






pybreathe: a python package for respiratory airflow rates analysis

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Summary

Breathing is the vital function that enables air to flow into the lungs during inhalation and out during exhalation. Inhalation delivers (di)oxygen to the tissues, while exhalation flushes out carbon dioxide. In physiology, breathing is widely studied to investigate a whole range of respiratory diseases as well as physical abilities. A consistent and robust analytical framework is essential to cope with the large volume of data and to address the often time-consuming nature of routine analysis procedures. pybreathe is a python package that allows breathing to be formally analysed. It lets users to extract essential features such as the volume inhaled and exhaled, the inspiratory and expiratory times. It also provides the breathing frequency. The package has been designed to be user-friendly, relying solely on a user-supplied discretised air flow rate considered as a time series (instantaneous flow rate).

Statement of need

In 2017, half a billion people worldwide lived with a chronic respiratory disease ([Soriano et al., 2020](#)). Concurrently, the role of breathing has garnered growing attention in research focused on both athletic/sport performance ([Contreras-Briceño et al., 2024](#); [Harbour et al., 2022](#)) and overall well-being ([Fincham et al., 2023](#)). Due to the large amount of respiratory data acquired over the last few years, numerous algorithms have been developed to structure analysis and open up new insights. Such tools complement commercial analysis software used historically ([Lusk et al., 2023](#)).

On the one hand, most of the open source software dealing with breathing relies heavily on peak/hollow detection ([Bishop et al., 2022](#); [Brammer, 2020](#); [Makowski et al., 2021](#)) to extract signal features such as amplitude and breathing period. However, such detection methods often require human correction, manual curation or advanced algorithms to guarantee the accuracy of the results ([Vanegas et al., 2020](#)). Besides, such local extrema detection approaches are more suited for the characterization of instantaneous volume than of instantaneous flow. Although the former can be deduced from the latter ([Figure 1](#)), it is generally flow rates, themselves derived from pressure differences that are supplied ([Criée et al., 2011](#)). In some cases, however, signals and related algorithms may also originate from chest/abdominal belts ([Holm et al., 2024](#)).

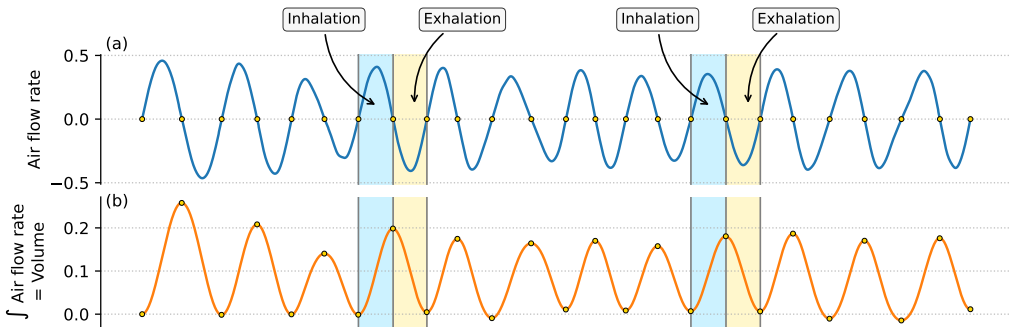


Figure 1: Relationship between instantaneous flow rate (a) and instantaneous volume (b). The volume is obtained by integrating the flow rate over time. Thus, when the flow rate is positive (inhalation; blue areas), the volume increases, whereas when the flow rate is negative (exhalation; yellow areas), the volume decreases.

36 On the other hand, some advanced algorithms use cutting-edge clustering methods to detect
37 respiratory patterns that go beyond the features mentioned above (Germain et al., 2023).
38 Although this kind of approach is particularly valuable for providing a deeper understanding of
39 respiratory physiology across various experimental conditions, it requires advanced programming
40 skills and knowledge and may be complicated to set up in practice for non-computer users.

41 In this paper, we sought to implement an easy-to-use framework specially designed to facilitate
42 respiratory analyses derived from instantaneous air flow rates (recorded by plethysmography).
43 pybreathe is a python package with an API designed to be used by both experimenters and
44 developers. Users can acquire their respiratory data using any standard software. A necessary
45 and sufficient condition for using pybreathe is to export the data (instantaneous air flow rate)
46 and discretise it into a classic text format (e.g., .txt, .csv). Most software applications used for
47 measuring respiratory air flow rates include this functionality and can output a two-column
48 file: the first column represents the discretised time vector, while the second provides the
49 corresponding flow values at each time point (Table 1).

Table 1: Example of a two-column table depicting the instantaneous discretised air flow rate required for the use of pybreathe. Instantaneous air flow rate is a time series. User files should have the same configuration. To enable the calculation of volumes in absolute values, the flow rate should also be in absolute values (e.g., mL.s⁻¹ or L.s⁻¹). The time vector format should also represent actual timepoints.

time	values
0.0	0.0650
0.004	0.0660
0.008	0.0671
0.012	0.0681
0.016	0.0692
...	...

50 The main difference with other respiratory analysis algorithms is that pybreathe is based on
51 ventilatory flow and not on volume. To our knowledge, there is no open-source algorithm that
52 simply extracts elementary but essential features from air flow recordings.

53 The main feature of a respiratory signal is the tidal volume (i.e., the volume passing through
54 the lungs during a single breath). In the case of air flow rates, peak/hollow analysis cannot
55 be applied because the amplitude (i.e., height) depends on the 'speed' at which the air flows
56 in and out: for the same exhaled or inhaled volume, the faster the airflow, the greater the
57 amplitude (Figure 2).

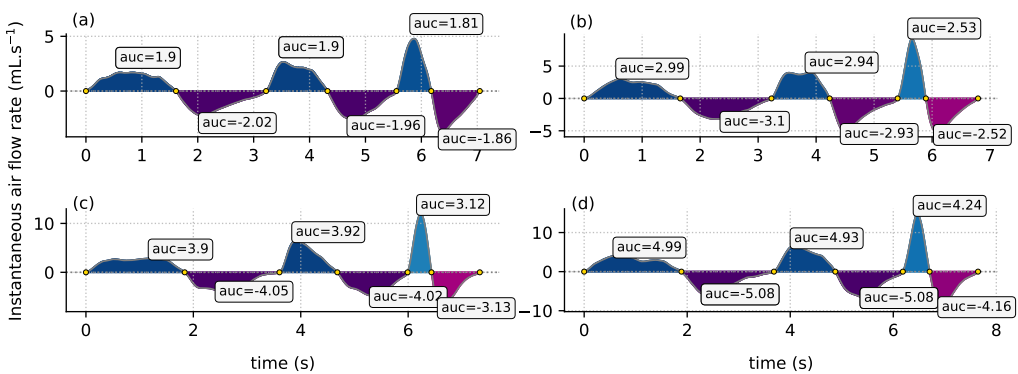


Figure 2: Manual injection/aspiration of different quantities of air into a chamber with a syringe at three different speeds: slow, moderate and fast. (a) 2 mL; (b) 3 mL; (c) 4 mL; (d) 5 mL. Injection corresponds to the positive parts (blue) while aspiration corresponds to the negative parts (purple). AUCs values were obtained with pybreathe.

58 In this situation, to really grasp the tidal volume, we need to get the Area Under the Curve
59 (AUC) instead of the amplitude (Table 2).

Table 2: Comparison of the integral (Area Under the Curve) and amplitude (height) of several volumes of air manually injected/aspirated into a chamber.

actual volume	speed	positive integral	negative integral	positive amplitude	negative amplitude
≈ 2 mL	slow	1.90	- 2.02	1.70	- 2.26
≈ 2 mL	moderate	1.90	- 1.96	2.66	- 2.54
≈ 2 mL	fast	1.81	- 1.86	4.79	- 3.75
≈ 3 mL	slow	2.99	- 3.10	3.04	- 3.19
≈ 3 mL	moderate	2.94	- 2.93	3.98	- 5.07
≈ 3 mL	fast	2.53	- 2.52	9.24	- 5.2
≈ 4 mL	slow	3.90	- 4.05	2.91	- 3.71
≈ 4 mL	moderate	3.92	- 4.02	6.46	- 4.81
≈ 4 mL	fast	3.12	- 3.13	12.03	- 7.09
≈ 5 mL	slow	4.99	- 5.08	4.21	- 5.76
≈ 5 mL	moderate	4.93	- 5.08	6.58	- 6.70
≈ 5 mL	fast	4.24	- 4.16	14.88	- 9.04

60 For each quantity of air, the integral faithfully represents the volume injected and aspirated.
61 The amplitude is not representative of the volume injected or aspirated. Interestingly, regardless
62 of the volume of air injected, high injection speeds consistently compromise measurement
63 precision. This issue arises solely because the air is injected manually by an experimenter with
64 a syringe and does not originate from pybreathe.

65 For a given respiratory signal, pybreathe detects zero-crossings (Figure 1a). AUC (integral)
66 of these zero-separated segments therefore corresponds to the volume inhaled or exhaled
67 (depending on the configuration of the primary acquisition software). The duration of these
68 segments (time between two zeros) corresponds to the inspiratory or expiratory time. Breathing
69 frequency is also provided based either on the frequency of peaks or hollows, or using a more
70 sophisticated spectral analysis.

71 pybreathe fundamentals

72 The pybreathe package is accompanied by a *BreathingFlow* object which is the core of the
73 algorithm. Users should instantiate a *BreathingFlow* object with their own data (e.g., [Table 1](#)).

```
74 from pybreathe import BreathingFlow

75 # Loading a discretised respiratory flow rate
76 my_signal = BreathingFlow.from_file(
77     filename="path_to_your_discretised_flow",
78     identifier="my data"
79 )
```

74 where `path_to_your_discretised_flow` is a two-column discretised file (e.g., .txt, .csv)
75 representing instantaneous airflow as a function of time (e.g., [Table 1](#)).

76 The package comes with [example scripts](#) based on simulated breathing signals that are
77 representative of the data that can be collected experimentally. They explain the milestones
78 involved in carrying out an analysis (feature extraction) and they supply useful documentation.
79 To get started with pybreathe API, users are strongly advised to refer to these scripts using
80 example signals.

81 Proof

82 To ensure that the package worked correctly and that the methods returned the desired output,
83 we checked the volumes extracted by pybreathe when we injected/aspirated known quantities
84 of air ([Figure 2](#) and [Table 2](#)). We observed that the manually tested volumes (2 mL, 3 mL, 4
85 mL, 5 mL) corresponded well to the integral values (AUCs) for each injection or aspiration.
86 However, because the manual injection/aspiration of air into a chamber can be imprecise due to
87 the experimenter and the precision of the syringe, we also created an artificial respiratory signal
88 corresponding to the sine function ([Figure 3](#)). Based on the sine, we checked that the signal
89 features obtained with pybreathe were indeed the same as those obtained *mathematically*.
90 Users can access this documentation in the [validation notebook](#).

91 Let f the sinus function.

$$f : \mathbb{R} \longrightarrow \mathbb{R}$$

$$x \longmapsto \sin(x)$$

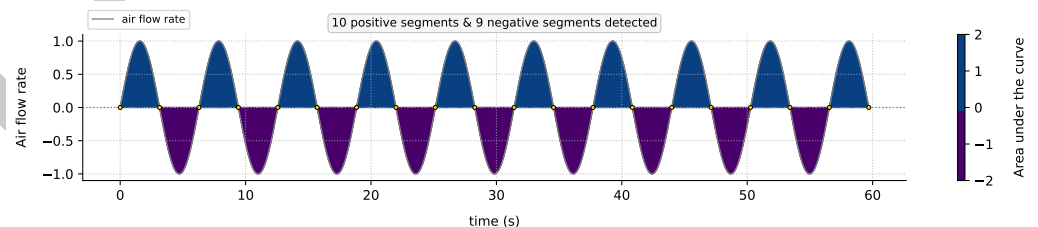


Figure 3: Graph of the sine function on the interval $[0, 10\pi]$.

92 Positive time (~ inspiratory time)

93 Statement: the mean length of the interval where the sine function is positive is exactly equal
94 to π .

95 **Mathematical proof**

96 Let $x \in \mathbb{R}$.

97 $\sin(x) \geq 0 \iff x \bmod 2\pi \in [0, \pi]$

98 Thus, the duration (interval length) of all positive segments is $\pi - 0$, which is equal to π .

99 **pybreathe validation**

```
>>> from pybreathe import BreathingFlow
>>> sinus = BreathingFlow.load_sinus()
>>> sinus.get_positive_time()
mean = 3.14 ± 9.19e-10 (n = 10).
```

100 **Positive Area Under the Curve (~ inhaled volume)**

101 Statement: the mean AUC (integral) of the positive segments of the sine function is exactly 2.

102 **Mathematical proof**

103 Let $x \in \mathbb{R}$.

104 $\sin(x) \geq 0 \iff x \bmod 2\pi \in [0, \pi]$

$$\begin{aligned} \int_0^\pi \sin x \, dx &= [-\cos x]_0^\pi \\ &= -\cos(\pi) - (-\cos(0)) \\ &= -\cos(\pi) + \cos(0) \\ &= -(-1) + 1 \\ &= 1 + 1 \\ &= 2 \end{aligned}$$

105 Thus, the mean AUC of all positive segments is 2.

106 **pybreathe validation**

```
>>> from pybreathe import BreathingFlow
>>> sinus = BreathingFlow.load_sinus()
>>> sinus.get_positive_auc()
mean = 2.0 ± 8.4e-12 (n = 10).
```

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112 **References**

- 113 Bishop, M., Weinhold, M., Turk, A. Z., Adeck, A., & SheikhBahaei, S. (2022). An open-source
114 tool for automated analysis of breathing behaviors in common marmosets and rodents.
115 *eLife*, 11, e71647. <https://doi.org/10.7554/eLife.71647>

- 116 Brammer, J. (2020). Biopeaks: A graphical user interface for feature extraction from heart-
117 and breathing biosignals. *Journal of Open Source Software*, 5(54), 2621. [https://doi.org/](https://doi.org/10.21105/joss.02621)
118 [10.21105/joss.02621](https://doi.org/10.21105/joss.02621)
- 119 Contreras-Briceño, F., Cancino, J., Espinosa-Ramírez, M., Fernández, G., Johnson, V.,
120 & Hurtado, D. E. (2024). Estimation of ventilatory thresholds during exercise using
121 respiratory wearable sensors. *Npj Digital Medicine*, 7(1). [https://doi.org/10.1038/](https://doi.org/10.1038/s41746-024-01191-9)
122 [s41746-024-01191-9](https://doi.org/10.1038/s41746-024-01191-9)
- 123 Criée, C. P., Soricther, S., Smith, H. J., Kardos, P., Merget, R., Heise, D., Berdel, D., Köhler,
124 D., Magnussen, H., Marek, W., Mitfessel, H., Rasche, K., Rolke, M., Worth, H., & Jörres,
125 R. A. (2011). Body plethysmography – its principles and clinical use. *Respiratory Medicine*,
126 105(7), 959–971. <https://doi.org/10.1016/j.rmed.2011.02.006>
- 127 Fincham, G. W., Strauss, C., Montero-Marin, J., & Cavanagh, K. (2023). Effect of breathwork
128 on stress and mental health: A meta-analysis of randomised-controlled trials. *Scientific*
129 *Reports*, 13(1). <https://doi.org/10.1038/s41598-022-27247-y>
- 130 Germain, T., Truong, C., Oudre, L., & Krejci, E. (2023). Unsupervised classification of
131 plethysmography signals with advanced visual representations. *Frontiers in Physiology*, 14,
132 1154328. <https://doi.org/10.3389/fphys.2023.1154328>
- 133 Harbour, E., Stöggel, T., Schwameder, H., & Finkenzeller, T. (2022). Breath tools: A synthesis
134 of evidence-based breathing strategies to enhance human running. *Frontiers in Physiology*,
135 13. <https://doi.org/10.3389/fphys.2022.813243>
- 136 Holm, B., Borsky, M., Arnardottir, E. S., Serwatko, M., Mallett, J., Islind, A. S., & Óskarsdóttir,
137 M. (2024). BreathFinder: A method for non-invasive isolation of respiratory cycles utilizing
138 the thoracic respiratory inductance plethysmography signal. *Nature and Science of Sleep*,
139 16, 1253–1266. <https://doi.org/10.2147/NSS.S468431>
- 140 Lusk, S., Ward, C. S., Chang, A., Twitchell-Heyne, A., Fattig, S., Allen, G., Jankowsky, J. L.,
141 & Ray, R. S. (2023). An automated respiratory data pipeline for waveform characteristic
142 analysis. *The Journal of Physiology*, 601(21), 4767–4806. [https://doi.org/10.1113/](https://doi.org/10.1113/JP284363)
143 [JP284363](https://doi.org/10.1113/JP284363)
- 144 Makowski, D., Pham, T., Lau, Z. J., Brammer, J. C., Lespinasse, F., Pham, H., Schölzel,
145 C., & Chen, S. H. A. (2021). NeuroKit2: A python toolbox for neurophysiological signal
146 processing. *Behavior Research Methods*, 53(4), 1689–1696. [https://doi.org/10.3758/](https://doi.org/10.3758/s13428-020-01516-y)
147 [s13428-020-01516-y](https://doi.org/10.3758/s13428-020-01516-y)
- 148 Soriano, J. B., Kendrick, P. J., Paulson, K. R., Gupta, V., Abrams, E. M., Adedoyin, R.
149 A., Adhikari, T. B., Advani, S. M., Agrawal, A., Ahmadian, E., Alahdab, F., Aljunid,
150 S. M., Altirkawi, K. A., Alvis-Guzman, N., Anber, N. H., Andrei, C. L., Anjomshoa,
151 M., Ansari, F., Antó, J. M., ... Vos, T. (2020). Prevalence and attributable health
152 burden of chronic respiratory diseases, 1990–2017: A systematic analysis for the global
153 burden of disease study 2017. *The Lancet Respiratory Medicine*, 8(6), 585–596. [https://doi.org/10.1016/S2213-2600\(20\)30105-3](https://doi.org/10.1016/S2213-2600(20)30105-3)
154 [https://doi.org/10.1016/S2213-2600\(20\)30105-3](https://doi.org/10.1016/S2213-2600(20)30105-3)
- 155 Vanegas, E., Igual, R., & Plaza, I. (2020). Sensing systems for respiration monitoring: A
156 technical systematic review. *Sensors (Basel, Switzerland)*, 20(18), 5446. [https://doi.org/](https://doi.org/10.3390/s20185446)
157 [10.3390/s20185446](https://doi.org/10.3390/s20185446)