
hrv

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Contents

| | | |
|----------|--|----------|
| 1 | Contents | 3 |
| 1.1 | First Steps | 3 |
| 1.1.1 | Installation | 3 |
| 1.1.2 | Basic Usage | 3 |
| 1.2 | Read RRi files | 5 |
| 1.2.1 | Read .txt files | 5 |
| 1.2.2 | Read Polar® (.hrm) files | 5 |
| 1.2.3 | Read .csv files | 6 |
| 1.2.4 | RRi Sample Data | 6 |
| 1.3 | RRI statistics | 8 |
| 1.3.1 | Basic Statistics | 8 |
| 1.3.2 | RRI Basic Information | 9 |
| 1.4 | RRI Visualization | 9 |
| 1.4.1 | Plot RRi Series | 9 |
| 1.4.2 | RRI histogram and Heart Rate Histogram | 10 |
| 1.5 | Time Slicing | 11 |
| 1.6 | Pre-Processing | 13 |
| 1.6.1 | Filters | 13 |
| 1.6.2 | Detrending | 16 |
| 1.7 | Analysis | 19 |
| 1.7.1 | Time Domain Analysis | 19 |
| 1.7.2 | Frequency Domain Analysis | 19 |
| 1.7.3 | Non-linear Analysis | 20 |
| 1.8 | Non-stationary RRi series | 21 |
| 1.8.1 | Time Varying | 23 |
| 1.8.2 | Short Time Fourier Transform | 24 |
| 1.9 | Contribution start guide | 24 |
| 1.9.1 | Preparing the environment | 24 |
| 1.9.2 | Running the tests | 24 |
| 1.9.3 | Coding and Docstring styles | 25 |

hrv is a simple Python module that brings the most widely used techniques to extract information about cardiac autonomic functions through RRI series and Heart Rate Variability (HRV) analyses without losing the **Power** and **Flexibility** of a native Python object.

In other words, the **hrv** module eases the manipulation, inspection, pre-processing, visualization, and analyses of HRV-related information. Additionally, it is written with idiomatic code and tries to implement the API of a built-in object, which might make it intuitive for Python users.

CHAPTER 1

Contents

1.1 First Steps

1.1.1 Installation

To install use pip:

```
pip install hrv
```

Or clone the repo:

```
git clone https://github.com/rhenanbartels/hrv.git
python setup.py install
```

1.1.2 Basic Usage

Create an RRi instance

Once you create an RRi object you will have the power of a native Python iterable object. This means, that you can loop through it using a **for loop**, get a just a part of the series using native **slicing** and much more. Let us try it:

```
from hrv.rri import RRi

rri_list = [800, 810, 815, 750, 753, 905]
rri = RRi(rri_list)

print(rri)
RRi array([800., 810., 815., 750., 753., 905.])
```

Slicing

```
print(rri[0])
800.0

print(type(rri[0]))
numpy.float64

print(rri[::-2])
RRi array([800., 815., 753.])
```

Logical Indexing

```
from hrv.rri import RRi

rri = RRi([800, 810, 815, 750, 753, 905])
rri_ge = rri[rri >= 800]

rri_ge
RRi array([800., 810., 815., 905.])
```

Loop

```
for rri_value in rri:
    print(rri_value)

800.0
810.0
815.0
750.0
753.0
905.0
```

Note: When time information is not provided, time array will be created using the cumulative sum of successive RRi. After cumulative sum, the time array is subtracted from the value at $t[0]$ to make it start from 0s

RRi object and time information

```
from hrv.rri import RRi

rri_list = [800, 810, 815, 750, 753, 905]
rri = RRi(rri_list)

print(rri.time)
array([0. , 0.81 , 1.625, 2.375, 3.128, 4.033]) # Cumsum of rri values minus t[0]

rri = RRi(rri_list, time=[0, 1, 2, 3, 4, 5])
print(rri.time)
[0. 1. 2. 3. 4. 5.]
```

Note: Some validations are made in the time list/array provided to the RRi class, for instance:

- RRi and time list/array must have the same length;
- Time list/array can not have negative values;
- Time list/array must be monotonic increasing.

Basic math operations

With RRi objects you can make math operatins just like a numpy array:

```
rri
RRi array([800., 810., 815., 750., 753., 905.])

rri * 10
RRi array([8000., 8100., 8150., 7500., 7530., 9050.])

rri + 200
RRi array([1000., 1010., 1015., 950., 953., 1105.])
```

Works with Numpy functions

```
import numpy as np

rri = RRi([800, 810, 815, 750, 753, 905])

sum_rri = np.sum(rri)
print(sum_rri)
4833.0

mean_rri = np.mean(rri)
print(mean_rri)
805.5

std_rri = np.std(rri)
print(std_rri)
51.44171459039833
```

1.2 Read RRi files

1.2.1 Read .txt files

Text files contains a single column with all RRi values. Example of RRi text file

```
800
810
815
750
```

```
from hrv.io import read_from_text

rri = read_from_text('path/to/file.txt')

print(rri)
RRi array([800., 810., 815., 750.])
```

1.2.2 Read Polar® (.hrm) files

The .hrm files contain the RRi acquired with Polar®

A complete guide for .hrm files can be found [here](#)

```
from hrv.io import read_from_hrm

rri = read_from_hrm('path/to/file.hrm')

print(rri)
RRI array([800., 810., 815., 750.])
```

1.2.3 Read .csv files

Example of csv file:

```
800,
810,
815,
750,
```

```
from hrv.io import read_from_csv

rri = read_from_csv('path/to/file.csv')

print(rri)
RRI array([800., 810., 815., 750.])
```

Note: When using `read_from_csv` you can also provide a column containing time information. Let's check it.

```
800,1
810,2
815,3
750,4
```

```
rri = read_from_csv('path/to/file.csv', time_col_index=1)

print(rri)
RRI array([800., 810., 815., 750.])

print(rri.time)
array([0., 1., 2., 3., 4.])
```

1.2.4 RRI Sample Data

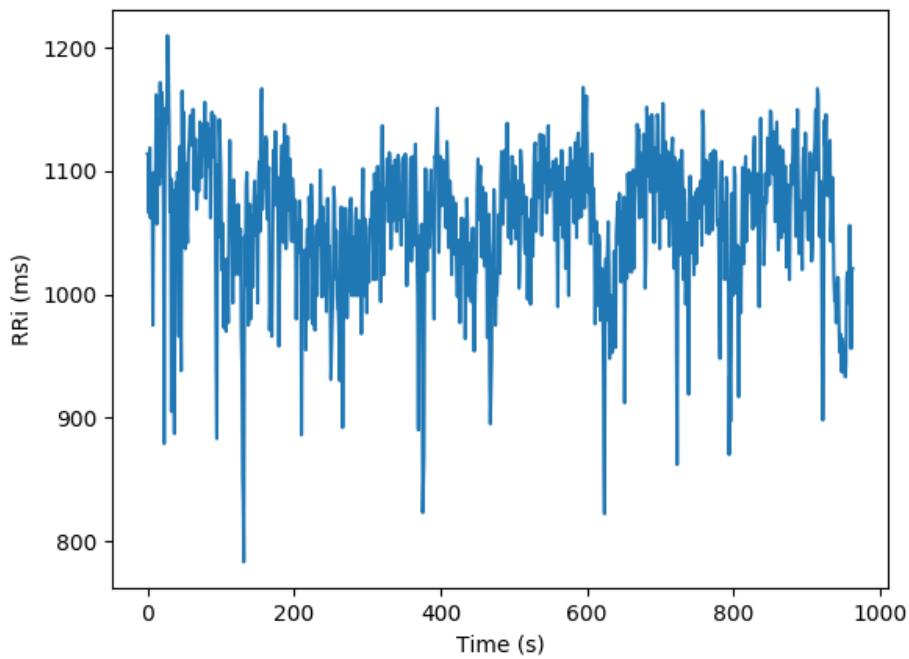
The hrv module comes with some sample data. It contains:

- RRI collected during rest
- RRI collected during exercise
- RRI containing ectopic beats

Rest RRI

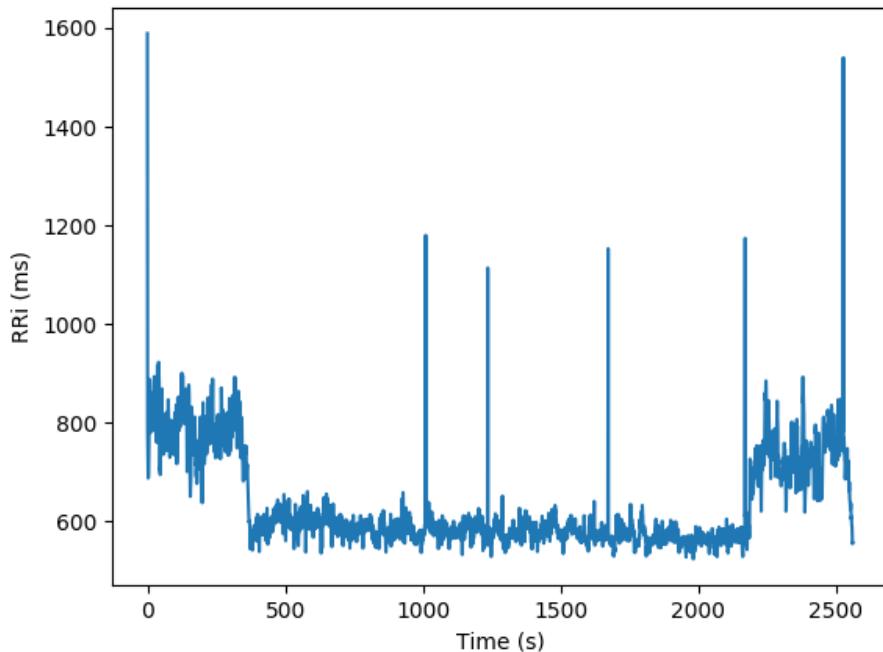
```
from hrv.sampledata import load_rest_rri

rri = load_rest_rri()
rri.plot()
```



Exercise RRi

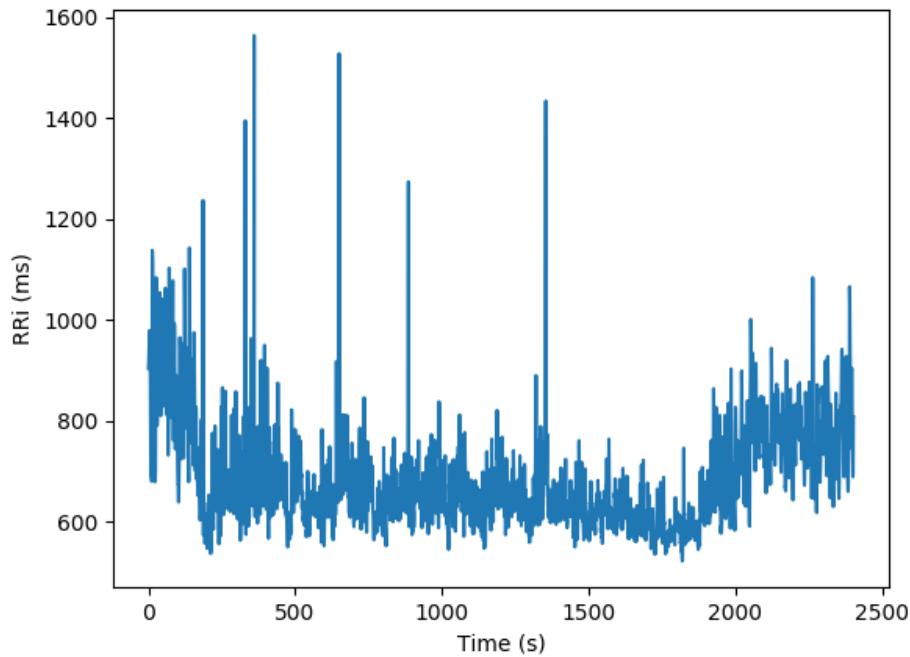
```
from hrv.sampledata import load_exercise_rri  
  
rri = load_exercise_rri()  
rri.plot()
```



Noisy RRI

```
from hrv.sampledata import load_noisy_rri

rri = load_noisy_rri()
rri.plot()
```



1.3 RRI statistics

1.3.1 Basic Statistics

The RRI object implements some basic statistics information about its values:

- mean
- median
- standard deviation
- variance
- minimum
- maximum
- amplitude

Some examples:

```
from hrv.rri import RRI
```

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```
rri = RRi([800, 810, 815, 750, 753, 905])

# mean
rri.mean()
805.5

# median
rri.median()
805.0
```

You can also have a complete overview of its statistical characteristic

```
desc = rri.describe()
desc

-----  

          rri           hr  

-----  

min        750.00      66.30  

max        905.00      80.00  

mean       805.50      74.78  

var        2646.25     20.85  

std         51.44       4.57  

median      805.00      74.54  

amplitude   155.00      13.70  

print(desc['std'])
{'rri': 51.44171459039833, 'hr': 4.5662272355549725}
```

1.3.2 RRi Basic Information

```
rri = RRi([800, 810, 815, 750, 753, 905])
rri.info()

N Points: 6
Duration: 4.03s
Interpolated: False
Detrended: False
Memory Usage: 0.05Kb
```

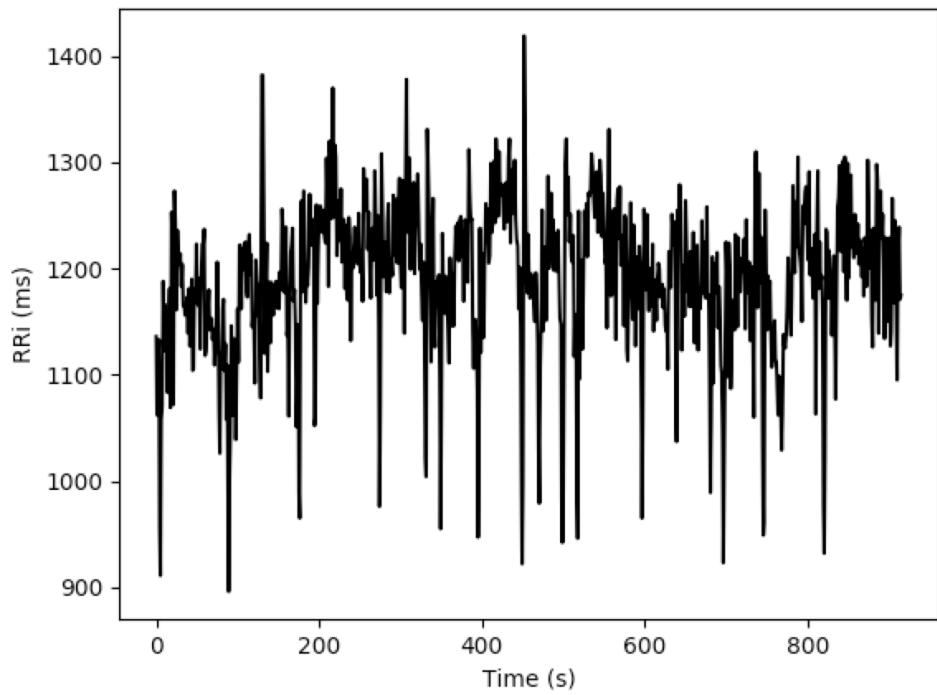
1.4 RRi Visualization

The RRi class brings a very easy way to visualize your series:

1.4.1 Plot RRi Series

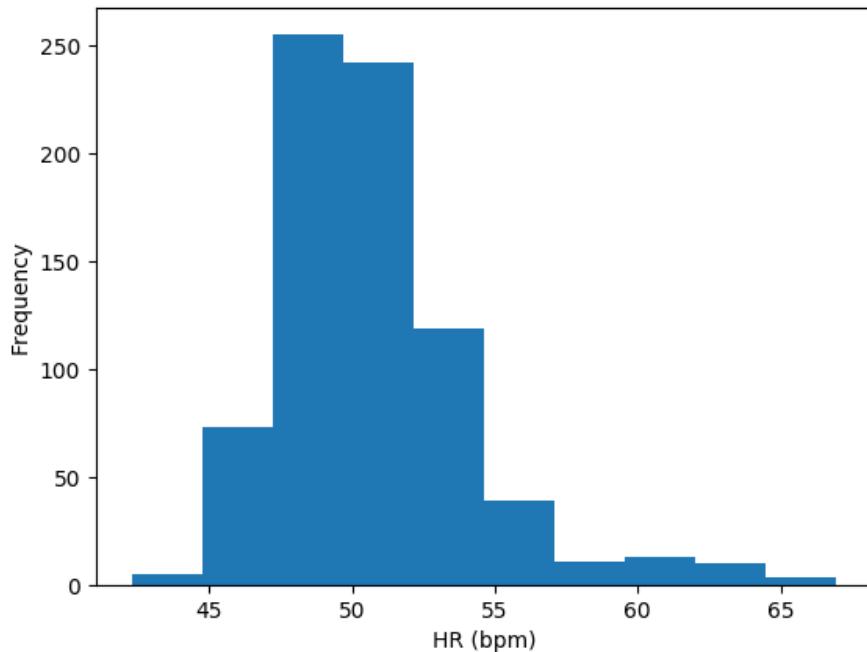
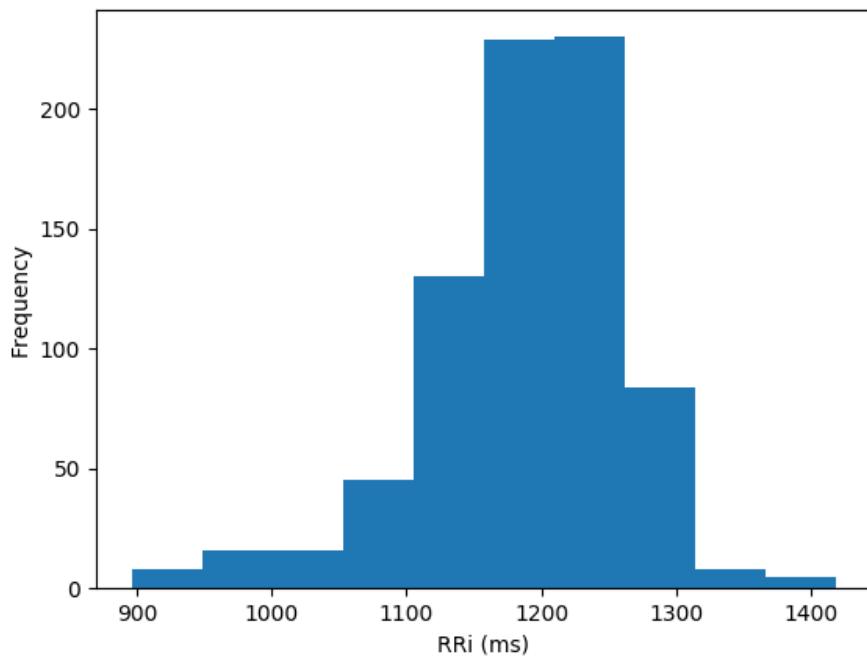
```
from hrv.io import read_from_text

rri = read_from_text('path/to/file.txt')
fig, ax = rri.plot(color='k')
```



1.4.2 RRI histogram and Heart Rate Histogram

```
rri.hist()  
rri.hist(hr=True)
```



1.5 Time Slicing

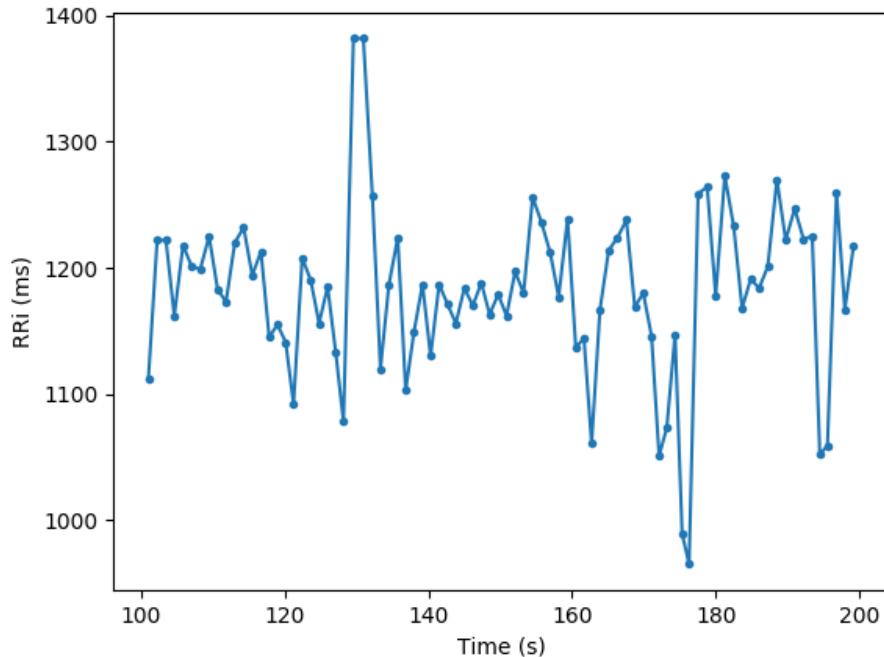
It is also possible to slice RRI series with time range information (in **seconds**).

In the following example, we are taking a slice that starts at 100s ‘and ends at’ 200s.

```
from hrv.io import read_from_text

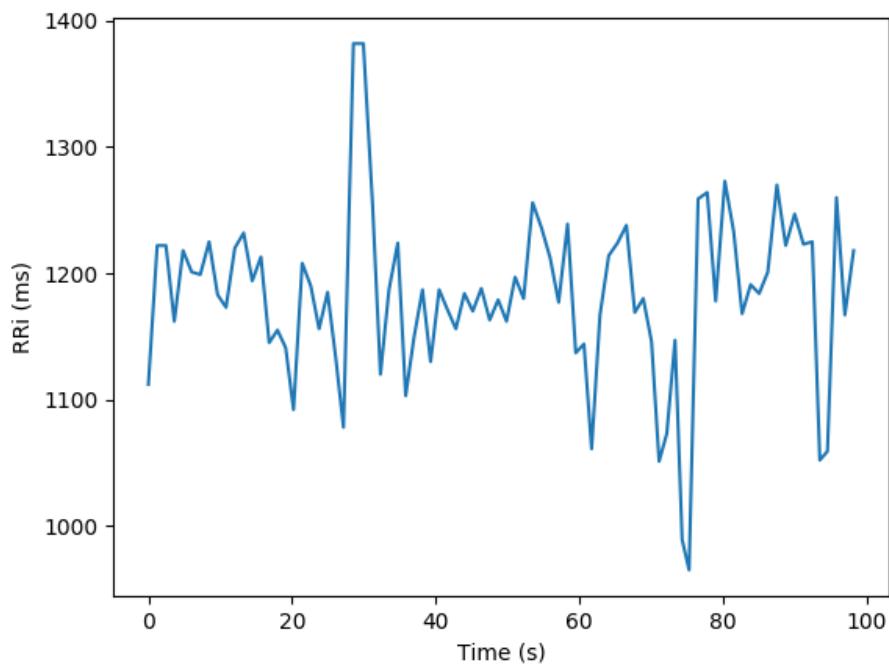
rri = read_from_text('path/to/file.txt')
rri_range = rri.time_range(start=100, end=200)

fig, ax = rri_range.plot(marker='.')
```



Time offset can be reset from the RRI series range:

```
rri_range.reset_time(inplace=True)
```



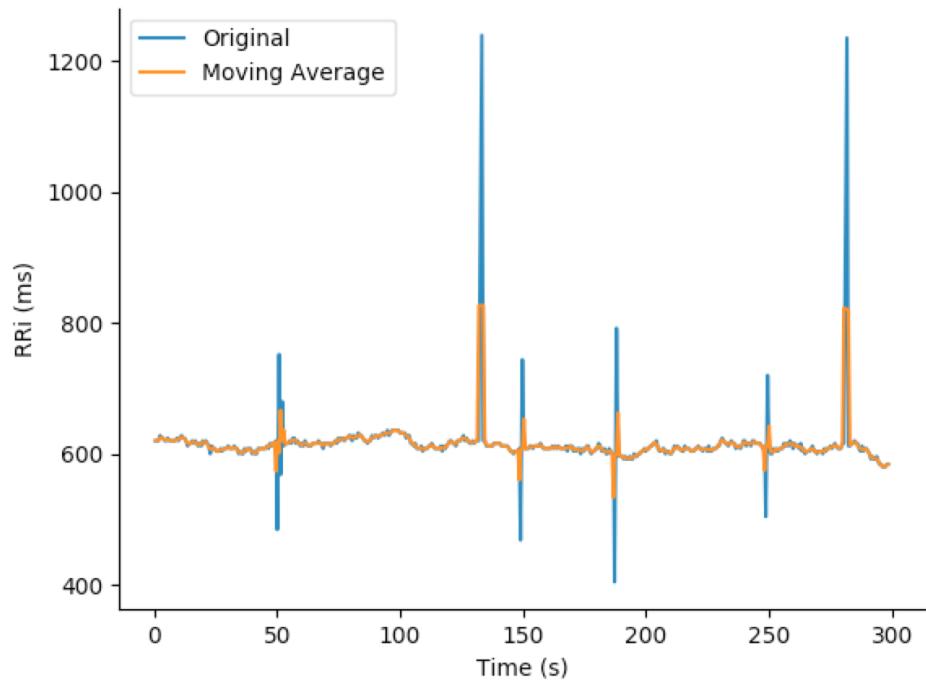
1.6 Pre-Processing

1.6.1 Filters

Moving Average

```
from hrv.filters import moving_average
filt_rri = moving_average(rri, order=3)

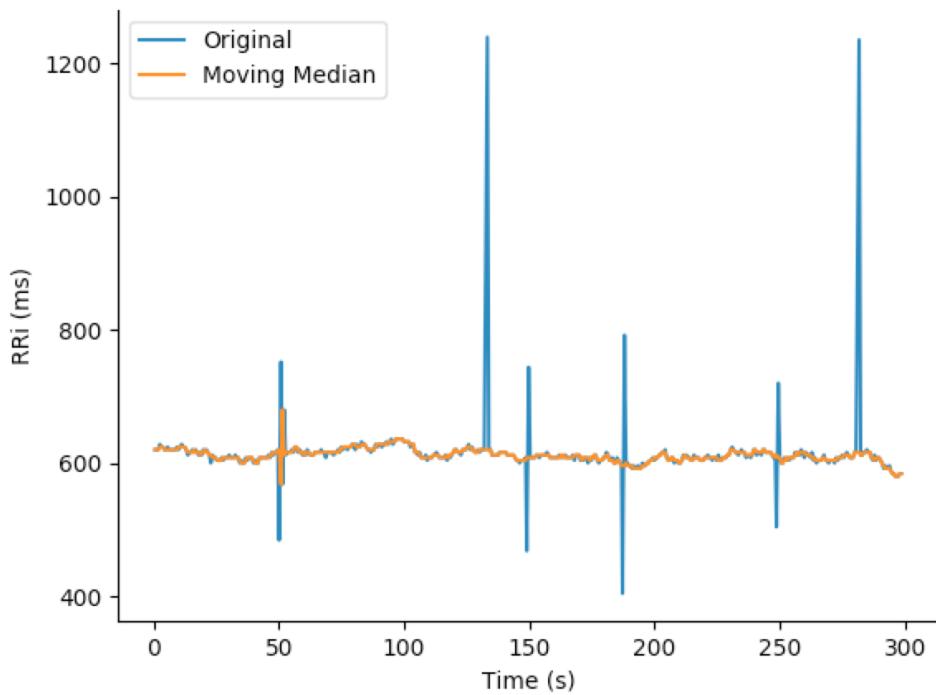
fig, ax = rri.plot()
filt_rri.plot(ax=ax)
```



Moving Median

```
from hrv.filters import moving_median
filt_rri = moving_median(rri, order=3)

fig, ax = rri.plot()
filt_rri.plot(ax=ax)
```

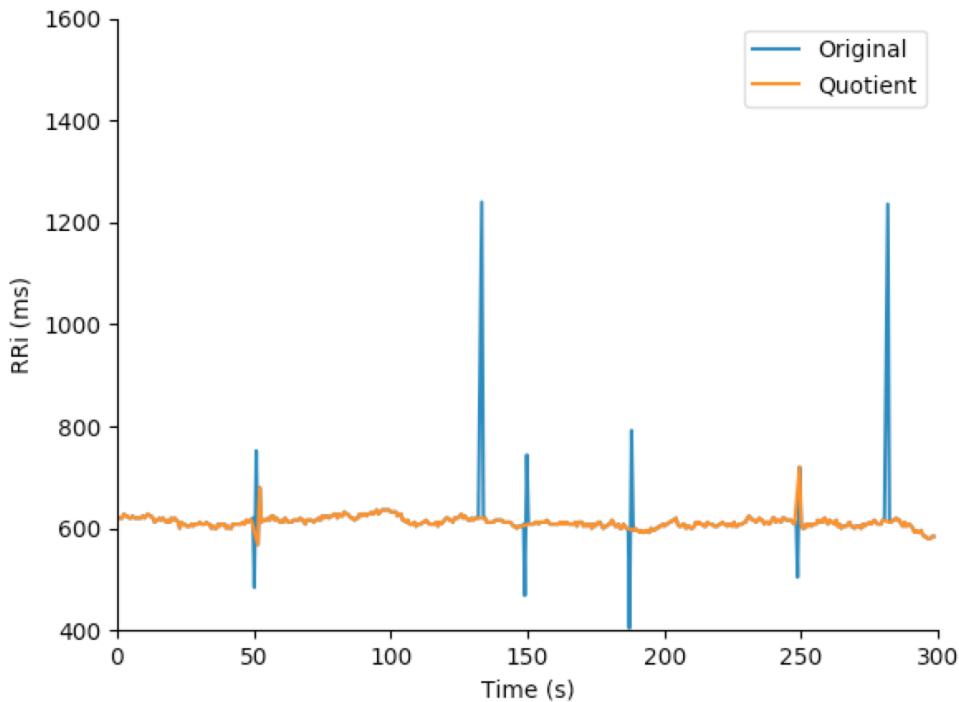


Quotient

[Read more](#)

```
from hrv.filters import quotient
filt_rrri = quotient(rrri)

fig, ax = rrri.plot()
filt_rrri.plot(ax=ax)
```



Threshold Filter

This filter is inspired by the threshold-based artifact correction algorithm offered by [kubios](#). To detect outliers in the tachogram series, each RRI is compared to the median value of local RRIs (default N=5). All the RRIs which the difference is greater than the local median value plus a threshold is replaced by [cubic](#) interpolated RRIs.

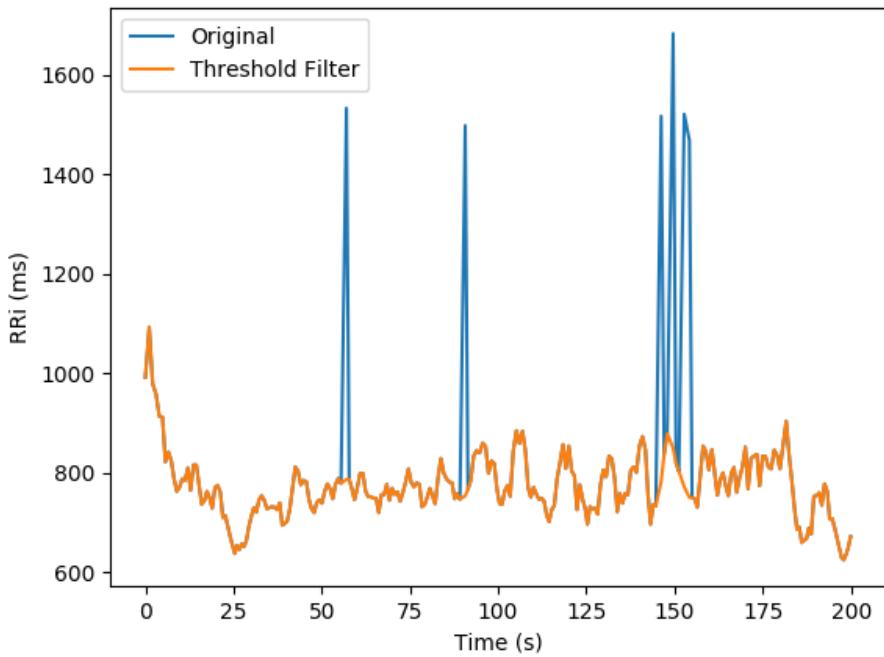
The threshold filter has five pre-defined strength values:

- Very Low: 450ms
- Low: 350ms
- Medium: 250ms
- Strong: 150ms
- Very Strong: 50ms

It also accepts custom threshold values (in milliseconds). The following snippet shows the ectopic RRI removal:

```
from hrv.filters import threshold_filter
filt_rrri = threshold_filter(rrri, threshold='medium', local_median_size=5)

fig, ax = rrri.plot()
filt_rrri.plot(ax=ax)
```



1.6.2 Detrending

The **hrv** module also offers functions to remove the non-stationary trends from the RRi series. It allows the removal of slow linear or more complex trends using the following approaches:

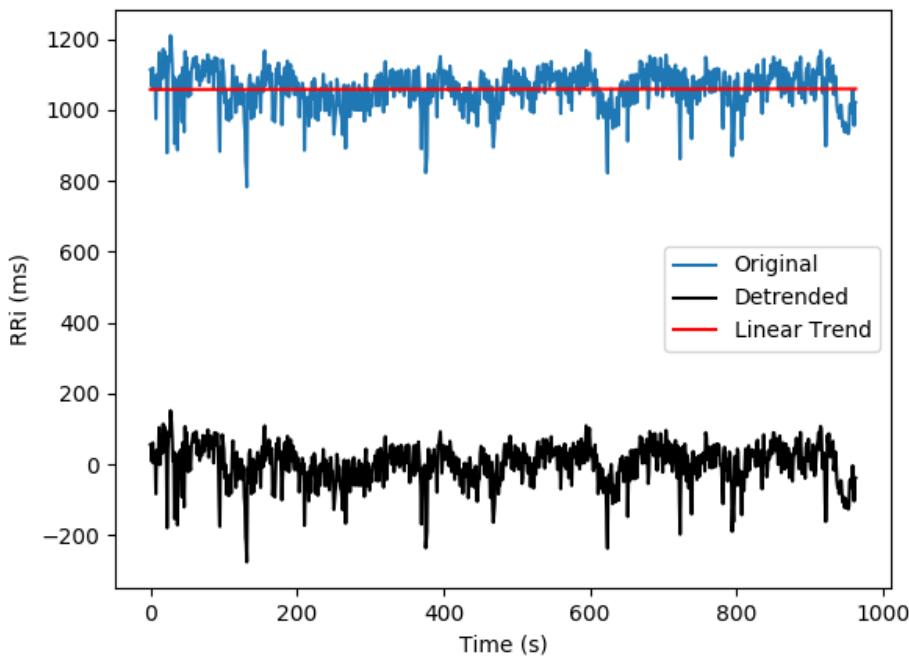
Polynomial models

Given a degree a polynomial filter is applied to the RRi series and subtracted from the tachogram

```
from hrv.detrend import polynomial_detrend

rri_detrended = polynomial_detrend(rri, degree=1)

fig, ax = rri.plot()
rri_detrended.plot(ax, color='k')
```



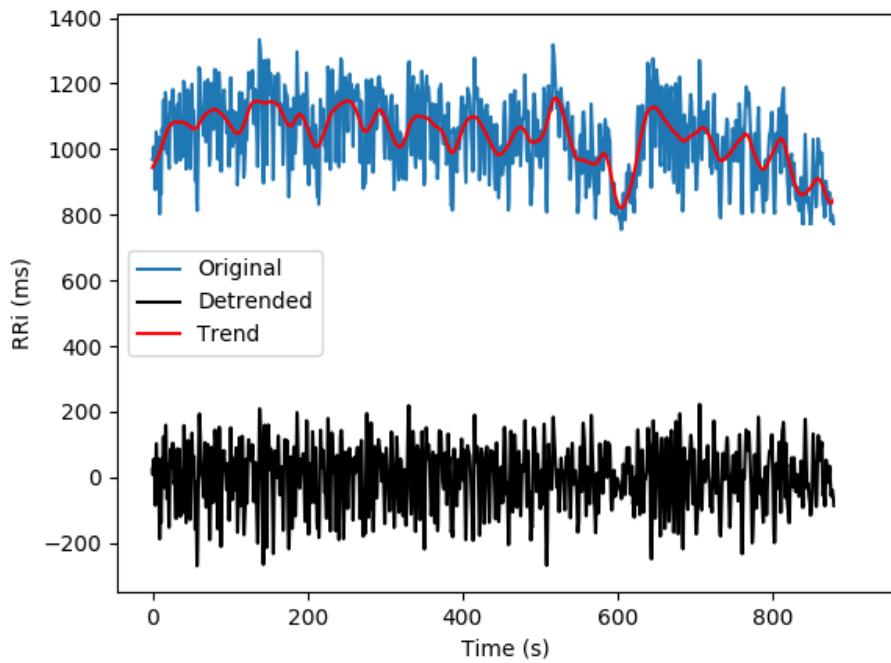
Smoothness priors

Developed by Tarvainen *et al.*, allow the removal of complex trends. Visit [here](#) for more information. It worth noticing that the detrended RRI with the Smoothness priors approach is also interpolated and resampled using frequency equals to `fs`.

```
from hrv.detrend import smoothness_priors

rri_detrended = smoothness_priors(rri, l=500, fs=4.0)

fig, ax = rri.plot()
rri_detrended.plot(ax, color='k')
```



Note: this approach depends on a numpy matrix inversion and due to floating-point precision it might present round-off errors in the trend calculation

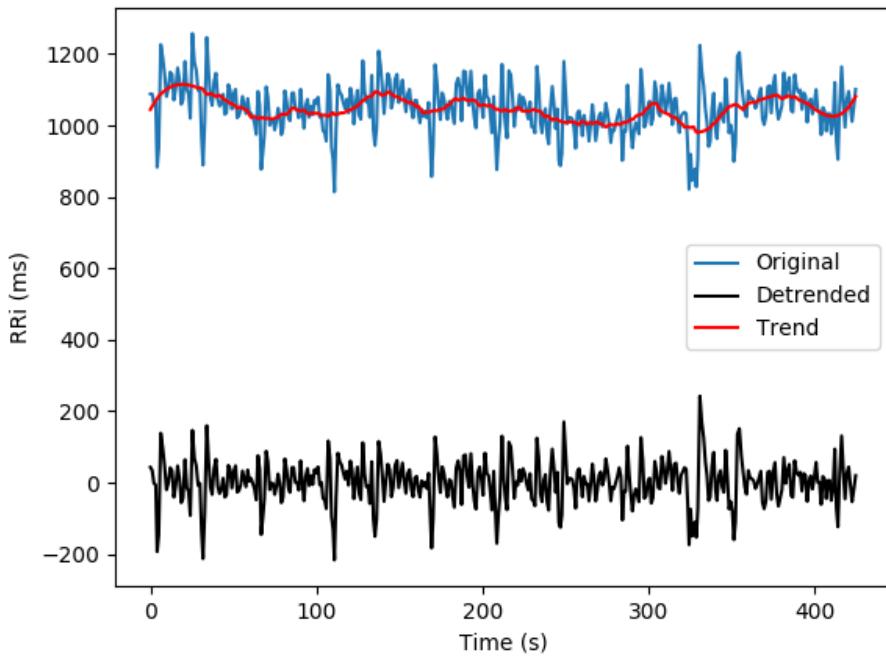
Savitzky-Golay

Uses the lowpass filter known as Savitzky-Golay filter to smooth the RRi series and remove slow components from the tachogram

```
from hrv.detrend import sg_detrend

rri_detrended = sg_detrend(rri, window_size=51, polyorder=3)

fig, ax = rri.plot()
rri_detrended.plot(ax, color='k')
```



1.7 Analysis

1.7.1 Time Domain Analysis

```
from hrv.classical import time_domain
from hrv.io import read_from_text

rri = read_from_text('path/to/file.txt')
results = time_domain(rri)
print(results)

{'mhr': 66.528130159638053,
 'mrri': 912.50302419354841,
 'nn50': 337,
 'pnn50': 33.971774193548384,
 'rmssd': 72.849900286450023,
 'sdnn': 96.990569261440797,
 'sdsd': 46.233829821038042}
```

1.7.2 Frequency Domain Analysis

```
from hrv.classical import frequency_domain
from hrv.io import read_from_text

rri = read_from_text('path/to/file.txt')
results = frequency_domain(
```

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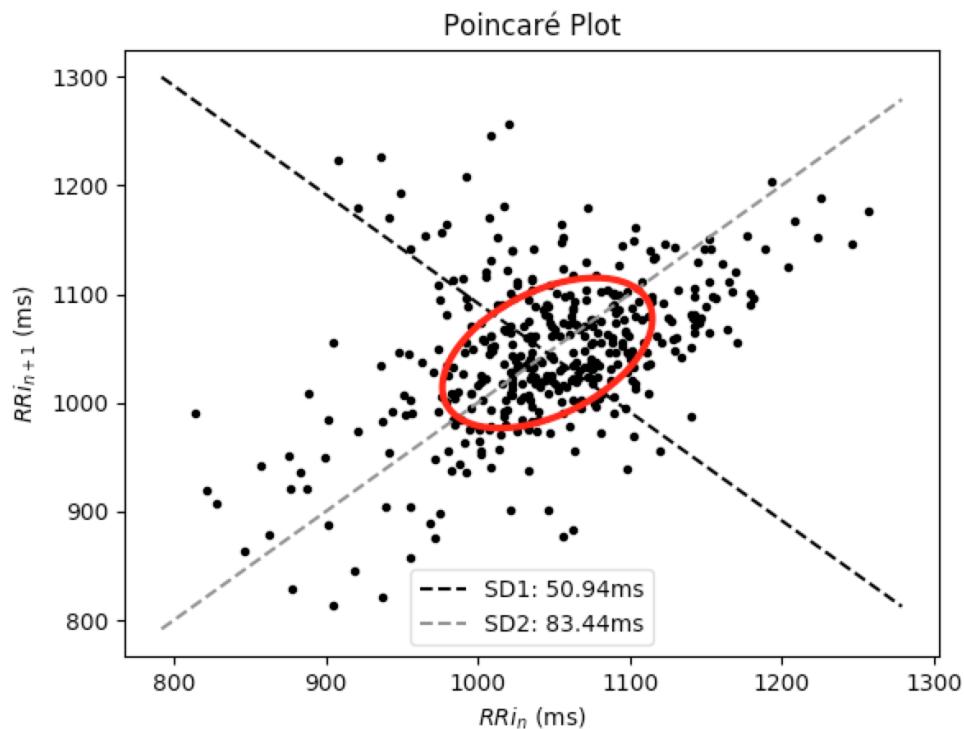
```
rri=rri,  
fs=4.0,  
method='welch',  
interp_method='cubic',  
detrend='linear'  
)  
print(results)  
  
{'hf': 1874.6342520920668,  
'hfnu': 27.692517001462079,  
'lf': 4894.8271587038234,  
'lf_hf': 2.6110838171452708,  
'lfnu': 72.307482998537921,  
'total_power': 7396.0879278950533,  
'vlf': 626.62651709916258}
```

1.7.3 Non-linear Analysis

```
from hrv.classical import non_linear  
from hrv.io import read_from_text  
  
rri = read_from_text('path/to/file.txt')  
results = non_linear(rri)  
print(results)  
  
{'sd1': 51.538501037146382,  
'sd2': 127.11460955437322}
```

It is also possible to depict the Poincaré Plot, from which SD1 and SD2 are derived:

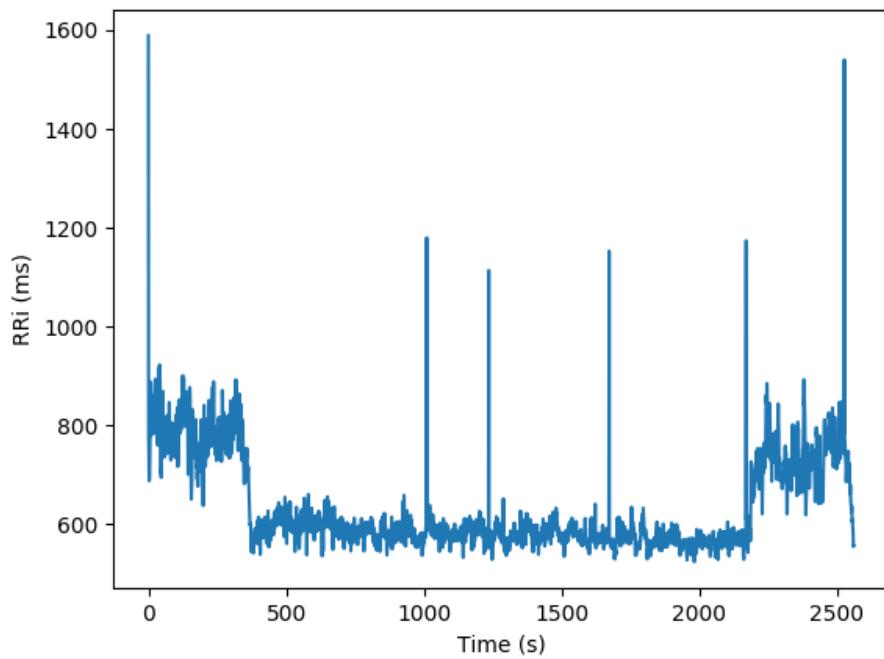
```
rri.poincare_plot()
```



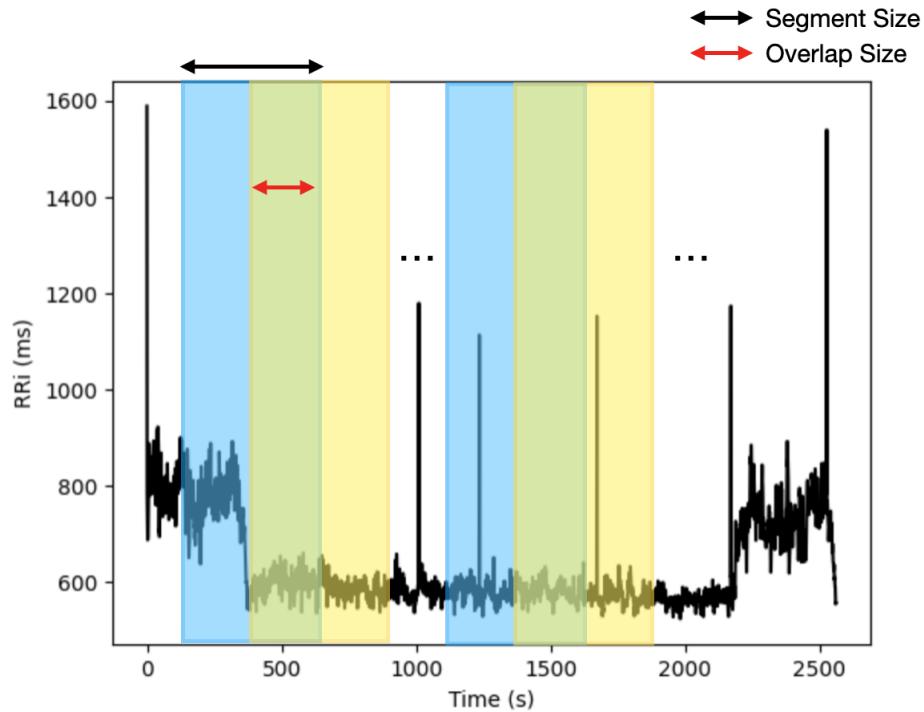
1.8 Non-stationary RRi series

In some situations like physical exercise, the RRi series might present a non-stationary behavior. In cases like these, classical approaches are not recommended once the statistical properties of the signal vary over time.

The following figure depicts the RRi series recorded on a subject riding a bicycle. Without running analysis and only visually inspecting the time series, is possible to tell that the average and the standard deviation of the RRi are not constant as a function of time.



In order to extract useful information about the dynamics of non-stationary RRI series, the following methods applies the classical metrics in shorter running adjacent segments, as illustrated in the following image:



For example, for a segment size of **30s** (S) and **15s** (O) overlap a signal with **300s** (D) will have P segments:

$$P = \text{int}((D - S) / (S - O)) + 1$$

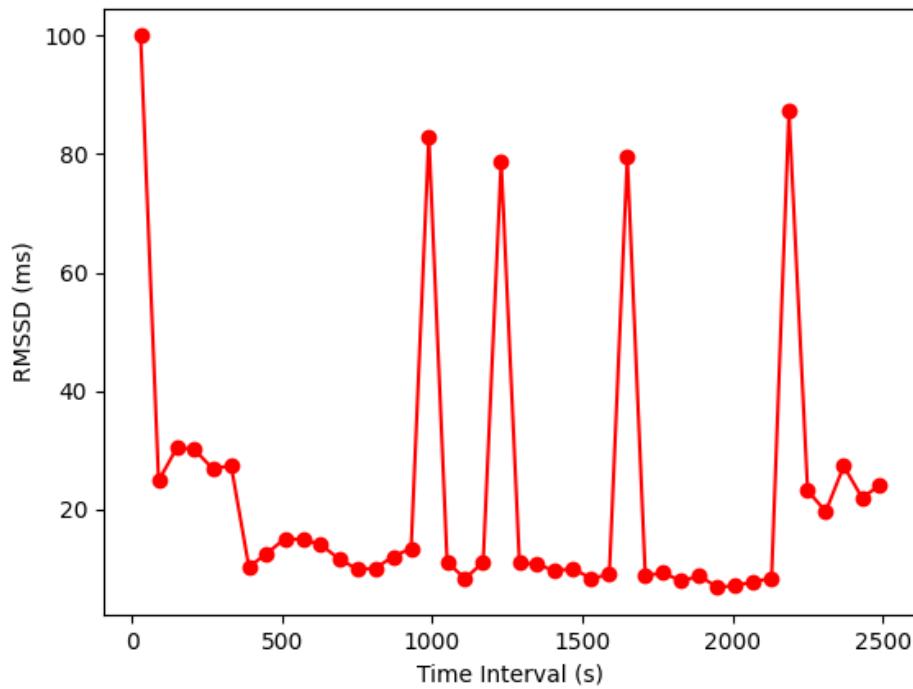
$$P = \text{int}((300 - 30) / (30 - 15)) + 1 = 19 \text{ segments}$$

1.8.1 Time Varying

Time domain indices applied to shorter segments

```
from hrv.sampledata import load_exercise_rri
from hrv.nonstationary import time_varying

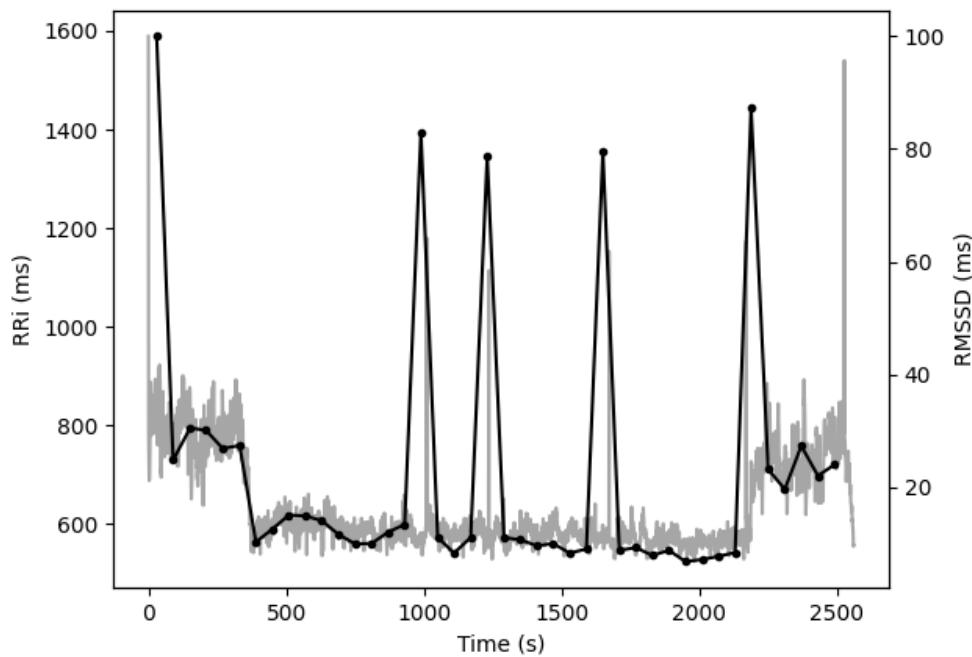
rri = load_exercise_rri()
results = time_varying(rri, seg_size=30, overlap=0)
results.plot(index="rmssd", marker="o", color="r")
```



Plot the results from **time varying** together with its respective RRi series

```
from hrv.sampledata import load_exercise_rri
from hrv.nonstationary import time_varying

rri = load_exercise_rri()
results = time_varying(rri, seg_size=30, overlap=0)
results.plot_together(index="rmssd", marker="o", color="k")
```



1.8.2 Short Time Fourier Transform

To be implemented.

1.9 Contribution start guide

The preferred way to start contributing for the project is creating a virtualenv (you can do by using virtualenv, virtualenvwrapper, pyenv or whatever tool you'd like). Only **Python 3.x** are supported

1.9.1 Preparing the environment

Create the virtualenv:

```
mkvirtualenv hrv
```

Install all dependencies:

```
pip install -r requirements.txt
```

Install development dependencies:

```
pip install -r dev-requirements.txt
```

1.9.2 Running the tests

In order to run the tests, activate the virtualenv and execute pytest:

```
workon <virtualenv>
pytest -v
# or
make test
```

1.9.3 Coding and Docstring styles

Generally, we try to use Python common styles conventions as described in [PEP 8](#) and [PEP 257](#), which are also followed by the [numpy](#) project.

Example

```
def moving_average(rrl, order=3):
    """
    Low-pass filter. Replace each Rrl value by the average of its N/2
    neighbors. The first and the last N/2 Rrl values are not filtered

    Parameters
    -----
    rrl : array_like
        sequence containing the Rrl series
    order : int, optional
        Strength of the filter. Number of adjacent Rrl values used to calculate
        the average value to replace the current Rrl. Defaults to 3.

    .. math::
        \text{considering movinge average of order equal to 3:}
        Rrl[j] = sum(Rrl[j-2] + Rrl[j-1] + Rrl[j+1] + Rrl[j+2]) / 3

    Returns
    -----
    results : Rrl array
        instance of the Rrl class containing the filtered Rrl values

    See Also
    -----
    moving_median, threshold_filter, quotient

    Examples
    -----
    >>> from hrv.filters import moving_average
    >>> from hrv.sampledata import load_noisy_rrl
    >>> noisy_rrl = load_noisy_rrl()
    >>> moving_average(noisy_rrl)
    Rrl array([904., 918., 941.66666667, ..., 732.66666667, 772.333333, 808.])
    """
```

We also encourage the use of code linters, such `isort`, `black` and `autoflake`.

```
autoflake --in-place --recursive --remove-unused-variables --remove-all-unused-
imports .
sort -rc .
black .
```