Imperial College London

# QUANTIFYING COGNITIVE STRESS PATTERN THROUGH TIME, FREQUENCY AND NONLINEAR ANALYSIS

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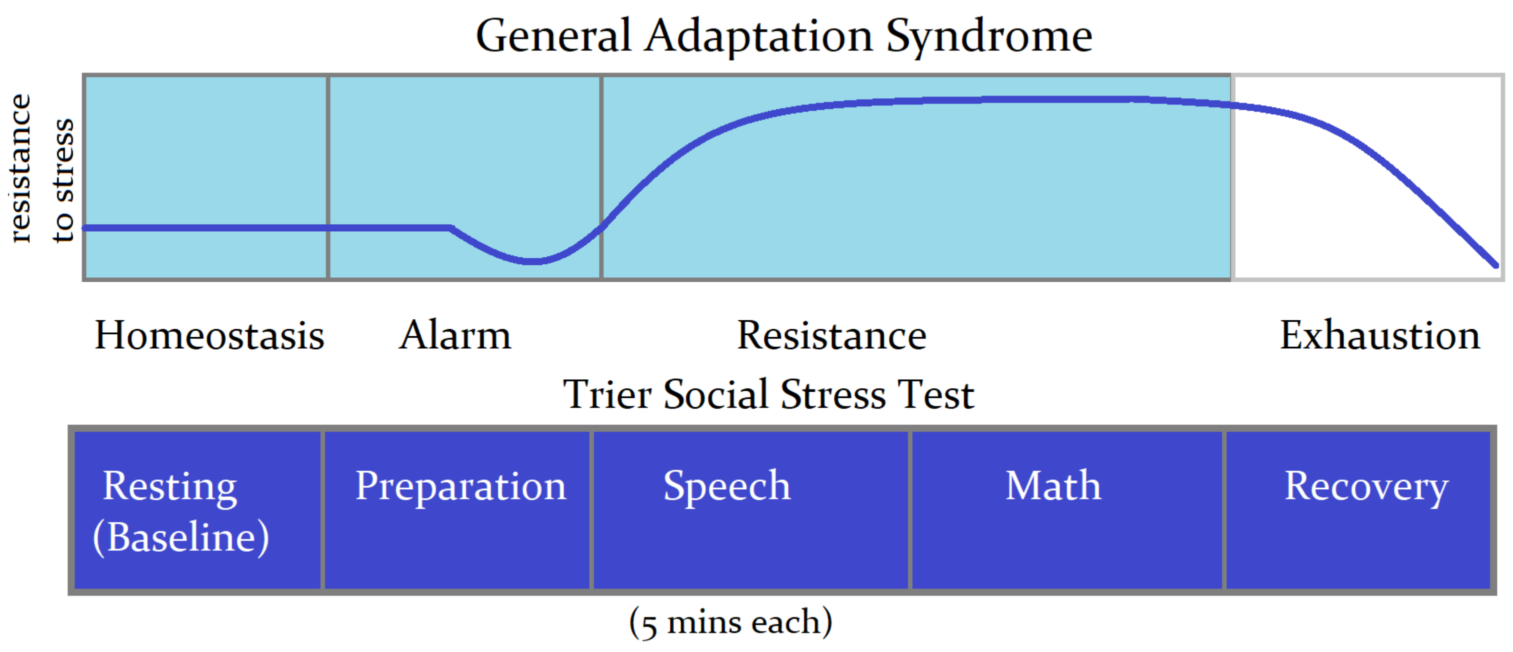
## Introduction

Long exposure to cognitive stress could cause mental and physical issues. Identifying the patterns of stress in our physiological signal is beneficial for stress management and prevention. The project applied signal processing and machine learning techniques to quantitatively identify cognitive stress pattern with respect to the model of 'General Adaptation Syndrome' (GAS) [1].




Abbreviation for each stage: B;P;S;M;R

## Method

Data acquisition:

16 subjects participated in the TSST experiment where they went through a series of events that invoked stress. ECG data were collected via e-health V1.0 platform. Heart Rate Variability (HRV) were extracted from the ECG recordings, followed by a novel noise filtering scheme and feature extraction.

Feature extraction:

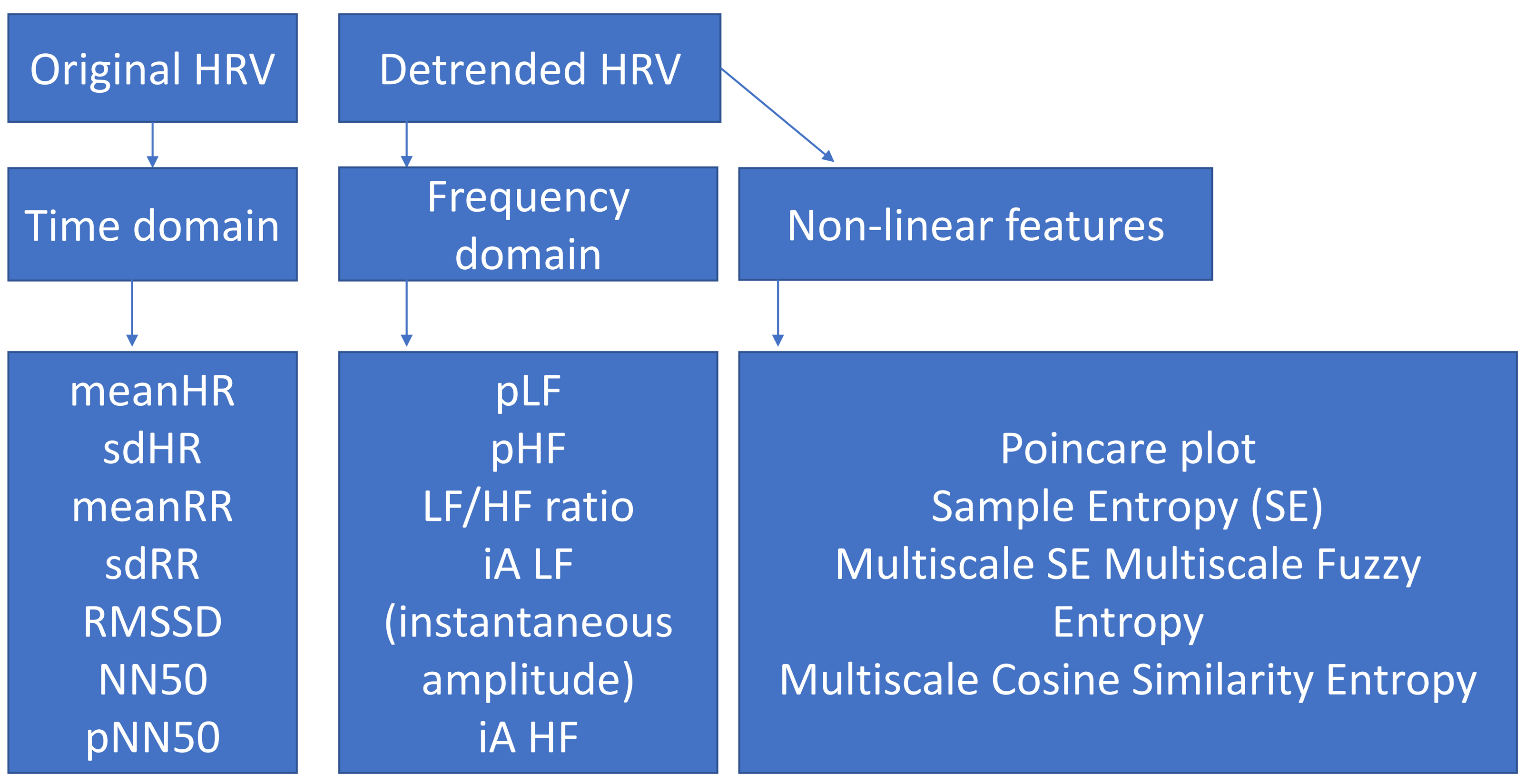
Signal processing techniques were applied to extract time-domain and frequency-domain features, as well as entropy-based complexity measures. 47 features were extracted from the ECG signals.

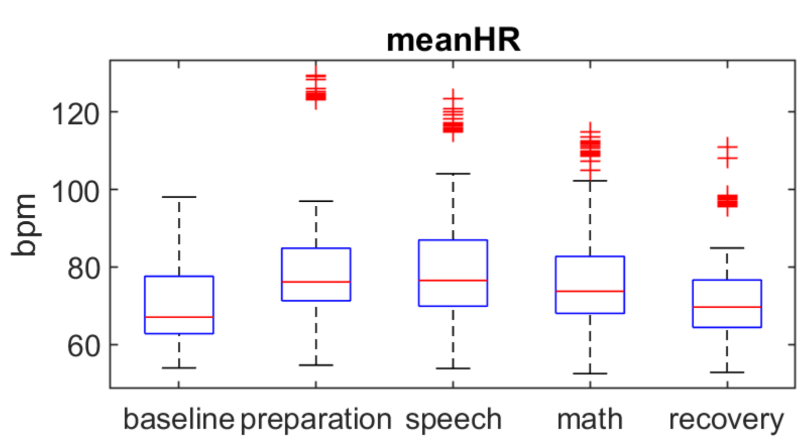
Statistical analysis:

The effects of stress on the sympathovagal balance were analysed through visualising the distribution of several features. Statistics of features were evaluated through analysis of variance (ANOVA) and Wilcoxon rank sum test.

Classification:

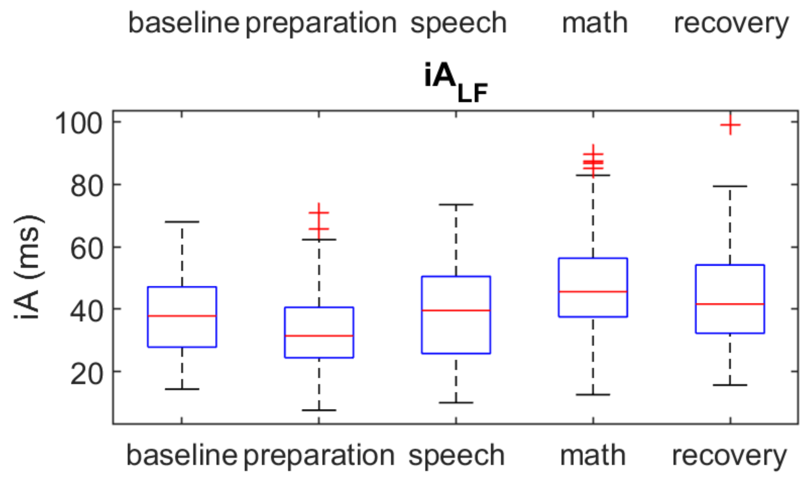
Support Vector Machine (SVM), feed-forward neural network and recurrent neural network were employed for stress state classification.

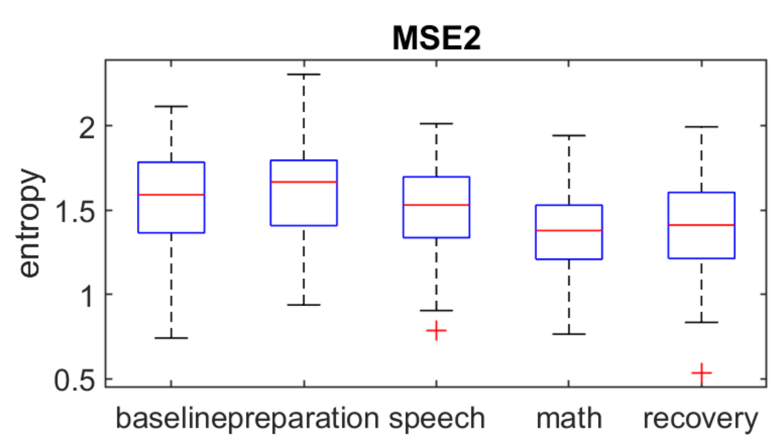



LF increases in stress stages, indicates high SNS activity.

MSE declines in stress stages: verifies the complexity loss theory.




## Stress State Classification

Classification of 6 combinations of states: Baseline, Preparation and Speech; Baseline, Preparation and Math; Baseline, Preparation and Speech/Math (randomly sampled to create a new class); Baseline and Preparation; Baseline and Speech/Math; Preparation and Speech/Math.

Two partition method:

Leave-one-out: data from one subject allocated to testing set, the rest to the testing set (repeating over 16 times).

Shuffled: training and testing sets were pooled from the whole data set, irrespective of which subject they belong to.

## Support Vector Machine

Dimension reduction using principal component analysis (PCA) achieved higher average accuracy than feature selection method based on their statistical discrimination scores provided by ANOVA and Wilcoxon sum rank test.

Classification accuracy converges when the dimension of subspace equals to 10.

Sequential feature selection outperformed other algorithms, however it was underwhelming under the leave-one-out partition.

Leave-one-out struggled with 3-class classification, suggesting individual physiological difference cannot be ignored.

| | Shuffled partition | | | | | Leave-one-out partition | |
|---|---|---|---|---|---|---|---|
| Stages: | SVM-RBF | SVM-Poly | PCA-SVM | PCA-SVM (k = 10) | Sequential-SVM(k = 14) | SVM (all features) | PCA-SVM |
| BPS | 84.65% | 78.22% | 83.76% | 81.04% | **89.21%** | 52% | 55.74% |
| BPM | 89.66% | 73.89% | 83.00% | 82.07% | **92.41%** | 52.61% | 59.16% |
| BPS/M | 81.77% | 70.44% | 80.89% | 78.42% | **89.95%** | 49.11% | 58.01 |
| BP | 85.07% | 76.12% | 89.25% | 87.61% | **93.13%** | 57.39% | 68.18% |
| BS/M | 91.18% | 80.88% | 87.57% | 86.25% | **95.55%** | 63.56% | 75.2% |
| P/SM | 90.30% | 85.82% | 87.01% | 87.84% | 92.99% | 72.24% | 75.27% |

## Artificial Neural Network

| | Shuffled | | Leave-one-out | | |
|---|---|---|---|---|---|
| Stages: | Feedforward NN | Stages: | RNN (mean) | RNN (max) | RNN (min) |
| BPS | 75.53% | BPS | 88.20% | 96.77% | 40.63% |
| BPM | 73.82% | BPM | 80.80% | 96.83% | 59.26% |
| BPS/M | 73.49% | BPSM | 72.51% | 92.11% | 47.67% |
| BP | 80.99% | BP | 93.87% | 100% | 75.00% |
| BS/M | 82.16% | BS | 93.53% | 100% | 78.00% |
| P/SM | 83.66% | PS | 89.31% | 100% | 49.28% |

Feedforward neural network (patternnet) contains one input layer, one hidden layer with 40 neurons and an output layer.

Recurrent neural network (RNN) consists of a sequence input layer, a long-short-term-memory (LSTM) layer with 100 hidden units, a fully connected layer, a softmax layer and the classification layer.

RNN achieved higher accuracies than feed-forward NN. Classification directly using HRV series only achieved 78.73% for 2-class and 51.63% for 3-class.

## Conclusion

Classification results show that it is feasible to categorize one's stress state with respect to the GAS model. Moreover, we verified the existence of the 'alarm' stage, as several learning machines were capable to quantitatively recognize its statistical difference among other stress states.

## REFERENCES

[1] H. Selye, "The general adaptation syndrome and the diseases of adaptation."Journal of Clinical Endocrinology, vol. 6:117-230, 1946.