpose, CD quantifies the self-similarity of the points in state space for a thorough analysis of the attractor's dimensional features [33].

The most commonly used algorithm for CD computation was introduced by Grassberger & Procaccia [34]. Given the embedding dimension m and time delay τ, $N-(m-1)\tau$ possible vectors of size m are constructed as:

$$X_i = \{x(i), x(i+\tau), \ldots, x(i+(m-1)\tau)\}, \tag{13}$$

for every $i \leq N-(m-1)\tau$. The Chebyshev distance between two vectors X_i and X_j, i.e., $d[X_i, X_j]$, is then defined as the maximum difference in their scalar components and, for every $i \leq N-(m-1)\tau$, $C_i^m(r)$ is the number of $j \leq N-(m-1)\tau$ with which $d[X_i, X_j] \leq r$, being r the radial distance around a reference point. Hence:

$$C_i^m(r) = \frac{1}{N-(m-1)\tau} \sum_{j=1}^{N-(m-1)\tau} \Theta(r - \|X_i - X_j\|), \tag{14}$$

where Θ is the Heaviside function ($\Theta(x)=0$ if $x \leq 0$ and $\Theta(x)=1$ if $x>0$). Then, the correlation integral function $C^m(r)$ is defined as

$$C^m(r) = \frac{1}{N-(m-1)\tau} \sum_{i=1}^{N-(m-1)\tau} C_i^m(r). \tag{15}$$

Finally, CD value is calculated as

$$\text{CD} = \lim_{r\to 0} \frac{\log\ C^m(r)}{\log r}, \tag{16}$$

which corresponds to the line fitting slope in the log-log plot of correlation function $C(r)$.

Other well-established metrics to characterize the attractor reconstructed from a time series are Lyapunov exponents (LE) which evaluate the convergence or divergence of the trajectories in that geometric figure [33]. The exponential deviation of the attractor from the initial point represents the degree of chaos of the nonstationary signal, being it higher for more divergent trajectories. In the multimodal case, there are as many LEs as scales in the system. Nevertheless, it is usual to compute only the largest Lyapunov exponent (LLE), because it presents most complexity information from the system [35].

The LLE computation model was introduced by Wolf *et al.* [35]. First of all, two points of the reconstructed phase space, $x(n_0)$ and $x(n_0+k)$, being k a time delay, are selected. The separation between them, denoted as $D(n_0)$, evolves to $D'(n_1)$ at a later time. The next data point should present a small separation from the evolved fiducial point and a small angular differentiation between the evolved and replacement points. Finally, LLE denoted as λ, is computed as:

$$\lambda = \frac{1}{n_M - n_0} \sum_{i=1}^{M} \log_2 \frac{D'(n_i)}{D(n_i-1)}, \tag{17}$$

being M the number of replacement steps within the fiducial trajectory.

Finally, the reconstructed attractor from a time series has also been broadly characterized through the Kolmogorov entropy (KolmEn) [36]. This metric quantifies the average rate at which the information about the state of the system is lost over time. KolmEn is determined from the embedded time series data by finding points on the trajectory that are close together in the phase space (i.e., have a small separation) which occurred at different times (i.e. were not time-correlated). These two points are then followed into the future to observe how rapidly they move apart from one another. The time it takes for point pairs to move apart is related to the so-called KolmEn (K) by $\langle \text{t}_{\text{div}} \rangle = 2^{-Kt}$, where $\langle \text{t}_{\text{div}} \rangle = 2^{-Kt}$ is the average time for the pair to diverge apart, being K expressed in bits per second. Thus, KolmEn reflects how well the behavior of each respective part of the trajectory from the other can be predicted.

B. Regularity Indices

Irregularity is given by the rate of repetitiveness of sequences, being higher for non-repetitive and disordered signals and lower for patterns with a high rate of incidence. Regularity is usually calculated by means of entropy, which is based on the quantification of disorder or rate of information reported by a time series [33].

One variety of entropy algorithm for regularity assessment is approximate entropy (ApEn), which is the logarithmic likelihood that two patterns matching for m points will also match for $m+1$ points (within a tolerance r) [37]. Hence, ApEn assigns a non-negative number to each pattern according to its repetitiveness, where more recurrence is related to a lower level of ApEn.

The correlation integral $C_i^m(r)$ defined in Eq. (15) represents the likelihood that a vector X_j is within r of X_i. Starting from Eq. (15), ApEn is computed as:

$$\text{ApEn}(m,r) = C^m(r) - C^{m+1}(r). \tag{18}$$

However, ApEn also considers self-matching of each pattern, this way influencing on the results obtained. For this reason, an improved version called sample entropy (SampEn) was developed [38]. SampEn eliminates self-matches with the aim of making results independent of the pattern length m chosen for the calculations. $B_i^m(r)$ is defined as the number of $j \leq N - m\tau$, ($j \neq i$ to exclude self-matches) where $d[X_i, X_j] \leq r$. Hence, $B^m(r)$ is the probability of having two sequences matching for m points:

$$B^m(r) = \frac{1}{N - m\tau} \sum_{i=1}^{N-m} B_i^m(r). \tag{19}$$

Finally, SampEn is calculated as:

$$\text{SampEn}(m,r) = B^m(r) - B^{m+1}(r). \tag{20}$$

In addition, a second improvement called quadratic SampEn (QSampEn) is insensitive to threshold r selected for its computation [39]. The independence of r is achieved by adding term $\ln(2r)$ to SampEn expression:

$$\text{QSampEn}(m,r) = \text{SampEn}(m,r,N) + \ln(2r). \tag{21}$$

Another metric with a low dependence on its computation parameters is distribution entropy (DistEn) [40]. This index quantifies time series' regularity from the inherent information underlying vector-to-vector distances. Thus, a distance matrix is firstly constructed by comparing every pair of vectors X_i and X_j, i.e. $D_{ij} = \{d[X_i, X_j]\}$, for $1 \leq i, j \leq N-(m-1)\tau$. Next, the probability density function of this matrix is empirically estimated through a histogram with M bins. To reduce bias, elements with $i=j$ are excluded before computing the index as:

$$\text{DistEn}(m,M) = -\frac{1}{\log_2(M)} \sum_{k=1}^{M} p_k \cdot \log_2(M), \tag{22}$$

being p_k the probability of each bin. Notice that M should be chosen as an integer power of 2, but its value is not as critical as the selection of r in ApEn or SampEn. Indeed, values of 256 or 512 bins successfully quantify the distribution of D_{ij} [40].

The recurrent quantification analysis (RQA) is also based on characterizing the distance matrix D_{ij}. However, in this case the Euclidean distance between pairs of vectors X_i and X_j is often computed instead of the Chebyshev one, and similar patterns are quantified by displaying the distance matrix on a 2-D graph named recurrent plot. Briefly, a binary matrix is first obtained as

$$R_{ij} = \Theta(r - D_{ij}), \tag{23}$$

such that if two vectors X_i and X_j are sufficiently close (within tolerance r) then $R_{ij} = 1$, otherwise $R_{ij} = 0$. Once this matrix is plotted, the resulting recurrent plot presents a dot for every pair of similar vectors. Then, a variety of variables has been proposed to characterize this plot. For instance, percent recurrence (REC) is defined as the sum of all dots, or determinism (DET) is computed as the proportion of points forming diagonal line structures [41].

In a slightly different way from these entropy-based indices, SVD entropy (SVDEn) has quantified time series' regularity by exploiting redundancy among vectors X_i [42]. Thus, an embedding matrix is firstly constructed from these vectors as

$$\mathbf{X} = [X_1, X_2, \ldots, X_{N-(m-1)\tau}]^T \tag{24}$$

Next, a singular value decomposition (SVD) is applied to this matrix to produce P singular values $\lambda_1, \lambda_2, \ldots, \lambda_P$. Then, normalizing these values such that:

$$\overline{\lambda_i} = \frac{\lambda_i}{\sum_{k=1}^{P} \lambda_k}, \tag{25}$$

SVDEn is estimated by computing common Shannon entropy as:

$$\text{SVDEn}(P) = -\sum_{i=1}^{P} \overline{\lambda_i} \log_2 \overline{\lambda_i}. \tag{26}$$

Since P is not known a priori, the embedding dimension m must be selected large enough such that redundancy among patterns can be successfully estimated. In fact, condition $m \geq 2P+1$ should be always satisfied [42].

On the other hand, because a wide variety of time series, including physiological ones, present different characteristics at different time scales, the described entropy-based metrics can also be computed according to a multiscale approach. Hence, for multiscale entropy (MSE) computation, the original time series $x(n)$ is firstly decomposed into coarse-grained signals, $y^{(\kappa)}$, being κ a scale factor:

$$y^{(\kappa)} = \frac{1}{\kappa} \sum_{i=(j-1)\kappa+1}^{j\kappa} x(i), \quad 1 \leq j \leq \frac{N}{\kappa}. \tag{27}$$

Then, any entropy (i.e. ApEn, SampEn, QSampEn, DistEn or SVDEn) can be computed for each coarse-grained signal as defined above.

Other alternatives to compute time series' regularity at different time scales are based on transforming the original signal through well-known tools, such as wavelet transform (WT) or empirical mode decomposition (EMD). In fact, WT is a high-resolution time-frequency representation of a signal based on its decomposition in q different scales or levels [43]. Thus, considering how the original signal is spread among the different scales, its regularity can be computed via wavelet entropy (WEn). More concisely, having a series of wavelet coefficients $C_j(k)$, where j is the scale and k is the position in time, the energy at each decomposition level is computed as [44]:

$$E_j = \sum_k |C_j(k)|^2. \tag{28}$$

Then, the total energy of the signal is calculated as:

$$E_{total} = \sum_{j=1}^{q} E_j, \tag{29}$$

and the probability distribution of the energy is therefore defined as:

$$p_j = \frac{E_j}{E_{total}}. \tag{30}$$

Finally, WEn is estimated by means of well-established Shannon entropy, such that:

$$\text{WEn} = -\sum_{j=1}^{q} p_j \cdot \ln(p_j). \tag{31}$$

EMD also allows to decompose a time series into many oscillations, called intrinsic mode functions (IMFs), at different time-frequency scales [45]. For each IMF, the number of extrema and zero crossings must be equal or differ by one at most, and the mean value between upper and lower envelopes must always be equal to zero. In this sense, an original signal $x(n)$ is represented by means of extracted IMFs and their residuals, which corresponds to the difference between the original time series and the IMFs, i.e.

$$x(n) = \sum_{i=1}^{M} c_i(n) + r(n), \tag{32}$$

being $c_i(n)$ the i-th IMF extracted, and $r(n)$ the residue. By computing any of the previously described indices (mainly, SampEn) from these IMFs, regularity estimates for different time scales are also obtained [46].

C. Predictability and Symbolic Indices

Predictability of a time series depends on the deterministic and stable temporal evolution of a nonstationary system. In the literature, many methods for predictability assessment are symbolic metrics that evaluate the predictability of a signal by transforming it into discrete symbols forming words or sequences [47]. There are many different manners of symbolizing and characterizing a time series. Once the symbolic sequences have been obtained, many techniques can be applied to assess the underlying dynamics of the temporal signals. For example, common ShEn has been widely used for this purpose [48]. In this context, this index can be defined as:

$$\text{ShEn}(m) = -\sum_{i=1}^{m} p(x_i) \cdot \ln\big(p(x_i)\big) \tag{33}$$

where $p(x_i)$ is the probability of appearance of each m symbolic words x_i. A generalized version of ShEn, i.e. Rényi entropy (REn), has also been widely used to quantify underlying dynamics in symbolized time series [49]. In this case, the metric can be computed as [50]:

$$\text{REn}(m, \alpha) = -\frac{1}{1-\alpha} \ln \sum_{i=1}^{m} p(x_i)^{\alpha}, \tag{34}$$

where order α is a bias parameter that offers a more flexible and accurate characterization of time dynamics [50]. This value should satisfy conditions $\alpha \geq 0$ and $\alpha \neq 1$. In fact, ShEn is recovered in the limit as $\alpha \to 1$ [50].

Furthermore, permutation entropy (PerEn) is a fast and noise-robust method for quantifying predictability. In this case, PerEn evaluates the predictability of a time series by assessing the ordering of the data within a sequence [51]. In short, each vector X_i is associated to an ordinal pattern defined as permutation $\kappa_i = \{r_0, r_1, \ldots, r_{m-1}\}$ of $\{0, 1, \ldots, m-1\}$ fulfilling that $x(i+r_0) \leq x(i+r_1) \leq \ldots \leq x(i+r_{m-2}) \leq x(i+r_{m-1})$. Hence, $m!$ different ordinal sequences π_k are obtained from vectors X_i. After that, the probability of appearance of each π_k is estimated by means of its relative frequency:

$$p(\pi_k) = \frac{\sum_{i=1}^{N-(m-1)\tau} \delta(\pi_k, \kappa_i)}{N-(m-1)\tau}, \tag{35}$$

being $\delta(u, v)$ the Kronecker delta function modified to work with sequences:

$$\delta(u,v) = \begin{cases} 1, & \text{if } u(i) = v(i), \text{ for every } i = 1, 2, \ldots, m; \\ 0, & \text{for otherwise.} \end{cases} \tag{36}$$

Finally, PerEn is calculated making use of common ShEn:

$$\text{PerEn}(m) = -\frac{1}{\ln(m!)} \sum_{k=1}^{m!} p(\pi_k) \cdot \ln\Big(p(\pi_k)\Big). \tag{37}$$

However, PerEn only evaluates the temporal ordering of the data, thus discarding the information related to the amplitudes of the signal. As an improvement, amplitude-aware permutation entropy (AAPE) has been recently introduced [52]. In this case, the probability $p^*(\pi_k)$ of sequences' occurrence is calculated considering the average absolute (AA) and relative amplitudes (RA) of vectors X_i:

$$AA_i = \frac{1}{m} \sum_{l=1}^{m} |x(i+l-1)|, \text{ and} \tag{38}$$

$$RA_i = \frac{1}{m-1} \sum_{l=2}^{m} |x(i+l-1) - x(i+l-2)|. \tag{39}$$

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Hence, the occurrence probability of π_k is calculated as:

$$p^*(\pi_k) = \frac{\sum_{i=1}^{N-(m-1)\tau} \delta(\pi_k, \kappa_i) \cdot \Big(K \cdot AA_i + (1-K) \cdot RA_i\Big)}{\sum_{i=1}^{N-(m-1)\tau} K \cdot AA_i + (1-K), \cdot RA_i} \tag{40}$$

being K an adjusting coefficient (from 0 to 1) to weight terms AA and RA. Finally, AAPE is calculated similarly to PerEn [52]:

$$\text{AAPE}(m) = -\frac{1}{\ln(m!)} \sum_{k=1}^{m!} p^*(\pi_k) \cdot \ln\Big(p^*(\pi_k)\Big). \tag{41}$$

On the other hand, conditional entropy (CEn) represents the amplitudes of the signal by means of symbolic sequences [53]. In this case, the dynamic range of the time series is divided into ξ levels of quantization. Then, the symbolized signal is divided into $N-(m-1)\tau$ vectors of length m, which are converted into integer numbers $w_m(n)$ by multiplying by positive powers of ξ. Then, CEn is calculated as the difference between ShEn of the occurrence probability of each integer number for dimensions $m-1$ and m:

$$\begin{aligned} \text{CEn}(m,\xi) = &\sum_{k=1}^{\xi^{m-1}} p\big(w_{m-1}(k)\big) \cdot \ln\big(p\big(w_{m-1}(k)\big)\big) \\ &- \sum_{k=1}^{\xi^{m}} p\big(w_{m}(k)\big) \cdot \ln\big(p\big(w_{m}(k)\big)\big). \end{aligned} \tag{42}$$

Another symbolic metric is proposed by Lempel & Ziv [54] to evaluate the randomness of time series called Lempel-Ziv complexity (LZC). This metric is based on the assessment of the temporal occurrence rate of binary patterns to obtain the complexity level of a sequence, being it higher for higher values of LZC. For its computation, time series $x(n)$ is firstly converted into a binary sequence $s(n)$, where

$$s(n) = \begin{cases} 0 & if \quad x(n) \leq h, \\ 1 & if \quad x(n) > h, \end{cases} \tag{43}$$

being h the median value of the original signal and typically used as threshold. After that, $s(n)$ is scanned in the search of new patterns, such that every time a new sequence of consecutive symbols is detected, a complexity counter $c(n)$ is increased by one unit. Finally, $c(n)$ has to be normalized in order to obtain a complexity measure which does not depend on the data length. Thus, for a symbol set of β different symbols, LZC can be obtained as

$$\text{LZC}(\beta) = c(n)\frac{\log_\beta(N)}{N}. \tag{44}$$

Although LZC is easy to estimate, widely used and gives meaningful results in most cases, it can lead to wrong interpretations of some time dynamics due to over-coarse graining preprocessing [55]. To overcome this limitation, a new index named C0 complexity (C0Comp) has been proposed [55]. Briefly, the power spectrum of the original time series $X(f)$ is firstly estimated via fast Fourier transform (FFT) and its mean value is then computed as:

$$\mathcal{G} = \frac{1}{N}\sum_{i=1}^{N} |X(f)|^2. \tag{45}$$

Next, a new spectrum is obtained by maintaining those spectral components with amplitude greater than $\mathcal{G}$ and zeroing the remaining ones. By taking an inverse FFT of this new spectrum, a new time series is obtained $\widetilde{x}(n)$, which is considered as the regular component of the original time series. Then, index C0Comp is computed as [55]:

$$\text{C0Comp} = \frac{\sum_{k=1}^{N} |x(k) - \widetilde{x}(k)|^2}{\sum_{k=1}^{N} |x(k)|^2}. \tag{46}$$

Another metric computing complexity of a time series from its power spectrum is spectral entropy (SpEn) [56]. Once power spectral density of $x(n)$ is obtained, the power level for each frequency P_f is summed to estimate the total power. Then, normalization of P_f with respect to the total spectral power, referred to as p_f, yields a probability density function and SpEn is computed by applying ShEn or REn [56].

IV. Advances in nonlinear recognition of emotions from the EEG

This section includes all the studies found in the scientific literature related to emotion recognition by means of EEG signal analysis with nonlinear metrics. These works have been distributed in three different groups, according to the type of nonlinear indices applied in each case.

The consulted databases in this review include IEEE Xplore, Springer, Elsevier, Web of Science, Scopus, PubMed and Google Scholar, using keywords related to emotions, EEG and nonlinear analysis methods (i.e., "EEG emotion correlation dimension", "EEG emotion entropy", etc.), and choosing papers published between 2007 and 2018. Moreover, many works found in bibliographies of the reviewed studies were also included.

It is important to highlight that all works found have been included in this review, independently of several aspects such as experiment protocol, number of participants, or kind and amount of emotions detected. Finally, 62 works are included in the survey. In addition, the tendency of publications in this field has notably increased in recent years. Indeed, only 8 out of 62 studies included in this review were published before 2012, while the rest have been disseminated between years 2013 and 2018.

A. Correlation and Dimensional Complexity Indices

FD metrics have been widely applied in emotion recognition research area in the last years. For example, four different emotions have been detected by means of Katz's and Petrosian's FD algorithms and other nonlinear methods [57]. The study reported 70% classification accuracy when distinguishing among the four quadrants in the valence-arousal space. In addition, the effectiveness of FD metrics to detect positive, negative and neutral emotional states has also been studied [58]. In this case, the Higuchi algorithm reported a discriminatory power greater than 70%. In a posterior work, the Higuchi's FD algorithm was applied in a real-time system capable of discerning among six emotional states using music stimuli [59]. Higuchi's FD has also been computed to recognize happiness, pleasantness, fear and fright feelings [60].

Nevertheless, only 5 subjects participated in that experiment, and 2 of them had already been involved in a similar experiment before, thus probably biasing the final results [60]. The same FD algorithm was applied to discern among 4 emotions, obtaining the highest complexity for humor and the lowest for neutral stimuli [61]. Higuchi FD was also compared with spectral and functional connectivity metrics to identify positive and negative emotional states [62]. However, the results obtained with FD did not overcome the other measures reported in this work. In addition, the GHFDS algorithm has been used to detect up to 8 emotional states (happy, surprised, satisfied, protected, angry, frightened, unconcerned and sad) [63]. The results reported 54.58% classification rate for all emotions, and a maximum accuracy of 85.83% when only classifying 2 emotional states.

On the other hand, DFA has recently been combined with both linear and nonlinear metrics for emotion recognition with EEG signals. This kind of analysis has been applied to detect three different emotions (fear, happiness and sadness) elicited by music [64]. The results reported higher fluctuations in parietal than in frontal brain regions. Moreover, DFA, FD and spectral measures of EEG recordings from patients with Parkinson's disease were computed under six emotional states (happy, sad, surprised, angry, fear and disgust) [65]. Nonetheless, some linear metrics slightly outperformed the results reported by DFA and FD metrics in that work. In a different research, DFA was applied to distinguish between happy and sad emotional states with Indian music [66]. A hysteresis effect in brain behavior was found before, during and after musical stimuli. Another proposal distinguished between positive and negative emotions with multifractal DFA and several classification models [67]. In that case, a discriminatory power of 84.5% for positive feelings and 82.5% for negative emotions was reported. Another work combined multifractal DFA with HE to study the effect of music in *alpha* and *theta* bands [68]. The results reported an increase of complexity in those frequency bands of frontal areas during musical stimulation.

HE has also been used in emotion recognition field. For instance, a combination of HE with wavelet, spectral and nonlinear indices has been presented to detect positive and negative emotional states [69]. Nevertheless, in this case, linear techniques reported slightly better results than HE and the rest of nonlinear metrics calculated. Another research recognized 6 basic emotions in stroke patients with left and right brain damage (LBD and RBD, respectively) [70]. In this case, RBD patients showed an impairment with respect to LBD and healthy subjects, thus showing more difficulties in emotion recognition. The opposite results were obtained when Parkinson's disease patients tried to distinguish between the same emotional states [71]. In that work, HE and other nonlinear metrics demonstrated a higher impairment for left-side affected Parkinson patients with respect to right-side affected ones.

Some recent studies have demonstrated the efficacy of CD algorithms applied on EEG signals for emotion recognition. In this sense, positive, negative and neutral emotional states have been identified with CD [72], proving that both positive and negative emotions provoke an increase of CD with respect to neutral stimuli. This difference was specially relevant in frontal, temporal and parietal brain areas, which could indicate a major implication of those regions in emotional processes. Finally, it has also been possible to detect positive, negative and rest states by means of CD with EEG and other peripheral signals [73]. The results revealed that EEG recordings alone are more efficient for emotion recognition than the combination of EEG and the rest of peripheral variables [73].

In the literature, some studies have reported interesting results when LLE metric was used for emotion recognition by means of EEG signals. For instance, LLE and other nonlinear methods have been combined to discern between calmness and distress with EEG and other peripheral recordings [74]. In that case, EEG signals showed 80% accuracy, thus outperforming the discriminatory power of the rest of physiological variables. In another work, LLE and other nonlinear metrics, combined with machine learning approaches, have been applied to classify depressed and healthy subjects, achieving a maximum accuracy rate of 90% [75]. Furthermore, LLE was combined with CD to detect positive, negative and neutral states in patients with schizophrenia [76]. Results of both metrics reported lower levels of complexity for control subjects than for participants with schizophrenia.

Although KolmEn has reported valuable results in different research areas, it has not been commonly used in emotion recognition with EEG signals. Only in one study KolmEn has been applied with other nonlinear metrics to discern among positive, negative and neutral states in depression patients [77]. However, results provided by nonlinear measures only reported classification accuracies around 50%, being CD the metric with the best performance (60.59%) when an SVM-based classifier was used [77].

More details on these studies are offered in Table I. As can be observed, the majority of works included in this group have been published since 2014, being that the year with more studies in this field. With respect to the number of emotions identified, most studies have limited the quantity to two, three or four different emotional states, while only four works have recognized more than four emotions. Furthermore, the preferred stimuli are images (mainly from the International Affective Picture System, IAPS [78]), music and sounds (including those contained in the International Affective Digitized Sounds, IADS [79]) and film clips. On the other hand, there is no consensus in terms of the number of subjects and EEG electrodes to be used in this kind of experiments. Hence, the amount of participants ranges from 5 to 90, while the number of EEG channels is between 2 and 128. Only one study has registered brain signals with a considerably higher number of channels, i.e., 257 electrodes [62]. In relation with the classification models, support vector machine (SVM), K-nearest neighbor (KNN) and linear and quadratic discriminant analyses (LDA and QDA, respectively) classification approaches are the most used in these studies.

B. Regularity Indices

In the literature, there is a good number of works based on the use of regularity-based entropy metrics. According

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TABLE I
EMOTION RECOGNITION STUDIES THROUGH EEG SIGNALS AND DIMENSIONAL COMPLEXITY METRICS.

Ref.	Authors (year)	Experimental Design	Feature Extraction	Statistics / Classifier	Results
[64]	Gao *et al.* (2007)	3 emotions, 12 subjects, 4 EEG channels, music	DFA	–	Higher fluctuations in parietal than in frontal areas
[73]	Khalili & Moradi (2009)	3 emotions, 5 subjects, 54 EEG channels + peripheral signals, IAPS	CD	QDA[1]	EEG Acc[2]= 76.66%
[74]	Hosseini *et al.* (2010)	2 emotions, 15 subjects, 5 EEG channels + peripheral signals, IAPS	LE, FD Higuchi, CD, WEn	LDA,[3] SVM[4]	EEG Acc = 84.9%
[58]	Sourina & Liu (2011)	4 emotions, two experiments: (10 subjects, 3 EEG channels, music subjects) and (12 subjects, 3 EEG channels, IADS)	FD Higuchi and box-counting	SVM	Acc = 70% in both cases
[72]	Hoseingholizade *et al.* (2012)	3 emotions, 5 subjects, 19 EEG channels, audio	CD	ANOVA	Lower complexity for emotions than in rest
[75]	Hosseinifard *et al.* (2013)	Depression, 90 subjects, 19 EEG channels, eyes closed, no stimuli	LLE, FD Higuchi, CD, DFA, SP[5]	KNN,[6] LDA, LR[7]	Acc = 90% with all nonlinear metrics and LR classifier
[69]	Wang *et al.* (2014)	2 emotions, 6 subjects, 128 EEG channels, film clips	HE, ApEn, FD, SP	SVM	SP better than nonlinear
[65]	Yuvaraj *et al.* (2014)	6 emotions, 40 subjects, 14 EEG channels, IAPS, IADS and video clips	DFA, HE, ApEn, SP, bispectrum	SVM, fuzzy KNN	Bispectrum better than nonlinear
[57]	Hatamikia & Nasrabadi (2014)	4 emotions, 32 subjects, 4 EEG channels, video clips	FD Katz and Petrosian, ApEn, SpEn	SOM[8]	Entropy better than FD. Acc = 55.14%
[63]	Lui & Sourina (2014)	8 emotions, two experiments: (32 subjects, 32 channels, video clips) and (16 subjects, 4 EEG channels, IAPS)	Multifractal FD Higuchi	SVM	Acc = 85.83% for 2 emotions, 54.58% for 8 emotions
[67]	Paul *et al.* (2015)	2 emotions, 8 subjects, 7 EEG channels, audio	Multifractal DFA	SVM, LDA, QDA, KNN	Acc positive emotions = 84.5%, negative emotions = 82.5% with SVM
[68]	Maity *et al.* (2015)	Effect of music in alpha and theta bands, 10 subjects, 19 EEG channels, Indian music	Multifractal DFA, HE	–	Higher complexity in frontal alpha and theta bands during stimulus
[76]	Akar *et al.* (2015)	3 emotions in patients with schizophrenia, 44 subjects, 6 EEG channels, noise and music	LLE, CD	ANOVA	Higher complexity for patients than for healthy subjects during stimuli
[60]	Lan *et al.* (2016)	4 emotions, 5 subjects, 5 EEG channels, IADS	FD, SP and statistical	SVM	Stable results during successive days
[66]	Banerjee *et al.* (2016)	2 emotions, 10 subjects, 19 EEG channels, Indian music	DFA	ANOVA	Cerebral hysteresis effect before, during and after musical stimuli
[71]	Yuvaraj & Murugappan (2016)	6 basic emotions in Parkinson patients, 30 subjects, 14 EEG channels, IAPS, IADS and video clips	CD, FD, DFA, HE, LLE, ApEn, SampEn	Fuzzy KNN, SVM	Left Parkinson patients have more impairment than right Parkinson patients in emotion recognition
[77]	Cai *et al.* (2016)	3 emotions, 178 subjects, 3 EEG channels, sounds	CD, KolmEn, SpEn, ShEn, C0Comp, spectral	SVM, KNN, ANN, DBN	Nonlinear metrics Acc around 50%. Best results 60% with CD and SVM
[70]	Zheng Bong *et al.* (2017)	6 basic emotions in stroke patients, 57 subjects, 14 EEG channels, video clips	HE	KNN, PNN[9]	RBD patients have more difficulties for emotion recognition than LBD and healthy
[62]	Becker *et al.* (2018)	2 emotions, 40 subjects, 257 EEG channels, film clips	Higuchi FD, spectral and functional connectivity metrics	SVM	Spectral and connectivity measures report better results than FD with different numbers of channels
[61]	Ruiz-Padial & Ibáñez-Molina (2018)	4 emotions, 21 subjects, 28 EEG channels + ECG, video clips	Higuchi FD	ANOVA	Higher complexity for humor, lower for neutral emotion

[1] QDA: Quadratic discriminant analysis
[2] Acc: Accuracy
[3] LDA: Linear discriminant analysis
[4] SVM: Support vector machine
[5] SP: Spectral power
[6] KNN: K-nearest neighbor
[7] LR: Logistic regression
[8] SOM: Self-organization map
[9] PNN: Probabilistic neural network

to the analytical and quantitative results obtained with these indices, many of them outperform the results reported by other linear and nonlinear methods computed in similar works. For example, SampEn has been calculated to detect different levels of valence and arousal [80], concluding that prefrontal areas are highly interrelated with emotions. A recent work [81] has proved that the combination of QSampEn and DistEn is able to discern between calmness and negative stress with only left frontal channel F3 and right parietal electrode P4 with an accuracy over 75%. Furthermore, this work has reported that the brain follows a more irregular behavior under distressful conditions with respect to calm situations. In addition, a multivariate-multiscale version of SampEn (MMSE) has been applied to detect 5 different emotional states with only 6 EEG channels [82]. The outcomes reported higher levels of MMSE for emotions with higher levels of arousal and vice versa. Moreover, high and low levels of valence and arousal have been detected by using MSE with SampEn, obtaining mean accuracy results around 50% in both cases [83]. On the other hand, ApEn and two predictability-based metrics have been employed to detect three different emotions (angry, happy and sad) in patients with schizophrenia [84]. ApEn results outperformed the other measures, reaching a maximum accuracy of 75.5% at frontal channel Fz. In addition, ApEn,

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SampEn and SVDEn have been applied to discern among three emotional states in post-traumatic stress disorder patients [85]. The best results in that study were obtained with audiovisual stimuli including traumatic content.

On the other hand, RQA has also been applied recently for emotion recognition with EEG recordings. For example, positive excitement, negative excitement and neutral states have been detected with RQA and 3 electrodes (Fz, Cz and Pz) [86]. Results reported a better performance in parietal area and a higher irregularity for positive excitement than for the rest of emotional states. Moreover, high and low levels of valence and arousal have been assessed with RQA and other nonlinear metrics, obtaining a maximum accuracy of 87.43% for arousal and 88.74% for valence classification [87].

WEn has been applied to discriminate among four emotions (happy, sad, relaxed and angry) with a classification accuracy of 60.9% [88]. Another work has discerned between positive, negative and neutral emotional states in depressed patients and healthy controls by means of WEn [89]. The results revealed higher levels of entropy for depressed subjects, with relevant differences in right posterior brain region. WEn has also been compared and combined with energy metrics and different classifiers to identify four emotions, obtaining the best results with the highest number of combinations of metrics and classification models [90]. This index has also been combined with other features to create a classification process that reported an accuracy of 76.8% for valence and 74.3% for arousal [91]. In another study, different window lengths were chosen for WEn computation to discern among different levels of valence and arousal, obtaining the best results with lengths of 3–10 seconds for arousal and 3–12 seconds for valence [92]. Moreover, ApEn and WEn have been calculated to detect depression from EEG recordings [93]. Results obtained in this study reported a higher level of entropy for healthy controls than for depressed subjects, thus indicating that depression leads to a loss of chaotic brain behavior. In addition, ApEn and WEn were also applied to classify between calm and negatively excited participants, reaching a discriminatory ability of 73% [94].

EMD with multiscale entropy approaches has been used to detect several emotional states with a maximum accuracy around 70% [95]. In addition, a recent paper has discerned among the four quadrants of the valence-arousal space by means of EMD and SampEn with a discriminatory power of 95% [96]. Moreover, EMD with SampEn and other nonlinear metrics has been used to detect emotional states of high and low levels of arousal and valence [46]. The results reported classification accuracies of 75% and 72.9% for arousal and valence, respectively.

For more information, see Table II. In this case, it can be observed that regularity metrics have been mainly applied since 2014 until nowadays, while only two studies used these indices before that period of time. Moreover, the number of emotions detected is lower than 5 in all works. Contrarily to dimensional complexity studies, papers included in this table are more consistent in terms of the number of subjects and EEG electrodes in each experiment. Hence, a total of 32 subjects participated in many of the works, and 32 EEG channels were registered in almost all of them. Furthermore, the preferred stimuli in those cases were video clips. In fact, this consistency is due to the use of a publicly-available dataset of EEG recordings called DEAP (Database for Emotions Analysis using Physiological Signals) [97] in those studies. The rest of works presented different parameters in their experiment design. With respect to the classification approaches, SVM is more used than other models.

C. Predictability and Symbolic Indices

Common ShEn, in combination with some linear indices, has been applied to detect disgust, happiness, surprise, fear and rest emotional states [98]. In that work, ShEn presented a classification accuracy of 83%, which was better than the performance of the linear features calculated. On the other hand, a total of four emotions has also been detected with the combination of ShEn levels from left parietal and right central brain regions [99]. The best discriminatory result of ShEn in that work was over 94% of accuracy.

On the other hand, REn has also been applied in several research works for emotion recognition with EEG signals. For instance, the level of chronic stress of mothers of mentally retarded children and mothers of healthy children has been evaluated by means of REn, spectral power and other nonlinear metrics [100]. The results showed a generally decreased REn level of the stressed mothers' group with respect to control subjects. Furthermore, the findings reported by nonlinear metrics considerably outperformed those provided by linear methods in that study. In another work, four emotional states (happy, sad, fear and neutral) have been identified by means of REn and ShEn, obtaining a maximum classification accuracy of 84.79% [101].

Symbolic metrics have been applied in different emotion recognition studies with EEG recordings. For instance, a recent paper has discerned between fear and excitement emotional states with PerEn, reaching an accuracy around 80% [102]. In addition, predictability-based metrics PerEn and AAPE, in combination with regularity-based QSampEn, have been computed to detect emotional states of calmness and negative stress [103]. That work demonstrated complementarity between regularity and predictability-based entropy metrics, since only two EEG channels (left parietal P3 from AAPE and right parietal P4 from QSampEn) were necessary to obtain an accuracy over 80% with a simple decision tree-based classification model. Similar results in terms of classification accuracy and brain activation patterns have been recently obtained in a study that combined QSampEn with CEn for distress recognition [104], and in other works where AAPE and CEn have also been computed for calmness and distress detection [105], [106]. Multiscale versions of AAPE and QSampEn have also been applied to detect calm and distress states [107]. In that study, results overcame those obtained in previous works where the one-scale form of the metrics were computed [81], [103].

The LZC algorithm has been applied to detect several emotional states, reporting an accuracy of 80% by using a single index and a simple classifier [108]. Furthermore, brain responses of major depression patients against different

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TABLE II
EMOTION RECOGNITION STUDIES THROUGH EEG SIGNALS AND REGULARITY METRICS.

Ref.	Authors (year)	Experimental Design	Feature Extraction	Statistics / Classifier	Results
[89]	Wei *et al.* (2009)	3 emotions, 32 subjects, 60 EEG channels, images of faces	WEn	ANOVA	Higher WEn for depressed patients
[94]	Hosseini & Nahibi (2011)	2 emotions, 15 subjects, 5 EEG channels, IAPS	ApEn, WEn	SVM	Acc = 73.25%
[93]	Puthankattil & Joseph (2014)	Depression, 60 subjects, 24 EEG channels, eyes open/closed, no stimuli	ApEn, WEn	–	Higher irregularity for healthy than for depressed
[80]	Jie *et al.* (2014)	4 emotions, 32 subjects, 32 EEG channels, video clips	SampEn	SVM	Acc = 80.43%
[85]	Rozgic *et al.* (2014)	3 emotions in PTSD patients, 30 subjects, 20 EEG channels, images, sounds and video clips	ApEn, SampEn, SVDEn	AUC-ROC[1]	Better results with audiovisual stimuli with traumatic content
[88]	Candra *et al.* (2015)	4 emotions, 32 subjects, 32 EEG channels, video clips	WEn	SVM	Acc = 60.9%
[92]	Candra *et al.* (2015)	Valence and arousal, 32 subjects, 32 EEG channels, video clips	WEn	SVM	Better results with windows of 3-10 s for arousal and 3-12 s for valence (Acc over 64%)
[95]	Li *et al.* (2015)	–	EMD, MSE	–	Acc = 70%
[96]	Zhang *et al.* (2016)	4 emotions, 32 subjects, 32 EEG channels, video clips	EMD, SampEn	SVM	Acc = 94.98% for two classes, 93.20% for four classes
[46]	Mert & Akan (2016)	High/low arousal, high/low valence, 32 subjects, 18 EEG channels, video clips	Multivariate EMD	KNN, ANN[2]	Acc = 75% for arousal, 72.9% for valence
[81]	García-Martínez *et al.* (2016)	2 emotions, 32 subjects, 32 EEG channels, video clips	SampEn, QSampEn, DistEn	DT[3]	QSampEn + DistEn Acc = 75.29%. Higher irregularity for distress than for calmness
[82]	Tonoyan *et al.* (2016)	5 emotions, 30 subjects, 6 EEG channels, video clips	MMSE	–	Higher irregularity for higher arousal levels
[86]	Goshvarpour *et al.* (2016)	3 emotions, 5 subjects, 3 EEG channels, images	RQA	ANOVA	More irregularity for positive excitation than for negative and neutral. Better results in parietal Pz
[84]	Chu *et al.* (2017)	3 emotions, 44 subjects, 31 EEG channels, IAPS	ApEn, PerEn and AAPE	SVM	ApEn Acc = 75.5%
[83]	Michalopoulos & Bourbakis (2017)	High-low valence and arousal, 32 subjects, 32 EEG channels, video clips	MSE (SampEn)	ROC	Acc = 50% for valence and arousal
[91]	Candra *et al.* (2017)	High-low valence and arousal, 32 subjects, 32 EEG channels, video clips	WEn	SVM	Max Acc 76.8% valence and 74.3% arousal
[90]	Guo *et al.* (2017)	4 emotions, 32 subjects, 32 EEG channels, video clips	WEn, energy, combination of both	SVM, HMM[4]	Best results with a combination of all features and all classifiers
[87]	Soroush *et al.* (2018)	High low valence and arousal, 32 subjects, 32 EEG channels, video clips	RQA, SampEn, CD, LLE, FD	MLP[5], DST[6]	Max Acc 87.43% for arousal and 88.74% for valence

[1] AUC-ROC: Area under curve of the receiver operating characteristic
[2] ANN: Artificial neural network
[3] DT: Decision tree
[4] HMM: Hidden Markov model
[5] MLP: Multi-layer perceptron
[6] DST: Dempster-Shafer theory

emotional stimuli have been evaluated [17]. In that case, LZC reported relevant results with respect to other nonlinear metrics when discerning between depressed subjects and healthy controls.

C0Comp has been applied in a few emotion recognition studies with EEG. For instance, C0Comp, SpEn and ShEn were computed to discern among 4 emotional states, obtaining a maximum discriminatory power of 86.67% for positive excitement recognition [109]. On the other hand, C0Comp was combined with other linear and nonlinear metrics for depression identification [110]. However, the authors do not report concrete results about the performance of the nonlinear measures computed in their study.

SpEn has been calculated in some emotion recognition works with EEG signals. For instance, an accuracy of 93.66% for valence and 93.29% for arousal was obtained with a combination of SpEn and linear features with different classification models [111]. In another study, SpEn has been recently compared with some spectral and statistic parameters to detect different levels of valence and arousal in two different datasets [112]. Nevertheless, SpEn reported the worst classification results in both cases. In addition, SpEn and ShEn were combined in another study to reach a maximum accuracy of 78.96% for arousal and 71.43% for valence classification [113].

The continuous version of ShEn, i.e., differential entropy (DEn), has recently gained increasing attention in a number of emotion recognition studies, because it is equivalent to the logarithm of its power spectrum density in a certain frequency band for a fixed length EEG signal [114]. For example, DEn was applied to detect positive, negative and neutral states, obtaining the best classification results in *beta* and *gamma* bands [115]. In a similar study, DEn has reported better results than spectral and statistical features, reporting a mean accuracy of 90% in a subject-dependent test, and 80% for a subject-independent trial [116]. The assessment of the same emotional states (positive, negative and neutral) with DEn has also reported better results than spectral and statistical features in another research, reaching an accuracy of 71.77% with SVM [117], and over 85% with a DBN classifier [114]. DEn has also been applied in two different databases, DEAP [97]) and SEED (SJTU Emotion EEG Database [114]), to recognize positive, negative and neutral emotional states, obtaining better results with the latter [118]. In another work, both databases were also studied with DEn to discern among four emotional states [119]. In this case, the application of DEn in SEED database also reported better results (91.07% of accuracy) than in DEAP (69.67% of accuracy) [119]. Finally, DEn and Higuchi FD were computed to identify three emotions (happy, sad and neutral), reaching a maximum accuracy of 80.27% with DEn and 72.09% with FD [120].

More information about these papers can be found in Table III. As can be observed, the interest in these indices started growing in 2015, becoming increasingly used in 2017 and 2018. Note that the number of detected emotions ranges between 2 and 4, with only one study recognizing more than 4 emotional states. Moreover, the amount of participants was quite variable, ranging from 5 to 32 (the most common value in this group of metrics). On the other hand, the number of EEG electrodes ranged between 3 and 64, although 32 and 62 EEG channels are the most common values due to an extensive use of DEAP and SEED databases. In addition, most of the papers applied video and film clips as elicitation stimuli. In regard to the classifiers, no concrete approach was notably more used than others.

V. Discussion

A. *Global findings*

Nonlinear indices have already revealed notable insights in the study of dozens of mental conditions with EEG recordings. In fact, the interest in their application for emotion detection with EEG signals has considerably increased in the last years. As an example, 70% of the studies included in this survey have been published between 2015 and 2018, while only 30% were developed during the previous eight years. In addition, no relevant studies have been discarded in this survey, despite presenting notable differences in terms of experimental and analytical procedures followed by each research group.

Precisely, these differences might be the cause of the high variability of results presented in the literature:

- Since there are no standard models for experimentation, each author designs and implements a different procedure, thus increasing the variability of discoverings. For instance, the participants are different in aspects like age, gender or culture in each experiment, which may bias the results.
- In addition, some studies analyze EEG signals of healthy volunteers, while others evaluate brain processes of people with physical or mental diseases. The results are clearly not comparable.
- Moreover, some experiments involve a too small number of participants. Hence, the results derived from these studies may not be representative of the population.
- The number of EEG channels that should be used is another point of discrepancy between works, covering a range from 2 to 257 EEG electrodes used in different experiments. In this sense, many studies analyzed signals from only some brain areas without considering the rest of regions.

Moreover, there is no consensus in determining whether a stimulus is or not suitable for the elicitation of a concrete emotion:

- Most works use stimuli from international databases of images (IAPS) or sounds (IADS). These databases present a wide quantity of stimuli corresponding to a high number of emotional states according to valence and arousal classifications. Nevertheless, it has not been demonstrated which type of stimuli (e.g. images, sounds, or videos) is optimum for triggering strong emotional responses that can be unequivocally interpreted from a clinical point of view.
- The stimuli duration is also an important aspect that has not been accurately defined in literature. Hence, each research has considered different criteria for choosing the duration of stimuli in their experiments. Again, this possibly biases the results. Finally, the experimental methodology of many works is not thoroughly described in their publication, which leads to difficulties when trying to reproduce other researchers' tests.

All these differences among the works reviewed are the reason why results must be interpreted and compared with caution. As a solution, many other authors have decided to study brain signals from publicly available databases containing recordings of EEG and other peripheral variables for emotion detection (e.g. DEAP or SEED). This facilitates the reproducibility of results since the analyzed signals are the same for all research groups that work with these databases. Hence, differences between works should only appear due to the assessment of EEG signals with different methods and classification models.

It is important to remark that there are variable results because of the dissimilarities between the three different groups of nonlinear methods used for EEG signal analysis:

- Precisely, each group of nonlinear metrics presented in this review is based on a different viewpoint for complexity estimation. For this reason, the results derived from the application of two different groups of metrics for the analysis of the same recordings and for the same problem may be completely different. Nevertheless, inequalities should not be considered as contradictory.
- Instead of it, differences in algorithms might be a sign of complementarity of different types of metrics, since each group of indices evaluates nonstationary systems from different points of view. In this sense, some metrics reveal complexity characteristics that other indices cannot describe, and vice versa.
- As a result, there are no measures more interesting or useful than others, but rather a combination of metrics from different groups might report much more valuable information than techniques applied separately.

According to the promising results previously described, nonlinear methods might be key for an improved understanding of the brain's behavior under different emotional states, outperforming and complementing the results reported by traditional linear metrics in most cases. Nevertheless, it is necessary to modify the way of analyzing the results from

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TABLE III
EMOTION RECOGNITION STUDIES THROUGH EEG SIGNALS AND PREDICTABILITY METRICS.

Ref.	Authors (year)	Experimental Design	Feature Extraction	Statistics / Classifier	Results
[98]	Murugappan *et al.* (2011)	5 emotions, 20 subjects, 24 and 62 EEG channels, videos	ShEn, SP	LDA, KNN	Entropy better than linear. Acc = 83.04% with 62 channels
[100]	Peng *et al.* (2013)	High-stress and moderate-stress, 13 subjects, 3 EEG channels, eyes closed, no stimuli	REn, CD, LZC, LLE, SP	ANOVA	For REn and LLE, lower complexity in stress than in calmness. Opposite results with LZC and CD
[117]	Zheng *et al.* (2014)	3 emotions, 5 subjects, 62 EEG channels, film clips	DEn	SVM	Max Acc 71.77% with all frequency bands
[101]	Bajaj *et al.* (2015)	4 emotions, 8 subjects, 20 EEG channels, audiovisual stimuli	ShEn, REn	MC-LSSVM[1]	Max Acc 84.79%
[99]	Aravind *et al.* (2015)	4 emotions, 32 subjects, 12 EEG channels, video clips	ShEn	SVM	Acc = 94%
[17]	Akar *et al.* (2015)	2 emotions, 30 subjects, 16 EEG channels, music and noise	LZC, ShEn, FD Katz and Higuchi	ANOVA	LZC better than others. Higher complexity for noise than for music
[111]	Naji *et al.* (2015)	4 emotions, 25 subjects, 3 EEG channels, music	SpEn	SVM, KNN, CFNN[2]	Mean Acc 93.66% for valence and 93.29% for arousal
[114]	Zheng *et al.* (2015)	3 emotions, 5 subjects, 62 EEG channels, film clips	DEn, SP, statistics	KNN, LR, SVM, DBN[3]	DEn better than SP and statistics. Max Acc 85% with DBN
[102]	Li *et al.* (2016)	2 emotions, –	PerEn	–	–
[103]	García-Martínez *et al.* (2017)	2 emotions, 32 subjects, 32 EEG channels, video clips	QSampEn, PerEn, AAPE	DT	Acc = 80%. Higher predictability in stress than in calmness
[105]	García-Martínez *et al.* (2017)	2 emotions, 32 subjects, 32 EEG channels, video clips	AAPE	LR	Acc = 73.75%. Higher predictability in stress than in calmness
[106]	García-Martínez *et al.* (2017)	2 emotions, 32 subjects, 32 EEG channels, video clips	CEn	DT	Acc = 70.7%. Higher predictability in stress than in calmness
[108]	Chen *et al.* (2017)	–	LZC	–	–
[113]	Yin *et al.* (2017)	High-low valence and arousal, 32 subjects, 32 EEG channels, video clips	SpEn, ShEn	LSSVM[4] D-RFE[5]	Max Acc 78.96% for arousal and 71.43% for valence
[109]	Chen *et al.* (2017)	4 emotions, 32 subjects, 32 EEG channels, video clips	SpEn, ShEn, C0Comp	Three-stage decision method	Max Acc 86.67% for positive excitement recognition
[110]	Shen *et al.* (2017)	Depression, 170 subjects, 3 EEG channels, eyes open and closed, no stimuli	C0Comp, Rényi entropy, CD, SP	SVM	–
[104]	García-Martínez *et al.* (2018)	2 emotions, 32 subjects, 32 EEG channels, video clips	QSampEn, CEn	DT, SVM	Max Acc 80.31% with QSampEn+CEn. Higher predictability in stress than in calmness
[119]	Zheng & Lu (2018)	4 emotions, two experiments: (DEAP database, 32 subjects, 32 EEG channels, video clips) and (SEED database, 15 subjects, 62 EEG channels, film clips)	DEn, SP, statistics	KNN, LR, SVM, GELM[6]	Max Acc 69.67% for DEAP and 91.07% for SEED with DEn and GELM
[115]	Li *et al.* (2018)	3 emotions, 15 subjects, 62 EEG channels, film clips	DEn	HCNN[7] SAE[8] SVM, KNN	Better results with HCNN in beta and gamma bands
[120]	Li *et al.* (2018)	3 emotions, 14 subjects, 64 EEG channels, film clips	DEn, Higuchi FD	GRSLR[9]	Max Acc 80.27% with DEn and 72.09% with FD
[118]	Lan *et al.* (2018)	3 emotions, two experiments: (DEAP database, 32 subjects, 32 EEG channels, video clips) and (SEED database, 15 subjects, 62 EEG channels, film clips)	DEn	–	Better results with SEED database than with DEAP
[116]	Song *et al.* (2018)	3 emotions, 15 subjects, 62 EEG channels, film clips	DEn, SP, statistics	DGCNN[10]	DEn better than SP and statistics. Max Acc 90% subject dependent and 80% subject independent
[112]	Piho & Tjahjadi (2018)	Arousal and valence, two experiments: (DEAP database, 32 subjects, 32 EEG channels, video clips) and (30 subjects, 32 EEG channels, video clips)	SpEn, spectral and statistics	SVM, KNN, NB[11]	Better results with spectral and statistics than with SpEn
[107]	Martínez-Rodrigo *et al.* (2018)	2 emotions, 32 subjects, 32 EEG channels, video clips	Multiscale QSampEn, Multiscale AAPE	SVM	Better results with multiscale variations of QSampEn and AAPE

[1] MC-LSSVM: Multiclass least-square support vector machine
[2] CFNN: Cascade-forward neural network
[3] DBN: Deep belief networks
[4] LSSVM: Least-square support vector machine
[5] D-RFE: Dynamical recursive feature elimination
[6] GELM: Graph-regularized extreme learning machine
[7] HCNN: Hierarchical convolutional neural network
[8] SAE: Stacked autoencoder
[9] GRSLR: Graph regularized sparse linear regression
[10] DGCNN: Dynamical graph convolutional neural network
[11] NB: Naive Bayes

using nonlinear indices to discover relevant facts about the brain's complex performance. Most of the works presented in this review are focused on implementing mathematical models able to reach large discrimination accuracy values when discerning among different emotional states. For this purpose, hundreds of variables are included in advanced classification approaches, providing notable numerical outcomes in most cases. Nevertheless, the use of complex classifiers derives in a loss of clinical interpretation of the results after combining all input features. Thus, it becomes almost impossible to know, for instance, which electrodes report more information to the model, or which brain areas are more

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activated or deactivated under certain emotional conditions. Therefore, the evaluation of nonlinear methods from a clinical point of view may lead to new discoverings about how the brain responds to emotional stimuli. In addition, the outcomes derived from the application of nonlinear indices for EEG signal analysis might considerably improve the performance of systems for automatic emotion detection. Taking all the previous considerations into account, it is possible to evaluate which experimental procedures and analysis processes have revealed more relevant results for each group of metrics.

B. Correlation and dimensional complexity metrics

In the case of dimensional complexity metrics, the most relevant classification outcomes were reached by combining different indices with SVM-based classifiers. Thus, accuracy values between 70-85% were reported [58], [63], [67], [74]. It is important to remark that the divergence of discriminatory power results may be due to different aspects:

- In this sense, classification accuracy varies depending on the number of emotions to identify. Thus, the lower the number of emotions, the higher the classification results [63].
- In addition, the amount of variables used as input features of a classifier, such as the number of metrics [75], EEG channels [73] and participants [77], may also affect the results.

On the other hand, there are some works that have compared the efficiency of nonlinear dimensional complexity metrics with linear approaches based on spectral, statistical and functional connectivity features [60], [62], [65], [69], [75]. However, in most cases nonlinear metrics have not been able to overcome results reported by linear techniques [62], [65], [69]. Similarly, two FD algorithms for dimensional complexity assessment have been compared with regularity-based ApEn and SampEn indices. Nevertheless, the results of dimensional complexity metrics were not as relevant as those of regularity measures in terms of classification accuracy [57]. The reason could be that complexity metrics require longer signals with lower noise levels than regularity indices. All in all, it seems that parietal and frontal brain areas are the most involved in emotion processing, according to results reported by different studies with dimensional complexity indices [64], [68].

Finally, it is important to highlight that some studies have applied these methodologies to compare emotion recognition processes of healthy subjects and patients of different diseases. In this sense, dimensional complexity indices suggest that emotional processes are different according to the mental health of the patient. More concretely, left and right brain hemispheres play different roles conforming to the underlying mental disorder, thus the effect of having one or the other hemisphere damaged is different for each brain disease [70], [71], [76].

C. Irregularity metrics

As in the previous group of metrics, some studies based on regularity measures have reported numerical results in terms of classification accuracy, although outcomes are even more divergent than in the first group:

- In this sense, SVM classification models have reported accuracy results ranging from 50 to 90% [77], [80], [84], [88], [90]–[92], [94], [96], [110].
- Fortunately, most of those works have studied the same 4 emotional states with EEG signals contained in the DEAP database [80], [88], [91], [92], [96].
- Therefore, it is possible to compare them since the differences in the classification results are mainly produced by the nonlinear metrics applied in each case.
- It can be affirmed that SampEn might be more suitable than WEn for emotion recognition, since researches computing SampEn reported accuracy results from 80 to 94% [80], [96], while those that applied WEn obtained values around only 60 to 75% accuracy [88], [91], [92].

Besides, and contrarily to what occurred in the group of complexity metrics, studies performed with regularity indices did not compare their performance with spectral or statistical features. On the other hand, only a few works have compared or combined regularity-based metrics with indices from other groups [57], [84], [87]:

- In the case of the comparison between ApEn and predictability-based permutation entropies, the second ones seemed to have a better performance in terms of classification accuracy [84].
- With respect to the comparison with complexity-based measures, it has been mentioned in the previous section that ApEn and SampEn reported better accuracy results than FD complexity indices [57].

Apart from classification results, other relevant information has been reported by regularity metrics:

- In this sense, the brain might follow a more irregular behavior for high arousal emotions [81], [82], and even more irregular for positive high-aroused than for negative high-aroused states [86].
- Moreover, in accordance with findings made with complexity-based metrics, regularity indices have also revealed that frontal and parietal brain regions may play an important role in emotional processes [81], [86].

In addition, regularity-based metrics have also been applied for emotion detection in patients with depression, offering different results. While WEn reported a higher irregularity for depressed patients [89], the opposite results were reported with ApEn [93]. However, apart from the methodological differences of both metrics, these contradictory results may also be provoked by a crucial difference in their experimental procedures. In this sense, one study used face images as stimuli [89], whereas the other did not apply any kind of stimulus [93]. This fact may suggest the possible influence of stimuli selection on the final results obtained in a study.

D. Predictability and symbolic metrics

Classification accuracy results obtained in these studies range between 70 and 90%. However, there is a considerable disparity in terms of the selection of classifiers. On the

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contrary, SVM was clearly the most widely used in groups of complexity and regularity metrics. In addition, in the case of predictability metrics, there is an important number of classification models that have not been applied neither in complexity nor in regularity groups, such as LSSVM [101], [113], SAE [115] or NB [112], among many others. Nevertheless, it is important to remark that although those classifiers may have reported the highest accuracies, this does not mean that they are suitable than others. Instead, prior to decide which could be the best classification models it is necessary to evaluate the number and type of input features, together with the experimental procedure followed in each research.

Some works compared nonlinear predictability indices with linear spectral and statistical measures [98], [112], [114], [116]:

- In most cases predictability metrics reported better results than linear techniques in all the cited studies [98], [114], [116].
- On the other hand, predictability-based LZC and DEn might be more suitable than complexity-based FD for emotion recognition [17], [120]. Indeed, DEn has reported really valuable outcomes in all works where it has been applied, improving the performance of both linear and nonlinear metrics computed simultaneously [114], [116], [119], [120].
- With respect to symbolic metrics, it is important to remark that both permutation and conditional entropy metrics present a similar performance when applied to emotion recognition [103]–[107]. Hence, any of them is suitable in this research field.

In other terms, predictability-based metrics have demonstrated higher levels of predictability for high arousal than for low arousal emotions [103]–[107]. Furthermore, in accordance with results reported by complexity and regularity indices, frontal and parietal brain regions may be the most relevant brain areas for emotion processing [103]–[107]. Moreover, two of these studies applied regularity-based QSampEn and predictability-based AAPE in their one-scale [103] and multiscale forms [107]. In both works the same results were obtained in terms of activation or deactivation of brain regions. However, the multiscalar analysis demonstrated to be a suitable tool for nonlinear signal analysis with both short and long-term dynamical fluctuations, thus overcoming the limitations of one-scale metrics [107].

On the other hand, there are two studies that have used predictability metrics to evaluate EEG signals from two different databases, DEAP and SEED [118], [119]:

- In both cases, results obtained with SEED were notably better than those gotten with DEAP, probably due to the considerable difference in the number of EEG channels recorded in each database (32 for DEAP, and 62 for SEED).
- Hence, the higher the number of electrodes, the better the spatial resolution and thus the results obtained. This was also concluded in another approach which developed the same experiment with two different numbers of EEG channels obtaining a higher classification accuracy with 62 than with 24 electrodes [98].

E. Future lines

There are still dozens of nonlinear metrics that have already reported valuable insights in other fields but have never been applied to emotion recognition. For instance, the wavelet-chaos methodology combined EEG sub-bands with the computation of CD and LLE to detect seizure in epilepsy [121]. This methodology was later applied to the analysis of frontal brain areas to detect major depression disorder [122]. Although CD and LLE metrics have been used in emotion recognition both separately and together, the specific analysis proposed by the wavelet-chaos methodology could yield new results in the emotion recognition field. Furthermore, a dynamic similarity index, which is an improvement of statistical behavior of local extrema method, was created to measure the similarity of nonlinear long-term signals [123]. This metric was successfully applied [124] to assess the nonlinear changes in intra cranial activities prior to seizure in epilepsy. It could be also interesting to apply this metric in the emotion recognition field, comparing similarity of patterns among several EEG signals when eliciting different emotional states.

Another work *et al.* [125] deserves special attention. In this study, a visibility graph (VG) based method was applied to diagnose autism spectrum disorder [122]. VG is an algorithm that characterizes a time series by means of complex networks, and it can capture the presence of nonlinear correlations and chaotic dynamics of nonstationary signals, including EEG time series [126]. In fact, this method has recently been applied successfully in seizure detection with EEG recordings [127]. This methodology has not been applied to emotion recognition so far.

It is worth noting that MSE has been increasingly applied in the emotion recognition area in the last few years [82], [83], [107]. MSE allows to extract nonlinear long-term time-dependent information from time series that cannot be obtained by means of one-scalar indices [128]. Since any metric can be modified by previously adapting the time series to a multiscalar context, multiscale approaches offer an extensive number of future exploration possibilities in the area of emotion recognition with EEG recordings. This is the case of permutation min-entropy [129], based on Rényi entropy and with an intrinsic multiscale behavior. This metric has been recently applied in ECG recordings to successfully detect different emotions [130]. However, it has never been used for the purpose of emotion detection with EEG signals. Similarly, the dynamic and asymmetrical information of EEG using multiscale transfer entropy to detect seizures in epilepsy has been analyzed [131]. Here, symbolic transfer entropy, related to Granger causality, is effective to analyze dynamical and directional information in EEG signals. However, this index has never been used in the field of emotion recognition with EEG recordings.

It is also interesting to note that a new entropy metric called dispersion entropy, based on the quantification of the uncertainty of nonstationary time series, has been recently introduced [132]. Their authors compare this new entropy metric with other existing ones like permutation entropy, sample entropy or Lempel-Ziv complexity on various physiological datasets [132]. They claim that dispersion entropy is the most consistent technique able to distinguish various dynamics of biomedical signals and, consequently, dispersion entropy is expected to be broadly used for the characterization of a wide variety of real-world time series [132]. One area of application could be the emotion detection field.

In addition, it is important to remark the main future lines proposed by studies included in this survey. Accordingly, there are certain common aspects that could be addressed in future studies:

- Some of them suggest the application of different nonlinear metrics, an increase of the number of features, or the use of different methodologies [70], [88], [91], [96]. The enlargement of the population size [68], [71], [74], [116] and the number of emotions to recognize [65], [92], [104], [111], [114] has also been proposed.
- The application of different classification strategies and more advanced classification models [57], [73], [76], [90], together with the combination of EEG signals with other physiological recordings [62], [69], [81], [109] would also be a key point in future works.
- On the other hand, new types of stimuli could be used as a different manner of eliciting emotions [66], [86], [115].
- The importance of considering external factors such as gender or age of participants has also been stated [119].
- With the aim of offering new insights about the brain's behavior in emotional conditions, some authors have addressed the need of discovering which brain areas are involved in emotion processing [75], [87], [93], [100], [116].
- Finally, all these improvements could also be applied to develop real-time monitoring systems for emotion recognition [98], [113].

VI. Conclusions

This work has introduced a thorough review of the state-of-the-art in relation to the use of nonlinear metrics for EEG signal analysis in the emotion recognition research field. In the scientific literature, nonlinear metrics have revealed promising information that traditional linear techniques are not able to report. In this sense, nonlinear methods have demonstrated to be complementary to linear features, thus improving our knowledge of mental processes under different emotional states.

Furthermore, the methods described in this survey evaluate the brain's complexity from different points of view, which increases even more the possibilities of completely defining the brain's emotional behavior. Nevertheless, only a few nonlinear metrics have been applied to emotion detection with EEG signals. In this sense, further research is still required in this field, with the purpose of applying new nonlinear metrics that have already reported promising results in the study of a wide variety of physical and mental conditions.

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