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A sliding window approach to detrended fluctuation analysis of heart rate variability

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PÓS-GRADUAÇÃO EM ENGENHARIA DE SISTEMAS ELETRÔNICOS E DE AUTOMAÇÃO

GPSIM Grupo de Processamento de Sinais e Imagens Médicas

Introduction

- Heart rate variability (HRV): study of the nervous system control over circulatory function [1]
- Traditional analysis:
  - Time-domain, frequency-domain, geometrical techniques
  - Generally require the signal to be stationary
  - Analysis of long duration signals not recommeded
- Detrended Fluctuation Analysis (DFA) [2]
  - Quantifies long–term correlations
  - Able to distinguish intrinsic HRV features from non-stationary external trends [2,3]
  - Allows analyzing long duration signals
  - Two coefficients:
    - α_1: short-term correlations
    - α_2: long-term correlations
- DFA involves segmenting the signal into windows
  - Detrended signal: discontinuities at the edges of each window
  - At least one window will have fewer samples
- In this paper:
  - We propose a sliding window approach for DFA
  - Evaluation using random signals and real HRV signals
  - Results are compared with the traditional approach

DFA: Traditional Calculation [2,3]

1) Obtain "integrated signal": $\mathbf{y(n)} = \sum_{\eta=0}^{n} [\mathbf{RR}(\eta) - \overline{\mathbf{RR}}]$, where $\overline{\mathbf{RR}}$ is the mean value the HRV signal $\mathbf{RR(n)}$
2) $\mathbf{y(n)}$ is segmented into windows of length $\mathbf{l_k}$. The "trend signal", $\mathbf{y_k(n)}$, is a piecewise-linear approximation of $\mathbf{y(n)}$, obtained by replacing the samples of $\mathbf{y(n)}$ with the values obtained by linear fitting within each window
3) Calculate "detrended signal": $\mathbf{e_k(n) = y(n) - y_k(n)}$
4) Calculate RMS approximation error: $\mathbf{E_k} = \sqrt{\frac{1}{\mathbf{N}} \sum_{\mathbf{n=0}}^{\mathbf{N-1}} |\mathbf{e_k(n)}|^2}$
5) Repeat steps 2 through 4 for multiple values of $\mathbf{l_k}$
6) Obtain $\mathbf{f(x) = 20\log_{10}(E_k)}$, where $\mathbf{x = 20\log_{10}(l_k)}$ (Fig. 1)
7) α_1: angular coefficient of first-order approximation of $\mathbf{f(x)}$, for $\mathbf{x}$ s.t. $\mathbf{4 \leq l_k \leq 16}$
8) α_2: angular coefficient of first-order approximation of $\mathbf{f(x)}$, for $\mathbf{x}$ s.t. $\mathbf{16 \leq l_k \leq N}$, where $\mathbf{N}$ is the length of $\mathbf{RR(n)}$

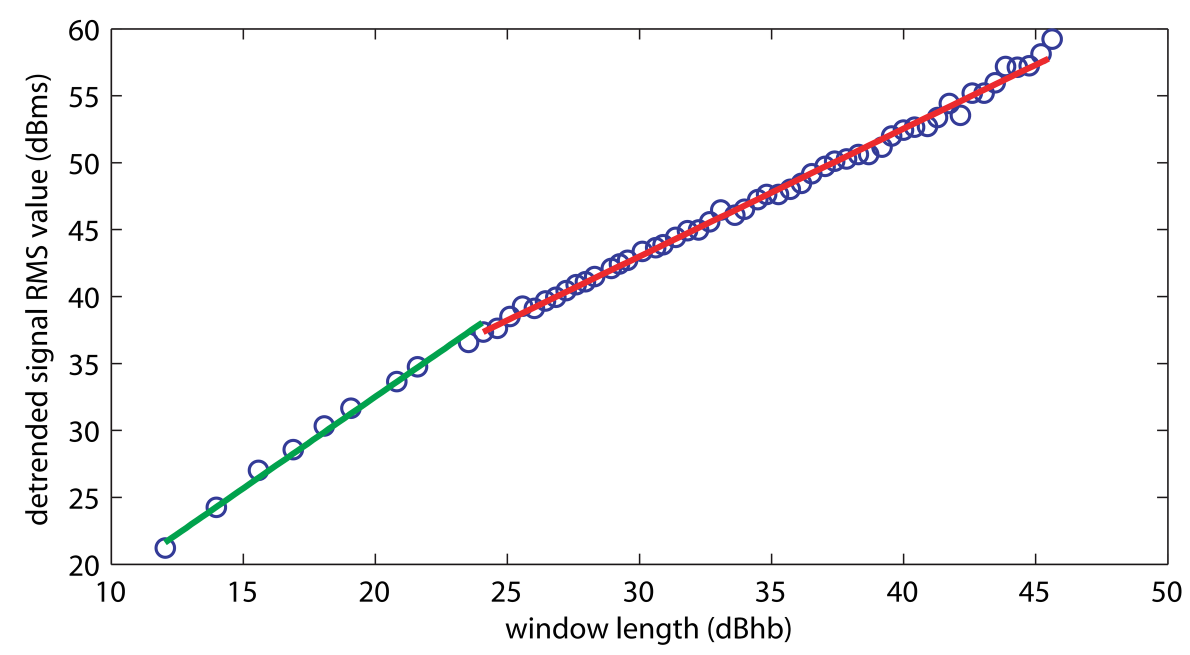

Figure 1: Calculating α_1 and α_2: RMS approximation error vs. window length

A Sliding Window Approach to DFA

- If $\mathbf{N/l_k} \notin \mathbb{Z}$, last window would have fewer samples (Fig. 2a)
- Overlapping windows (Fig. 2b):
  - Good: Makes all windows exactly $\mathbf{l_k}$-sample long
  - Bad: Does not eliminate discontinuities in detrended signal (Fig. 3a)
- Sliding window approach (Fig. 2c):
  - Replace step 2 with: *"For $\eta = 1, 2, \ldots, \mathbf{N}$, the value of $\mathbf{y_k}(\eta)$ is obtained by: (i) taking a segment of $\mathbf{y(n)}$, with $\mathbf{l_k}$ samples, centered around the η-th sample of $\mathbf{y(n)}$; (ii) least-square fitting a first-order polynomial, $\mathbf{y'(n)}$, to said segment; (iii) evaluating this polynomial at $\mathbf{n} = \eta$, and making $\mathbf{y_k}(\eta) = \mathbf{y'}(\eta)$."*
  - Results in a smooth trend signal (Fig. 3b)
  - No discontinuities in detrended signal (Fig. 3b)

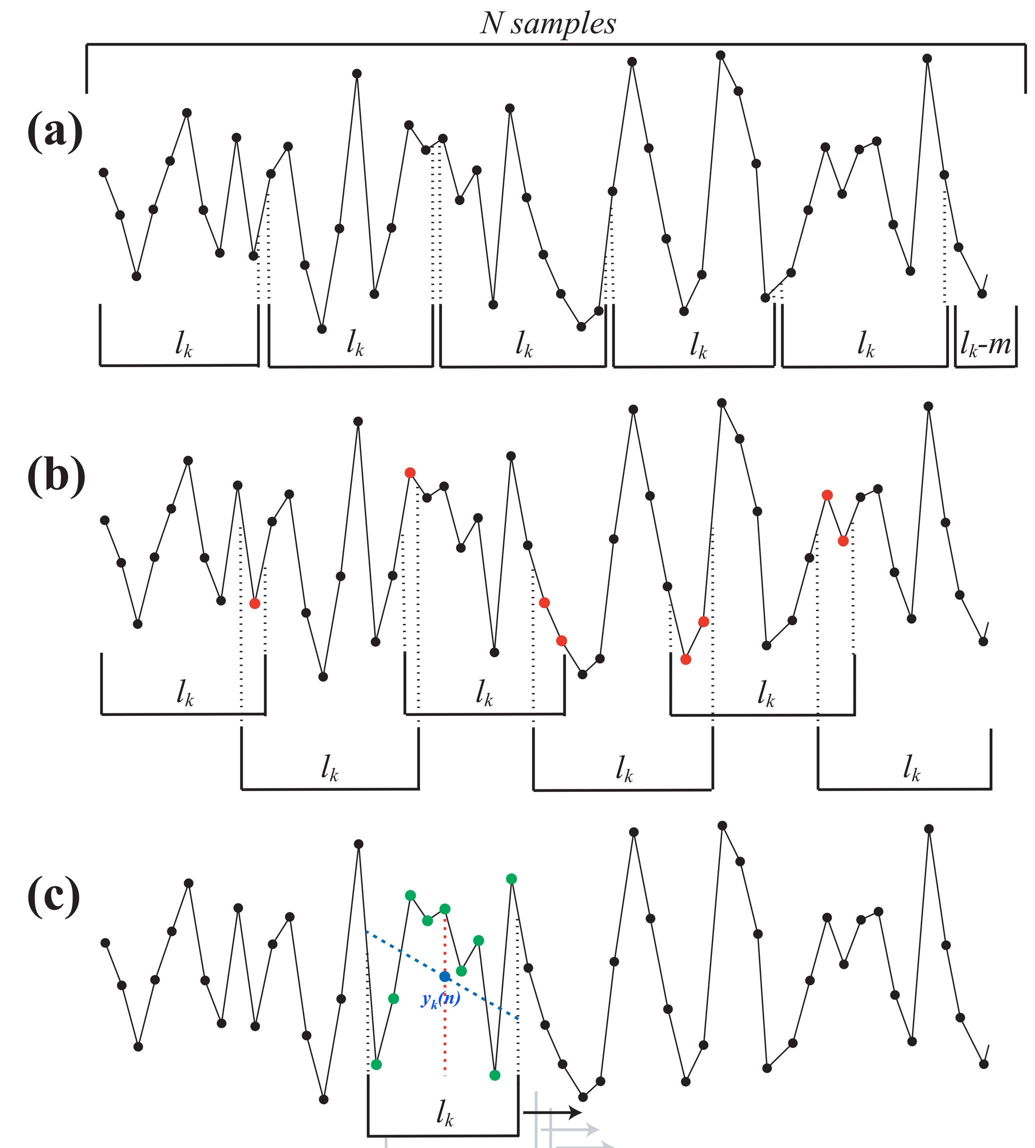

Figure 2: Different approaches for segmenting the signal: (a) traditional approach; (b) overlapping window approach; (c) sliding window approach

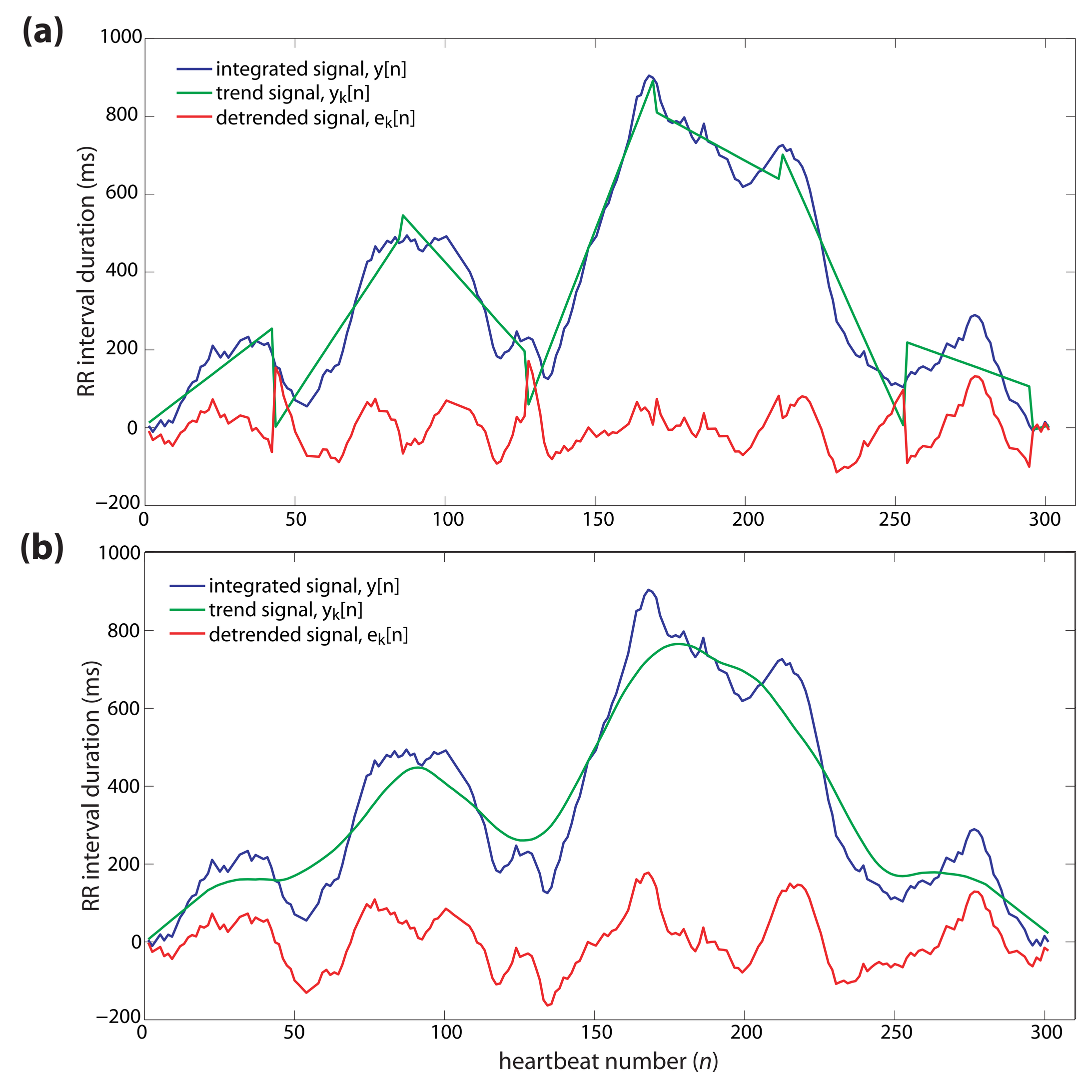

Figure 3: Integrated, trend, and detrended signals, obtained with: (a) traditional approach; (b) sliding window approach

Evaluation: Random Signals

- Created with different power-law correlation characteristics: white noise, pink noise $(\mathbf{1/f})$ and Brownian noise $(\mathbf{1/f^2})$
  - Expected α for each of these is 0.5, 1.0 and 1.5, respectively [2]
  - 250 signals of each type; 4096 samples each
- Table 1: mean error and standard deviation for each approach
- Student's t-test: α_1 and α_2 coefficients for sliding window approach are different from those for traditional approach $(\mathbf{p < 0.05})$

Table 1: Mean error (from expected value, α) and standard deviation for α_1 and α_2 for traditional and proposed approaches

		mean ($\times 10^{-3}$) trad.	mean ($\times 10^{-3}$) prop.	std. deviation ($\times 10^{-3}$) trad.	std. deviation ($\times 10^{-3}$) prop.
e_1 †	white	90	64	12	11
	pink	29	38	16	13
	Brownian	2	25	16	12
e_2 ‡	white	−8	−16	29	30
	pink	−19	−25	42	42
	Brownian	−23	−25	54	52
$\|(e_1,e_2)\|$ ♯	white	95	72	13	14
	pink	51	58	25	25
	Brownian	51	57	33	31

† where $e_1 = \alpha_1 - \alpha$
‡ where $e_2 = \alpha_2 - \alpha$
♯ Euclidian norm of the error vector, (e_1,e_2)

Evaluation: Real HRV Signals

- Signals obtained from Physiobank: 11 normals, 9 elite athletes, 8 Chi meditators (during meditation and during rest), 12 apneics, 7 with mild epileptic seizures [4,5,6]
- Each signal has ≈20,000 interbeat intervals
- Ectopic beats and false +/− were removed and corrected using ECGLab [7]
- Figure 4: α_1 and α_2 for each group (sliding window approach)
- Statistical tests: nonparametric Friedman ANOVA test, as some groups tested negative for normality (Table 2)
- Table 3: correlation $(\mathbf{r})$ and regression $(\mathbf{m})$ coefficients between traditional and proposed approaches

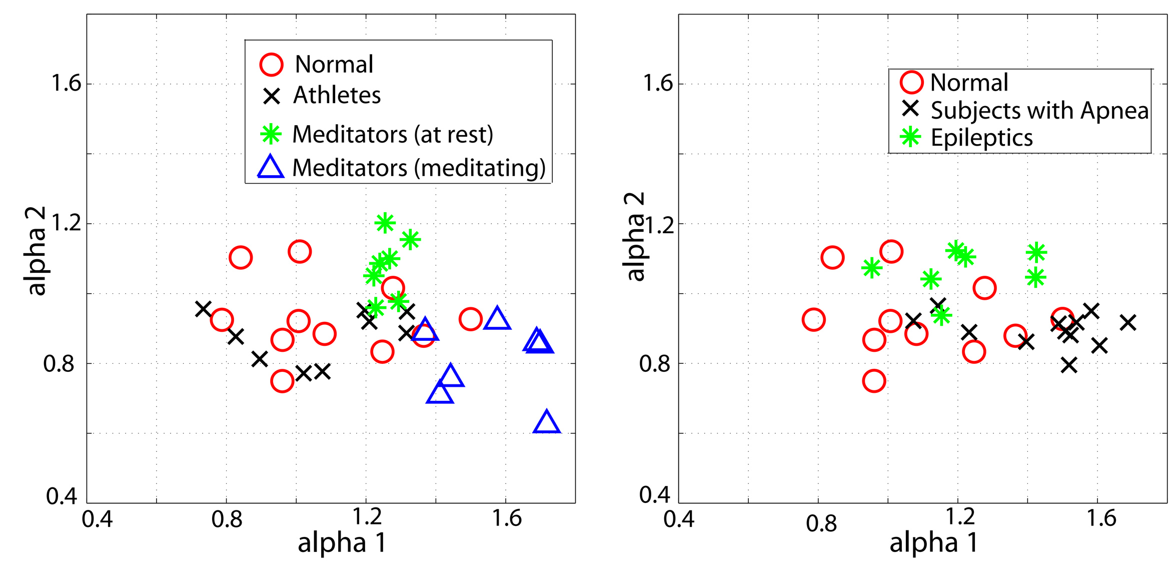

Figure 4: α_1 and α_2 for HRV signals from different groups of subjects (sliding window approach)

Table 2: ANOVA: traditional vs. sliding window approach ($\mathbf{p}$ values)

	α_1	α_2
normals	0.37	0.04*
athletes	0.74	0.10
meditators (rest)	0.26	0.01*
meditators (meditating)	0.01*	0.01*
apneics	0.00*	0.02*
epileptics	0.71	0.01*

* statistically significant difference ($p < 0{,}05$)

Table 3: Comparison between traditional and sliding window approaches

	α_1 correlation coefficient	α_1 regression coefficient	α_2 correlation coefficient	α_2 regression coefficient
white noise	0.87	0.84	0.98	1.03
pink noise	0.83	0.68	0.98	0.98
Brownian noise	0.78	0.60	0.97	0.95
real HRV signals	1.00	1.06	1.00	1.01

Conclusions

- While the results from the two approaches are quantitatively similar, extremely correlated, and with similar precision for both α_1 and α_2, the proposed approach presented some advantages, e. g., a better accuracy for white noise signals
- Both approaches seem able to visually differentiate between most of the studied groups

References

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Financial Support

PIBIC/CNPq; FAP-DF; PROAP/CAPES; PGEA/ENE/UnB