Robust Signal Processing With Biomedical Applications

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The presented material is part of the lecture Robust Signal Processing With Biomedical Applications taught at Technische Universität Darmstadt.

The lecture material is only intended for the students of this class.

All remaining lecture material, figures and content is used in the legal framework of §60a UrhG¹.

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https://www.e-learning.tu-darmstadt.de/dienstleistungen/rechtsfragen/urhwissg/index.de.jsp
SPG Lab for Body Worn Sensing of Physiological Parameters
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

Bitalino (r)evolution Plugged Kit BT

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

AD Instruments Teaching Suite, Mobil-O-Graph

- respiration (RSP)
- electrocardiography (ECG)
- photoplethysmography (PPG)
- blood pressure (BP)
- pulse-wave velocity (PWV)
- vascular age index (VAI)
Possible Topics
Robust and Biomedical Signal Processing Seminar (WS20/21)

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

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
Electrocardiogram (ECG) Basics

Cardiac cycle:

- Systole (pumping)
- Diastole (filling)

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

**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

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

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
Electrocardiogram (ECG)

Popular R Peak Detection Algorithm

Pan and Tompkins Algorithm:

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

Real-data example of ECG signal.


Electrocardiogram (ECG)

Popular R Peak Detection Algorithm

Pan and Tompkins Algorithm:

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Result after bandpass filtering.


Electrocardiogram (ECG)

Popular R Peak Detection Algorithm

Pan and Tompkins Algorithm:

- Most commonly used method for R peak detection
- General steps:
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Result after derivation.


Electrocardiogram (ECG)
Popular R Peak Detection Algorithm

Pan and Tompkins Algorithm:

- Most commonly used method for R peak detection
- General steps:
  1. Bandpass filtering
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  4. Threshold computation & peak finding

Result after squaring.


Pan and Tompkins Algorithm:

- Most commonly used method for R peak detection
- General steps:
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  4. Threshold computation & peak finding


RMSSD: A popular metric of HRV is defined as

\[ RMSSD = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (RR_{i+1} - RR_i)^2} \]
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 $\text{RMSSD} = \sqrt{\text{mean}(\mathbf{x})}$.

Application of robust estimators:
- Median: $\text{RMSSD} = \sqrt{\text{median}(\mathbf{x})}$
- Huber’s $M$: $\text{RMSSD} = \sqrt{\hat{\mu}_{H,c}(\mathbf{x})}$
- Tukey’s $M$: $\text{RMSSD} = \sqrt{\hat{\mu}_{T,c}(\mathbf{x})}$
Electrocardiogram (ECG)

Example: Robust Location Estimation for RMSSD

Excerpt of high-quality ECG.

RMSSD using different estimators for the mean.

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>median</th>
<th>Huber’s $M$, $c_{.95}$</th>
<th>Tukey’s $M$, $c_{.95}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSSD (s)</td>
<td>1.0212</td>
<td>1.0156</td>
<td>1.0192</td>
<td>1.0192</td>
</tr>
</tbody>
</table>
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.

<table>
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<th>Tukey’s $M$, $c = c_{0.95}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSSD (s)</td>
<td>2.5809</td>
<td>0.8340</td>
<td>0.8313</td>
<td>0.8327</td>
</tr>
</tbody>
</table>
Electrocardiogram (ECG)
Artifact Cancellation

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.


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

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![Diagram showing wavelet coefficients and thresholding](image)

Threshold on fifth SWT coefficient.


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Electrocardiogram (ECG)
Artifact Cancellation

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

ISWT of ECG and artifact signal.
Electrocardiogram (ECG)
Artifact Cancellation

Multi-Resolution Thresholding Algorithm:

- An existing method for artifact cancellation.
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  3. Artifact estimation via inverse stationary wavelet transform (ISWT)

![Cleaned ECG signal.](https://www.spg.tu-darmstadt.de/media/spg/dwonloads/multi-resolution-thresholding.zip)


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Electrocardiogram (ECG)
Robust Location Estimation for RMSSD

Excerpt of ECG after artifact cancellation.

RMSSD using different estimators for the mean.

<table>
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<tr>
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<tbody>
<tr>
<td>RMSSD (s)</td>
<td>0.8316</td>
<td>0.8359</td>
<td>0.8345</td>
<td>0.8363</td>
</tr>
</tbody>
</table>
SDRR: A second popular metric of HRV is defined as

- The standard deviation of the differences between adjacent RR intervals (SDRR).
Electrocardiogram (ECG)
Robust Scale Estimation for SDRR

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

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

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

Application of robust scale estimators:

- Median absolute deviation: \( SDRR = \text{madn}(x) \), see Eq. (11) of Slides 03.
- Laplace MLE: \( SDRR = \hat{\sigma}_{\text{MLE,Laplace}}(x) \), see Eq. (3) of Slides 04.
- Huber’s \( M \): \( SDRR = \hat{\sigma}_{H,c}(x) \)
- Tukey’s \( M \): \( SDRR = \hat{\sigma}_{T,c}(x) \)
Electrocardiogram (ECG)
Robust Scale Estimation for SDRR

Excerpt of high-quality ECG.

SDRR using different estimators for the scale.

<table>
<thead>
<tr>
<th></th>
<th>std</th>
<th>madn</th>
<th>Laplace MLE</th>
<th>Huber’s $M$, $c_{.95}$</th>
<th>Tukey’s $M$, $c_{.95}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SDRR (s)</td>
<td>0.1178</td>
<td>0.1332</td>
<td>0.1126</td>
<td>0.1121</td>
<td>0.1108</td>
</tr>
</tbody>
</table>
Excerpt of ECG with multiple motion artifacts. 2 % trimmed histogram of \( x \) (ignoring outliers).

SDRR using different estimators for the scale.

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<th>Tukey’s ( M, c_{.95} )</th>
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</thead>
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<tr>
<td>SDRR (s)</td>
<td>2.3911</td>
<td>0.0492</td>
<td>0.0416</td>
<td><strong>0.2695</strong></td>
<td><strong>0.0399</strong></td>
</tr>
</tbody>
</table>
Excerpt of ECG after artifact cancellation.

SDRR using different estimators for the scale.

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<tbody>
<tr>
<td>SDRR (s)</td>
<td>0.1120</td>
<td>0.0463</td>
<td>0.0392</td>
<td>0.0635</td>
<td>0.0408</td>
</tr>
</tbody>
</table>
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