Robust Signal Processing With Biomedical Applications

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SPG Lab for Body Worn Sensing of Physiological Parameters

Wearable Devices

Wearable Devices for Monitoring of Vital Signs:

- emerging technology enabling continuous monitoring of human vital signs
- great potential both for self-health tracking and for clinical applications
- combining multiple sensors yields “body area sensor networks”
- real-time physiological information via dynamic, noninvasive measurements

Available Hardware

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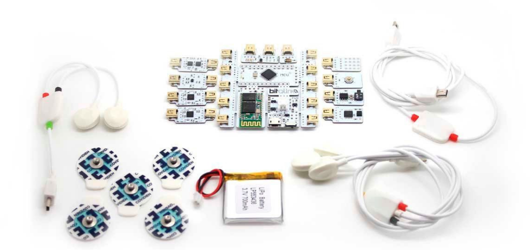
Bitalino (r)evolution Plugged Kit BT

- electrodermal activity (EDA)
- electroencephalography (EEG)
- electrocardiography (ECG)
- electromyography (EMG)
- photoplethysmography (PPG)
- acceleration (ACC)
- blood pressure (BP)

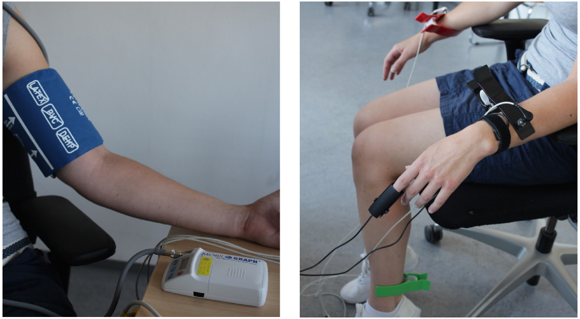


Bitalino (r)evolution Plugged Kit BT-Set.

Available Hardware

AD Intstruments Teaching Suite, Mobil-O-Graph

- respiration (RSP)
- electrocardiography (ECG)
- photoplethysmography (PPG)
- blood pressure (BP)
- pulse-wave velocity (PWV)
- vascular age index (VAI)



AD Intstruments Teaching Suite, Mobil-O-Graph.

Possible Topics

Robust and Biomedical Signal Processing Seminar (WS20/21)

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Possible topics using newly collected and available data from SPG Biolab

- Robust ECG Signal Estimation in Presence of Artifacts
- Robust HR Estimation for ECG Signals
- Robust HR Estimation for PPG Signals
- Robust HRV Estimation for PPG Signals
- Robust Cuffless Blood Pressure Monitoring
- ... your own project that uses our available hardware

Electrocardiogram (ECG)

Overview

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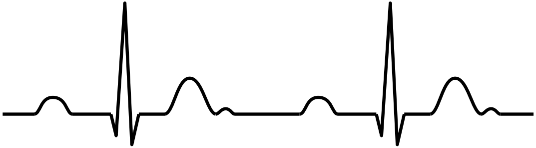
Basics of ECG

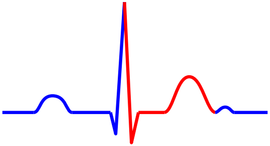


- R-Peak detection algorithm
- Applications of robust location and scale estimation in ECG
- Artifact cancellation algorithm

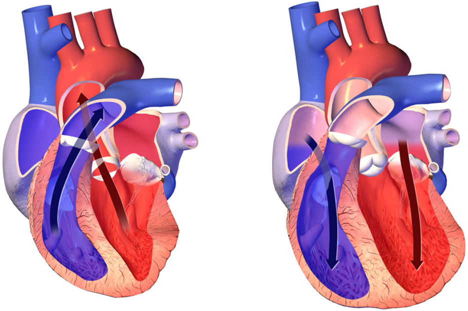
Later in the course

- Robust spectral analysis
- Robust location-based filtering

Cardiac cycle:



- Systole (pumping)
- Diastole (filling)



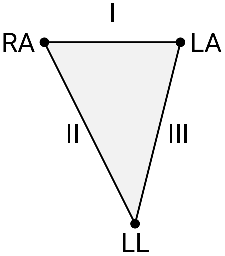
Systole *(pumping)*   **Diastole** *(filling)*

https://en.wikipedia.org/wiki/Cardiac_cycle

Electrocardiograph:

- graph of voltage versus time of the electrical activity of the heart using electrodes placed on the skin.
- electrodes measure the small electrical changes that are a consequence of cardiac muscle depolarization followed by repolarization during each cardiac cycle

Einthoven's triangle:



three bipolar limb leads

- Lead I: negative electrode on right arm, positive on left arm
- Lead II: negative electrode on right arm, positive on left leg
- Lead III: negative electrode on left arm, positive on left leg

Electrocardiogram (ECG)

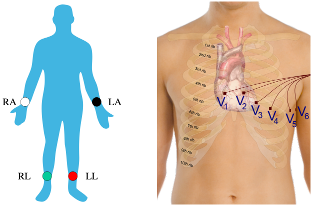
Basics

Electrocardiograph:

- graph of voltage versus time of the electrical activity of the heart using electrodes placed on the skin.
- electrodes measure the small electrical changes that are a consequence of cardiac muscle depolarization followed by repolarization during each cardiac cycle

12-Lead ECG:

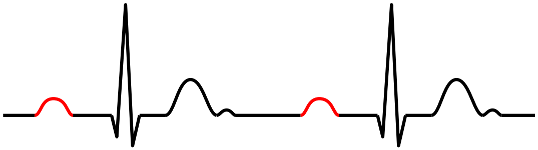
- clinical gold standard
- 6 precordial electrodes and 4 electrodes on limbs are used to get 12 leads
- combines the lead systems from Einthoven, Goldberger and Wilson
- provides information about vertical and horizontal axes



https://en.wikipedia.org/wiki/Electrocardiography

Electrocardiogram (ECG)

Basics



Three main components:

1. P wave: represents the depolarization of the atria
2. QRS complex: represents the depolarization of the ventricles
3. T wave: represents the repolarization of the ventricles

Electrocardiogram (ECG)

Basics

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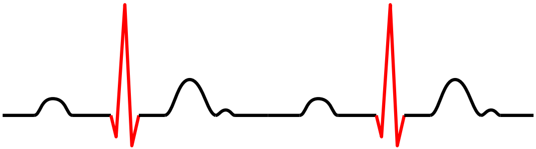

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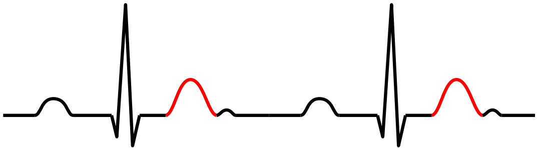
Electrocardiogram (ECG)

Basics

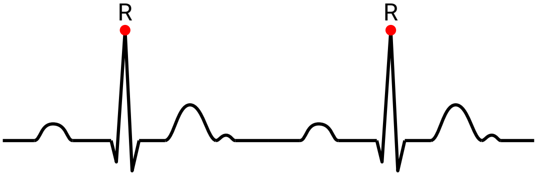


Three main components:

1. P wave: represents the depolarization of the atria
2. QRS complex: represents the depolarization of the ventricles
3. T wave: represents the repolarization of the ventricles

Heart rate variability (HRV):

- variation in the time interval between heartbeats



- nonstationary signal
- variation may contain indicators of current disease, or warnings about impending cardiac diseases
- popular noninvasive tool for assessing the activities of the autonomic nervous system
- requires estimating beat-to-beat interval from ECG

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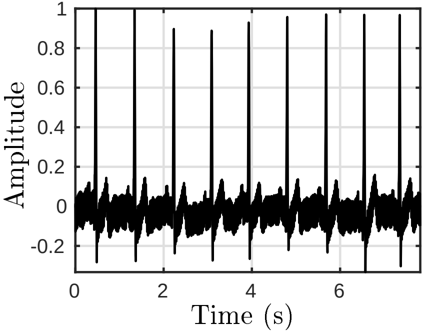
Pan and Tompkins Algorithm:

- Most commonly used method for R peak detection
- General steps:
  1. Bandpass filtering
  2. Differentiation
  3. Squaring
  4. Theshold computation & peak finding



Real-data example of ECG signal.

Pan, J., & Tompkins, W. J. (1985). A real-time QRS detection algorithm. IEEE Trans. Biomed. Eng, 32(3), 230-236.

https://de.mathworks.com/matlabcentral/fileexchange/45840-complete-pan-tompkins-implementation-ecg-qrs-detector

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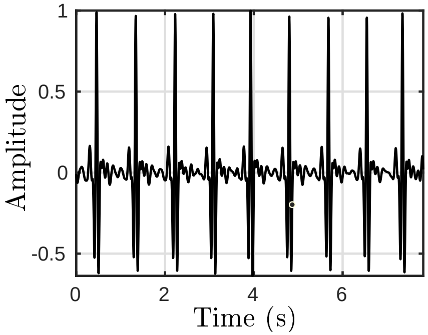

Result after bandpass filtering.

Pan, J., & Tompkins, W. J. (1985). A real-time QRS detection algorithm. IEEE Trans. Biomed. Eng, 32(3), 230-236.

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Electrocardiogram (ECG)

Popular R Peak Detection Algorithm

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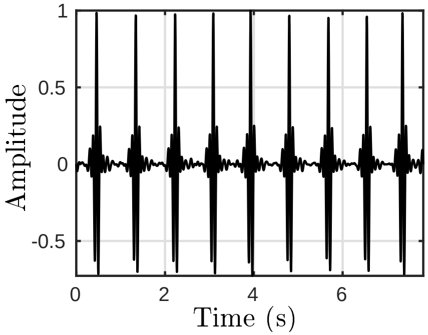

Result after derivation.

Pan, J., & Tompkins, W. J. (1985). A real-time QRS detection algorithm. IEEE Trans. Biomed. Eng, 32(3), 230-236.

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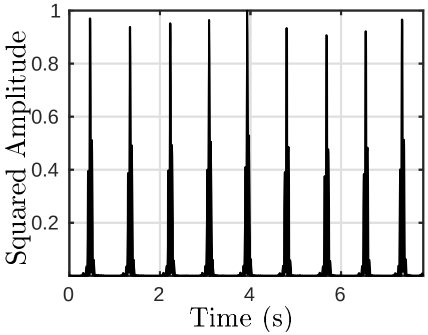

Result after squaring.

Pan, J., & Tompkins, W. J. (1985). A real-time QRS detection algorithm. IEEE Trans. Biomed. Eng, 32(3), 230-236.

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Electrocardiogram (ECG)

Popular R Peak Detection Algorithm

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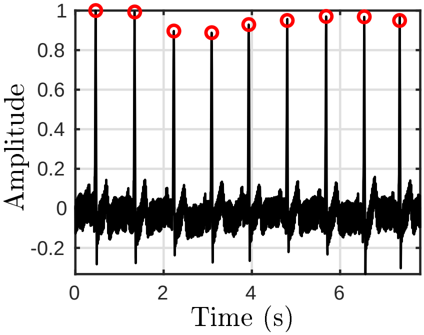

Detected R peaks.

Pan, J., & Tompkins, W. J. (1985). A real-time QRS detection algorithm. IEEE Trans. Biomed. Eng, 32(3), 230-236.

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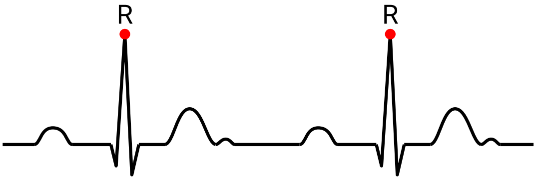
RMSSD: A popular metric of HRV is defined as



- The square root of the mean of the sum of the squares of differences between adjacent RR intervals

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1}-RR_i)^2} \qquad (1)$$

Electrocardiogram (ECG)

Robust Location Estimation for RMSSD

- Note that for a vector $\mathbf{x} = (x_1, \ldots, x_{N-1})^\top$:

$$\text{mean}(\mathbf{x}) = \frac{1}{N-1}\sum_{i=1}^{N-1}(x_i)$$

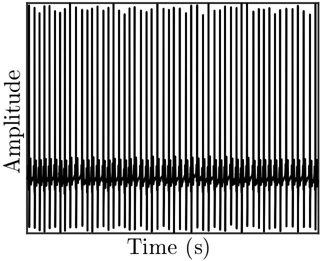
with $x_i = (RR_{i+1} - RR_i)^2$, Eq. (1) becomes $RMSSD = \sqrt{\text{mean}(\mathbf{x})}$.

Application of robust estimators:

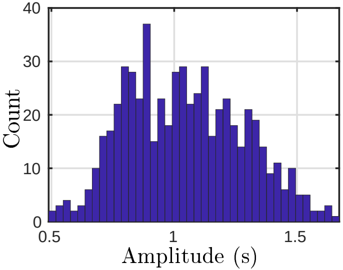
- Median: $RMSSD = \sqrt{\text{median}(\mathbf{x})}$
- Huber's M: $RMSSD = \sqrt{\hat{\mu}_{\mathrm{H},c}(\mathbf{x})}$
- Tukey's M: $RMSSD = \sqrt{\hat{\mu}_{\mathrm{T},c}(\mathbf{x})}$

Electrocardiogram (ECG)

Example: Robust Location Estimation for RMSSD



Excerpt of high-quality ECG.



Histogram of **x**.

RMSSD using different estimators for the mean.

	mean	median	Huber's M, $c_{.95}$	Tukey's M, $c_{.95}$
RMSSD (s)	1.0212	1.0156	1.0192	1.0192

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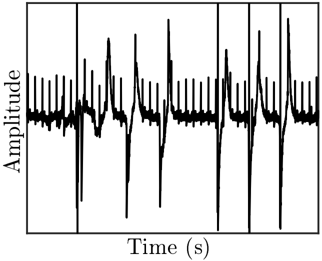
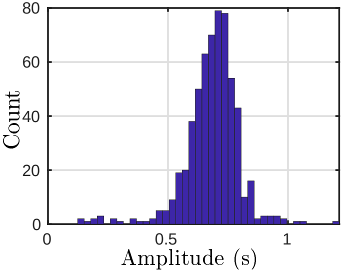
Electrocardiogram (ECG)

Robust Location Estimation for RMSSD



Excerpt of ECG with multiple motion artifacts.



2 % trimmed histogram of **x** (ignoring outliers).

RMSSD using different estimators for the mean.

	mean	median	Huber's M, $c = c_{.95}$	Tukey's M, $c = c_{.95}$
RMSSD (s)	2.5809	0.8340	0.8313	0.8327

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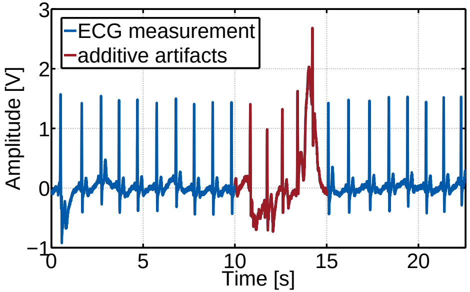
Multi-Resolution Thresholding Algorithm:

- An existing method for artifact cancellation.
- General steps:
    1. Stationary wavelet transform (SWT) of ECG
    2. Thresholding in each coefficient series
    3. Artifact estimation via inverse stationary wavelet transform (ISWT)



Real-data example of ECG signal.

Strasser, F., Muma, M., & Zoubir, A. M. (2012). Motion artifact removal in ECG signals using multi-resolution thresholding. In Proceedings of the 20th European Signal Processing Conference (EUSIPCO) (pp. 899-903)

`https://www.spg.tu-darmstadt.de/media/spg/dwonloads/multi-resolution-thresholding.zip`

Electrocardiogram (ECG)

Artifact Cancellation

Multi-Resolution Thresholding Algorithm:

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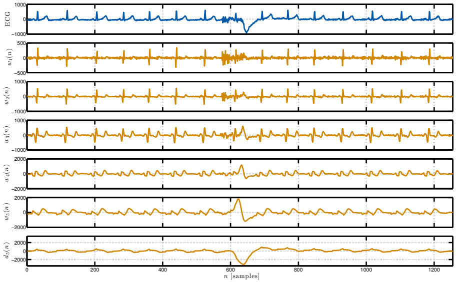

SWT of ECG signal.

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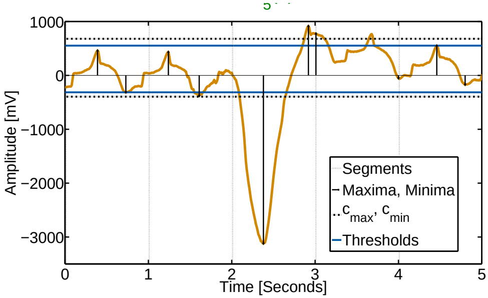

Threshold on fifth SWT coefficient.

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Multi-Resolution Thresholding Algorithm:

- An existing method for artifact cancellation.
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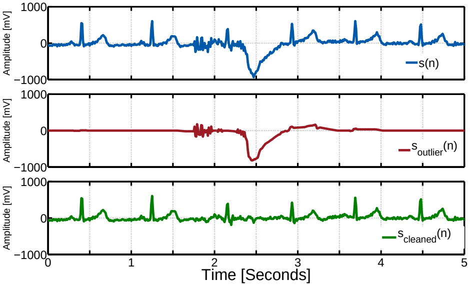

ISWT of ECG and artifact signal.

Strasser, F., Muma, M., & Zoubir, A. M. (2012). Motion artifact removal in ECG signals using multi-resolution thresholding. In Proceedings of the 20th European Signal Processing Conference (EUSIPCO) (pp. 899-903)

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Multi-Resolution Thresholding Algorithm:

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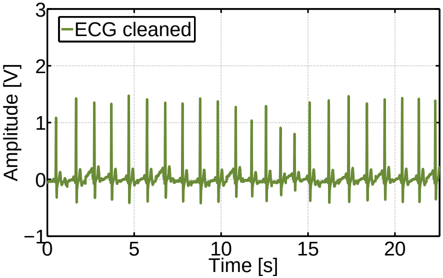

Cleaned ECG signal.

Strasser, F., Muma, M., & Zoubir, A. M. (2012). Motion artifact removal in ECG signals using multi-resolution thresholding. In Proceedings of the 20th European Signal Processing Conference (EUSIPCO) (pp. 899-903)

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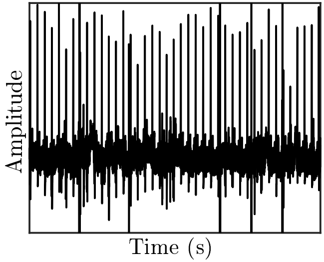
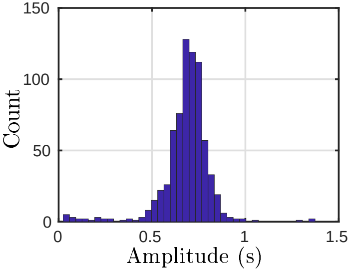
Robust Location Estimation for RMSSD



Excerpt of ECG after artifact cancellation.



Histogram of **x**.

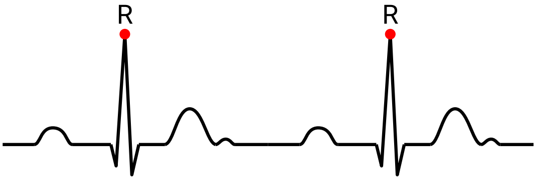
RMSSD using different estimators for the mean.

	mean	median	Huber's M, $c = c_{.95}$	Tukey's M, $c = c_{.95}$
RMSSD (s)	0.8316	0.8359	0.8345	0.8363

Electrocardiogram (ECG)

Robust Scale Estimation for SDRR

SDRR: A second popular metric of HRV is defined as



- The standard deviation of the differences between adjacent RR intervals (SDRR).

- *SDRR* using sample standard deviation for vector $\mathbf{x} = (x_1, \ldots, x_{N-1})^\top$:

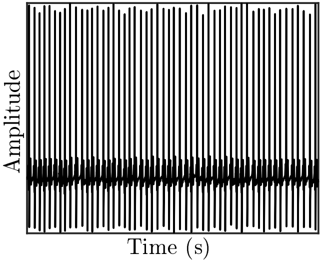
$$\hat{\sigma}(\mathbf{x}) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(x_i - \hat{\mu})^2}.$$

with $x_i = (RR_{i+1} - RR_i)^2$.

Application of robust scale estimators:

- Median absolute deviation: $SDRR = \text{madn}(\mathbf{x})$, see Eq. (11) of Slides 03.
- Laplace MLE: $SDRR = \hat{\sigma}_{\text{MLE},Laplace}(\mathbf{x})$, see Eq. (3) of Slides 04.
- Huber's *M*: $SDRR = \hat{\sigma}_{\text{H},c}(\mathbf{x})$
- Tukey's *M*: $SDRR = \hat{\sigma}_{\text{T},c}(\mathbf{x})$

Robust Scale Estimation for SDRR



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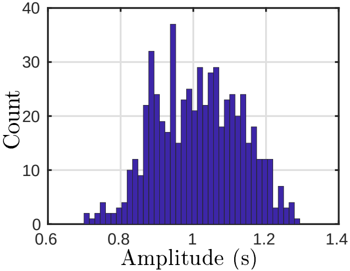


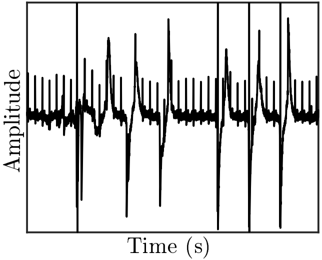
Histogram of **x**.

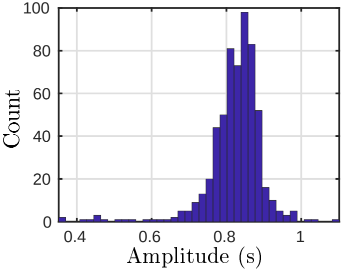
SDRR using different estimators for the scale.

	std	madn	Laplace MLE	Huber's M, $c_{.95}$	Tukey's M, $c_{.95}$
SDRR (s)	0.1178	0.1332	0.1126	0.1121	0.1108

Electrocardiogram (ECG)

Robust Scale Estimation for SDRR





Excerpt of ECG with multiple motion artifacts.

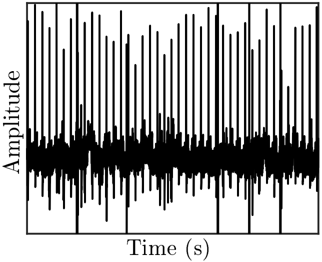
2 % trimmed histogram of **x** (ignoring outliers).

SDRR using different estimators for the scale.

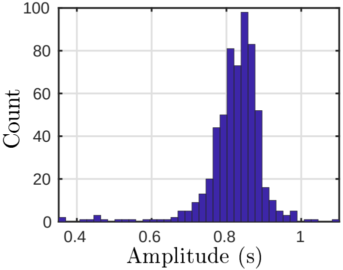
	std	madn	Laplace MLE	Huber's M, $c_{.95}$	Tukey's M, $c_{.95}$
SDRR (s)	2.3911	0.0492	0.0416	0.2695	0.0399

Electrocardiogram (ECG)

Robust Scale Estimation for SDRR



Excerpt of ECG after artifact cancellation.



Histogram of **x**.

SDRR using different estimators for the scale.

	std	madn	Laplace MLE	Huber's M, $c_{.95}$	Tukey's M, $c_{.95}$
SDRR (s)	0.1120	0.0463	0.0392	0.0635	0.0408

Outlook

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Coming sections:

- will extend the basic concepts to enable robust regression, filtering, clustering, classification, time-series and spectral estimation,
- important tools, in biomedical engineering, for example, intracranial pressure monitoring, body-worn sensing, eye research