

Breathing Dynamics Formula Sheet

PolarH10 breath interval and amplitude entropy features

Data path

- input waveform: calibrated **VolumeBase01** from the Breathing tracker
- event extraction: alternating peaks and troughs from that calibrated waveform
- derived series:
 - interval series: spacing between same-polarity extrema
 - amplitude series: absolute peak-trough excursion

This is the main adaptation relative to the cited paper: the paper uses a respiration-belt signal, while this app uses the repository's calibrated ACC breathing waveform.

Unless a section says otherwise, the formulas below are applied separately to the derived breath-interval series and the derived breath-amplitude series. In the notation below, t_j is the time of extremum j , x_j is its amplitude, s_i is a generic element of whichever derived series is currently being analyzed, μ is the mean of that series, and $\rho(\ell)$ is autocorrelation at lag ℓ .

Derived breath series

For accepted extrema times t_k and values x_k :

$$\text{interval}_j = t_j - t_{j-1}$$

where the two extrema belong to the same polarity family, for example peak to peak or trough to trough.

This turns the waveform into a timing series, so it describes how long one breath cycle segment takes from one like-extremum to the next.

$$\text{amplitude}_j = |x_j - x_{j-1}|$$

where the two extrema are alternating peak and trough partners in a completed breath excursion.

This turns the waveform into an excursion-depth series, so it describes how large each completed breath movement is.

Basic statistics

For either derived series $s_1 \dots s_n$:

$$\mu = \frac{1}{n} \sum_{i=1}^n s_i$$

μ is the typical interval or excursion size over the current window.

$$SD = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (s_i - \mu)^2}$$

SD measures absolute variability around that typical value.

$$CV = \frac{SD}{|\mu|}$$

CV rescales variability by the mean so two sessions with different average breath size or timing can still be compared on a relative basis.

ACW50

The autocorrelation window is the first lag where the normalized autocorrelation falls below 0.5:

$$ACW50 = \min \{ \ell \geq 1 : \rho(\ell) < 0.5 \}$$

Large $ACW50$ values mean the series stays self-similar across more lags; small values mean the pattern decorrelates quickly.

PSD slope

The implementation now follows the cited NeuroKit2 path more closely:

- linearly detrend the series
- standardize it with population SD
- compute a one-sided FFT power spectrum
- keep the lower-frequency quartile of the spectrum
- fit the slope in log-log space

$$\text{PSD slope} = \text{slope}(\log_{10}(f), \log_{10}(PSD(f)))$$

Here f is frequency and $PSD(f)$ is the one-sided power spectral density of the detrended, standardized series. The fitted slope summarizes how strongly slower fluctuations dominate over faster ones in the low-frequency region.

Lempel-Ziv complexity

The series is binarized around its mean:

$$b_i = \begin{cases} 1 & s_i \geq \mu \\ 0 & s_i < \mu \end{cases}$$

This binary step asks only whether each sample is above or below the series mean, turning the waveform-derived series into a symbolic pattern string.

The Lempel-Ziv counter then scans the binary string left-to-right and adds a new phrase whenever it encounters a substring not yet present in the discovered pattern set. The app publishes a normalized form:

$$LZC_{norm} = \frac{c(n)}{n/\log_2(n)}$$

Higher normalized LZC means new binary patterns keep appearing; lower values mean the sequence is more repetitive.

Sample entropy

Default settings:

- $m = 2$
- delay = 1
- $r = 0.2 \cdot SD$

Here m is embedding dimension, delay is the lag between points in the embedded vectors, r is the matching tolerance, and N is the series length.

$$SampEn(m, r, N) = -\ln\left(\frac{A}{B}\right)$$

In plain language, sample entropy asks how often similar short patterns remain similar when extended by one more sample.

where B counts matching embedded vectors of length m , A counts matching embedded vectors of length $m + 1$, and matching uses the Chebyshev-distance tolerance r .

If the conditional probability is undefined, the app now suppresses the headline instead of inventing a finite fallback value.

Multiscale entropy

Default settings:

- $m = 3$
- delay = 1
- $r = 0.2 \cdot SD$ of the original series
- scales 1..5
- published summary: area under the entropy-by-scale curve divided by the count of usable scales

For each scale τ , the series is coarse-grained by averaging non-overlapping blocks:

$$y_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} s_i$$

This creates a slower, coarser version of the same series at each scale τ .

Sample entropy is then computed on each coarse-grained series with the same base tolerance. The reported MSE summary is:

$$MSE_{AUC} = \frac{\text{trapz}(SampEn_{\tau})}{K}$$

where K is the number of usable finite scales kept for the summary.

This summary asks whether irregularity persists across multiple time scales rather than only at the native sample-to-sample resolution.

Alignment status

This implementation is aligned to the cited method family for interval and amplitude series extraction from extrema; mean, SD, CV, ACW50, PSD slope, LZC, SampEn, and MSE; NeuroKit2-style SampEn and MSE defaults; NeuroKit2-style handling of undefined entropy values; and NeuroKit2-style PSD slope preprocessing and low-frequency fit region.

The remaining explicit adaptation is the waveform source: the paper uses respiration-belt input, while this repository uses the calibrated ACC breathing waveform from `PolarBreathingTracker`.

References

- Goheen et al., “It’s About Time: Breathing Dynamics Modulate Emotion and Cognition” (2025).
- <https://doi.org/10.1111/psyp.70149>
- <https://mesmerprism.github.io/PolarH10/reference/breathing-dynamics-workflow.html>
- <https://mesmerprism.github.io/PolarH10/reference/references.html>