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Ruslan Zhulduzbayev

Master's Degree, School of Information Technology and Engineering
r.zhulduzbayev@kbtu.kz, orcid.org/0009-0008-7881-4289
Kazakh-British Technical University, Kazakhstan

Bauyrzhan Zhakenov

Master's Student, School of Information Technology and Engineering
b_zhakenov@kbtu.kz, orcid.org/0009-0006-8845-5991
Kazakh-British Technical University, Kazakhstan

Almira Kustubayeva

PhD, Director, Brain Institute
almkusto@kaznu.kz, orcid.org/0000-0001-6575-6288
Al-Farabi Kazakh National University, Kazakhstan

Altyngul Kamzanova

PhD, Postdoctoral Researcher, Brain Institute
kamzanova.altyngul@kaznu.kz, orcid.org/0000-0002-7097-3460
Al-Farabi Kazakh National University, Kazakhstan

Manzura Zholdassova

PhD, Researcher, Brain Institute
manzur777@gmail.com, orcid.org/0000-0002-8186-9650
Al-Farabi Kazakh National University, Kazakhstan

Diana Arman

PhD, Assistant Professor, School of Information Technology and Engineering
d.arman@kbtu.kz, orcid.org/0000-0003-4259-9296
Kazakh-British Technical University, Kazakhstan

**LYAPUNOV EXPONENT OF EEG SIGNALS AND BRAIN NETWORKS
DURING AN EMOTIONAL CONFLICT TASK.**

Abstract: Electroencephalography (EEG) provides a non-invasive means to investigate the dynamic behavior of the brain through electrical activity. This study uses the largest Lyapunov exponent (LLE) as a nonlinear measure of EEG dynamics, together with standard repeated measures analysis and machine learning classification. We do not argue that LLE is better than conventional linear EEG features, because we did not compare them in this work. This study applies nonlinear dynamic analysis - the Largest Lyapunov Exponent (LLE) - to EEG data recorded during an emotional conflict task in children and young adults. One hundred sixty participants completed the emotional conflict protocol. The aim of the study was to define age and sex differences during emotional conflict task performance in Lyapunov exponent of EEG signal. EEG were recorded as participants performed task with viewing facial expressions and hearing auditory words corresponding to four emotions: angry, sad, happy and fearful. EEG preprocessing included filtering, artifact removal by using Independent Component Analysis (ICA). Electrodes were grouped into functional brain networks: anterior, posterior, executive, z-network and left and right hemispheres. LLE was calculated for each epoch from broadband data to capture how quickly nearby signal trajectories diverge in reconstructed phase space, and the same was done for alpha and theta as separate nonlinear features. In repeated measures ANOVA, brain network was a significant factor, and network differed with age group and with sex in broadband and alpha. Emotion, age group, and sex did not show significant main effects on LLE after correction where sphericity required it.

Keywords: EEG (Electroencephalography); age; sex; emotion; nonlinear analysis; Lyapunov exponent.

Introduction

Linear spectral measures are widely used to characterize EEG despite its nonstationary structure. Nonlinear indices offer complementary information about local instability in the signal. The largest Lyapunov exponent (LLE) quantifies the average divergence of neighbouring trajectories in a reconstructed phase space and is commonly applied to EEG time series [1-2]. In the present study, positive LLE values are interpreted as greater local dynamical instability rather than as evidence of deterministic chaos, whereas near-zero or negative values indicate more constrained dynamics. We did not test whether LLE provides information beyond band power or spectral entropy.

Most studies have focused on resting-state EEG or clinical abnormalities [3] or emotion classification [4], leaving a gap in our understanding of how nonlinear complexity behaves during typical cognitive functions. Emotional processing is one such domain where this question is highly relevant [5]. Emotional stimuli engage multiple cortical systems simultaneously, including frontal, parietal and limbic related regions and involve rapid switching between perception, interpretation and regulation [6-7]. If brain complexity is associated with cognitive flexibility and the ability to adapt, it is reasonable to expect that it would change depending on emotional demands or stages of development.

When decoding was run separately for men and women, the sex difference depended on frequency band. With broadband LLE features, four-way classification was somewhat more accurate in men than in women (30.1% vs. 23.5%). In the alpha band the ranking reversed (27.6% vs. 19.8%, women vs. men).

The sex effect on LLE-based emotion separability is therefore band-specific rather than uniform across the spectrum. Emotion recognition function develops with age. Children able accurately recognize basic emotions in mid-childhood and start to differentiate more complex emotions later to teen age [8]. Those improvements in emotion recognition correlated with development of networks interaction between limbic and cortical regions. Early childhood characterized by bottom-up reaction with strong amygdala engagement and less frontal regulation, while top-down modulation from prefrontal cortex observed with brain development engagement leading to nuanced and contextually appropriate emotion recognition [8]. Additionally, empathy as a capacity to elicit emotions similar to someone's emotional facial expression develops with age and associated with mirror neurons [9-10]. In fact, EEG and neuroimaging studies have consistently demonstrated the involvement of mirror neuron systems in emotional processing [11]. Based on EEG research mirror activity defined by the suppression of the mu rhythm an oscillatory pattern in the 8-13 Hz range from the motor cortex [12]. Mu suppression is not confined to motor imitation. Observing another person's facial expression or gesture can elicit the same pattern.

Most EEG classification pipelines use either raw time series or summary features derived from each epoch. End-to-end models on raw data can perform well, but they often require substantial computation and careful preprocessing. A more common approach is to compute basic descriptors such as average power or band-limited metrics [13] which keeps the analysis tractable but may overlook nonlinear structure in the signal.

Nonlinear approaches are often used when the system may amplify small perturbations, as in neural activity. Entropy, fractal measures, and the LLE are typical EEG descriptors of irregular dynamics that linear spectra do not target directly [1, 14]. Among these, LLE summarizes local trajectory divergence in reconstructed phase space.

In the present study, we focus on LLE. The LLE quantifies the average exponential rate at which nearby trajectories (1) in a reconstructed phase space move apart over time [15], where λ is Lyapunov exponent.

$$\|\delta x(t)\| \approx e^{\lambda t} \|\delta x_0\| \quad (1)$$

Positive LLE estimates indicate faster local divergence of reconstructed trajectories, whereas near-zero or negative values point to more constrained or convergent dynamics. We use these values descriptively and do not treat them as a formal test for deterministic chaos. Nonlinear measures, including the largest Lyapunov exponent, have been used to characterize sleep EEG and sleep staging [16], seizure-related EEG [3], and clinical contrast groups [14, 17], and later to brain-computer interface (BCI) decoding with strong performance in some reports [18]. Here we ask how LLE differs across broadband, alpha, and theta recordings during an emotional conflict task, and whether it varies with facial emotion, scalp network, age, and sex. We expected band and network to matter most, with possible but weaker effects of emotion, age, and sex on epoch-wise LLE.

Methods and Materials

160 children and young adults took part in the study. One hundred fifty-three entered the mixed ANOVA because sex and age group were known and enough trials remained after quality control. This group included sixty-one participants from 7 to 12 years, fifty-two from 13 to 17 years, and forty from 18 to 20 years. Seven others were dropped for missing demographics or too few usable epochs. Machine learning at the participant level used one hundred fifty-two records with single-band features and one hundred fifty with complete broadband, alpha, and theta fusion. In the ANOVA sample, [X] were female and [Y] were male.

EEG data were conducted at the Brain Institute of the Farabi University. It was recorded with the use of the eegmylab system and a cap equipped with 64 electrodes. The cap was fitted onto the participant's head and an adhesive gel, commonly used in clinical electrophysiological studies, was applied to improve electrode contact and reduce impedance. The initial sampling rate was set at 4 000Hz, during preprocessing were resampled to 512 Hz. Before the main EEG recording, baseline activity was registered when participants sat quietly with closed eyes, followed by two minutes with their eyes open.

Behavioral tasks for emotion recognition, such as facial expression recognition tasks are widely used in psychodiagnostics to assess different aspects of emotional and social functioning. These tasks allow researchers to assess how accurately a person perceives and recognizes emotional facial expressions. That capacity is relevant to social interaction and to broader accounts of emotional intelligence.

Behavior task

In the present experiment, the behavioral task was run in a separate room under artificial lighting at 200 watts. Participants sat about one meter from the screen. The emotion conflict recognition task was delivered with E-Prime 2 [19] while EEG was recorded at the same time. Instructions and stimuli were presented in sequence.

Stimuli came from the Databrary emotions dataset, with permission [20]. Each trial showed a black-and-white face with one of four expressions, happiness, sadness, fear, or anger. A spoken emotion label was played together with the image. On congruent trials the word matched the face. On incongruent trials it did not. Participants judged whether the audio and the image agreed, as quickly and accurately as possible. Written instructions appeared on screen before the task began. A fixation cross was shown for three seconds between trials.

If the emotion on the face matched the spoken word, participants pressed the 1 key. If the auditory stimulus did not match the visual stimulus, they were instructed to press the "2" button. Both reaction time and accuracy were measured (reaction time was observed indirectly). The goal was to provide fast and correct evaluations of the stimulus congruence.

Before beginning the main task, participants completed a practice task, during which they were familiarized with the task instructions. The practice phase lasted two minutes and aimed to teach participants how to distinguish between target and non-target stimuli, respond using the computer mouse and interpret the cues presented before each stimulus.

The experimental part of the task comprised four blocks of 60 stimuli each, 240 trials in total. Stimuli were shown in random order. The fourth block contained only incongruent trials. The experimental phase lasted about 20 minutes.

EEG preprocessing

Raw EEG data were preprocessed in EEGLAB [21] using MATLAB 2021b [22]. The aim was to remove artifacts and prepare the signals for analysis. Several filters were applied. To retain the full signal content, data were first filtered from 0.3 to 40 Hz. LLE was computed on this broadband dataset to capture nonlinear dynamics across the full band. Separate filters were then used for the alpha band from 8 to 13 Hz and the theta band from 4 to 8 Hz. Those band-limited datasets were used to examine oscillatory activity related to cognitive and emotional processing.

Independent component analysis (ICA) was performed to correct for remaining artifacts, such as eye movements, eye blinks and cardiac activity. ICA works by decomposing the EEG signals into statistically independent components based on the assumption that the observed EEG signals are linear mixtures of independent neural and non-neural sources. Components representing artifacts were identified based on their characteristic spatial topographies and time courses and were removed before reconstructing the cleaned EEG signals. This step allowed for the separation of brain-related activity from typical non-brain artifacts without the loss of important neural information.

In the ICA model, X is the matrix of recorded EEG signals from all electrodes, A is the unknown mixing matrix that linearly combines the underlying sources into each channel, and S is the matrix of those independent source signals. The goal of ICA is to estimate a matrix W ($\approx A^{-1}$), and then recognize the original sources (2) from EEG recordings.

$$S \approx WX \quad (2)$$

Then we divide the components by inspecting their scalp topographies and statistical properties. After marking artifactual components, we set their corresponding rows in S (3) to zero and reconstruct the cleaned EEG.

$$X_{clean} = A_{clean} S_{clean} \quad (3)$$

Continuous EEG was segmented into epochs time-locked to stimulus onset. Each epoch started 200 ms before onset and ended 800 ms after onset. The full window was 1000 ms.

Epochs were screened for contamination. Segments with large muscle or movement artifacts were inspected visually and removed by hand. Epochs with clean neural activity were kept for further analysis.

LLE analysis

LLE was estimated separately for every channel and epoch using the Rosenstein algorithm [15] as implemented in TISEAN 3.0.0 lyap_r from MATLAB R2021b. The method follows mean logarithmic divergence between neighbouring trajectories in a time-delay embedding and is commonly used for short noisy biological records.

Each one-second epoch at 512 Hz was embedded with dimension $m = 4$ and delay $\tau = 7$ samples, about 13.7 ms. The same TISEAN settings were applied throughout, including $m4$, $d7$, $s300$, $r0.50$, and $c1$, with the default temporal-neighbour exclusion of zero samples. Up to 300 divergence steps were evaluated, and λ was taken as the least-squares slope of the first 25 steps via MATLAB polyfit. Stored values are in inverse-sample units and can be scaled to s^{-1} by multiplying by 512 Hz.

Broadband, alpha from 8 to 13 Hz, and theta from 4 to 8 Hz were processed with this fixed pipeline. Theta epochs contain only about four to eight cycles per second, so theta LLE should be read with that limitation in mind. One LLE per channel per epoch entered all network summaries,

ANOVA models, and classifiers. Embedding choices were not tuned per subject, and surrogate controls were not run in the primary analysis.

$$X(i) = [x(i), x(i + \tau), \dots, x(i + (m - 1)\tau)] \quad (4)$$

Then compute the average Euclidean separation $d(j)$ between each vector and its nearest neighbor over subsequent sample steps j (5).

$$d(j) = \frac{1}{M} \sum_{i=1}^M \|X(i + j) - X_{NN}(i + j)\| \quad (5)$$

The mean distance between neighbouring trajectories is log-transformed and plotted across the early portion of the one-second window, as in equation 6. The largest Lyapunov exponent is obtained from the slope of the linear segment, here fit across the first 25 divergence steps. Positive slopes indicate faster local separation within the epoch and are not interpreted as proof of deterministic chaos.

$$\lambda_{max} \approx \frac{1}{\Delta t} \frac{d}{dj} \langle \ln d(j) \rangle \quad (6)$$

After LLE was obtained for each epoch and channel, cases were organized for statistics. Sex and age were included as grouping variables. The sample comprised 61 children aged 7 to 12 years, 52 adolescents aged 13 to 17 years, and 40 young adults aged 18 to 20 years.

Trials were also coded by the face shown, happiness, sadness, fear, or anger. Analyses then compared LLE across these emotion categories.

For spatial summaries, electrodes were assigned to networks [23]. The anterior network combined frontal and central sites associated with executive control, attention, and emotion regulation. The posterior network combined parietal and occipital sites involved in sensory and visual processing. The z network used midline electrodes. The executive network used FCz, Cz, and CPz. LLE was averaged within each network to yield one value per epoch per network.

All mixed repeated-measures ANOVAs were run in JASP [24] with separate models for broadband, alpha from 8 to 13 Hz, and theta from 4 to 8 Hz. Within participants, factors were emotion with angry, sad, happy, and fear levels and network with anterior, posterior, executive, midline, and mean left-right hemisphere composites. Between participants, factors were sex and age group with bands from 7 to 12, 13 to 17, and 18 to 20 years. Anyone missing sex or age group was omitted from between-subject terms. Mauchly's test checked sphericity and Greenhouse Geisser adjusted p values appear when the assumption failed. Partial η^2 reports effect size. Significant network effects were followed with Bonferroni adjusted paired comparisons. The broadband emotion by network by sex by age group interaction was exploratory only and was not broken down further.

Machine Learning Classification

A supervised machine learning analysis complemented the repeated-measures ANOVA. It used per-channel LLE feature tensors built for each epoch. Each case combined one participant, one frequency band, and one task condition. The input vector concatenated LLE across all 64 channels. That yielded a high-dimensional summary of the spatial distribution of nonlinear dynamics in the epoch. Models were run separately for broadband unfiltered data, alpha from 8 to 13 Hz, theta from 4 to 8 Hz, and an early-fusion condition that concatenated all three band vectors into one input.

Five classifiers were compared: L2-regularized logistic regression, a support vector machine with an RBF kernel, Random Forest, CatBoost, and XGBoost. Code was written in Python with scikit-learn and the respective libraries. Hyperparameters were left at defaults unless noted otherwise. Three trial-level targets were defined. Target 1 was an eight-way label crossing

emotion and congruency. Target 2 was four emotion categories, happiness, sadness, fear, anger. Target 3 was binary congruency. Participant-level targets were sex, three age bands from 7 to 12, 13 to 17, and 18 to 20 years, and a binary age split from 7 to 12 versus 13 to 20 years.

Trial-level tables (Tables 1–2) use one row per epoch; Table 3 uses one row per participant, with channel-level LLE features summarized at the participant level for that analysis.

Subject-stratified five-fold GroupKFold cross-validation was used throughout. All trials from one participant stayed on the same side of the split. This prevented identity leakage when one person contributed many epochs. Balanced accuracy was the primary metric. It averages recall across classes and therefore handles imbalance. For binary tasks we also report AUC. Results are summarized as mean $\pm$ standard deviation across folds.

All classifiers used library default hyperparameters and the same participant-stratified five-fold GroupKFold splits. The model labeled best in each table simply had the highest mean balanced accuracy and should not be read as the winner of formal model selection. We did not run subject-level permutation tests against chance, so four-class emotion accuracies only slightly above 25% are reported descriptively and are not claimed as reliable above-chance decoding.

For Target 2 we additionally ran emotion models on congruent trials only and on incongruent trials only. Cross-congruency transfer was tested by training on congruent data and testing on incongruent trials, and the reverse. That checked whether LLE patterns learned in one congruency context generalize to the other.

Ethics

Local Ethics Committee of the Farabi University provided approval to conduct the study. Written informed consent was obtained before beginning from legal guardians for children under 18 years old, and participants older 18 years old.

Results

Networks differences

Mauchly's test showed sphericity violations for network in all three bands, all p below 0.001, with Greenhouse Geisser epsilon from 0.46 to 0.51. Network remained significant after correction in broadband, $F(4, 608) = 50.01$, p_{GG} below 0.001, partial $\eta^2 = 0.25$, in alpha, $F(4, 600) = 29.19$, p_{GG} below 0.001, partial $\eta^2 = 0.16$, and in theta, $F(4, 600) = 9.24$, p_{GG} below 0.001, partial $\eta^2 = 0.06$. Emotion stayed non-significant with all p_{GG} above 0.10 and partial η^2 at most 0.014. Bonferroni follow-ups showed higher broadband LLE in posterior than executive network, p_{bonf} below 0.001, and higher alpha LLE in posterior than anterior and executive networks, p_{bonf} below 0.001. In theta, executive LLE exceeded anterior LLE, p_{bonf} below 0.001.

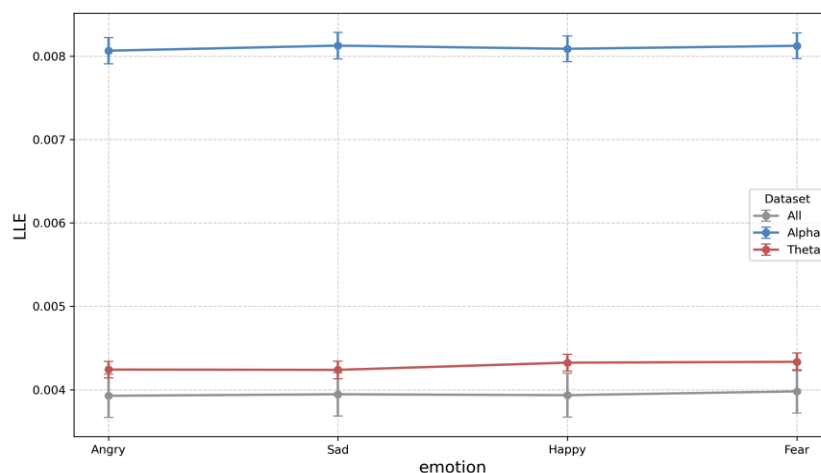


Figure 1. Emotion effects across filtering conditions

The main effect of network was significant, p below 0.01. In unfiltered data LLE was highest in PostNet and RightHem and lowest in ExNet. Broadband signals therefore separated posterior and executive regions, with more complex dynamics posteriorly and lower complexity in the executive network. Alpha filtering increased LLE overall. PostNet again showed the peak. AntNet had the lowest values. Theta filtering produced a different spatial pattern. LLE was similar across most networks but rose sharply in ExNet. That stood in contrast to the low ExNet values seen for broadband and alpha data.

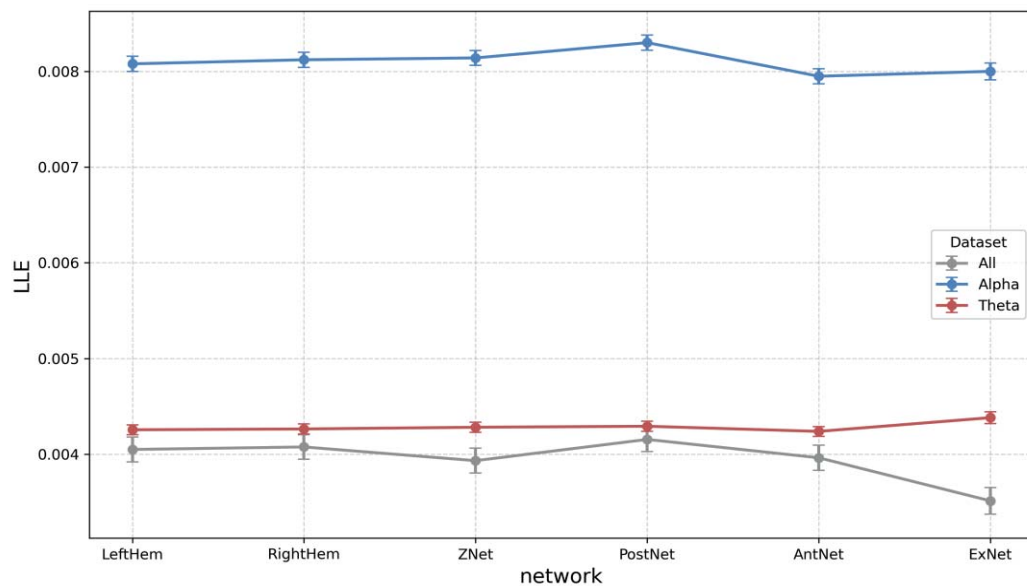


Figure 2. Network effects across filtering conditions

Sex and age did not show significant main effects on LLE under any of the three filtering conditions, p above 0.05. Significant interactions did emerge between sex and network, emotion, and age group.

Significant effects depended on filter band. Theta showed only a main effect of network. Alpha added network by sex, $F(4, 596) = 2.89$, $p = 0.022$, partial $\eta^2 = 0.019$, and network by age group, $F(8, 592) = 2.96$, $p = 0.003$, partial $\eta^2 = 0.039$, alongside the network main effect. Broadband showed the same pattern with network by sex, $F(4, 604) = 4.05$, $p = 0.003$, partial $\eta^2 = 0.026$, and network by age group, $F(8, 600) = 4.45$, p below 0.001, partial $\eta^2 = 0.056$. A four-way emotion by network by sex by age group term reached $p = 0.015$ in JASP while emotion itself was not significant, so we did not decompose that interaction and do not treat it as evidence that valence modulates LLE.

Table 1. Repeated-measures ANOVA results for alpha-band EEG data

Factor	F-value	p-value
Network	29.183	< 0.001
Network * Sex	3.071	0.009
Network * AgeGroup	2.805	0.002

Table 2. Repeated-measures ANOVA results for theta-band EEG data

Factor	F-value	p-value
Network	8.304	< 0.001

Table 3. Repeated-measures ANOVA results for unfiltered EEG data

Factor	F-value	p-value
Network	51.754	< 0.001
Network * Sex	3.575	0.003
Network * AgeGroup	4.084	< 0.001
Emotion * Network * Sex * AgeGroup	1.650	0.015

Age and sex differences

A network effect is visible in Age Groups 2 and 3. LLE is higher in PostNet and lower in AntNet and ExNet, as shown in Figure 3. Age Group 1 is relatively flat across networks. Younger participants show little spatial separation in alpha-band nonlinear dynamics. Older groups show clearer network-specific differences.

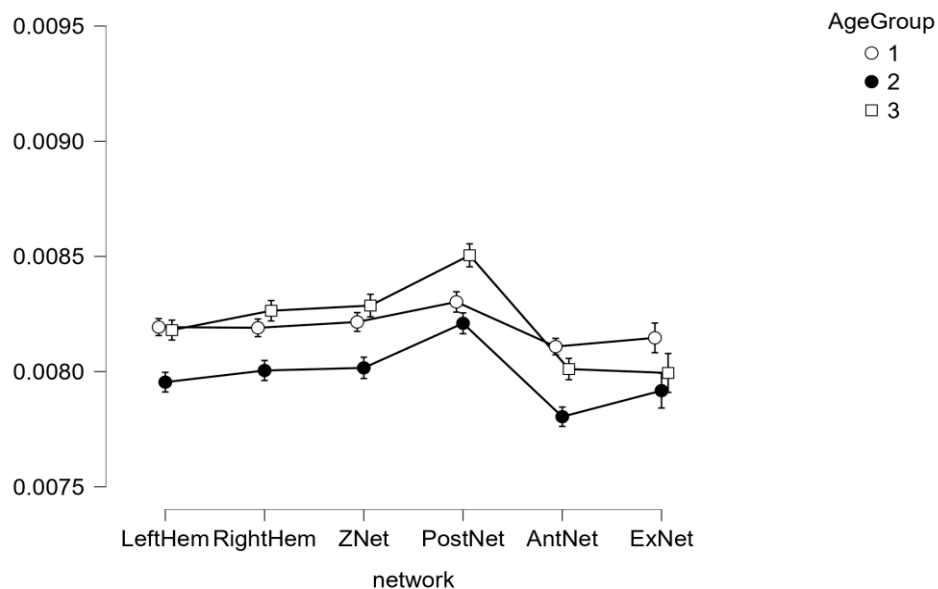


Figure 3. Network by age group interaction in alpha-band EEG

In broadband data for males, Figure 4, Age Groups 2 and 3 both show spatial structure. LLE peaks in PostNet and falls toward ExNet. Group 2 reaches the highest values. Group 3 follows a similar but slightly lower pattern. Group 1 stays flatter, with less spatial structure in younger males.

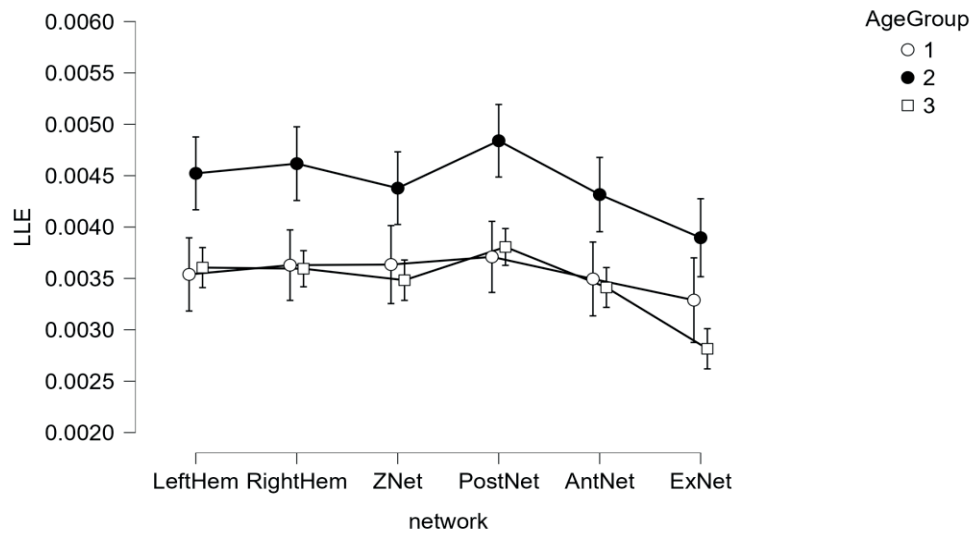


Figure 4. Network $\times$ age group interaction for male participants in unfiltered EEG data

Figure 5 suggests that in females LLE changes little between the middle and older age groups while posterior and executive networks still separate clearly. The youngest group again shows low flat profiles across networks. Nonlinear spatial structure generally increases with age in both sexes. Visual comparison hints those females may keep strong network contrast into adulthood and males may show a peak in adolescence with a slight later decrease. We did not test these sex-specific patterns with a sex by age group by network ANOVA, so they remain tentative.

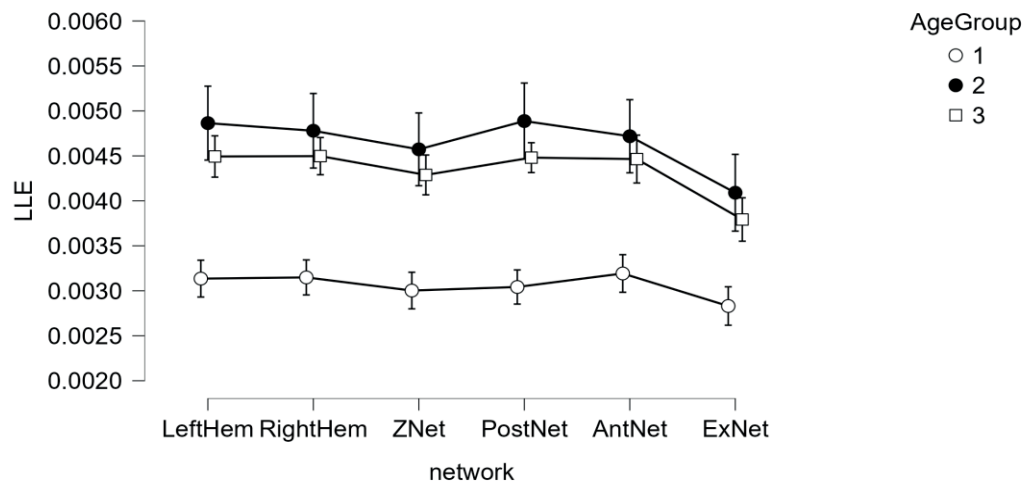


Figure 5. Network $\times$ age group interaction for female participants in unfiltered EEG data

Machine Learning Classification of LLE Features

Supervised classification was added alongside the univariate ANOVA. Each subject-band-condition observation was represented as a vector of per-channel LLE values. Five models were tested. These were L2 logistic regression, RBF support vector machines, Random Forest, CatBoost, and XGBoost. Splits used subject-stratified five-fold GroupKFold so that no participant appeared in both training and test within a fold. Balanced accuracy averaged across folds was the main outcome.

Four-way emotion decoding has a 25% chance level. The highest mean balanced accuracies were 28.9% with broadband features and 31.3% with theta on congruent trials only using the best

support vector machine model. Both figures are only slightly above chance and are not treated as significant emotion decoding because we did not run subject-level permutation tests. Eight-way bins and binary congruency stayed near chance, in line with the non-significant emotion effect in ANOVA. Table 4 gives accuracies by congruency subsample and frequency band.

Table 4. Four-way emotion decoding by congruence subsample (trial-level)

Subsampling	Band	Best classifier	BAC (mean $\pm$ SD)	Chance
Congruent-only	All	RandomForest	0.260 $\pm$ 0.043	25%
Congruent-only	Alpha	LogReg	0.273 $\pm$ 0.041	25%
Congruent-only	Theta	SVM	0.313 $\pm$ 0.024	25%
Incongruent-only	All	RandomForest	0.281 $\pm$ 0.051	25%
Incongruent-only	Alpha	CatBoost	0.247 $\pm$ 0.025	25%
Incongruent-only	Theta	XGBoost	0.257 $\pm$ 0.038	25%

Cross-congruency transfer was weak in both directions, training on congruent and testing on incongruent and the reverse. LLE patterns therefore appear tied to congruency context rather than one shared signal with noise.

Table 5 reports cross-validated balanced accuracy for all three factorial tasks, frequency bands, and classifier types.

Table 5. Factorial classification (trial-level tensors, stratified CV)

Task	K classes	Chance	All (best model)	Alpha (best model)	Theta (best model)
Eight-way factorial bin (T1)	8	12.5%	XGBoost: 0.145 $\pm$ 0.023	LogReg: 0.129 $\pm$ 0.022	XGBoost: 0.153 $\pm$ 0.013
Four-way emotion (T2)	4	25.0%	XGBoost: 0.289 $\pm$ 0.018	LogReg: 0.255 $\pm$ 0.014	LogReg: 0.279 $\pm$ 0.013
Binary congruency (T3)	2	50.0%	LogReg: 0.504 $\pm$ 0.037	LogReg: 0.523 $\pm$ 0.031	SVM: 0.519 $\pm$ 0.020

Demographic decoding was modest overall. Sex from broadband LLE reached about 0.59 to 0.61 balanced accuracy with ensemble methods, slightly above the 0.50 baseline. Three age categories were classified at roughly 0.48 balanced accuracy. The strongest demographic signal was a binary age split between children from 7 to 12 years and everyone from 13 to 20. Early fusion of all three bands with random forest yielded about 73% balanced accuracy and ROC-AUC near 0.80 under five-fold cross-validation stratified by participant, which indicates that multichannel LLE layouts differ between these age bands. We did not include band power or spectral entropy baselines, so this finding does not speak to LLE versus standard linear features. The roughly 77% figure from the larger sample comes from late probability fusion across models and folds in the one hundred fifty participants with complete broadband, alpha, and theta data, using the same labels as Table 6.

Table 6. Demographic decoding (participant-level)

Feature set	Target	N	Best classifier	BAC (mean $\pm$ SD)	Chance
All	Sex (binary)	152	RandomForest	0.605 $\pm$ 0.090; ROC-AUC 0.662 $\pm$ 0.088	50.0%
All	Age group (3 classes)	152	CatBoost	0.480 $\pm$ 0.074	33.3%
All	Age 7–12 vs 13–20 (binary)	152	XGBoost	0.705 $\pm$ 0.071; ROC-AUC 0.782 $\pm$ 0.050	50.0%
Fusion	Sex (binary)	150	XGBoost	0.566 $\pm$ 0.100; ROC-AUC 0.604 $\pm$ 0.118	50.0%
Fusion	Age group (3 classes)	150	CatBoost	0.466 $\pm$ 0.066	33.3%
Fusion	Age 7–12 vs 13–20 (binary)	150	RandomForest	0.731 $\pm$ 0.052; ROC-AUC 0.801 $\pm$ 0.082	50.0%

Fusion = early concatenation of All + Alpha + Theta (intersection cohort).

Sex-stratified emotion decoding again depended on band. Broadband features favored men in four-way classification, 30.1% versus 23.5% in women. Alpha favored women instead, 27.6% versus 19.8% in men. Sex effects on LLE-based emotion separability therefore differ between broadband and alpha activity.

Discussion

The present study aimed to investigate the nonlinear dynamics of brain activity during an emotion recognition task, using LLE as a measure of EEG signal complexity. By analyzing differences across emotional conditions, age groups, sexes and brain regions, we tried to better understand how emotional processing and developmental factors influence the brain's dynamic organization. To our knowledge, this the first study aimed to find age, sex, and emotional valence differences by calculating LLE of the EEG signal during emotional conflict task. Our hypothesis in relation to differentiation of emotional valence, age, and sex by measuring LLE were partly confirmed. The results showed that the emotional valence of the face expression did not significantly influence LLE values.

LLE values varied between the anterior, posterior, z- and executive networks. The study demonstrates that nonlinear brain dynamics vary systematically across different functional networks, reflecting the underlying roles of these brain regions in cognitive and emotional processing.

LLE of alpha band and broadband EEG identify specificity of age and sex differences depending on networks. In the early childhood, LLE under both broadband and alpha-band EEG showed minimal variability, indicating that nonlinear EEG complexity remains relatively undifferentiated at this early stage of development. Earlier studies link developmental changes in resting EEG and related complexity measures to age [25–26], although tasks and samples differ from our conflict paradigm. Ma et al. [26] studied resting adults, whereas we recorded task-related epochs in children and adolescents and saw clearer network structure in older groups without a

uniform drop in mean LLE across age, so the literature should be read as context rather than a direct prediction.

Sex effects on complexity appear in some reports. Jahromy [27] described higher entropy, Lyapunov, and Hurst estimates in women than men over parietal, frontal, and central sites across several bands. Our broadband models showed network by sex and network by age group interactions but no emotion main effect, and we treat the four-way emotion term as exploratory rather than evidence for valence-specific LLE, in line with variable nonlinear emotion decoding from EEG [28]. The stable ANOVA message is spatial network organization, not emotion category.

The ML analyses are broadly consistent with the ANOVA findings, but also it reveals nuances that univariate means-based tests cannot capture. The near-chance performance on emotion and congruency classification across most band-model combinations corroborates the null effects of emotion in the ANOVA framework. On congruent trials the best theta support vector machine model reached 31.3% balanced accuracy, six points above the 25% chance level for four emotions. Without permutation testing we do not treat that margin as reliable emotion information in LLE. That fits work linking theta to multisensory affect and the higher-order congruency interaction in unfiltered ANOVA. Poor cross-congruency transfer fits the same picture. Patterns trained in one congruency setting do not carry over, so emotion content and stimulus coherence may jointly shape nonlinear dynamics rather than acting as separate add-on effects. Age split into 7 to 12 versus 13 to 20 years decoded at 73 to 77% balanced accuracy with ROC-AUC near 0.80. Full channel covariance carries developmental structure even where age-group means on LLE did not differ in ANOVA. Sex-stratified emotion decoding also differed by band. Men were more decodable in broadband and women in alpha, in line with the Network $\times$ Sex interaction for alpha-filtered data and with reports of sex differences in frontal alpha during affective tasks.

LLE was derived from one-second event-related epochs, so cycle counts were short especially in theta. We therefore read LLE as an index of local trajectory divergence and dynamical instability within each window, not as proof of chaos. No surrogate series were generated in this revision, so we cannot separate nonlinear structure from linear spectral or noise contributions. Inference focused on networks and participant groups under one fixed embedding configuration for everyone.

Conclusion

During fast emotion recognition, trial-wise LLE changed little with the labeled emotion. Network contrasts and network by age group interactions were the clearest outcomes, while age and sex main effects were not significant. The youngest children showed low flat LLE across networks in broadband and alpha, and older participants showed sharper spatial structure, which suggests that network-specific nonlinear organization strengthens with development. Exploratory plots hinted at different sex trajectories, but sex by age group by network models were not run to confirm them.

Supervised models on full-channel LLE tensors rarely decoded emotion above chance, matching ANOVA. Theta on congruent trials reached 31.3% balanced accuracy and is noted only descriptively without permutation support. A children versus older age split decoded near 73 to 77% balanced accuracy with ROC-AUC near 0.80 even though mean LLE by age group did not differ in ANOVA, so that signal lives in multivariate spatial patterns. Band power, spectral entropy, and fused linear features were not benchmarked, and future studies should add those baselines.

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