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Emotions, entropy and the brain: Overview of a research line

Beatriz García-Martínez

Ph.D. Student

Escuela Superior de Ingenieros Industriales de Albacete

Universidad de Castilla-La Mancha (Spain)

Introduction

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- Emotions play a key role in daily experiences and human interaction
- It is necessary to make human-machine interfaces (HMIs) able to properly interpret human emotions
- However, it is not an easy task:
  - No standard definition of emotions
  - High intercorrelation of emotional states
  - Influence of external and subjective factors

Measurement of emotions

- Traditional methods are based on speech and facial expressions analysis
- Many works are based on the assessment of physiological signals:
  - Electrocardiogram (ECG)
  - Electromyogram (EMG)
  - Electro-dermal activity (EDA)
- Electroencephalogram (EEG) signals are especially interesting because they represent the first bodily response against an stimulus

EEG signals

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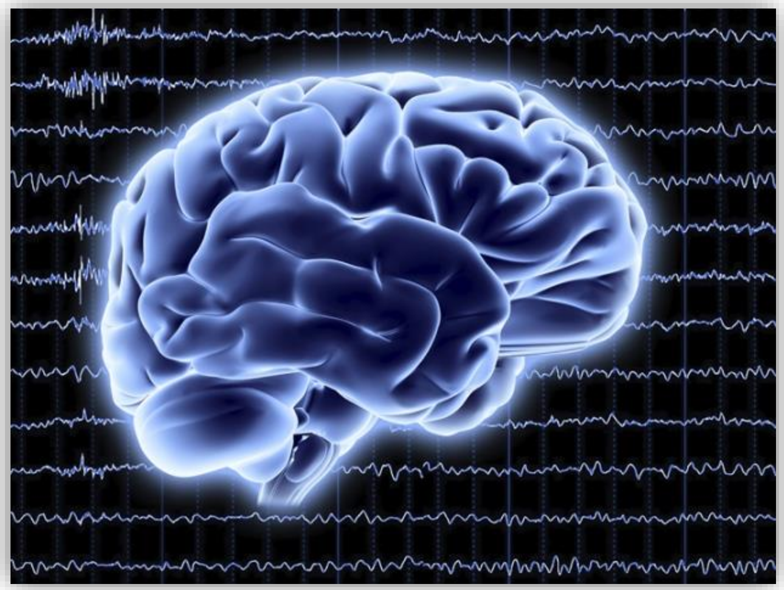
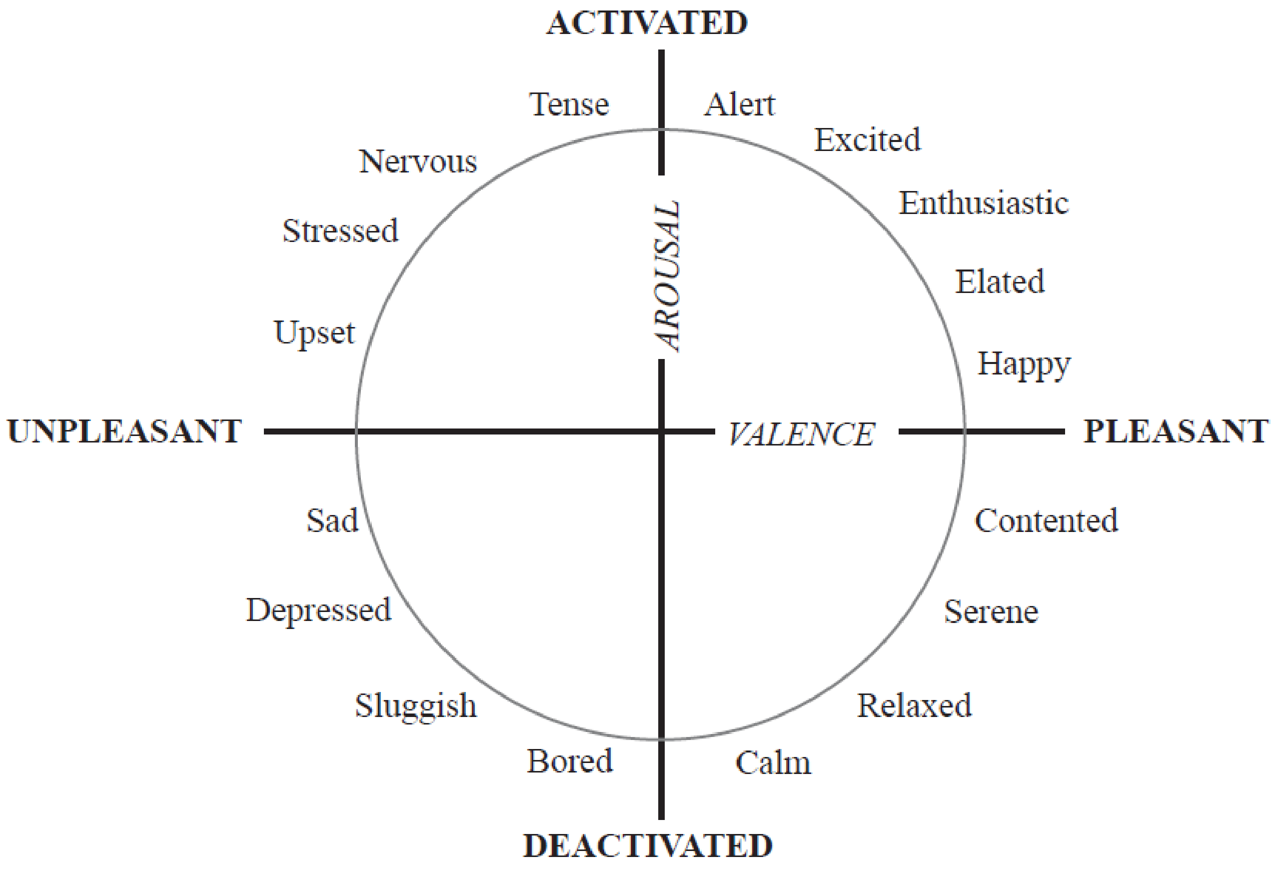
- Traditionally, EEG has been studied with frequency-domain methodologies
- It is known that the brain follows a complex and nonlinear behavior
- Hence, the application of nonlinear techniques could provide more valuable information about brain signals

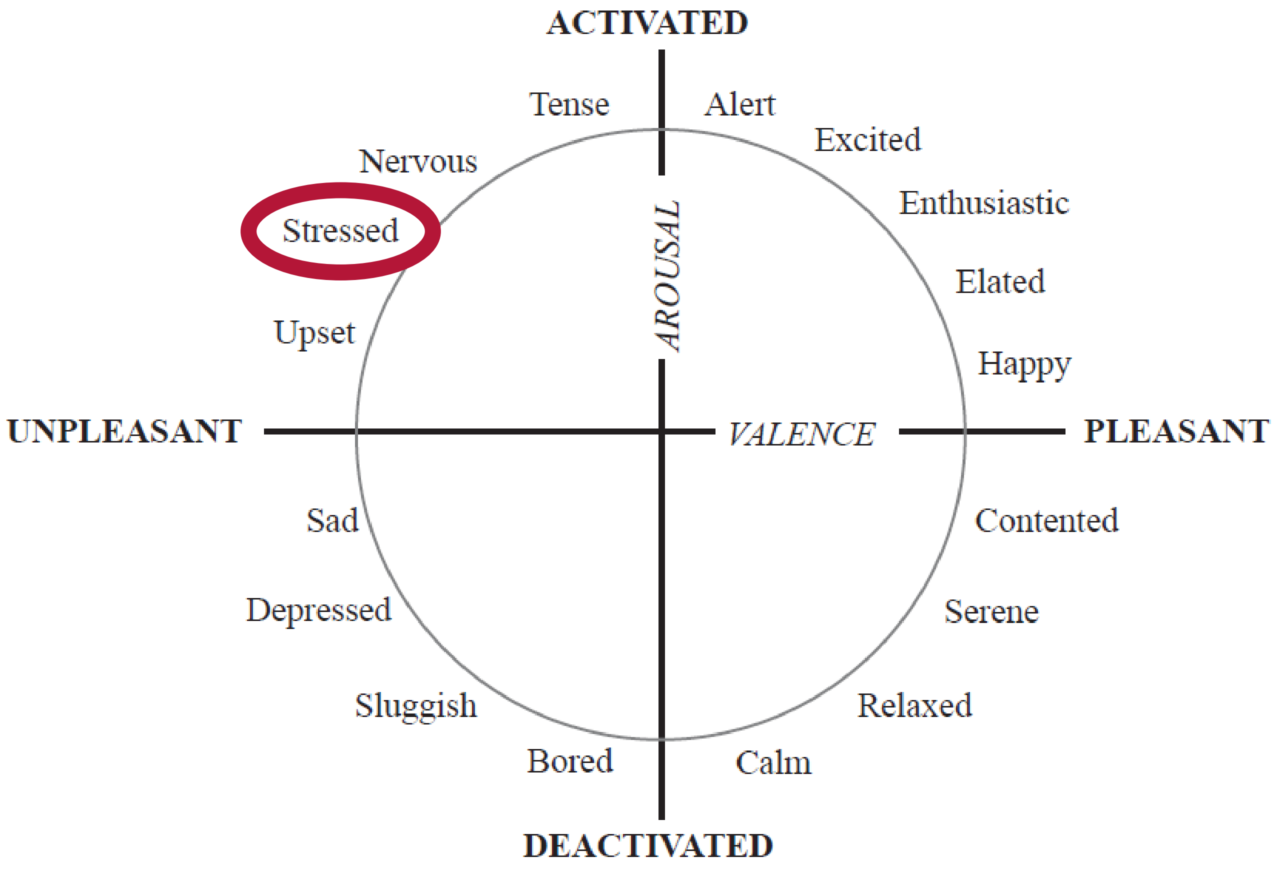


Negative stress (distress)



- Long-term distress conditions can cause different physical and mental disorders
- Due to its negative consequences, distress has become a major problem in developed countries
- Distress and calm are highly correlated and usually studied together

Negative stress (distress)



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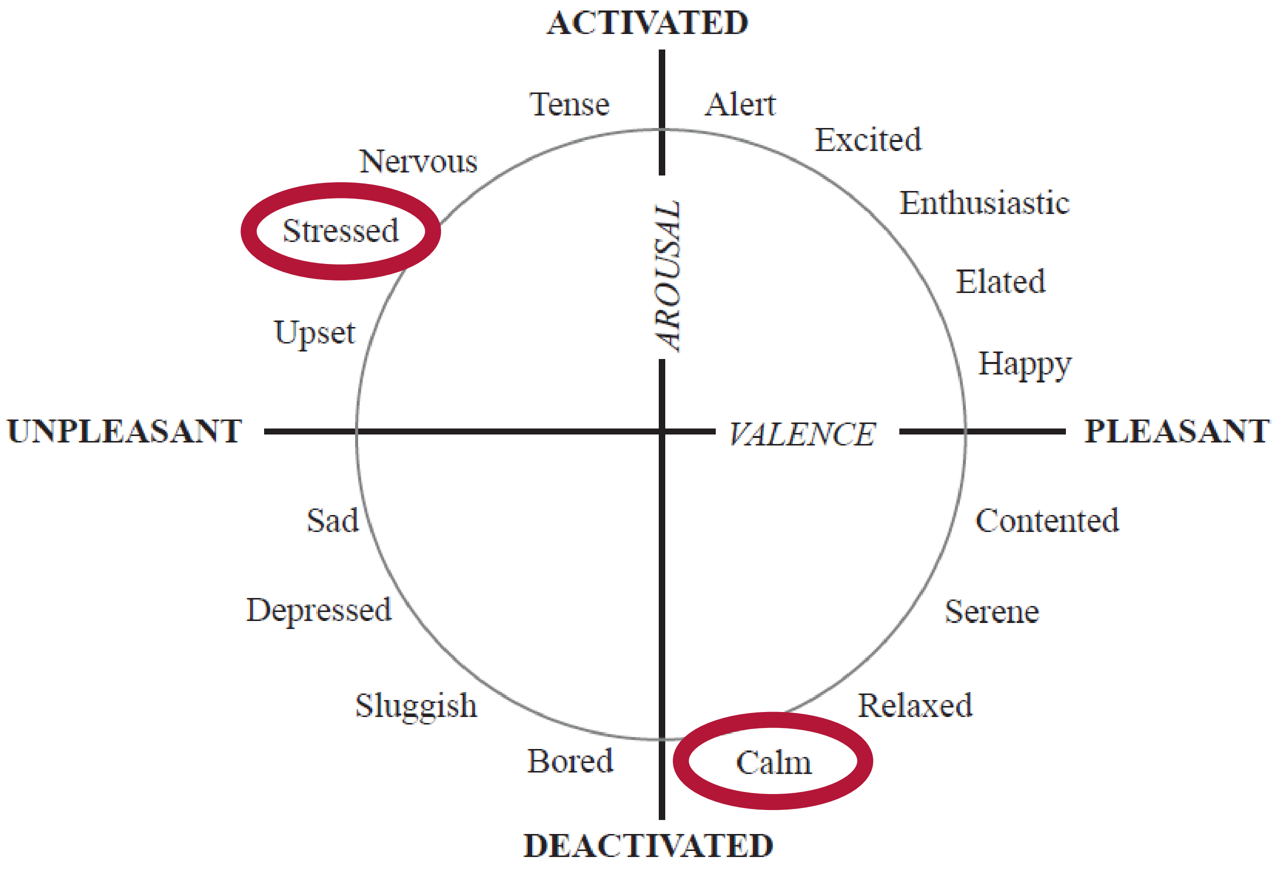

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Our research line

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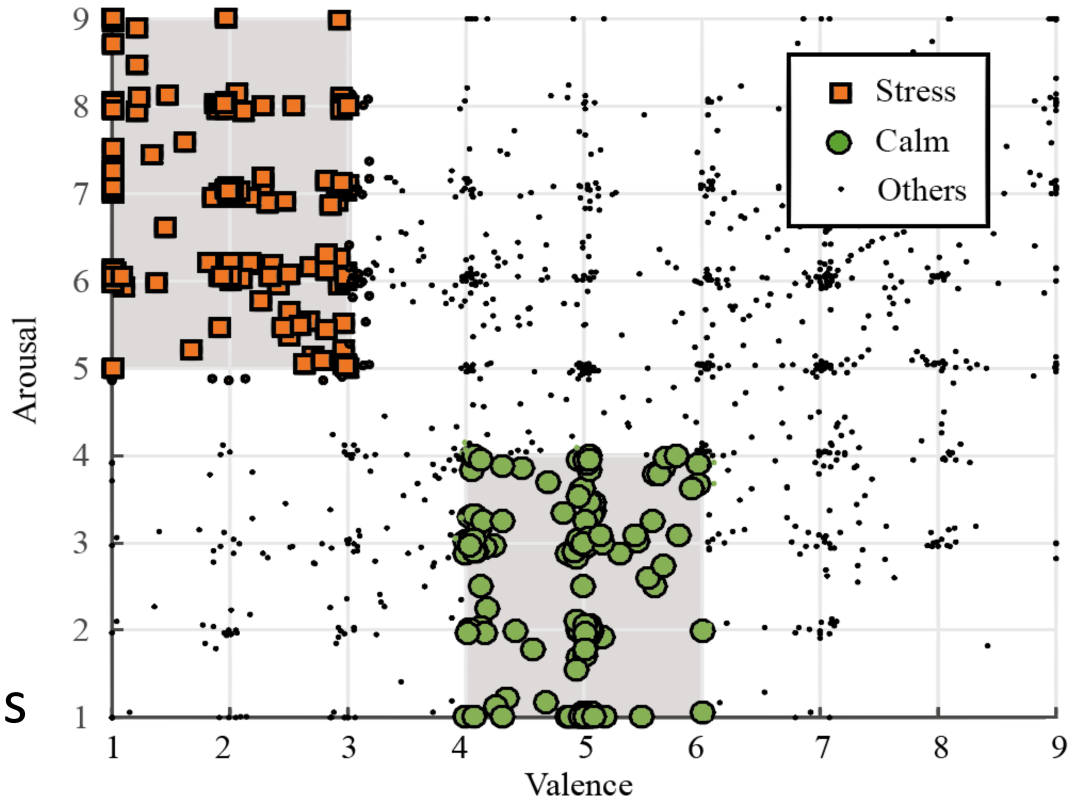
Study of calm and distress from EEG recordings with nonlinear metrics

ENTROPY INDICES
(rate of information given by a time series)

- Regularity
- Predictability
- Multiscale and multilag variants
- Coordination between areas

Database

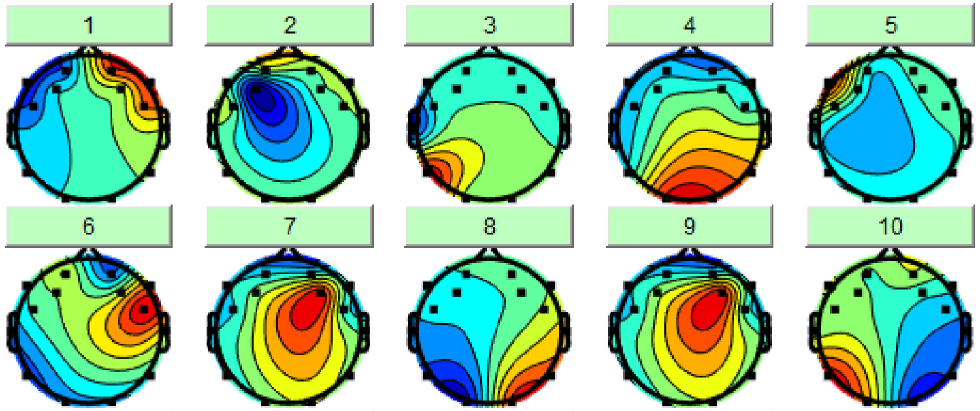
- DEAP: A Database for Emotion Analysis using Physiological Signals
  - 32 subjects
  - 40 emotional videoclips of 1 minute-length
  - EEG + peripheral variables
  - Emotional ratings
- Selection of subsets of calm and distress samples



EEG preprocessing

- EEG recordings require to be preprocessed before further analysis

- Preprocessing procedure - EEGLAB:
  - Downsampling from 512 Hz to 128 Hz
  - Band-pass filter between 3 Hz and 45 Hz
  - Baseline and power line removal



- Artifacts derived from physical and technical sources were removed with an independent component analysis (ICA)

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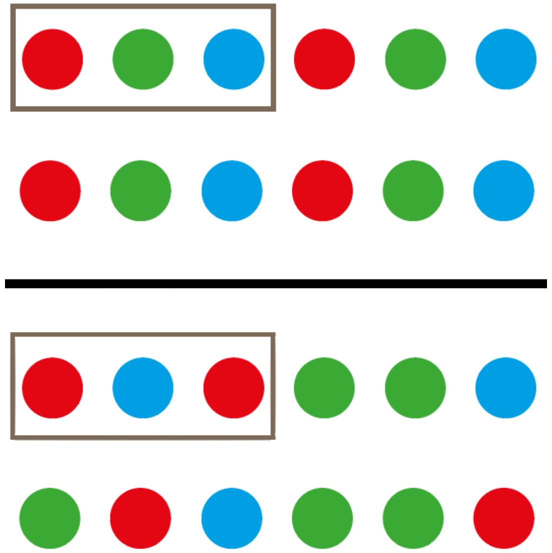
Regularity metrics - QSampEn

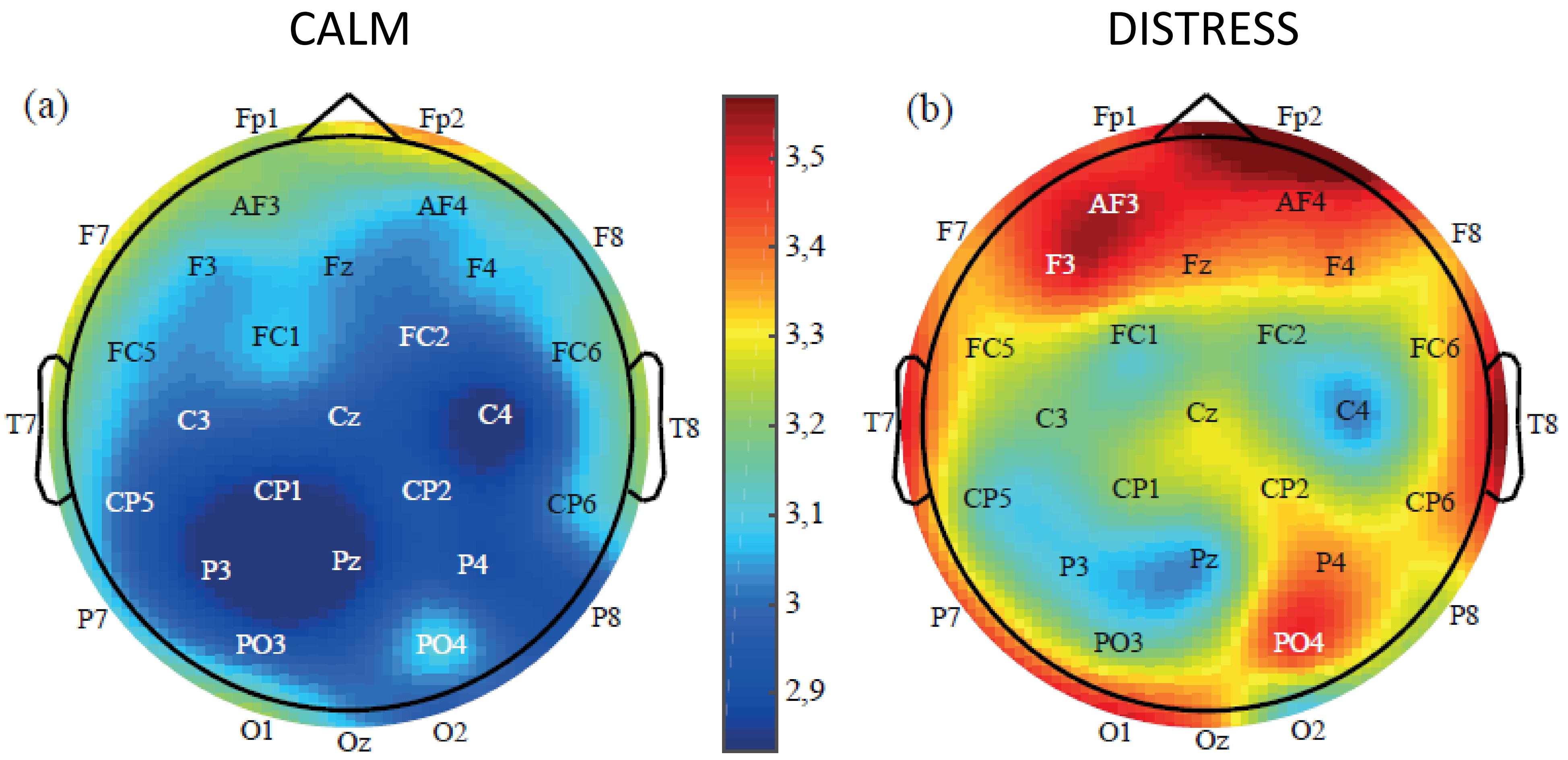
- Irregularity is given by the repetitiveness of sequences
- Quadratic sample entropy (QSampEn) evaluates the probability that two patterns match for *m* and for *m*+1 points within a tolerance *r*
- It is an improvement of sample entropy (SampEn) insensitive to selection of *r*



$$QSampEn(m,r) = -\ln\left(\frac{B^{m+1}(r)}{B^{m}(r)}\right) + \ln(2r)$$

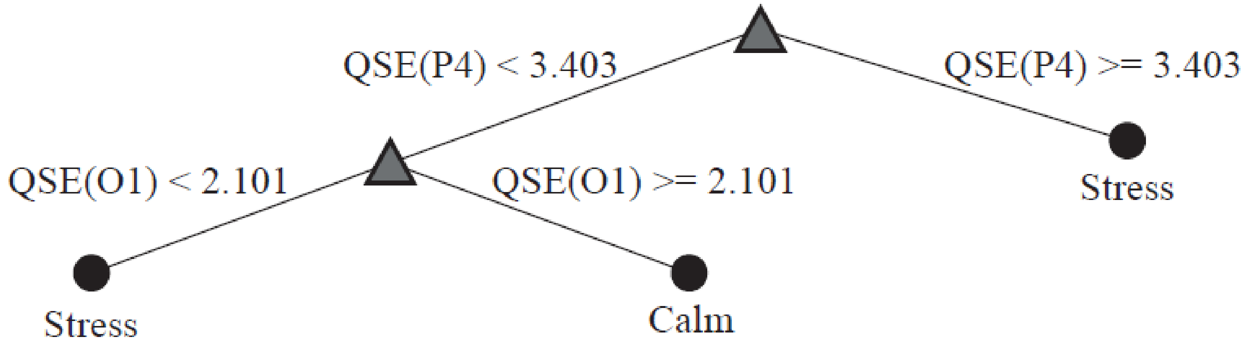
$m = 2$ $r = 0.25*\mathrm{std}$

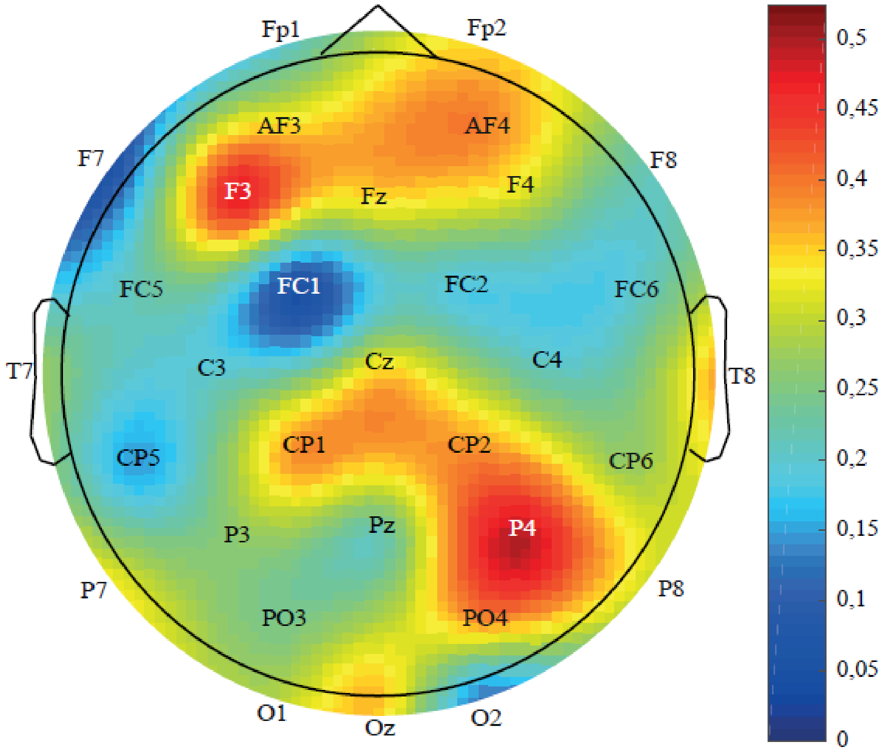
Results QSampEn



Results QSampEn

- ANOVA → **27 / 32** statistically significant EEG channels
- Best results in right parietal and left frontal areas
- Decision tree classifier → **Acc = 75.21%**





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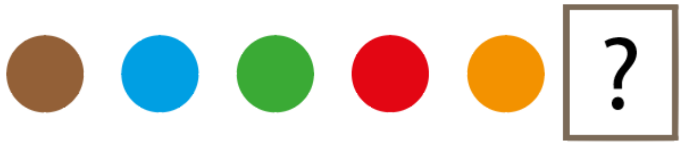
Predictability metrics

- Predictability depends on the deterministic and stable temporal evolution of a nonstationary system



- Predictability is usually assessed by symbolic metrics:
  - Transformation of original signal into sequences of symbols
  - Application of different techniques: Shannon entropy, Rényi entropy…

Predictability metrics – PerEn and AAPE

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- Permutation entropy (PerEn) evaluates the ordinal structure of symbolic patterns
- It evaluates the probability of appearance of symbolic sequences obtained from the original time series

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

- Amplitude-aware permutation entropy (AAPE) also takes into account the amplitudes of the data in a pattern

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

m = 6

Predictability metrics – CEn and CCEn

- Conditional entropy (CEn) is a symbolic representation of the amplitudes of a signal
- It transforms the time series into symbols and analyses their recurrence

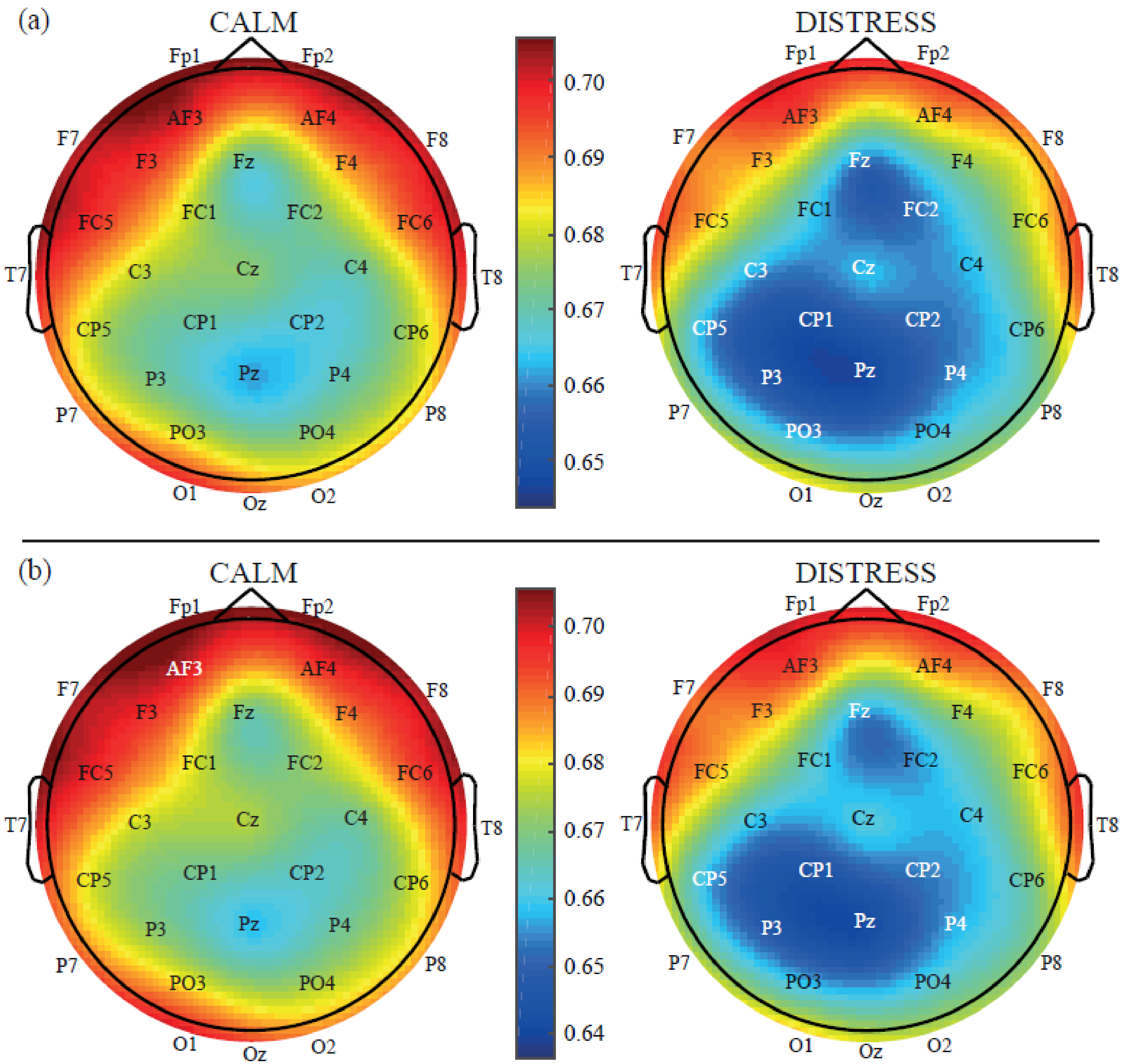
$$CEn(m,\xi) = \sum_{k=1}^{N_{m-1}+1} p(w_{m-1}(k)) \cdot \ln\Big(p\big(w_{m-1}(k)\big)\Big) - \sum_{k=1}^{N_m+1} p(w_m(k)) \cdot \ln\Big(p\big(w_m(k)\big)\Big)$$

- Corrected conditional entropy (CCEn) is insensitive to selection of *m*

$$CCEn(m,\xi) = CEn(m,\xi) + perc(m) \cdot \sum_{k=0}^{\xi-1} p_1(k) \cdot \ln\big(p_1(k)\big)$$

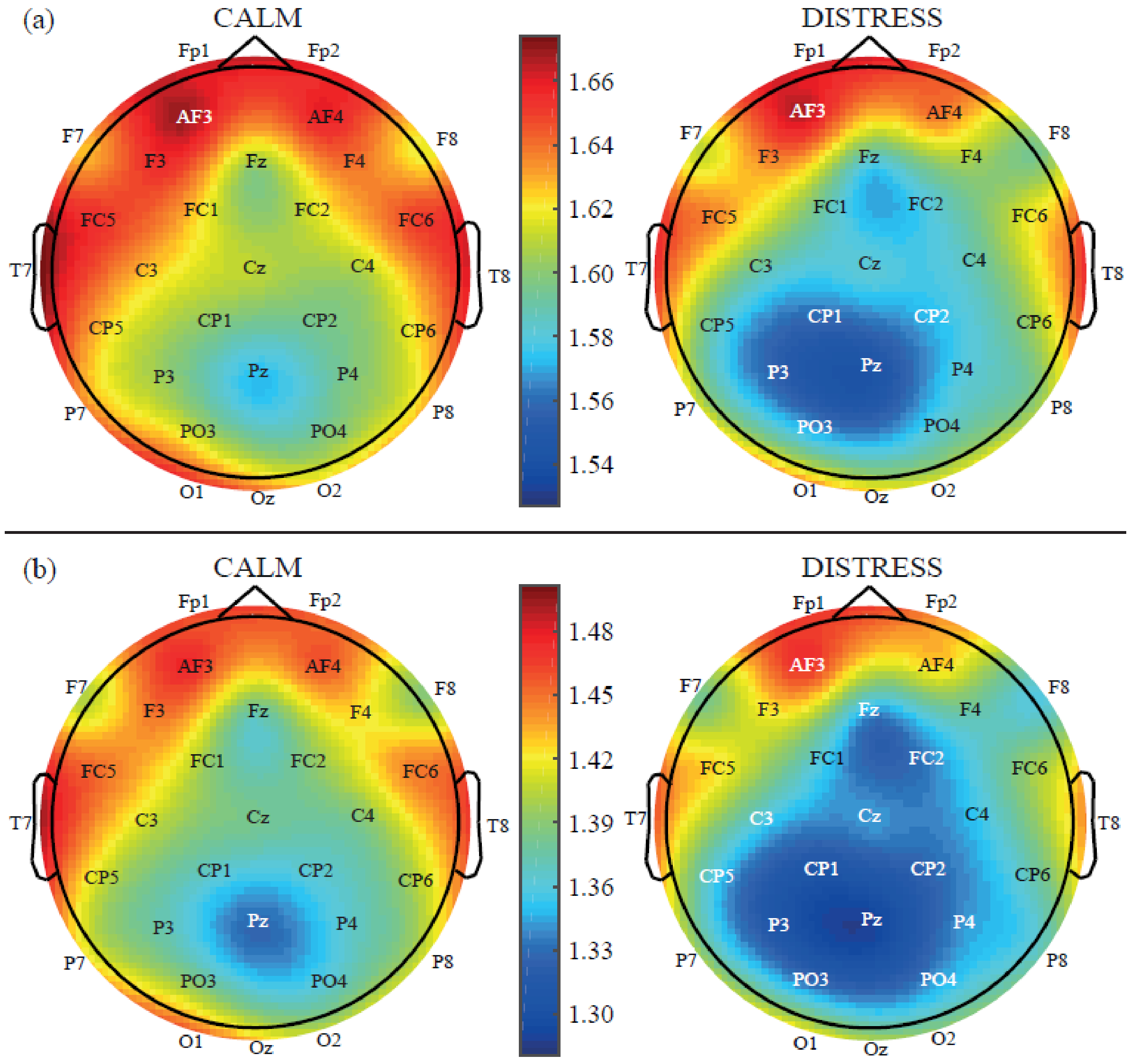
$m = 2 \qquad \xi = 10$

Results PerEn and AAPE



- ANOVA → <u>**21 / 32**</u> statistically significant EEG channels
- Best results in left parietal and right frontal areas
- Higher levels for calm than for distress in all brain regions

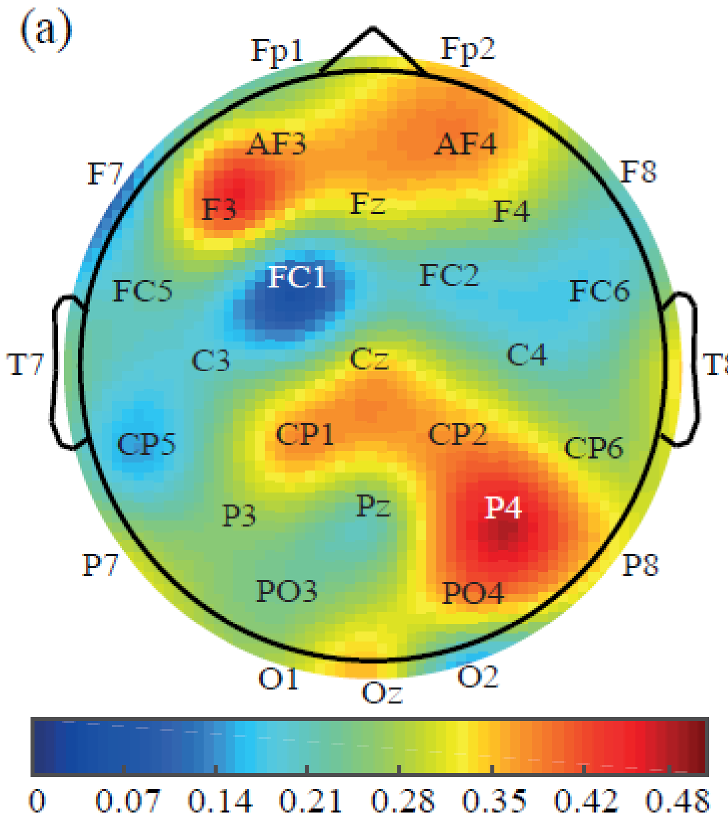
Results CEn and CCEn



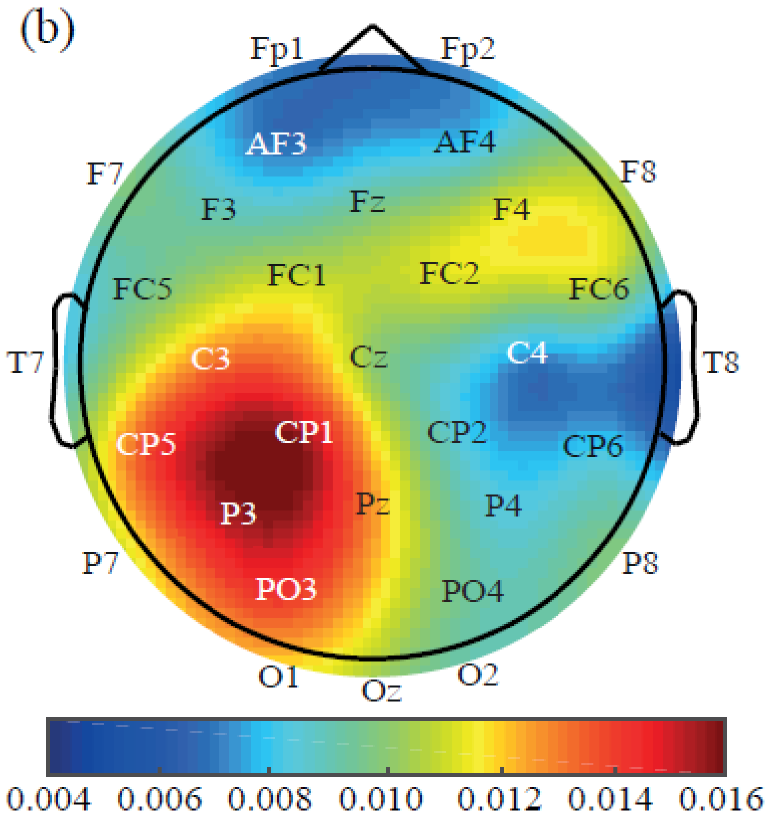
- ANOVA → **<u>15 / 32</u>** statistically significant EEG channels
- Best results in left parietal and right frontal areas
- Higher levels for calm than for distress in all brain regions

Regularity + Predictability

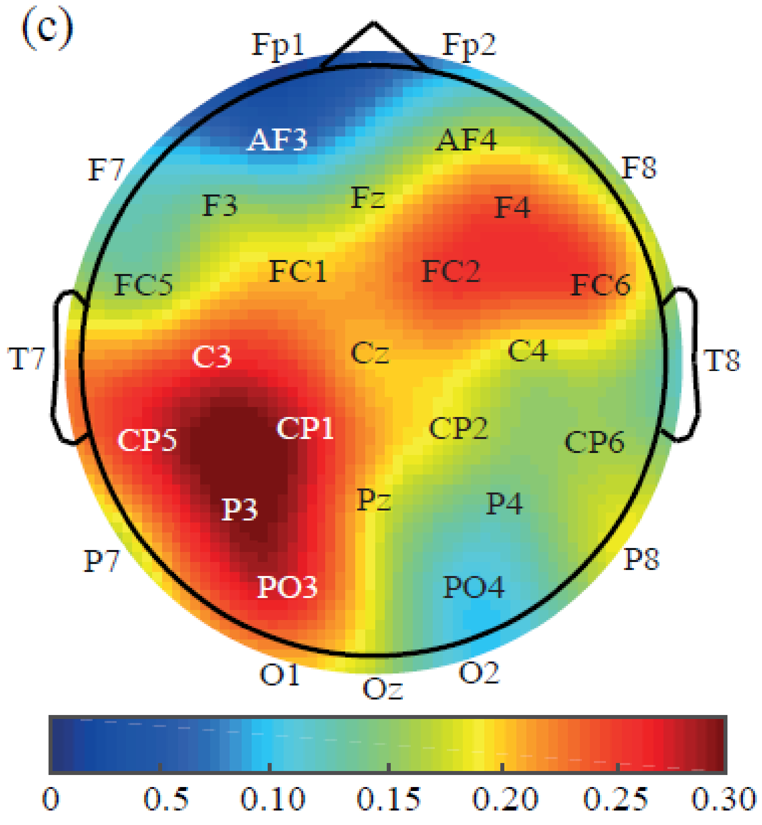
QSampEn



AAPE



CCEn



Regularity + Predictability

- Only AAPE and CCEn were studied (highly correlated with PerEn and CEn)

QSampEn + AAPE	QSampEn + CCEn
FSVS P4 of QSampEn and P3 of AAPE	**FSVS** P4 of QSampEn and P3 of CCEn
SVM Acc = 81.31%	**SVM** Acc = 80.31%

- Complementarity between regularity and predictability metrics
- AAPE and CCEn were not combined due to their high similarities

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Multiscale metrics

- Nonlinear systems present different simultaneous mechanisms that operate in multiple time scales → **Multiscale analysis**

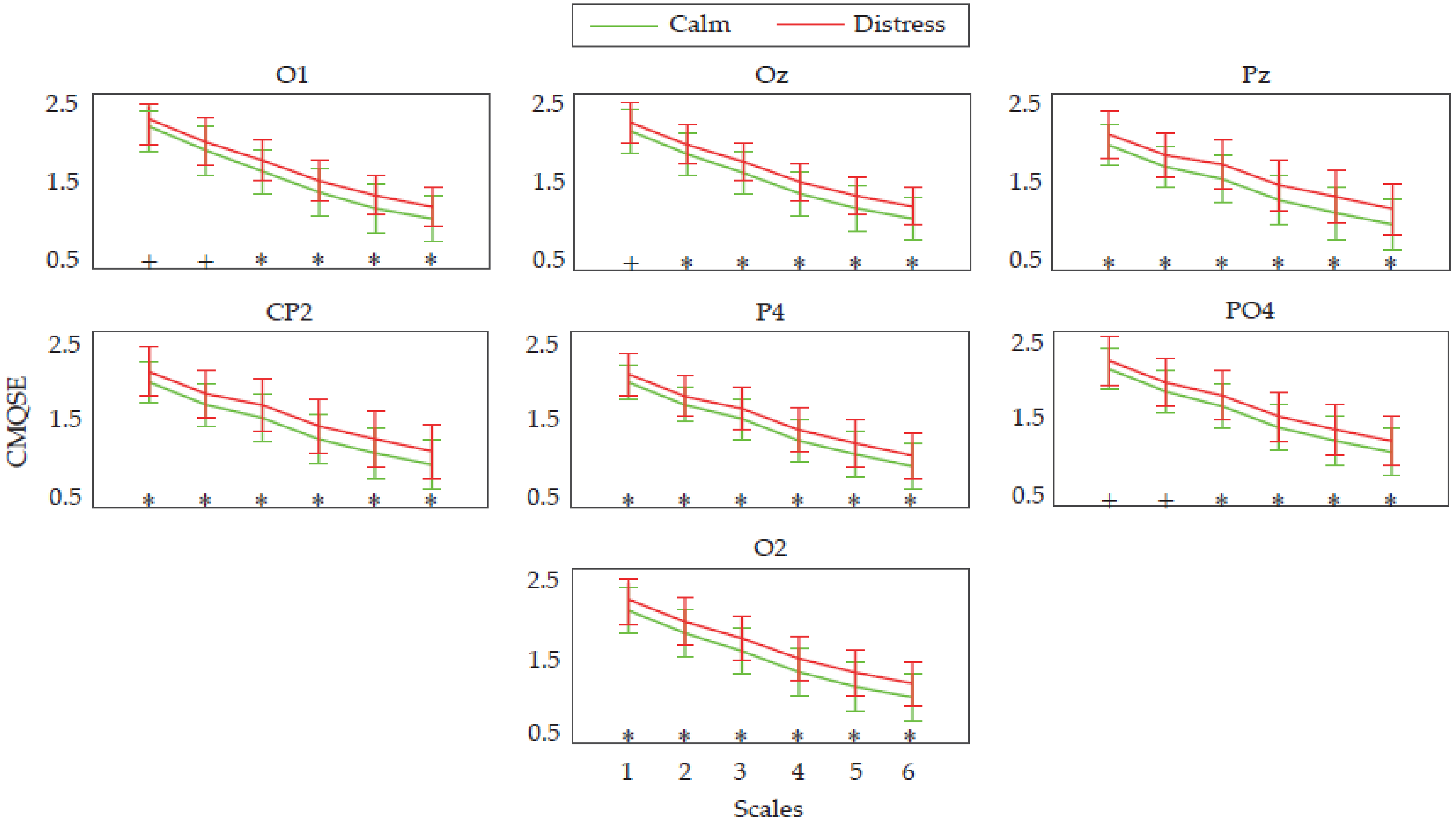
- Composite multiscale QSampEn and AAPE (CMQSampEn and CMAAPE)

$$CMQSampEn(x,\tau,m,r) = \frac{1}{\tau}\sum_{k=0}^{\tau} QSampEn\left(y_{\tau}^{k},m,r\right)$$

$$CMAAPE(x,\tau,m) = \frac{1}{\tau}\sum_{k=0}^{\tau} AAPE\left(y_{\tau}^{k},m\right)$$

Scales = 1,2,…,6

Results CMQSampEn and CMAAPE



- CMQSampEn and CMAAPE decreased with scales
- Relevance of areas as in single-scale analyses
- Calm-distress tendency as in single-scale analyses

Results CMQSampEn and CMAAPE

- Combination of CMQSampEn + CMAAPE at different scales
- Stepwise regression + decision tree and SVM classifiers
- Best results at scale 2 with both classifiers

	Channels from CMQSE	Channels from CMAAPE	ρ	Decision Tree Acc (%)	SVM Acc (%)
Scale 1	Oz	PO3	6.48×10^{-7}	76.47	79.82
Scale 2	Oz, FC1, Pz	CP1, C4	6.24×10^{-8}	82.61	86.35
Scale 3	O2, FC1, CP1	-	1.92×10^{-9}	79.51	80.79
Scale 4	O2, FC1, CP1	-	1.47×10^{-8}	80.30	79.57
Scale 5	Pz	-	1.04×10^{-6}	-	-
Scale 6	O2, FC1, CP1, C3	-	1.61×10^{-9}	79.96	85.24

Multilag metrics

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- Time-delayed analysis may reveal relevant underlying information of nonlinear systems, undiscovered with non-delayed or multiscale approaches

- Delayed AAPE (DPE) considers time-delayed samples for better evaluation of the nonlinear time series

$$DPE(m,\tau) = -\frac{1}{\ln(m!)} \cdot \sum_{k=1}^{m!} p^{\tau*}(\pi_k) \cdot \ln(p^{\tau*}(\pi_k))$$

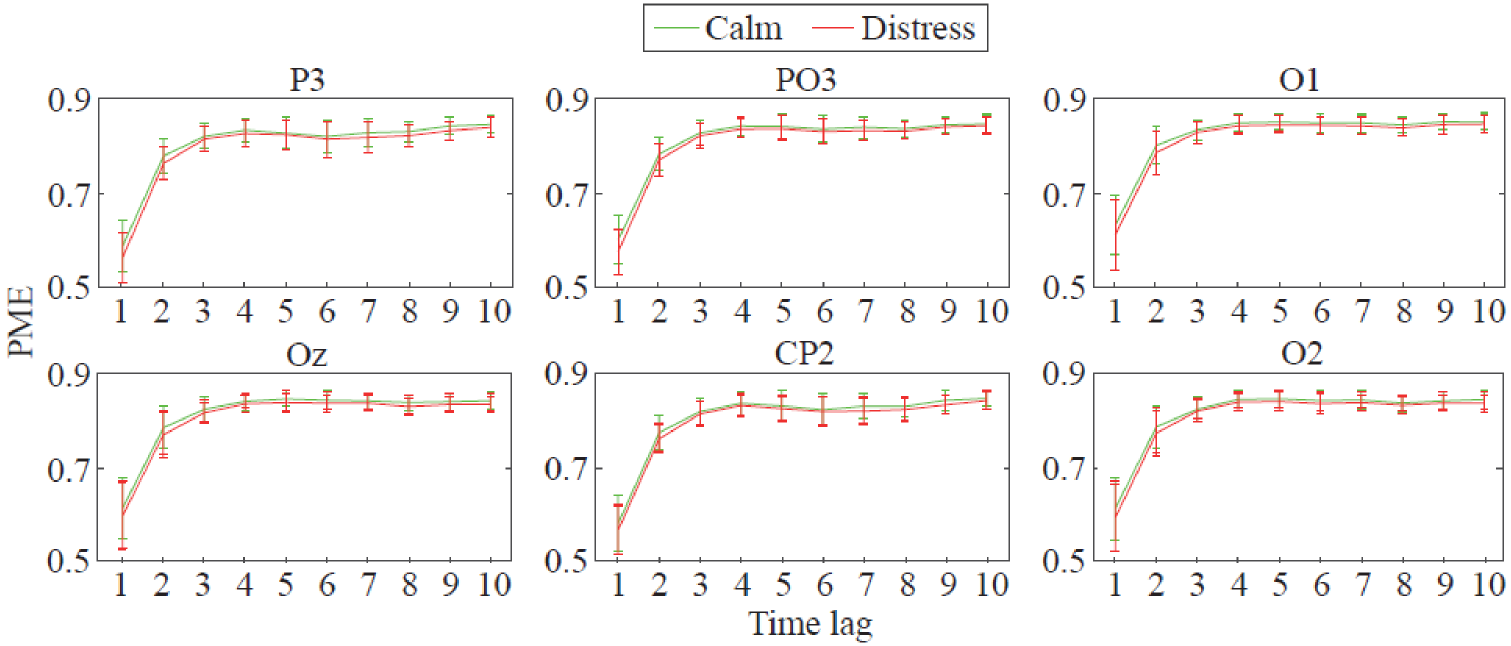
- Permutation min-entropy (PME) is an improvement based on Rényi entropy

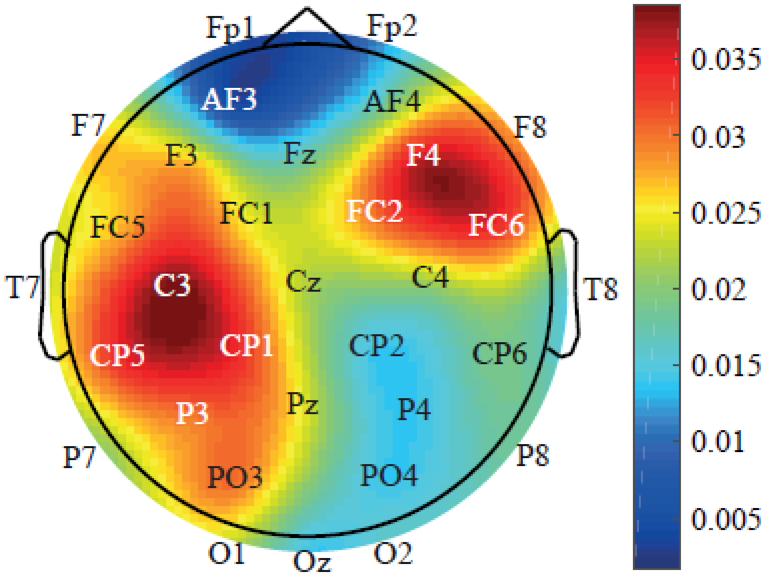
$$PME(m,\tau) = -\frac{1}{\ln(m!)} \ln\left(\max_{k=1,2,\ldots,m!} [p^{\tau}(\pi_k)]\right)$$

$m = 6$ $\quad \tau = 1,2,\ldots,10$

Results DPE and PME

- DPE and PME increased with τ
- Best results in parietal and occipital areas
- Higher levels for calm than for distress in all brain regions

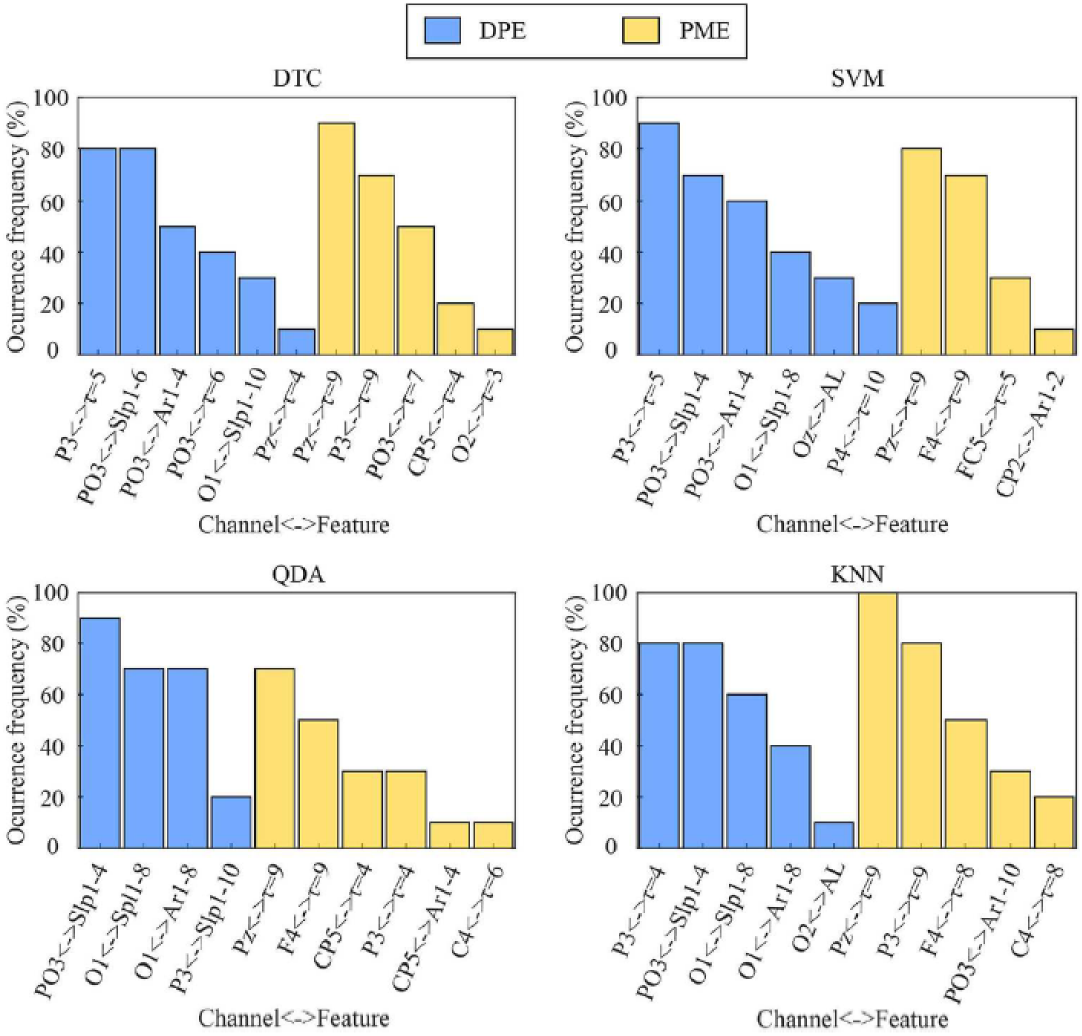




Results DPE and PME

- DPE + PME + curve-related parameters
- Sequential forward selection + different classifiers
- Best results:

KNN
Acc = 92.32%



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Cross-sample entropy

- Cross-sample entropy (CSE) evaluates the repetitiveness of patterns among two time series

$$CSE(m, r, N)(x_1||x_2) = -\ln \frac{\phi^{m+1}(r)(x_1||x_2)}{\phi^{m}(r)(x_1||x_2)}$$

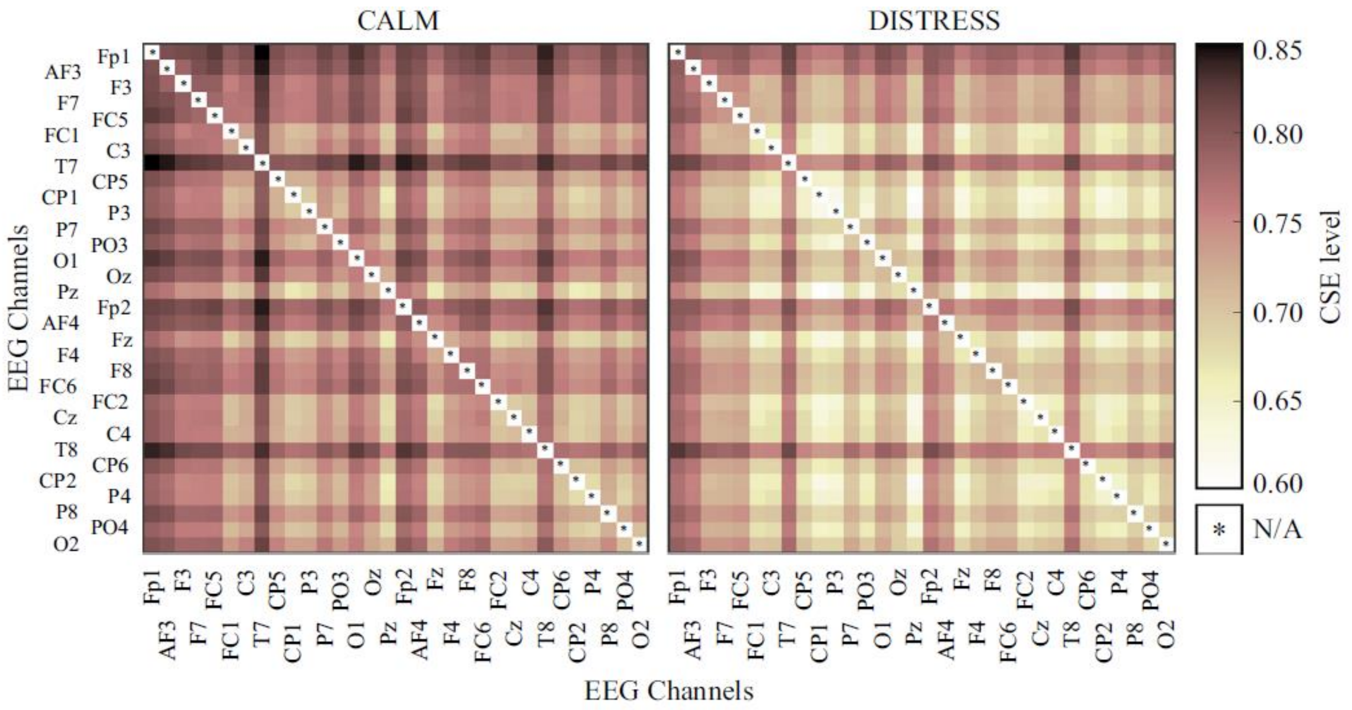
- Each time series represents an EEG channel

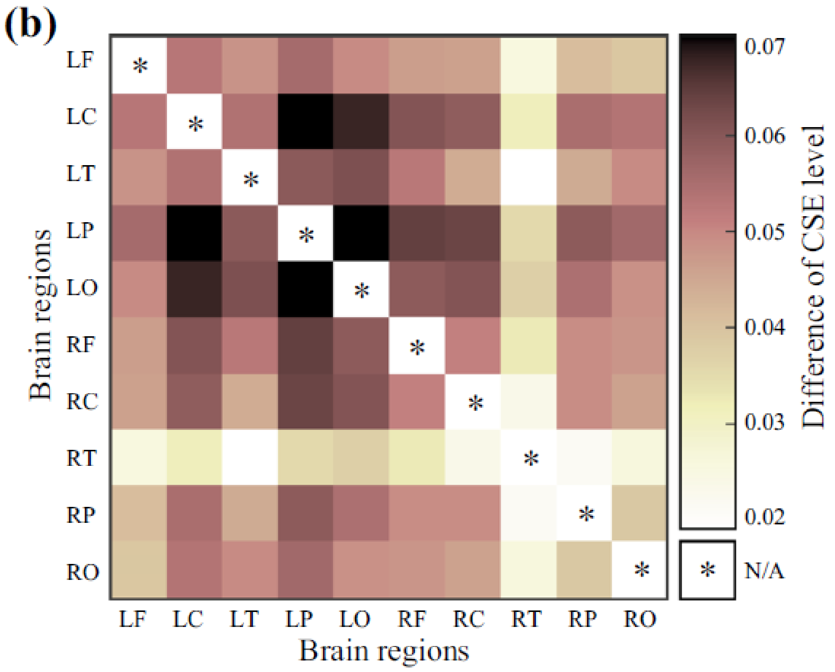
- Higher CSE → lower coordination between areas

m = 2 r = 0.25*std

Results CSE

- Higher coordination in distress → *Fight or flight*
- Strong coordination in central, parietal and occipital areas
  - Intrahemisphere
  - Interhemisphere





Conclusions

- It is possible to identify calm and distress from EEG recordings using entropy metrics
- Frontal and parieto-occipital brain areas are the most relevant
- Different entropy indices can be complementary
- The simplicity of classification models allows to give a clinical interpretation of the results

Thank you!