# MODELLING STRESS IN PUBLIC SPEAKING: EVOLUTION OF STRESS LEVELS DURING CONFERENCE PRESENTATIONS

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## ABSTRACT

The Electrocardiogram (ECG) collected in real-life scenarios is often noisy and contaminated with motion artefacts. This study proposes a new framework to analyse the heart rate variability (HRV) in mobile scenarios by introducing novel R-peak detection and HRV detrending algorithms. The R-peak detection combines matched filtering and Hilbert transform, while detrending the HRV is performed using empirical mode decomposition with novel physically meaningful stopping criteria. Next, four quantitative metrics – sample entropy, $\mathrm{LF_{HRV}}$, $\mathrm{HF_{HRV}}$ and LF/HF ratio – are used to estimate stress levels in two public speaking events: (i) a presentation in front of an audience and (ii) an interactive poster presentation, both at ICASSP 2015. We show that the proposed framework makes it possible to detect distinctive 'stress-patterns' in the structural complexity of the HRV, thus verifying the complexity-loss hypothesis in physiological research.

***Index Terms*—** R-peak detection, detrending, empirical mode decomposition, sample entropy, complexity science, LF/HF, heart rate variability, stress

## 1. INTRODUCTION

The analysis of the electrocardiogram (ECG) is a de-facto standard for providing insight into the state of the cardiovascular system. For example, it captures the atrial depolarization (P wave), the depolarization of the right and left ventricles (QRS complex) and the recovery of the ventricles (T wave). While the clinical use of ECG is well understood, much less is know about how to utilise ECG for the analysis of the balance between the sympathetic (SNS) and parasympathetic (PNS) nervous system, and hence mental and physical stress levels in real-life scenarios. The aim of this study is therefore two-fold: (i) to deal with the multiple artefacts in wearable scenarios, and (ii) to illuminate the usefulness of the proposed signal processing techniques through the study of the evolution of stress levels of two students presenting their work in an academic conference. For rigour, the analysis is cast into a framework of complexity science, whereby the *complexity-loss hypothesis* establishes that an organism under constraints (illness, ageing) exhibits lower structural complexity of physiological responses than a healthy organism [1]. Our hypothesis is that stress, being an psychophysiological impediment, modulates physiological responses so that they lose degrees of freedom, thereby reducing structural complexity. To this end, the analysis of HRV is performed by sample entropy (SampEn), as it is designed to operate on real-world nonlinear and non-stationary data [2], low frequency ($\mathrm{LF_{HRV}}$) and high frequency ($\mathrm{HF_{HRV}}$) power of the HRV frequency spectrum and their ratio (LF/HF). While a low SampEn designates a high regularity and may be linked to high levels of stress [3], an increased SampEn corresponds to an increase in randomness in the data, suggesting a physically relaxed state (baseline) [4]. Although not without controversy, the $\mathrm{LF_{HRV}}$ band in HRV, 0.04-0.15 Hz, is thought to reflect the activity of the sympathetic nervous system (SNS; high stress) and the baroreflex (blood pressure), while the $\mathrm{HF_{HRV}}$ band, 0.15-0.4 Hz, is believed to correspond to the activity of the parasympathetic nervous system (PNS; relaxed state) and respiratory sinus arrhythmia (RSA), naturally occurring heart rate modulations due to breathing [5, 6]. The ratio of the power in the $\mathrm{LF_{HRV}}$ and $\mathrm{HF_{HRV}}$ frequency bands reflects the degree of sympathovagal balance [7], with a higher ratio representing dominant sympathetic activity and a lower ratio indicating an increased vagal modulation [8].

In a previous study, we introduced a new algorithm to extract R-peaks from ECG using a combination of matched filtering and Hilbert transform (MF-HT) [9]. The approach is semi-automatic with the user required to select a QRS waveform mother pattern from the recorded ECG. To locate R-peaks in noisy ECG, the user is provided with several R-peak estimates when an abnormal QRS waveform or heart rate is detected. This is achieved through a user-friendly graphical interface facilitating straightforward data processing.

After detecting the R-peaks, the HRV is constructed from the R-R intervals, the temporal difference between two subsequent R-peaks, yielding an unevenly sampled time series. In order to perform spectral estimation, the HRV is resampled to create a regularly spaced time series using a linear or cubic spline interpolation with a sampling frequency in the

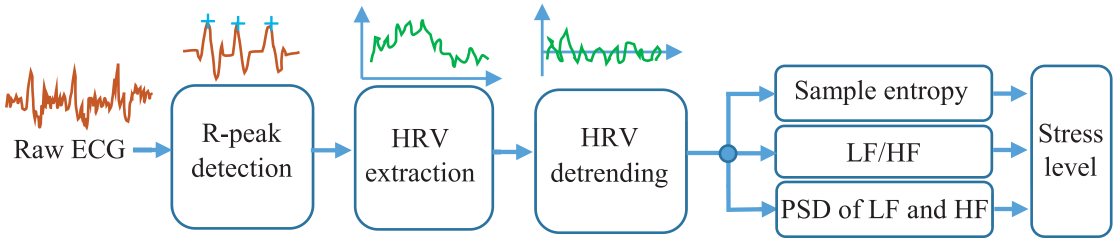


**Fig. 1**. Stress level estimation: Conceptual block diagram

range 2 Hz to 10 Hz [10]. However, oversampling typically leads to an oversampled LF/HF ratio when Fourier transform (FT) is applied [11], and consequently a wrong interpretation. To this end, the Lomb-Scargle periodogram (LSP) [12, 13], a spectral estimation technique for unevenly spaced data, has been applied to the original HRV yielding more reliable results compared to the classical FT [14, 15]. In order to apply the stress-related metrics including the LF/HF ratio and SampEn, it is assumed that the extracted HRV is weakly stationary, in other words, there is no change in the variance and mean in sliding data windows. However, real HRV is typically non-stationary, a signature of changes in psychological and physiological mechanisms [16], and the original HRV is therefore detrended in a pre-processing step. This is achieved based on the empirical mode decomposition (EMD) algorithm [17], whereby the analysis is made physically meaningful by the power spectrum density (PSD) of the $\mathrm{HF_{HRV}}$ as the stopping criterion.

This work aims to extract maximum information from HRV related to stress biomarkers by introducing a new signal processing framework (see Fig. 1) for mobile cardiovascular scenarios. This has made it possible to: i) detect correct R-peaks in noisy ECG, ii) robustly obtain accurate biomarkers of stress from HRV, and (iii) illuminate the utility of the proposed framework in identifying changes in physiological responses due to psychological stress in real-life scenarios. The concept is validated by analysing the stress levels of two presenters during their oral and poster presentations.

## 2. PROPOSED SIGNAL PROCESSING FRAMEWORK

### 2.1. R-peak detection

Our MF-HT algorithm for R-peak detection operates as summarised in Algorithm 1. It combines pattern matching with the Hilbert transform and first identifies possible QRS complexes from noisy mobile ECG, followed by the application of the Hilbert transform to identify the R-peak.

### 2.2. HRV detrending

The IMFs resulting from EMD have properties similar to filter banks and are arranged according to their average instantaneous frequency, where IMFs with the highest instantaneous frequencies have the lowest indices. The $\mathrm{HF_{HRV}}$ band is thus contained in the IMF indices ranging from the first to the highest one in which the PSD of $\mathrm{HF_{HRV}}$ band is still contained. It is therefore possible to use the ratio between the $\mathrm{HF_{HRV}}$ PSD of the current IMF and the $\mathrm{HF_{HRV}}$ PSD of the previous IMF as a threshold parameter to stop the sifting process of the EMD algorithm. In this work, the threshold of the ratio was set to 0.2 (the $\mathrm{HF_{HRV}}$ PSD of the current IMF is 5 times less than the $\mathrm{HF_{HRV}}$ PSD of the previous IMF) to ensure that the resulting IMF spectrum retains as much as possible of the original HRV spectrum. This is combined with the original stopping condition of the EMD algorithm, the standard deviation $sd$ of which is 0.2 - 0.3 [17].

Since the original HRV is irregularly sampled, the LSP is well suited to estimate the PSD. The detrending algorithm is described in Algorithm 2. Interpolation after detrending is still required because a low number of sample points is prohibitive for computing SampEn and may lead to unreliable results. A shape-preserving piecewise cubic interpolation was therefore applied to the detrended data. The 4 Hz sampling frequency is selected for interpolation based on the reasons

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**Algorithm 1.** R-peak detection using MF-HT

- Select a mother QRS waveform from the raw ECG.
- Locate the first R-peak.

For each $W_i$:

1. Create a window $W_i$ beginning at the previous R-peak and ending at the longest realistic heart beat interval.
2. Remove local trend by taking the difference between consecutive sample points.
3. Apply a matched filter between the mother QRS and the $W_i$, resulting in a degree of correlation $K_{mf}$.
4. Apply the Hilbert transform to $K_{mf}$ to identify candidate R-peaks $C_j$.
5. Locate the correct R-peak by selecting the peak $C_j$ with the highest cross-correlation with the mother QRS.

- Construct HRV from the time difference between subsequent R-peaks.

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**Algorithm 2.** Detrending the HRV signal

Denote by $x'(t)$ be the input of each iteration.
For each iteration:

1. Locate lower and upper maxima, $e_{min}$ and $e_{max}$ of $x'(t)$.
2. Apply cubic spline interpolation to $e_{min}$ and $e_{max}$.
3. Compute the local mean $m(t) = (e_{max} + e_{min})/2$.
4. Obtain the local oscillation $d(t) = x'(t) - m(t)$.
5. Examine whether $sd$ fulfils the stopping condition, compute $PSD_m$ of $d(t)$ using LSP and go to step 6, else set $x'(t) = d(t)$ and go to step 1.
6. Examine the ratio of $PSD_m/PSD_{m-1}$. If the ratio is less than 0.2, stop the sifting process and go to step 7 – otherwise extract the $IMF$, $IMF_m = d(t)$, where $m$ is the IMF number, and set $x'(t) := x'(t) - \sum_{i=1}^{m} IMF_i$.
7. Compute the detrended HRV by summing all released IMFs, $dt(t) = \sum_{i=1}^{m-1} IMF_i$.

outlined in [10, 11].

### 2.3. Sample entropy and LF/HF ratio

The parameters required for computing SampEn are the embedding dimension $m$, time lag $\tau$ and tolerance $r$. The appropriate selection of $m$ and $\tau$ relies on the underlying dynamics of time series. Pincus in [18] suggested that using $m$ = 2 or $m$ = 3 is sufficient for a low-dimensional system such as the human cardiovascular system. Kaffashi *et al.* [19] recommended that using $\tau = 1$ is sufficient to estimate the complexity of a system, while Pincus [20] recommended that $r$ can be taken as 0.1 – 0.2 times the standard deviation, in order to avoid small unpredictable changes in time series. Therefore, in this study, $m$ = 2, $\tau$ = 1 and $r$ = 0.15 were chosen as parameters for computing SampEn, given by:

$$SampEn = -ln \frac{P^m(r)}{P^{m+1}(r)} \tag{1}$$

where $P^m(r)$ is the probability of similar patterns found in each pairwise delay vector of length $m$, and $P^{m+1}(r)$ is the probability of similar patterns found in each pairwise of the length $(m+1)$. Periodogram based spectral estimation is then applied to the detrended HRV followed by a calculation of the PSD in the $\mathrm{LF_{HRV}}$ and $\mathrm{HF_{HRV}}$ bands and the computation of the LF/HF ratio.

## 3. EXPERIMENTAL SETUP

A wearable biosignal acquisition device was used which has a 24-bit analog to digital converter (ADC), ADS 1298, with an integrated built-in instrumentation amplifier as a front-end of the circuit. The Teensy-based microcontroller v. 3.1 was used as a central processor to manage and to store the acquired data obtained from the ADC to an SD-card. The sampling frequency of the device was set to $1000\,\mathrm{Hz}$.

The device was used to measure the ECG of two participants who presented their work at the International Conference on Acoustics, Speech and Signal Processing (ICASSP) 2015. The HRV was evaluated in terms of 'reactivity' and 'recovery'. Both are indicators of psychosocial stress states, with a greater degree of reactivity and longer recovery period reflecting a weaker ability to physically adapt towards the stressor. The presenters were graduate students from Imperial College London, whereby the first presenter gave a poster presentation, for which the pre- and post-performance baseline was set to $25\,\mathrm{min}$. The second presenter gave an oral presentation for which the pre- and post-performance period of $20\,\mathrm{min}$ was chosen. The poster presentation lasted for $120\,\mathrm{min}$ and the oral presentation for $20\,\mathrm{min}$.

## 4. ANALYSIS RESULTS

A sliding window based approach was used for computing the SampEn, PSD of $\mathrm{LF_{HRV}}$ and $\mathrm{HF_{HRV}}$, and the LF/HF ratio, the metrics chosen to quantify the evolution of stress levels. Different window lengths of $9\,\mathrm{min}$ and $3\,\mathrm{min}$ were set respectively for the poster and oral presentation, based on the duration of the recordings. A 15-second sliding time segment was chosen to maintain approximately constant statistical variations over time.
In Fig. 2 and Fig. 3, the graphs from the top to the bottom show the raw and the detrended HRV, SampEn values, LF/HF ratio and the PSD of $\mathrm{LF_{HRV}}$ and $\mathrm{HF_{HRV}}$. The whole recording was divided into three sections: Section (a) corresponds to the pre-presentation period; Section (b) to the presentation interval; and Section (c) to the post-presentation.

In the interactive poster presentation, the SampEn and the $\mathrm{LF_{HRV}}$ first exhibited a steady increase (Section (a-c)), followed by a slow decline after the performance, indicating the 'recovery' in the HRV. The presenter of the poster confirmed an increased level of stress and psychosocial engagement towards the end of the presentation due to the audience interacting well beyond the presentation end. In contrast, the $\mathrm{HF_{HRV}}$ remained similarly low throughout the scheduled performance, indicating a strong PNS withdrawal and thus a less relaxed state. The LF/HF ratio exhibited distinctive fluctuations, which were found neither in the SampEn nor $\mathrm{HF_{HRV}}$ power. In the oral presentation, the SampEn revealed a sharp increase (signature of high stress) at the end of Section (a) and a decline at the beginning of Section (b); this was followed by minor fluctuations during the presentation and a peak in Section (c) before returning to a resting state after approximately 45 min. The LF/HF ratio

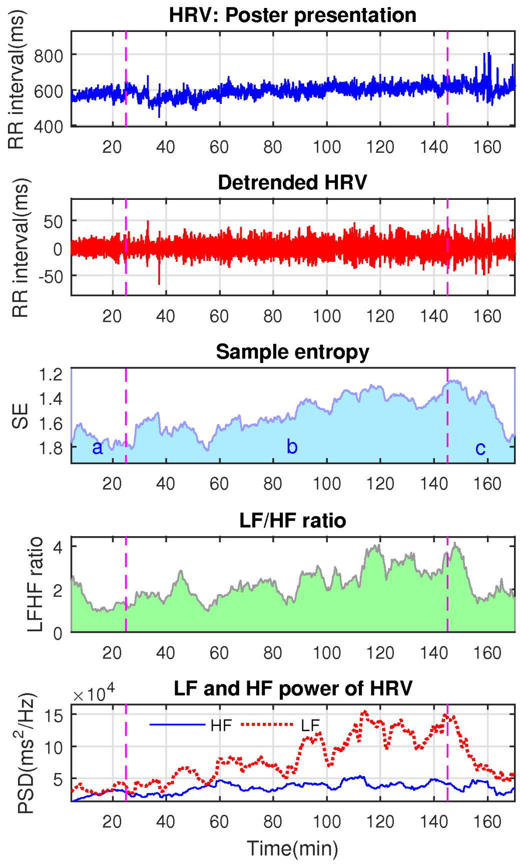


**Fig. 2**. Poster presentation – from top to bottom: HRV, detrended HRV, SampEn values (vertical axis reversed), LF/HF ratio and the PSD of $\mathrm{LF_{HRV}}$ and $\mathrm{HF_{HRV}}$. The segments a, b and c represent the pre-performance ($25\,\mathrm{min}$), performance ($120\,\mathrm{min}$) and post-performance ($25\,\mathrm{min}$).

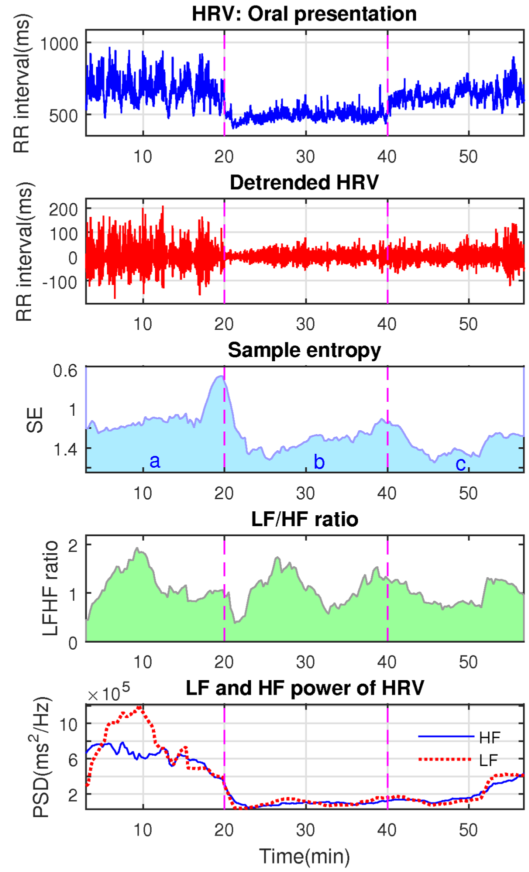


**Fig. 3**. Oral presentation – from top to bottom: HRV, detrended HRV, SampEn values (vertical axis reversed), LF/HF ratio and the PSD of $\mathrm{LF_{HRV}}$ and $\mathrm{HF_{HRV}}$. The segments a, b and c represent the pre-performance ($20\,\mathrm{min}$), performance ($20\,\mathrm{min}$) and post-performance ($20\,\mathrm{min}$).

underwent variations during the presentation (Section (a-c)), with peaks (i.e. high stress) occurring approximately $10\,\mathrm{min}$ before the presentation, in the middle, and right before the end of the presentation (Section (c)). The simultaneous investigation of the $\mathrm{LF_{HRV}}$ and $\mathrm{HF_{HRV}}$ demonstrated a pronounced $\mathrm{LF_{HRV}}$ and thus, as indicated in Section (a), a more alert state of body and mind during the pre-presentation.

## 5. CONCLUSION

Public presentations target to inform listeners in a structured, deliberate, and entertaining manner. They can take place in controlled environments – on stage – where the presenter regulates the process, or in settings which are highly interactive and require an increased engagement with the audience. Each event involves a great deal of stress, yet close quantitative examinations of distinctive physiological responses in those situations are few and far between. To this end, our study has proposed a new framework for the analysis of HRV in real-life public performances, in order to provide robust and accurate biomarkers of the evolution of stress. Novel R-peak and HRV analyses of mobile ECG in real-life scenarios have been established based on four quantitative metrics: Sample entropy, $\mathrm{LF_{HRV}}$ , $\mathrm{HF_{HRV}}$ and LF/HF ratio. The analysis has shown that: (i) LF/HF ratio is rather sensitive compared to the SampEn and PSD of $\mathrm{LF_{HRV}}$ and $\mathrm{HF_{HRV}}$; (ii) small differences in the $\mathrm{LF_{HRV}}$ and $\mathrm{HF_{HRV}}$ power may produce an unstable LF/HF ratio and this metric should be interpreted with caution (as seen in Fig 3., Section (c)); (iii) the SampEn has provided a meaningful approach for understanding the complex dynamics of HRV over time. Future studies will investigate more closely the three aspects of public performance on a larger sample size, both using the proposed method and standard protocols for systematic psychological and physiological stress assessment.

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