Multiscale Fractal Analysis on EEG Signals for Music-Induced Emotion Recognition

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Motivation

Affective Analysis:

- Emotion-driven Intelligence is underexplored
- Barriers: subjectivity / annotation / data availability
- Research: Speech, Language, Facial Expressions

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Brain Responses:

- Neural signals (EEG, fMRI) can be objective affective metrics
- Brain Operations and Emotions are highly affected by Music
- **But:** chaotic, nonlinear, fragmented, large amounts of noise
- Fractal Theory and Multifractality for Music and EEG
- Rehabilitative Applications, Decision Making & Human Behavior

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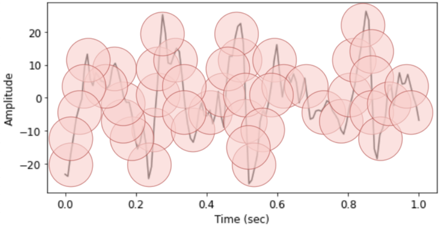
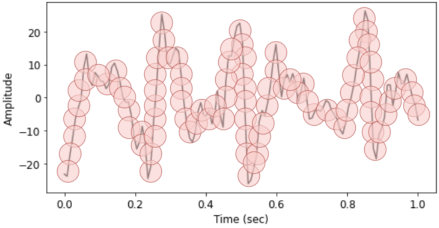
Multiscale Fractal Dimension (MFD)

- Determined by measuring the multiscale length of a curve via morphological coverings (just like the Box-Counting method).
- **Cover**: 2D morphological set dilations of the signal graph F by multiscale versions $sB = \{sb : b \in B\}$ of a unit-scale convex symmetric B. **Cover Area**: $A_B(s) = \mathrm{area}(F \oplus sB)$.





Multiscale Fractal Dimension (MFD)

$$D = \lim_{s \to 0} \frac{\log\left[A_B(s)/s^2\right]}{\log[1/s]}$$

In practice, D can be estimated by a least-squares line to find the slope of $\log\left[A_B(s)\right]$ vs $\log(s)$, assuming the power law $A_B(s) \approx s^{2-D}$ as $s \to 0$.

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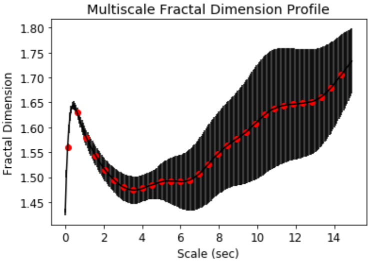
- **Fractogram**: We compute the slope of the data over a small scale window of w scales that move along the scale axis, creating a profile of local MFDs $D(s,t)$, from which D can be estimated:



Multifractal Detrended Fluctuation Analysis (MFDFA)

DFA estimates the Hurst exponent H in time series data $x[n]$ of length N.

- Signal cumulative sum: $y[n] = \sum_{n=1}^{N} (x[n] - \mu_x)$
- divided into non-overlapping windows $y[k,n], k = 1 \ldots N_s$ of length s
- for every window the local trend $r[k,n]$ is linearly obtained
- Detrended kth profile segment: $y_d[k,n] = y[k,n] - r[k,n]$
- RMS of each one is computed and averaged across segments:

$$F(s) = \sqrt{\frac{1}{N_s}\sum_{k=1}^{N_s} F_k^2(s)}, \quad F_k(s) = \sqrt{\frac{1}{s}\sum_{n=1}^{s} y_d[k,n]^2}$$

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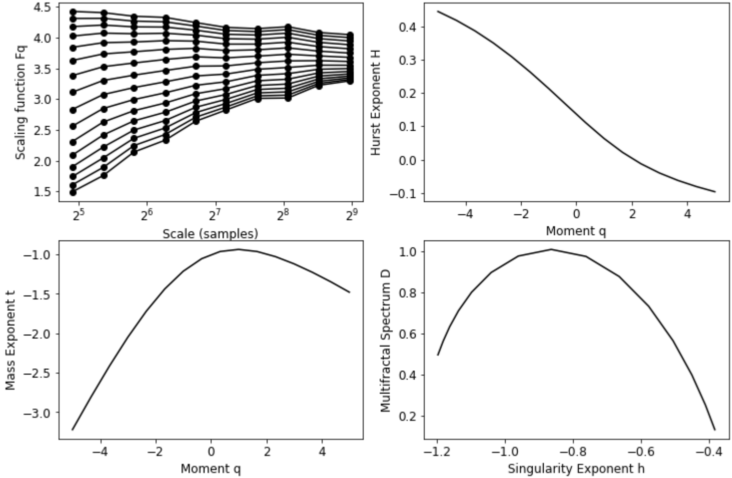
D is obtained by the power law $F(s) \propto s^H$, that determines $H = 2 - D$.
For MFDFA, the computation of $F(s)$ includes q moments.

$$F_q(s) = \sqrt[q]{\frac{1}{N_s} \sum_{k=1}^{N_s} F_k^q(s)}$$

Multifractal Detrended Fluctuation Analysis (MFDFA)

The resulting representation is a set of linear-like graphs of a specific value for each scale. H is determined through linear regression, for each moment.

$$t(q) = qH(q) - 1, \quad D(q) = q' h(q) - t\left(q'\right), \quad h\left(q_n\right) = \frac{t\left(q_n\right) - t\left(q_{n-1}\right)}{q_n - q_{n-1}}$$



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Experimental Setup

The DEAP Dataset: Widely used and competitive

- Preprocessed data from 32 subjects
- Each exposed to 40 1min music videos
- Each annotates their induced emotion
- Valence - Arousal Emotion Space
- EEG given at 128 Hz and 32 electrodes

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Classifier and Sessions: We make use of a single classifier unifying features from all available EEG channels. The model consists of a Standard Scaler and a Support Vector Machine (SVM) with an RBF kernel. Experiments consider valence or arousal in binary format. We perform 5-fold cross validation to compensate for the limited dataset size.

Feature Extraction

Stationarity: Physiological signals like the EEG are widely researched as noisy and non-stationary, due to external stimuli, interfering physiological operations and complex neural assemblies of brain functioning.

- ADF Test: evident strict stationarity, negative correlations
- observed after applying bandpass filtering
- Fractional Gaussian Noise (H close to 0)

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Utilized Features:

- Baselines: EEG Power Spectral Density, Higuchi Fractal Dimension
- **MFD**: 15 sec. windows on each signal. 30 linearly sampled features extracted out of each window's MFD, then summarized using theit mean, median and standard deviation.
- **MFDFA**: 10 scales / 16 moments for half signals, $h(q)$, $D(q)$ features

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Comparison to Baselines

Subject Dependent Task Accuracy in the form: Valence — Arousal

Features	Channels	Raw Signal	Alpha Band	Beta Band	Gamma Band	Combined
PSD	Front Left	**0.642** — 0.652	0.598 — 0.645	0.629 — 0.639	**0.635** — 0.620	0.631 — 0.648
HFD		0.615 — 0.638	0.605 — 0.655	0.591 — 0.643	0.601 — 0.634	**0.638** — 0.645
MFD		0.620 — 0.661	**0.626** — **0.669**	0.591 — **0.653**	0.594 — 0.636	0.612 — **0.661**
MFDFA		0.577 — **0.662**	0.571 — 0.643	0.577 — 0.649	0.592 — **0.651**	0.586 — 0.658
PSD	Front Right	0.627 — 0.644	0.616 — 0.645	**0.637** — 0.641	0.623 — 0.627	0.623 — 0.646
HFD		0.606 — 0.644	0.604 — 0.655	0.595 — 0.633	0.572 — 0.627	0.623 — 0.644
MFD		0.607 — 0.655	0.605 — 0.652	0.566 — 0.652	0.602 — 0.641	0.597 — 0.657
MFDFA		0.587 — 0.655	0.573 — 0.641	0.603 — 0.650	0.573 — 0.620	0.586 — 0.652

Subject Independent Task Accuracy in the form: Valence — Arousal

Features	Channels	Raw Signal	Alpha Band	Beta Band	Gamma Band	Combined
PSD	Front Left	0.554 — 0.569	0.547 — 0.564	0.549 — 0.562	0.553 — 0.570	0.546 — 0.564
HFD		0.541 — 0.601	0.552 — 0.588	0.541 — 0.616	0.545 — 0.584	**0.585** — **0.621**
MFD		0.553 — 0.606	**0.566** — **0.631**	0.545 — **0.618**	**0.554** — 0.580	0.559 — 0.615
MFDFA		**0.569** — **0.630**	0.546 — 0.600	0.545 — 0.598	0.532 — 0.545	0.553 — 0.608
PSD	Front Right	0.553 — 0.580	0.557 — 0.560	**0.558** — 0.573	0.552 — 0.579	0.555 — 0.575
HFD		0.525 — 0.573	0.566 — 0.582	0.544 — 0.595	0.549 — 0.567	0.571 — 0.605
MFD		0.552 — 0.601	0.556 — 0.605	0.547 — 0.587	0.545 — **0.588**	0.560 — 0.607
MFDFA		0.555 — 0.619	0.552 — 0.580	0.549 — 0.591	0.539 — 0.584	0.544 — 0.599

- Raw PSD efficient in the SD setting, drops significantly across subjects.
- Multifractal features more robust across subjects, especially in arousal.
- Raw EEG and the alpha rhythm provide better performance.

Aggregated Features

MFD-HFD AROUSAL ACCURACY

Feat/s	Exp	Raw	Alpha	Beta	Gamma	Comb
Left	Subject	**0.663**	**0.670**	**0.657**	**0.637**	0.656
Right	Dep.	0.654	**0.662**	0.618	0.640	0.655
Left	Subject	**0.613**	**0.641**	0.612	0.580	0.614
Right	Indep.	**0.604**	**0.610**	0.591	0.582	**0.615**

- MFD and HFD provide better arousal scores when combined, mainly α band.
- Single features adequate instead of combined / Left hemisphere preferred
- The differences are significant in the subject independent setting.

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Contributions & Future Work

- We analyzed the structure of EEG signals and demonstrated their multifractal properties (stationarity and fragmentation).
- We developed 2 novel algorithms, based on Multiscale Fractal Dimension and Multifractal Detrended Fluctuation Analysis.
- The proposed methods perform strongly against widely used baseline features, particularly in the SI setting and in arousal recognition.
- Ablation Study: Higher scores are achieved when raw EEG or alpha band signals are considered, especially of the left hemisphere. Also, fractal features perform better when aggregated.
- **Future Work**: feature extraction algorithms for determining asymmetrical multifractal properties, examination of multi-band energy EEG features, obtained through energy separation algorithms.