# Deep Learning Classification of Neuro-Emotional Phase Domain Complexity Levels Induced by Affective Video Film Clips

Serap Aydın

*Abstract*—**In the present study, a novel emotional complexity marker is proposed for classification of discrete emotions induced by affective video film clips. Principal Component Analysis (PCA) is applied to full-band specific phase space trajectory matrix (PSTM) extracted from short emotional EEG segment of 6 s, then the first principal component is used to measure the level of local neuronal complexity. As well, Phase Locking Value (PLV) between right and left hemispheres is estimated for in order to observe the superiority of local neuronal complexity estimation to regional neuro-cortical connectivity measurements in clustering nine discrete emotions (fear, anger, happiness, sadness, amusement, surprise, excitement, calmness, disgust) by using Long-Short-Term-Memory Networks as deep learning applications.**

**In tests, two groups (healthy females and males aged between 22 and 33 years old) are classified with the accuracy levels of $68.52\%$ and $79.36\%$ through the proposed emotional complexity markers and and connectivity levels in terms of PLV in amusement. The groups are found to be statistically different ($p \ll 0.5$) in amusement with respect to both metrics, even if gender difference does not lead to different neuro-cortical functions in any of the other discrete emotional states.**

**The high deep learning classification accuracy of $98.00\%$ is commonly obtained for discrimination of positive emotions from negative emotions through the proposed new complexity markers. Besides, considerable useful classification performance is obtained in discriminating mixed emotions from each other through full-band connectivity features. The results reveal that emotion formation is mostly influenced by individual experiences rather than gender. In detail, local neuronal complexity is mostly sensitive to the affective valance rating, while regional neuro-cortical connectivity levels are mostly sensitive to the affective arousal ratings.**

*Index Terms*—**Brain Biophysics, Emotion Recognition, Affective Neuroscience, Deep Learning**

## I. Introduction

Emotion can be defined as intentional affective state that occurs in response to something experienced. As well, emotions can be consciously recognized [1]. However, it is hard to give a unique definition about emotion. In past, six basic universal emotions (fear, disgust, anger, surprise, happiness, and sadness) were defined independently of cultures and seven additional mixed emotions (embarrassment, excitement, contempt, shame, pride, satisfaction, and amusement) were also defined discrete emotional states [2]. Several studies shows that emotions are experienced by individuals regardless of their culture, however, some researchers suggest that emotion formation depends on subjective experience. Considering the Thalamic theory of emotion, humans feel emotions and experience physiological reactions simultaneously [3]. Then, expression of emotions can be mentioned as behavioral response that is a major part of body language. In more recent studies, both affective (automatic and less controlled immediate response) and cognitive (rather controlled and less intense conscious process just after the immediate response) components of emotional formation have been commonly discussed [4], [5]. Later, the more complex definition of emotion is proposed to discuss the combination of philosophical and psychological elements of emotions [6]. Therefore, neural, physiological, and phenomenological components of emotions have been measured from individuals for emotion recognition: These metrics can be summarized as facial affective recognition tests [7], [8] and facial expressions [9], heart rate [10], eye-gaze pattern [11], functional near-infrared (fNIR) spectroscopy [12], functional magnetic resonance imaging (f-MRI) [13] and, combination of multiple physiological and behavioural scales [14].

In affective neuroscience, measurement of surface EEG series in response to emotional stimuli is the mostly used method for emotion recognition in order to detect emotional deficits and cortical dysfunctions suffered from many disorders such as ADHD [15], Parkinson's disease [16], social anxiety disorder (SAD) [17], schizophrenia in adults [18]. Moreover, EEG analysis has also been frequently assigned for emotion recognition as futuristic applications in both intelligent human-machine interaction systems [19] and emotion regulation systems [20], [21]. However, affective stimulus design is crucial in recognizing emotional states through EEG analysis. In nature, emotional formation is highly conveyed by combining visual and auditory perception together. The most frequently used affective stimuli are static colored pictures proposed by International Affective Picture System (IAPS) to evoke pleasant, unpleasant and neutral emotional states [22], [18], [23], [24], [25], [17] and short video clips to induce more specific discrete emotions such as fear, disgust, humour [26], and sadness, happiness, fear [19]. Presentation of schematic emotional facial expressions so called neutral, sad, and happy emoticons is rare [27]. Besides, task-relevant stroop tests have also been as emotional stimuli. Among them, a novel emotional video stroop test has been proposed to discuss the possible influence of emotional conflict processing on cognitive conflict processing [28]. The incongruent (mismatching face video and audio streams) and congruent (matching face video and audio streams) voices with neutral and negative (i.e.

S. Aydın was with Department of Biophysics, Faculty of Medicine, University of Hacettepe, Ankara, Turkey, e-mail: drserapaydin@hotmail.com

angry) emotional tones were presented in short face video clips of a young male and a young female semi-professional actors pronouncing the interjections 'A' and 'O' ranged between 1 or 2 $s$ [28]. In the following study, incongruent (opposite meaning of emotional face expression was written on the picture, i.e. distracter word and face expression are opposite) and congruent (the meaning of emotional face expression was written on the picture, i.e. distracter word and face expression are the same) trials were designed to detect impairment in facial emotional recognition [16].

It is shown that neural processing of emotional sounds in simultaneously combination with affective visual stimuli enhances parietal hemispheric activities in terms of ensemble averaging ERP components such as Late Positive Potential (LPP), P100 and P200 peaks [29]. Similarly, multisensory integration of emotional face pictures with simultaneously emotional voice is found to be influenced by selective attention from an early processing stage [30], [31]. Therefore, new EEG complexity marker is proposed for emotion recognition through analyze well defined emotional database so called DREAMER including surface EEG series collected from young females and males in response to 18 affective film clips for classification of nine different discrete emotional states in the present study.

Performance of emotion recognition studies is primarily dependent on feature extraction methodology, i.e. EEG analysis approach: The oldest concept is spectral estimation in processing emotional EEG data collected from either eyes-opened [32] or eyes-closed [33] individuals in response to musical auditory stimuli. In following studies, spectral EEG variations has been observed in both conditions (eyes-closed and eyes-opened) in accordance with musical affective melodies [34]. As well, Fourier Transform based spectral methods have also applied to EEG data transformed into 3-Dimensional tensor presentation in order to observe hemispheric asymmetry levels in sub-band frequency intervals in response to audio-visual affective stimuli [35]. Complexity estimation is more popular than spectral estimation for classification of discrete emotional states: Kolmogorov entropy and Lyapunov exponents of surface EEG epochs of 8.192 s were computed for estimation of emotional complexity levels in neutral, positive and negative emotional states induced by video films [36]. Sample Entropy has been examined as multi-scale complexity metric driven by multivariate empirical mode decomposition for classification of five self-reported emotions induced by video film clips of 20 min [37]. In this study, the last 100 s of EEG recordings have been analyzed. The other emotional EEG complexity methods so called singular value decomposition [22], and fractal dimensions [26] were applied to emotional short epochs of 2 s in response to in neutral, positive and negative emotional states mediated by static pictures. Another emotional feature extraction methods are recurrence quantification [19] and independent component analysis [38] in analyzing non-averaged single trials for development of futuristic Human-Machine-Interface systems. In recent studies, the influence of temporal EEG window size has been discussed in referenced Brain-Computer-Interface application study for emotion recognition [39]. In this study, optimum window length was proposed as 12 s for classification of positive and negative emotional states induced by video clips in order to provide the accuracy of $86.96\%$. Besides, segmentation length depends on mainly EEG analysis approach in association with experimental paradigm.

Traditional connectivity method is magnitude squared EEG coherence. This approach has been applied to emotional surface EEG series in association with both static affective pictures [23] and affective video film clips [40]. The same connectivity approach has also be computed by using Wavelet Transform into multi-scales for detection of cortical dysfunctions [18]. In order to estimate global cortical connectivity marker, global EEG coherence approach is applied to 64-channel emotional EEG series in response to positive and negative emotional facial expressions for detection of depression [41]. Directed transfer function is another two-channel connectivity method that is applied to non-averaged short epochs (of 2 s) induced by affective musical melodies (joyful, melancholic, neutral) [42].

In the present study, Principal Component Analysis (PCA) is combined with Phase Space Trajectory Matrix (PSTM) in order to propose a new phase domain emotional EEG complexity marker. In addition, time varying Phase Locking Value (PLV) is also applied to the emotional data for classification of nine different emotional states (happiness, sadness, calmness, fear, anger, disgust, amusement, surprise, excitement). Both approaches are used to determine emotional feature sets and then young females and males are classified with respect to each emotional state. Both methods are applied to non-averaged short epochs filtered by FIR filters in Matlab. Long-Short-Term Memory Network (LSTMN) that is a class of deep learning is used as performance criteria in addition to statistical one-way Anova tests.

In EEG research field, Support Vector Machines (SVMs) are mostly used for classification of discrete emotions [23], [43], [44], [45], [52], while multi-layer perceptron neural network is rarely used classifier [38]. In a few works, SVMs are compared with relevance vector machine classifiers [53] and K-nearest neighbor classifiers [47]. In the present study, emotional features obtained by using both complexity and connectivity approaches are deep learning classified to understand the underlying structure of discrete emotional state in accordance with valence and arousal ratings. For this purpose, international database, DREAMER [54], is analyzed. Methodological steps of the present study are described in following sections.

## II. METHODS

In this study, emotional EEG database called as DREAMER was analyzed to discuss neuro-cortical activity alterations depending on 3-dimensional affective scores of emotional stimuli. The database DREAMER includes 14-channel surface EEG measurements recorded from healthy young volunteers during presentation of video film clips, then EEG series were categorized into nine different discrete emotional states and baseline with respect to Self-Assessment of Manikind scores ranged between 1 and 5 in terms of arousal, valence and dominance as detailed described in reference [54]. Emotional data was classified with respect to 14-channel emotional features estimated by attempting a novel complexity estimation method in full-band and sub-band EEG frequency intervals to discuss both gender effect and close association between affective scores and band specific regional EEG complexity levels.

### *A. EEG Data Acquisition and Participants' Self-Assessment Evaluation*

The total sample included 23 healthy participants in single age group. The young female group age was between 23-31 years old (N =23, 9 females, median age=26 years, mean age=26.55 years, standard deviation (SD)=2.78) and the young male group age was between 22-29 years old (N=23, 14 males, median age=26 years, mean age=26.57 years, SD=2.70). The participants had BSc degree. They raised with the same culture. Declaration of Helsinki and contest form were signed by the volunteers. The study protocol was approved by the University of the West of Scotland University Ethics Committee (UWS UEC). The experimental protocol was implemented in MATLAB environment.

*1) Participants' Self-Assessment Evaluation:* Participants filled the assessment evaluation form after collecting EEG data in response to short video film clips. These forms were carefully analysed in order to detect any possible abnormalities, i.e. unexplained variations, because the same affective film clip elicit the same emotional state in all participants.

The coefficient of variation (CV) was computed for each affective video film clip in all participants in order to have a standardised measure of variability. This measure is defined as the ratio between the standard deviation (std) and the mean. Thus, CV is zero when there is no variability across the samples, while it is higher than zero when there is high variability. Regarding arousal ratings among participants, the mean CV was $0.29 \mp 0.07$. Regarding other ratings named as valence and dominance, CV were $0.31 \mp 0.15$ and $0.27 \mp 0.06$. Regarding three affective ratings, valence, arousal and dominance, the mean std of CV was 0.81, 0.88, 0.88 respectively for each film clip. It can be clearly said that there was no high variability between the assessments of participants. In other words, the self-assessments of participants were consistent with the discrete emotional states that were correlated with the film clips of interests in reference [55].

*2) Emotional EEG Recordings:* Regarding database called DREAMER, surface EEG series was recorded from participants while they were watching the video film clips presented on a $45''$ TV-monitor integrated with the embedded speakers for audio playback within an isolated room with controlled illumination. EEG series were measured by using an Emotiv EPOC system such that 16 gold-plated contact-sensors were fixed to flexible plastic arms of a wireless headset and were placed against the head in following locations with respect to the international 10-20 electrode placement system: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, M1 and M2. The ground reference point was the mastoid sensor at M1 to compare the voltage of all other sensors, while feed-forward reference was the mastoid sensor at M2 to reduce external electrical interference. Then, the signal from the remaining 14 contact-sensors was analyzed for feature extraction in the present study. The sampling rate was 128 Hz [54].

TABLE I
AUDIO-VISUAL STIMULI AND THEIR RATINGS [54].

| film clip | emotion | valence | arousal |
|---|---|---|---|
| The Ring | E1, fear | $2.04 \mp 1.02$ | $4.26 \mp 0.69$ |
| Psycho | E1, fear | $2.48 \mp 0.85$ | $3.09 \mp 1.00$ |
| D.O.A. | E2, surprise | $3.04 \mp 0.88$ | $3.00 \mp 1.00$ |
| The Departed | E2, surprise | $2.65 \mp 0.78$ | $3.91 \mp 0.85$ |
| My Girl | E3, sadness | $1.39 \mp 0.66$ | $3.00 \mp 1.09$ |
| The Shawshank Redemption | E3, sadness | $1.52 \mp 0.59$ | $3.00 \mp 0.74$ |
| The Hangover | E4, amusement | $4.57 \mp 0.73$ | $3.83 \mp 0.83$ |
| Modern Times | E4, amusement | $3.96 \mp 0.56$ | $2.61 \mp 0.89$ |
| Crash | E5, anger | $1.35 \mp 0.65$ | $3.96 \mp 0.77$ |
| Gentlemans Agreement | E5, anger | $2.35 \mp 0.65$ | $2.22 \mp 0.85$ |
| National Lampoon's VanWilder | E6, disgust | $2.70 \mp 1.55$ | $3.83 \mp 0.83$ |
| The Fly | E6, disgust | $2.17 \mp 1.15$ | $3.30 \mp 1.02$ |
| Wall-E | E7, happiness | $4.52 \mp 0.59$ | $3.17 \mp 0.98$ |
| Remember the Titans | E7, happiness | $4.39 \mp 0.66$ | $3.70 \mp 0.97$ |
| Searching for Bobby Fischer | E8, calmness | $3.17 \mp 0.72$ | $2.26 \mp 0.75$ |
| Pride and Prejudice | E8, calmness | $3.96 \mp 0.64$ | $1.96 \mp 0.82$ |
| 300 | E9, excitement | $3.22 \mp 1.17$ | $3.70 \mp 0.70$ |
| The Bourne Identity | E9, excitement | $3.65 \mp 0.65$ | $3.35 \mp 1.07$ |

18 different video film clips, which were proposed for eliciting emotions in the reference [55], include cut out scenes to evoke a wide range of emotions. Among them, two of each targeted one of the following discrete emotions: calmness, surprise, amusement, fear, excitement, disgust, happiness, anger, sadness as listed in Table I.

In psychology, the useful length of video stimuli has been proposed between 1 to 10 min to elicit single emotions [56]. The longer length may cause multiple emotions. Therefore, the min and max length of the film clips were 65 s and 393 s in this study. The volunteers were asked to read an information sheet which provided details about the experimental procedure and explained the rating scales used for affect assessment and then proceed to sign a Consent Form. The rating scale was thoroughly explained both verbally and through examples before data collection. During individual sessions, the volunteers were asked to provide an emotional assessment mediated by the film clip of interest.

At the beginning of the sessions, a neutral film clip was shown in order to establish the baseline signals. After viewing each film clip, the participants rated the film with three rating scores: arousal (from uninterested/bored (1) to excited/alert (5)), valence (from unpleasant/stressed (1) to happy/elated (5)), dominance (from helpless (1) to empowered (5)) by using a graphical user interface on computer screen regarding Self-assessment manikins (SAM) [57]. The experimental protocol was implemented using the MATLAB environment. The study was approved by the University of the West of Scotland University Ethics Committee [54].

In the present applications, single channel EEG series were firstly windowed by using a constant sliding window of 6 s, then principal components of PSTM are estimated for full-band and sub-band frequency intervals of short epochs.

### *B. EEG Analysis: Extraction of Emotional Phase Space Trajectory Components*

As a pre-process, the last recording interval of 10 min (10x60=600 s) was segmented into non-overlapped short epochs of 6 s for each participant in each emotional state. Then, 100 separate epochs were filtered by using finite-impulse-response (FIR) filter for each recording channel. FIR filter was implemented in Matlab2018R-b to extract artifact free full-band (0.5-64 Hz) emotional EEG epochs. The filter parameters were determined as follows: Transition band is 0.5 Hz at both cutoff frequency edges, pass-band ripple is 0.0575, stop-band ripple is 0.0232, density factor is 20. The optimal filter order is estimated by using Parks-McClellan optimal equi-ripple FIR order estimator.

Data phase space was proposed for estimation of the attractors in dynamic systems [58]. In past, this approach was used for EEG analysis based on the assumption that the brain is a complex and dynamic system in healthy persons [59] and patients under deep anesthesia [60]. In reference, both Auto-regressive Model order estimation and Fourier Transform based time-frequency estimation have been applied to EEG phase space trajectories as secondary processes in motor imagery task dependent brain-computer-interface (BCI) application [61]. In more recent study, graph dissimilarity embedding is applied to the normalized version of EEG phase space trajectory to detect emotional deficits in social anxiety disorder [62].

In the present study, Phase Space Trajectory Matrix (PSTM) is reconstructed from specified frequency intervals of short epochs for 14-channel emotional EEG series and then, Principal Component Analysis (PCA) is applied to this matrix in order to obtain EEG complexity marker for discrimination of emotional states from each other. The first PC of PSTM is defined as emotional feature. This novel combination is applied to both full-band and sub-band frequency intervals of the large number of epochs for each recording channel in discrete emotional states to determine huge feature sets.

In estimating PSTM, the common concept is that EEG phase space trajectories include meaningful information about the structure of the brain attractors. Methodologically, PSTM is reconstructed from short epoch denoted by a row vector, $\bar{x}_{i,j} = [x_{i,j}(1)...x_{i,j}(N)]$ in from,

$$Y_{i,j} = \begin{bmatrix} x_{i,j}(1) & x_{i,j}(1+\tau) & ... & x_{i,j}(1+(m-1)\tau) \\ x_{i,j}(2) & x_{i,j}(2+\tau) & ... & x_{i,j}(2+(m-1)\tau) \\ ... & ... & ... & ... \\ x_{i,j}(M) & x_{i,j}(N-m\tau) & ... & x_{i,j}(N) \end{bmatrix} \quad (1)$$

Here, $N = 6\ s\ x\ 128\ Hz = 768$ for single epoch of 6 $s$. The variable $i$ denotes the number of epoch, $j$ denotes the recording channel (ranged from 1 to 14).

Time delay (time lag) is denoted by $\tau$ in equation. Regarding the first local minimum of the mutual information between time-shifted versions of the EEG epoches [48], its optimum value is empirically found to be 1 in the present study. The other parameter, $m$ is the embedding dimension such that any two points in $m-$dimensional space can continue close in $m+1$ dimensional space [63]. Its optimum value that is common in each emotional state is empirically found to be 3.

In following step, Principal Component Analysis (PCA) is applied to emotional PSTMs for estimation of frequency specific dominant harmonics in short EEG segments included audio-visual Evoked Potentials (EPs) induced by affective stimuli.

Using PCA provides to decompose the data denoted by $Y_{i,j}$ into a linear combination of finite number of signal harmonics. Thus, the first Principal Component (PC) can be correlated with the highest variability in the data [64]. In literature, PCA is applied to ensemble averaged Event-Related-Potential waveform in order to observe the influence of musical experience on emotional neuro-activities mediated by emotional sounds [65]. In the present study, PCA is applied to PSTM extracted from non-averaged, non-overlapped short emotional EEG segments of 6 s.

Table I, the first Principal Component of band specific PSTM is estimated for each emotional state in addition to baseline (assumed as to be neutral state) with respect to both full-band and sub-band (Delta, Theta, Alpha, Beta and Gamma) frequency intervals of 10 min recordings through 14-channels. The resulting phase space trajectory matrix components (PSTMCs) are assigned as emotional complexity markers for classification of emotions.

### *C. Emotional EEG Connectivity Analysis: Extraction of Phase Locking Value*

Considering identical full-band two short EEG epochs ($x$ and ($y$)) extracted from right and left cortical regions, the neuronal phase difference between them can be estimated by using the following formula,

$$PLV_{xy} = \frac{1}{N} \exp j\,(\phi_x - \phi_y) \quad (2)$$

where $\phi_x$ and $\phi_y$ refer instant local EEG phase values in association with right ($x$) and left ($y$)) recording specific epochs. These instant phase values can be computed by using both Wavelet and Hilbert Transforms. Then, PLV gives the instant neuronal phase difference ($\Delta\phi = \phi_x - \phi_y$) with the name of Phase Locking Value (PLV). If two series rise/fall together with a certain lag, PLV becomes 1 due to consistency. In other words, PLV becomes zero when there is no relationship between two series. Thus, PLV estimation can measure trial-to-trial variability by means of phase lag between two dynamic series [66].

### *D. Classification of Emotional States: Deep Learning Application*

In he present study, females and males are classified by using a deep learning classifier driven by full-band 14-channel neuronal complexity levels and full-band 7-electrode pairs' connectivity levels in phase domain. As well, two-class deep learning classification is examined to discriminate nine discrete emotional states from each other with respect to phase domain neuronal complexity and connectivity features independently gender.

In applications, Long-Short-Term-Memory Networks (LSTMNs) are used to apply deep learning algorithms. LSTMN is a class of recurrent neural networks (RNNs), however, short-term dependency gap in RNN is eliminated through important modifications on memory blocks called cells in LSTMN [67]. Thus, the features can be selectively remembered/forgot as a result of information flow within a cell state mechanism along with multiple gating units (input gate, hidden (forget) gate, output gate) in LSTMN. The learning algorithm of LSTMN can control both addition and removal of information from the states. In summary, LSTMN becomes superior to conventional feed-forward NN due to its complex and intelligent feedback connections.

In tests, LSTMNs were implemented by using Deep Learning Toolbox in Matlab2018Rb. The optimizer was Adaptive Moment Estimation Method. The classification parameters were empirically determined as follows: Initial learning rate $= 0.03$, gradient threshold $= 1.5$, the number of hidden nodes $= 30$. Due to number of recording channels, feature dimension was 14 in complexity analysis, 7 in connectivity analysis in applications. The number of features were 32.200 ((# of recording channel) x (# of subjects) x (# of epochs) = 14 x 23 x 100=32.200) in complexity analysis and 16.100 (# of symmetrically located electrode pair) x (# of subjects) x (# of epochs) = 7 x 23 x 100=16.100) in connectivity analysis.

## III. Results

In primary step of this study, statistical one-way Anova test was used to investigate statistical differences between females and males in emotional states by means of neuronal complexity and connectivity levels.

Regarding 14-channel full-band PSTMC estimations, the groups were compared to each other with respect to recording location in nine emotional states separately. Considering 7-electrode pairs' connectivity estimations, i.e. full-band PLV estimations, the groups were compared to each other with respect to symmetric cortical lobes in nine emotional states separately. The resulting p-values were listed in Table II. For each single electrode location, full-band PSTMC estimations provided statistically meaningful differences ($p << 0.5$) in E4, amusement. As well, full-band PLV estimations also provided statistically significant differences at each cortical lobe in the same emotional state.

In following step, the groups were classified by using LSTMNs as a deep-learning applications. Two main feature sets included full-band PSTMCs (for 14-single recording channel) and full-band PLV (for 7 symmetric electrode pairs) values estimated for 100 non-overlapped short EEG epochs. The resulting classification performances were given in Table III in terms of mini-batch accuracy (%) levels obtained by completing 30th iteration.

Considering 14-channel full-band PSTMC, the highest classification accuracy of $71.53\%$ was obtained in E6, disgust. The other relatively useful classification accuracy of $68.52\%$ was obtained in E4, amusement. The other classification performance outputs were unsuccessful in discriminating the groups.

TABLE II
Statistical one-way Anova test results (p-values) between females and males in emotional states with respect to full-band specific features (* refers p<1e-5, ** refers p<<1e-5)

| | | E1 | E2 | E3 | E4 | E5 | E6 | E7 | E8 | E9 |
|---|---|---|---|---|---|---|---|---|---|---|
| PSTMCs | AF3 | 0.83 | 0.91 | 0.88 | ** | 0.97 | 0.91 | 0.85 | 0.96 | 0.93 |
| | F7 | 0.73 | 0.78 | 0.77 | ** | 0.72 | 0.91 | 0.66 | 0.84 | 0.81 |
| | F3 | 0.80 | 0.87 | 0.82 | ** | 0.80 | 0.95 | 0.80 | 0.91 | 0.90 |
| | FC5 | 0.90 | 0.94 | 0.92 | ** | 0.99 | 0.90 | 0.93 | 0.95 | 0.96 |
| | T7 | 0.84 | 0.94 | 0.87 | ** | 0.95 | 0.91 | 0.86 | 0.99 | 0.94 |
| | P7 | 0.96 | 0.97 | 0.96 | ** | 0.95 | 0.96 | 0.95 | 0.99 | 0.97 |
| | O1 | 0.95 | 0.99 | 0.98 | ** | 0.95 | 0.96 | 0.95 | 0.99 | 0.99 |
| | O2 | 0.96 | 0.93 | 0.99 | ** | 0.87 | 0.99 | 0.98 | 0.93 | 0.96 |
| | P8 | 0.98 | 0.99 | 0.97 | ** | 0.95 | 0.92 | 0.91 | 0.97 | 0.98 |
| | T8 | 0.82 | 0.91 | 0.89 | ** | 0.91 | 0.94 | 0.83 | 0.96 | 0.92 |
| | FC6 | 0.66 | 0.76 | 0.75 | ** | 0.56 | 0.95 | 0.57 | 0.96 | 0.76 |
| | F4 | 0.87 | 0.92 | 0.91 | ** | 0.95 | 0.91 | 0.83 | 0.96 | 0.98 |
| | F8 | 0.84 | 0.91 | 0.86 | ** | 0.93 | 0.88 | 0.81 | 0.96 | 0.92 |
| | AF4 | 0.79 | 0.83 | 0.82 | ** | 0.78 | 0.99 | 0.75 | 0.96 | 0.65 |
| PLV | AF3-4 | 0.93 | 0.94 | 0.89 | ** | 0.71 | 0.98 | * | 0.80 | 0.69 |
| | F7-8 | 0.80 | 0.91 | 0.84 | ** | 0.72 | 0.79 | 0.89 | 0.99 | 0.73 |
| | F3-4 | 0.73 | 0.83 | 0.86 | ** | 0.87 | 0.78 | 0.82 | 0.77 | 0.74 |
| | FC5-6 | 0.79 | 0.86 | 0.98 | ** | 0.87 | 0.90 | 0.69 | 0.95 | 0.96 |
| | T7-8 | 0.80 | 0.93 | 0.70 | ** | 0.57 | 0.82 | 0.96 | 0.96 | 0.82 |
| | P7-8 | 0.97 | 0.87 | 0.71 | ** | 0.82 | 0.88 | 0.77 | 0.80 | 0.86 |
| | O1-2 | 0.70 | 0.93 | 0.97 | ** | 0.73 | 0.91 | 0.66 | 0.68 | 0.86 |

Regarding 7-electrode pair specific full-band PLV estimations, the highest classification accuracy of $71.53\%$ was obtained in E4, amusement. Useful performance was not obtained in other emotional states.

TABLE III
Deep learning classification performance for classification of females and males with respect to full-band specific features

| | E1 | E2 | E3 | E4 | E5 | E6 | E7 | E8 | E9 |
|---|---|---|---|---|---|---|---|---|---|
| PSTMCs | 57.16 | 56.86 | 56.97 | **68.52** | 59.95 | **71.53** | 56.10 | 56.10 | 56.10 |
| PLV | 56.17 | 56.10 | 56.10 | **79.36** | 56.10 | 56.89 | 56.30 | 56.10 | 56.10 |

In following step, the normalized version of the statistical p-values were converted in colored topological maps as given in Fig.1 with respect to 14-channel neuronal complexity levels by full-band PSTMCs. Considering these topological maps, the most clear difference between females and males was observed in amusement. In four states (surprise, happiness, fear, sadness), slight differences were observed at commonly at right temporal regions.

Fig.1 shows EEG complexity spectra in terms of PSTMCs such that each emotion specific histogram was compared with baseline spectra. PSTMCs values were estimated from full-band frequency interval of short epochs ($6\ s$) in emotional states and baseline (neutral). The number of epochs was commonly 100 (recording length was ($10\ min$)) for each recording channel. Those emotional complexity histograms were independent of the groups (females and males).

Regarding Fig.2, the lowest complexity levels were generated in calmness, while the highest complexity levels were generated in happiness. Relative to sadness, the lower complexity levels were provided in disgust. Similar to fear, high EEG complexity levels were produced in amusement. Similar to surprise, medium level EEG complexity spectra were produced in excitement.

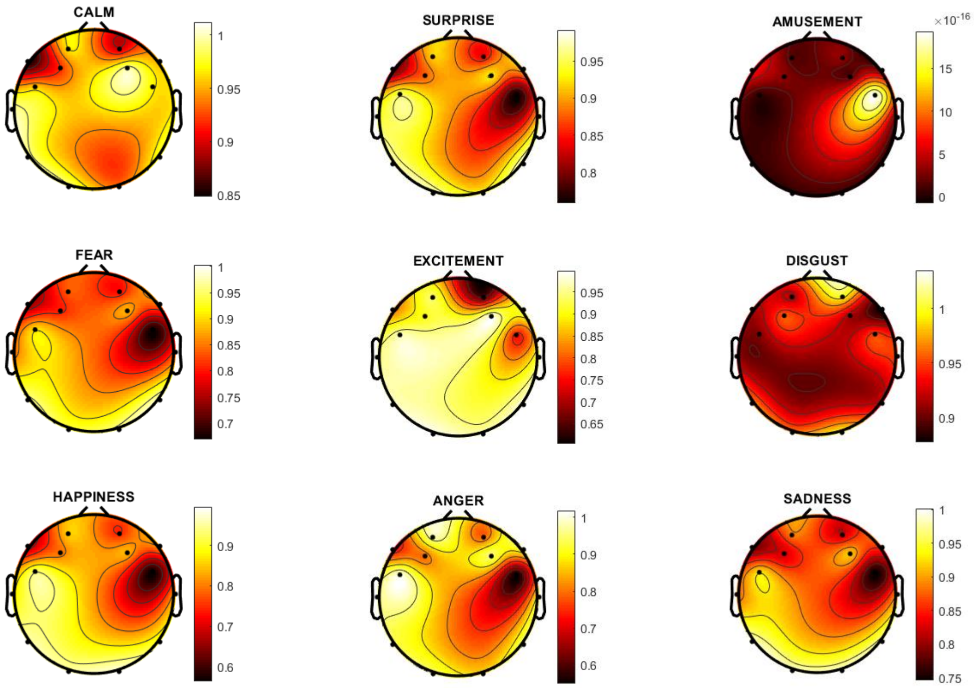


Fig. 1. Topological representation of statistical p-values listed in Table II.

In two-class emotion classification, the resulting performances (mini-batch accuracy (%) at 30th iteration) were listed in Table IV with respect to not only neuronal complexity levels (in terms of PSTMCs) but also phase domain connectivity levels (in terms of PLV).

Regarding PSTMC estimations, E9 (excitement) was discriminated from E1 (fear) with the highest accuracy of $97.28\%$. The other considerable performances of $95.75\%$ and $94.15\%$ were obtained for discrimination of E4 (amusement) from E2 (surprise) and E3 (sadness), respectively. As well, E5 (anger) and E8 (calmness) were also classified with considerable useful performance of $94.47\%$. Besides, the lowest and unsuccessful accuracy of $52.29\%$ was obtained for classification of E9 (excitement) and E2 (surprise).

Regarding PLV estimations, E9 (excitement) was discriminated from both E4 (amusement) and E7 (happiness) with high performances of $98.90\%$ and $98.89\%$, respectively. As well, E5 (anger) and E8 (calmness) were also classified with considerable useful performance of $87.97\%$. Besides, the lowest and unsuccessful accuracy of $50.00\%$ was obtained for classification of E9 (excitement) and E2 (surprise).

TABLE IV
DEEP LEARNING CLASSIFICATION PERFORMANCE FOR CLASSIFICATION OF EMOTIONAL STATES

| | | full-band PSTMCs | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | E1 | E2 | E3 | E4 | E5 | E6 | E7 | E8 | E9 |
| full-band PLV | E1 | | 86.78 | 88.32 | 84.41 | 75.13 | 75.02 | 89.65 | 76.35 | 97.28 |
| | E2 | 70.43 | | 75.83 | 95.75 | 75.46 | 87.96 | 92.38 | 71.80 | 52.29 |
| | E3 | 73.92 | 84.84 | | 94.15 | 83.99 | 72.05 | 91.83 | 74.81 | 75.46 |
| | E4 | 51.41 | 50.51 | 67.73 | | 86.22 | 82.28 | 85.29 | 80.98 | 73.95 |
| | E5 | 58.67 | 71.50 | 63.51 | 54.60 | | 84.74 | 89.96 | 94.47 | 79.25 |
| | E6 | 76.04 | 57.39 | 87.94 | 76.47 | 74.03 | | 79.23 | 68.29 | 75.00 |
| | E7 | 70.23 | 77.20 | 76.14 | 59.36 | 53.73 | 77.19 | | 77.00 | 76.55 |
| | E8 | 56.98 | 50.92 | 66.90 | 86.36 | 87.97 | 73.73 | 77.47 | | 69.00 |
| | E9 | 50.88 | 50.00 | 50.62 | 98.50 | 72.57 | 56.60 | 98.89 | 54.90 | |

## IV. CONCLUSION

In the present study, a new EEG based emotional complexity marker has been proposed in order to investigate the relationship between affective rating scores and neurocortical activities in young females and males in nine discrete emotional states (fear, anger, disgust, amusement, calmness, happiness, sadness, surprise, excitement). For this purpose, Principal Component Analysis (PCA) is applied to Phase Space Trajectory Matrix (PSTM) of short emotional segments of 6 s in association with 14-channel surface EEG measurements induced by affective video film clips with the duration of 10 min.

Females and males produces statistically different neuronal complexity levels at each brain region in amusement, while they produce statistically different neuronal connectivity levels for each symmetric lobes in disgust. These two main results are found to be compatible with deep learning classification accuracies of $68.52\%$ and $71.20\%$, respectively. Amusement is a prototypical positive mixed emotion with very high arousal rating, while disgust is a prototypical negative mixed emotion.

Regarding emotional complexity histograms, local neuronal complexity levels highly depend on the affective valence ratings such that the lowest and the highest complexity levels are commonly provided by females and males in calmness and

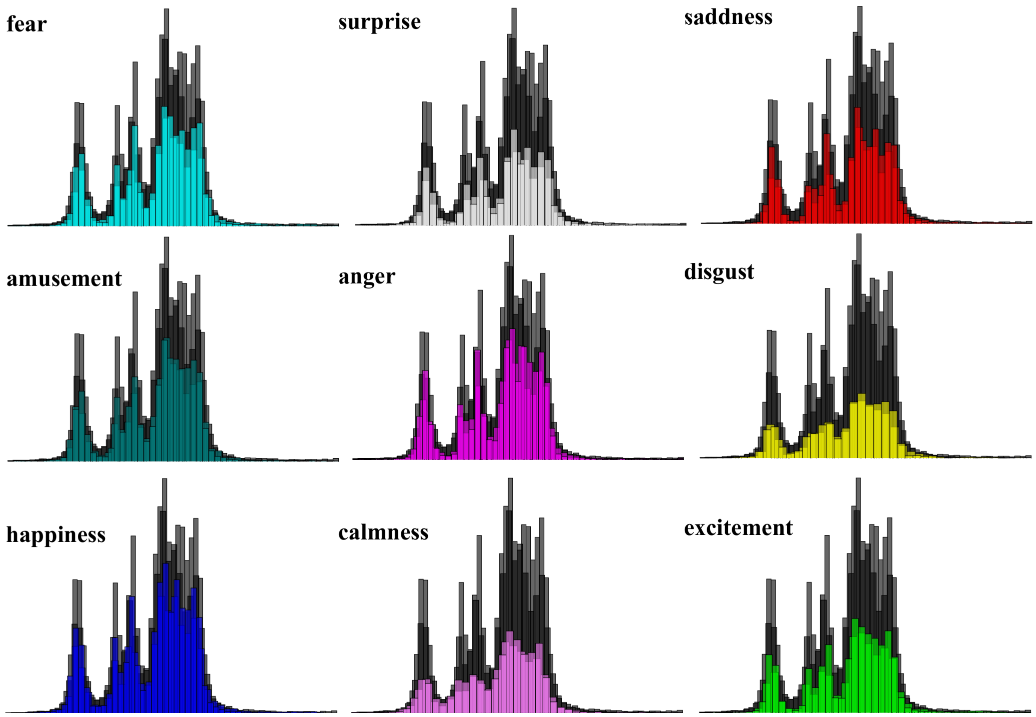


Fig. 2. Full-band PSTMC estimations in emotions with respect to that of baseline (in gray level).

happiness, respectively.

Regarding two-class emotion classifications, negative emotions are clearly discriminated from positive emotions by using neuronal complexity levels as features. Besides, mixed emotions are discriminated from each other by using regional connectivity levels as features. In conclusion, mixed emotions highly modulate the functional connectivity of the amygdala with the other regions of the brain. In particular, regional phase domain connectivity levels characterize the dynamic signature of emotion formation depends on individual experiences driven by ongoing perception and cognition processes.

From EEG signal processing point of view, primary extraction of PSTM provides reduction of background EEG in order to enhance signal-to-noise ratio. Then, application of PCA on PSTM highlights the main harmonics in association with audio-visual evoked potentials (EP) embedded in short epochs. Due to ongoing combination of excitatory and inhibitory post-synaptic potentials as well as Action Potentials (APs), EEG series are time-varying psychophysiological signals. In particular, time-varying audio-visual affective stimuli continuously cause both generation and propagation of nerve APs at auditory, visual and cognitive cortices simultaneously. Therefore, EEG segmentation and analysis of short non-overlapped epochs are crucial pre-processes for emotion recognition. As well, length of short epoch has to be 6 s. The larger length decreases the performance of emotion recognition.

In recent neuroscience studies, it is highlighted that emotional responsiveness of individuals can be clinical support in not only rare disease so called pre-symptomatic Huntington's disease [68] but also several important and widespread psychiatric conditions such as unipolar depression [69], Parkinson's disease with lack of dementia [46] and autism spectrum [70] as well as amygdalar lesions [71]. Full-band PSTMCs can be proposed as single-channel emotion recognition system. In order to increase the performance, phase domain two-channel connectivity features extracted by using PLV can be combined emotional complexity features estimated by using PSTMCs.

## Conflict of Interest

The author declares that she has no conflict of interest.

## References

[1] Cunningham, W.A., Kirkland, T. (2012). Emotion, Cognition, and the Classical Elements of Mind, *Emotion Review*, **4(4)**:369-370.

[2] Eckman, P. (1999). Basic emotions. In: T. Dalgleish, M. Power (Eds.), *Handbook of Cognition and Emotion*. John Wiley & Sons, Ltd., Sussex, U.K.

[3] Cannon, W.B. (1931). Again the James-Lange and the thalamic theories of emotion. *Psychological Review*, *38(4)*:281-295.

[4] Dan Glauser, E.S., Scherer, K.R. (2008). Neuronal processes involved in subjective feeling emergence, oscillatory activity during an emotional monitoring task, *Brain Topography*, **20**:224–231.

[5] Grandjean, D., Scherer, K.R. (2008). Unpacking the cognitive architecture of emotion processes, *Emotion*, **8**:341–351.

[6] Mulligan, K., Scherer, K.R. (2012). Toward a Working Definition of Emotion, *Emotion Review*, **4(4)**:345-357.

[7] Addington, J., Saeedi, H. (2006). Facial affect recognition, A mediator between cognitive and social functioning in psychosis?, *Schizophrenia Research*, **85(1-3)**:142-150.

[8] Catalan, A., Artaza, M.G., et al. (2016). Differences in facial emotion recognition between first episode psychosis, Borderline Personality Disorder and Healthy Controls, *PLoS One*, **11(7)**, e0160056.

[9] Leleu, A., Dzhelyova, M., et al. (2018). Tuning functions for automatic detection of brief changes of facial expression in the human brain, *NeuroImage*, **179**:235-251.

[10] Schaan, L., Schulz, A., et al. (2019). Interoceptive accuracy, emotion recognition, and emotion regulation in preschool children, *Int. J. of Psychophysiology*, **138**:47-56.

[11] Airdrie, J.N., Langley, K., et al. (2018). Facial emotion recognition and eye gaze in Attention-Deficit/Hyperactivity Disorder with and without comorbid conduct disorder, *Journal of the American Academy of Child and Adolescent Psychiatry*, **57(8)**:561-570.

[12] Reind, V., Gerloff, C., et al. (2018). Brain-to-brain synchrony in parent-child dyads and the relationship with emotion regulation revealed by fNIRS-based hyperscanning, *Neuroimage*, **178**:493-502.

[13] Williams, L.M., Das, P. et al. (2005). BOLD, sweat and fears: fMRI and skin conductance distinguish facial fear signals, *Neuroreport*, **16**:9–45.

[14] Nummenmaa, L.S., (2019). Emotions as discrete patterns of systemic activity, *Neuroscience Letters*, **693**:3-8.

[15] Christiansen, H., Hirsch, O., et al. (2019). Attention-Deficit/Hyperactivity Disorder (ADHD) and Emotion Regulation Over the Life Span, *Current Psychiatry Reports*, **21**:17.

[16] Fernández, R.M., Kibleur, A., et al. (2018). Different effects of levodopa and subthalamic stimulation on emotional conflict in Parkinson's disease, *Human Brain Mapping*, **39**:5014–5027.

[17] Kinneya, K.L., Burkhouseb, K.L., et al. (2019.) Self-report and neurophysiological indicators of emotion processing and regulation in social anxiety disorder, *Biological Psychology*, **142**:126-131.

[18] Aydın, S., et al. (2018). Cortical correlations in wavelet domain for estimation of emotional dysfunctions, *Neural Comput & Applic.*, **30**: 1085–1094

[19] Yang, Y.X., Gao, Z.K., et al. (2018). A recurrence quantification analysis-based channel frequency convolutional neural network for emotion recognition from EEG,*Chaos*, **28**:085724.

[20] Vergallito, A., Riva, P., et al. (2019). Modulation of negative emotions through anodal tDCS over the right ventrolateral prefrontal cortex, *Neuropsychologia*, **119**:128-135.

[21] Linhartova, P., Latalova, A., et al. (2019). fMRI neurofeedback in emotion regulation, A literature review, *NeuroImage*, **193**:75-92.

[22] Aydın, S., et al. (2016). Emotion recognition with eigen features of frequency band activities embedded in induced brain oscillations mediated by affective pictures, *International Journal of Neural Systems*, **26(3)**:1650013 (16 pages).

[23] Aydın, S., et al. (2018). Comparison of hemispheric asymmetry measurements for emotional recordings from controls, *Neural Comput & Applic.*, **30**:341–1351.

[24] Chen, D., Wu, J.(2018). Negative association between resilience and event-related potentials evoked by negative emotion, *Scientific Reports*, **8**:7149.

[25] Bondy, E., Stewart, J.G., et al. (2018). Emotion processing in female youth, Testing the stability of the late positive potential, *Psychophysiology*, **55(2)**:10.1111/psyp.12977.

[26] Padial, E.R., Ibanez-Molina, A.J. (2018). Fractal dimension of EEG signals and heart dynamics in discrete emotional states, *Biological Psychology*, **137**:42–48.

[27] Babiloni, C., Vecchio, F., et al. (2010). Cortical responses to consciousness of schematic emotional facial expressions, A high-resolution EEG study, *Human Brain Mapping*, **31**:1556–1569.

[28] Zinchenko, A., Kanske, P., et al. (2015). Emotion and goal-directed behavior, ERP evidence on cognitive and emotional conflict, *Social Cognitive and Affective Neuroscience*, 1577–1587.

[29] Gerdes, A.B.M., Antje, B.M., et al. (2013). Emotional sounds modulate early neural processing of emotional pictures, *Frontiers in Psychology*, **4(741)**:10.3389/fpsyg.2013.00741.

[30] Ho, H.T., Schroeger, E., Kotz, S.A. (2015). Selective Attention Modulates Early Human Evoked Potentials during Emotional Face-Voice Processing, *Journal of Cognitive Neuroscience*, **27(4)**:798-818.

[31] Kokinous, J., Kotz, S.A., et al. (2015). The role of emotion in dynamic audiovisual integration of faces and voices, *Social Cognitive and Affective Neuroscience*, **10(5)**:713-720.

[32] Schmidt, B., Hanslmayr, S. (2009). Resting frontal EEG alpha-asymmetry predicts the evaluation of affective musical stimuli, *Neuroscience Letters*, **460**:237–240.

[33] Lin, Y.P., Duann, J.R., et al. (2010). Electroencephalographic dynamics of musical emotion perception revealed by independent spectral components, *Neuroimage*, **21**:410–415.

[34] Chang, Y.H., Lee, Y.Y., et al. (2015). Experiencing affective music in eyes-closed and eyes-open states: an electroencephalography study, *Frontiers in Psychology*, **6(1160)**:1-8.

[35] Lee, G., Kwon, M., et al (2014). Emotion recognition based on 3D fuzzy visual and EEG features in movie clips, *Neurocomputing*, **144**:560-568.

[36] Aftanas,L.I., Lotova, N.V., et al. (1997). Non-linear analysis of emotion EEG: calculation of Kolmogorov entropy and the principal Lyapunov exponent , *Neuroscience Letters*, **226(1)**:13-16.

[37] Tonoyan, Y., Looney, D., Mandic, D.P., et al. (2016). Discriminating Multiple Emotional States from EEG Using a Data-Adaptive, Multiscale Information-Theoretic Approach, *International Journal of Neural Systems*, **26(2)**:

[38] Zangeneh, S.M., Maghooli, K., et al. (2018). A novel approach to emotion recognition using local subset feature selection and modified Dempster-Shafer theory, *Behav Brain Funct.*, **14(1)**:17.

[39] Sorinas, J., Grima, M.D., Ferrandez, J.M., Fernandez, E. (2019). Identifying Suitable Brain Regions and Trial Size Segmentation for Positive/Negative Emotion Recognition, *International Journal of Neural Systems*, **29(02)**:1850044.

[40] Lee, Y.Y., Hsieh, S. (2014). Classifying Different Emotional States by Means of EEG-Based Functional Connectivity Patterns, *PLOS ONE*, **9(4)**:e95415.

[41] Li, Y.J., Cao, O. (2015). Abnormal functional connectivity of EEG gamma band in patients with depression during emotional face processing, *Clinical Neurophysiology*, **126(11)**:2078-2089.

[42] Shahabi, H. Moghimi, S. (2016). Toward automatic detection of brain responses to emotional music through analysis of EEG effective connectivity, *Computers in Human Behavior*, **58**:231-239.

[43] Yuvaraj, R., Murugappan, M., et al. (2014). Emotion classification in Parkinson's disease by higher-order spectra and power spectrum features using EEG signals, A comparative study, *Journal of Integrative Neuroscience*, **1381)**:89-120.

[44] Zheng, W.L., Lu, B.L. (2015). Investigating critical frequency bands and channels for EEG based emotion recognition with deep neural networks, *IEEE Trans on Autonomous Mental Development*, **7**(3), 162-175.

[45] Hettich, D.T., Bolinger, E., et al. (2016). EEG responses to auditory stimuli for automatic affect recognition, *Front Neuroscience*, **10**:244.

[46] Yuvaraj, R., Murugappan, M., et al. (2016). Brain functional connectivity patterns for emotional state classification in Parkinson's disease patients without dementia, *Behavioural Brain Research*, **298**:248-260.

[47] Mohammadi, Z., Frounchi, J., Amiri, M. (2017). Wavelet-based emotion recognition system using EEG signal, *Neural Computing & Applications*, **28(8)**:1985-1990.

[48] Williams, G. (1997). Chaos Theory Tamed, Josheph Henery Press, Washington, D.C.

[49] Plichta, M.M., Gerdes, A.B.M. (2011). Auditory cortex activation is modulated by emotion, A functional near-infrared spectroscopy (fNIRS) study, *NeuroImage*, **55(3)**:1200-1207.

[50] Lin, G., Yunli, C., et al. (2019). Probing prefrontal cortex hemodynamic alterations during facial emotion recognition for major depression disorder through functional near-infrared spectroscopy, *J. of Neural Engineering*, **16(2)**:026026.

[51] Brown, S.S.G., Heather, C.W., et al. (2019). Decreased functional brain response to emotional arousal and increased psychiatric symptomology in FMR premutation carriers, *Psychiatry Research Neuroimaging*, **285**:9-17.

[52] Zhang, Y., Ji, X.M., et al. (2016). An approach to EEG-based emotion recognition using combined feature extraction method, *Neuroscience Letters*, **633**:152-157.

[53] Gupta, R., Laghari, K.U.R., Falk, T.H. (2016). Relevance vector classifier decision fusion and EEG graph-theoretic features for automatic affective state characterization, *Neurocomputing*, **174**:875-884.

[54] Katsigiannis, S., Ramzan, N. (2018). DREAMER, A Database for emotion recognition through EEG and ECG signals from wireless low-cost off-the-shelf devices, *IEEE J. of Biomed. and Health Informatics*, **22(1)**:98-107.

[55] Gabert-Quillen, C.A., Bartolini, E.E., Abravanel, B.T., Sanislow, C.A. (2015). Ratings for emotion film clips, *Behav. Res. Methods*, **47(3)**:773–787.

[56] Schaefer, A., Nils, F., Sanchez, X., Philippot, P. (2010). Assessing the effectiveness of a large database of emotion-eliciting films, A new tool for emotion researchers, *Cogn. Emotion*, **24(7)**:1153–1172.

[57] Morris, J.D. (1995). Observations, Sam, The self-assessment manikin; an efficient cross-cultural measurement of emotional response, *J. Advertising Res.*, **35(8)**:63–38.

[58] Packard, N.H., Crutchfield, J.P., et al. (1980). Geometry from a time series, *Phys. Rev. Lett.*, **45(9)**:712-715.

[59] Takens, F. (1981). Detecting strange attractors in turbulence, Dyn. Syst. Turbul. Warwick, 381.

[60] Watt, R.C., Hameroff, S.R. (1988). Phase space electroencephalography (EEG), A new mode of intraoperative EEG analysis, *Int. J. of Clinical Monitoring and Computing*, **5**:3-13.

[61] Fanga, Y., Chen, M., Zheng, X. (2015). Extracting features from phase space of EEG signals in brain–computer interfaces, *Neurocomputing*, **151(3)**:1477-1485.

[62] Xing, M., Lee, H., et al. (2019). Altered dynamic electroencephalography connectome phase-space features of emotion regulation in social anxiety, *NeuroImage*, **186**:338-349.
[63] Cao, L. (1997). Practical method for determining the minimum embedding dimension of a scalar time series, *Phys. D Nonlinear Phenom.*, **110(1-2)**:43-50.
[64] Jolliffe, I.T. (2002). Principal Component Analysis. 2nd ed., Springer.
[65] Nolden, S., Rigoulota, S., et al. (2017). Effects of musical expertise on oscillatory brain activity in response to emotional sounds, *Neuropsychologia*, **103**:96–105.
[66] Aydore, S., Pantazis, D., Leahya, R.M. (2013). A note on the Phase Locking Value and its properties, *Neuroimage*, **74**:231–244.
[67] Hochreiter, S., Schmidhuber, J. (1997). Long short-term memory, *Neural computation*, **9(8)**:1735–1780.
[68] Zarotti, N., Simpson, J., et al. (2018). Exploring emotion regulation and emotion recognition in people with presymptomatic Huntington's disease, The role of emotional awareness, *Neuropsychologia*, **112**:1-9.
[69] Koch, K., Stegmaier, S., et al. (2018). Neural correlates of processing emotional prosody in unipolar depression, *Human Brain Mapping*, **39(8)**:3419-3427.
[70] Grabowski, K., Rynkiewicz, A., et al. (2019). Emotional expression in psychiatric conditions, New technology for clinicians, *Psychiatry and Clinical Neurosciences*, **73(2)**:50-62.
[71] Vliet, L.V., Jastorff, J., et al. (2018). Anterior temporal lobectomy impairs neural classification of body emotions in right superior temporal sulcus and reduces emotional enhancement in distributed brain areas without affecting behavioral classification, *The Journal of Neuroscience*, **38(43)**:9263-9274.

**Serap Aydın** She received her B.Sc. degree from the EEE Department of Gazi University, and M.Sc. degree from the Ondokuz Mayıs Unv. Her M.Sc. studies were modeling and simulations in 2-Dimensional discrete-time systems. In 2005, she received her Ph.D. degree from Middle East Technical Unv. in the field of biomedical signal processing and with the focus on healthy electrical brain potentials in response to auditory stimuli. She had the title of Assoc. Prof. Dr. in Engineering Sciences in 2013. Her active research interests are quantitative bio-markers, complexity metrics, coherence analysis, brain connectivity, neuro-muscular synchronization, statistical analysis, neural-networks and neuro-marketing.