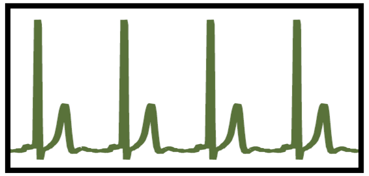
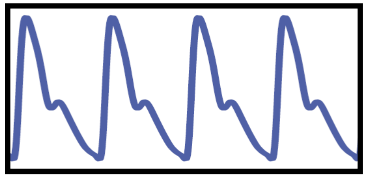
Physiological
Measurement

Estimating respiratory rate from the electrocardiogram and photoplethysmogram



Peter H Charlton

King’s College London

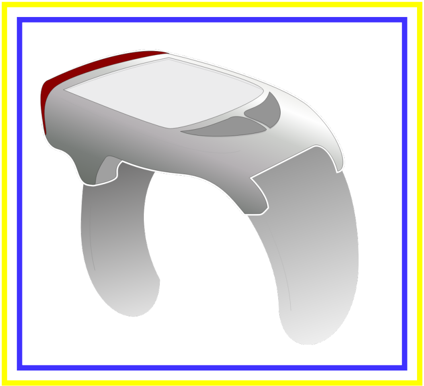


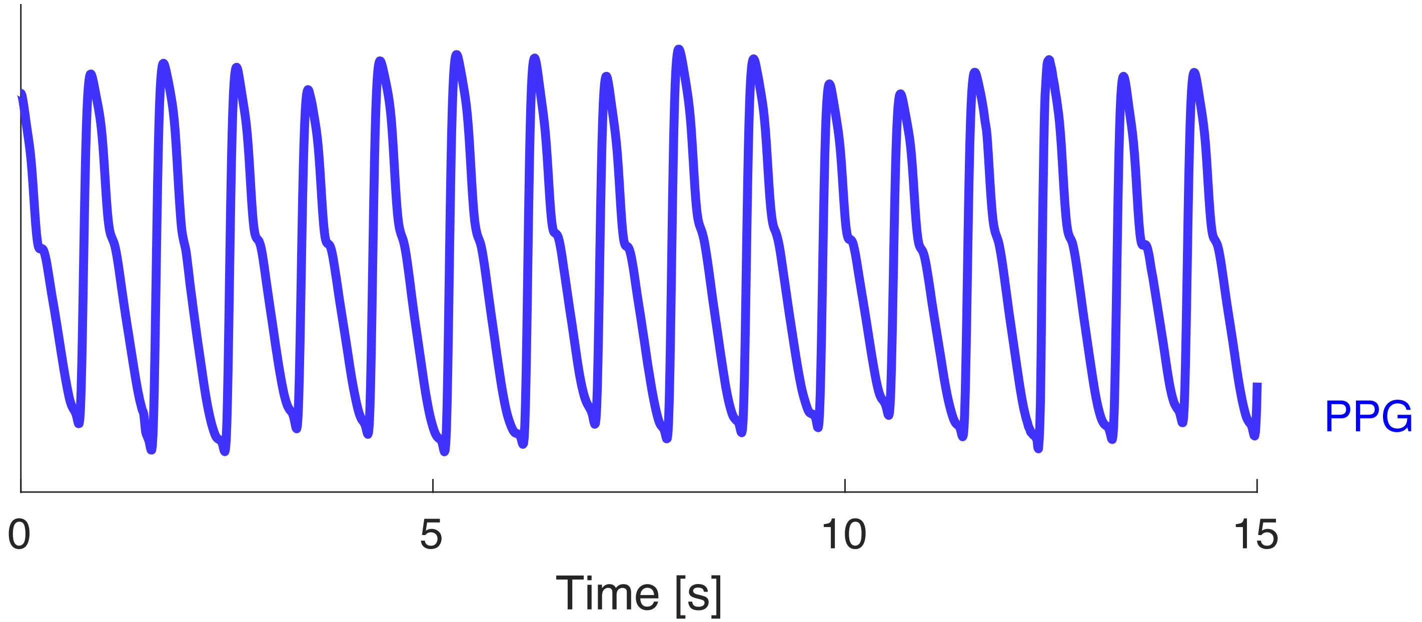
http://peterhcharlton.github.io/RRest

Overview

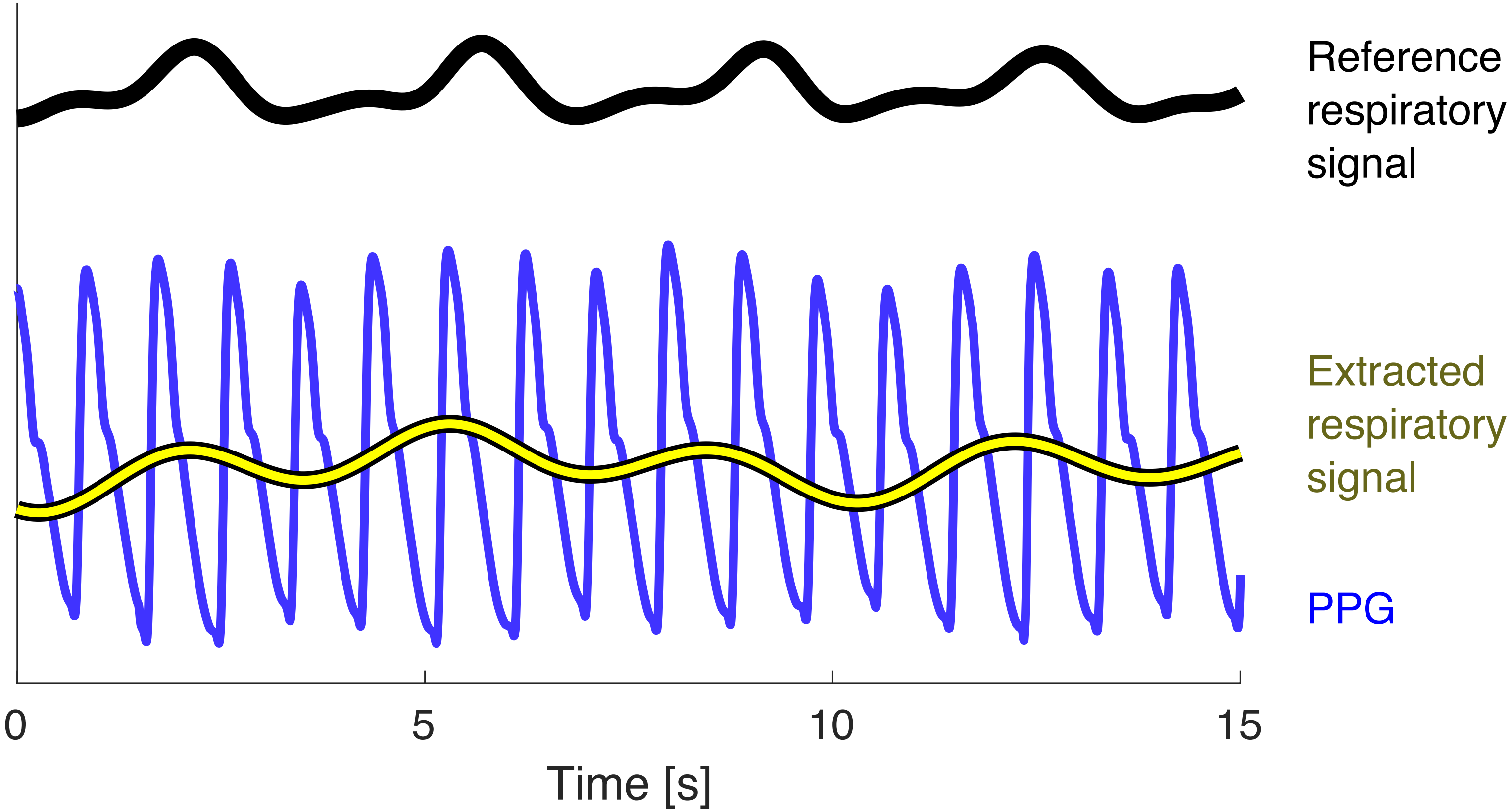
Overview

Overview



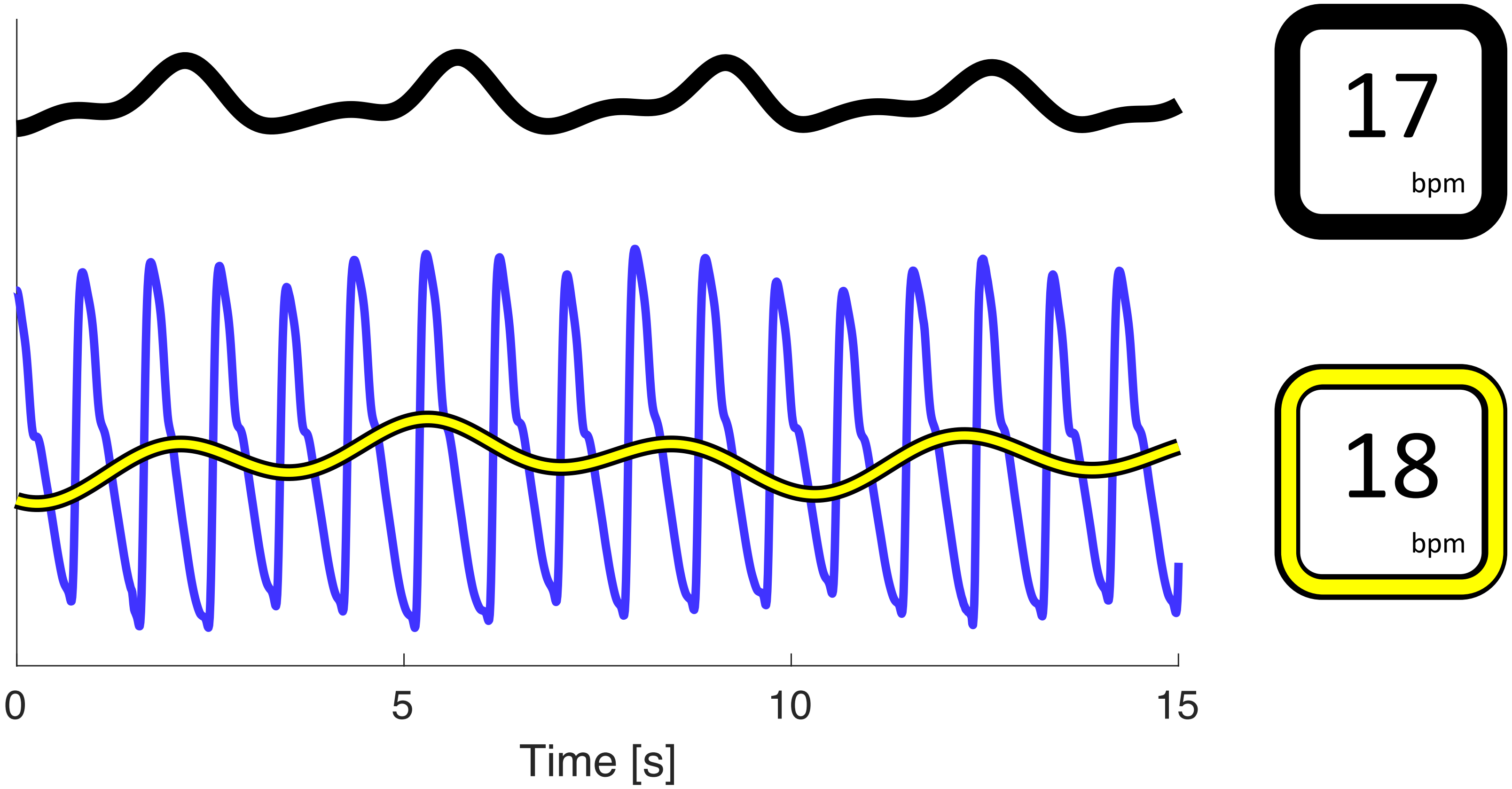


Overview



Reference respiratory signal
Extracted respiratory signal
PPG
0
5
10
15
Time [s]

Overview



Outline

- Background
  - *Case Study 1: Elevated RR prior to cardiac arrest*
- RR algorithms
  - *Case Study 2: Unobtrusive RR monitoring*
- Performance assessment
  - *Case Study 3: Predicting adverse events*
- Implementation
- Conclusion

Outline

- **Background**
  - *Case Study 1: Elevated RR prior to cardiac arrest*
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Definitions:

RR – respiratory rate

ECG – electrocardiogram

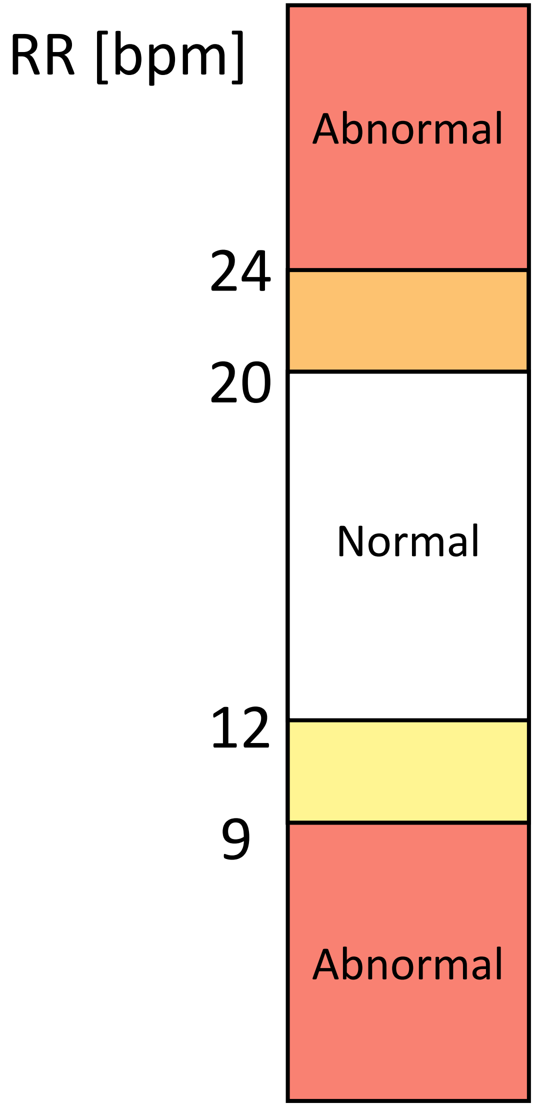
PPG – photoplethysmogram

Accompanying resources:

http://peterhcharlton.github.io/RRest/webinar.html

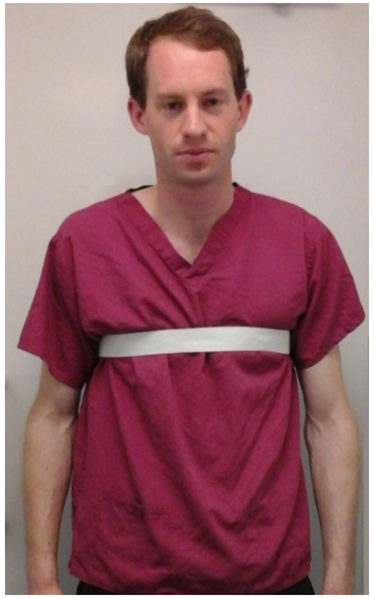
Importance of RR

- Diagnosis
  - Pneumonia
  - Sepsis
  - Pulmonary embolism
- Prognosis
  - Acute deteriorations
  - Cardiac arrest
  - In-hospital mortality
  - Emergency department screening



Further details at DOI: 10.1109/RBME.2017.2763681 , Section 1.A

Measuring RR



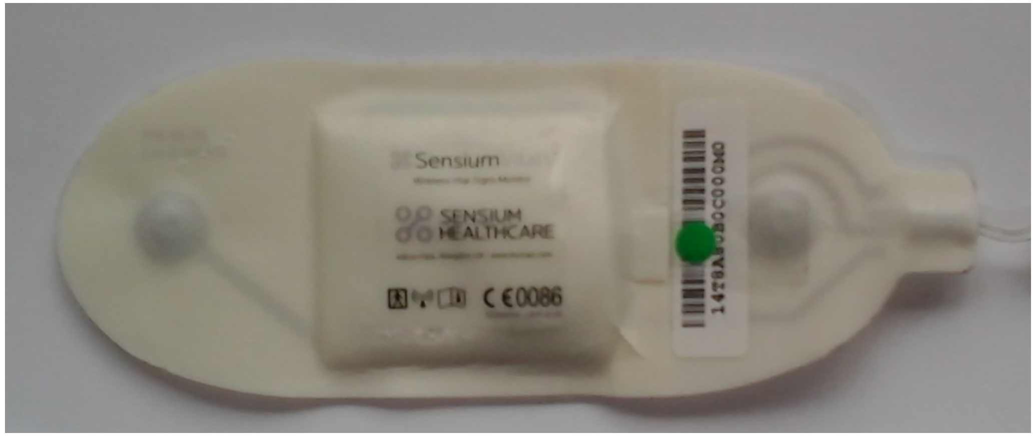
Thoracic Band

Face Mask

Oral-Nasal Cannula

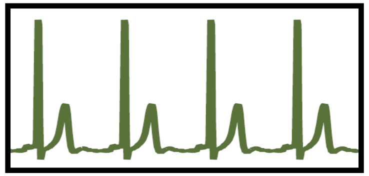
- Thoracic impedance / inductance
- Air flow / pressure
- Accelerometry

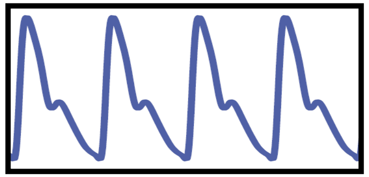
Measuring ECG and PPG



ECG Patch

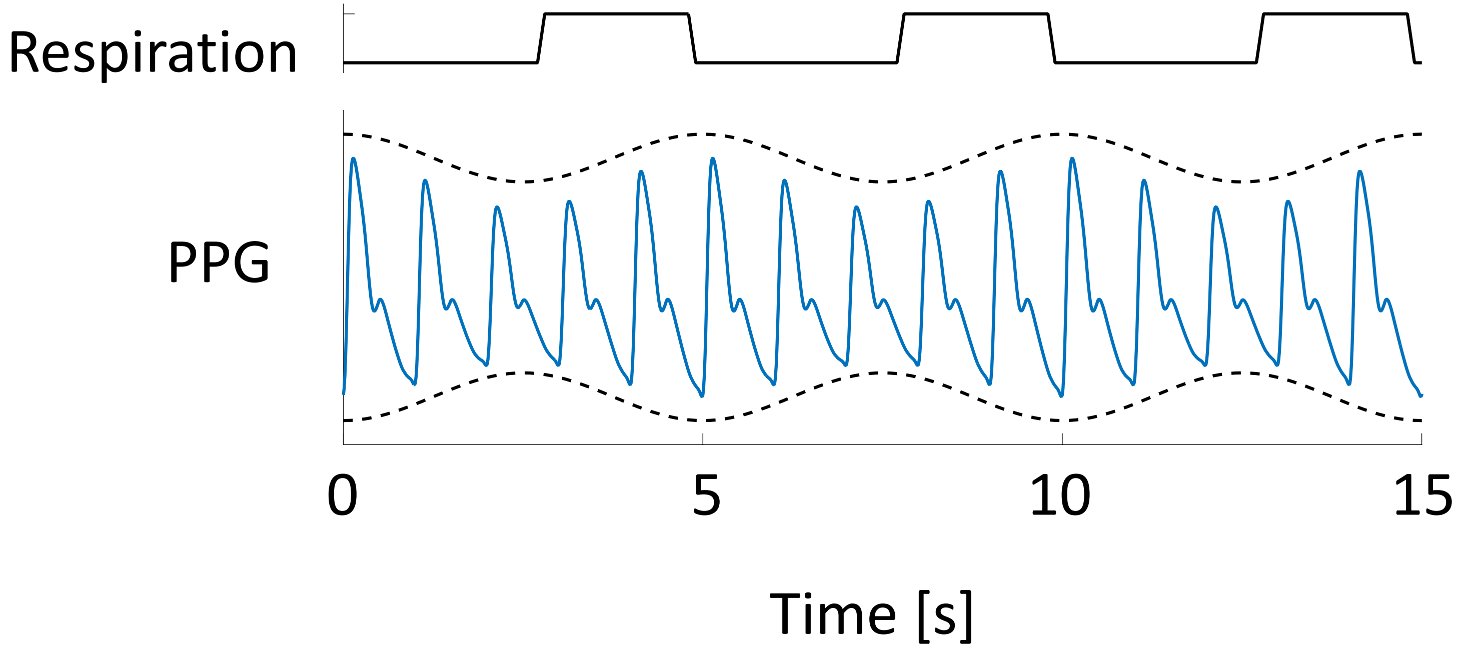
Wearable Pulse Oximeter



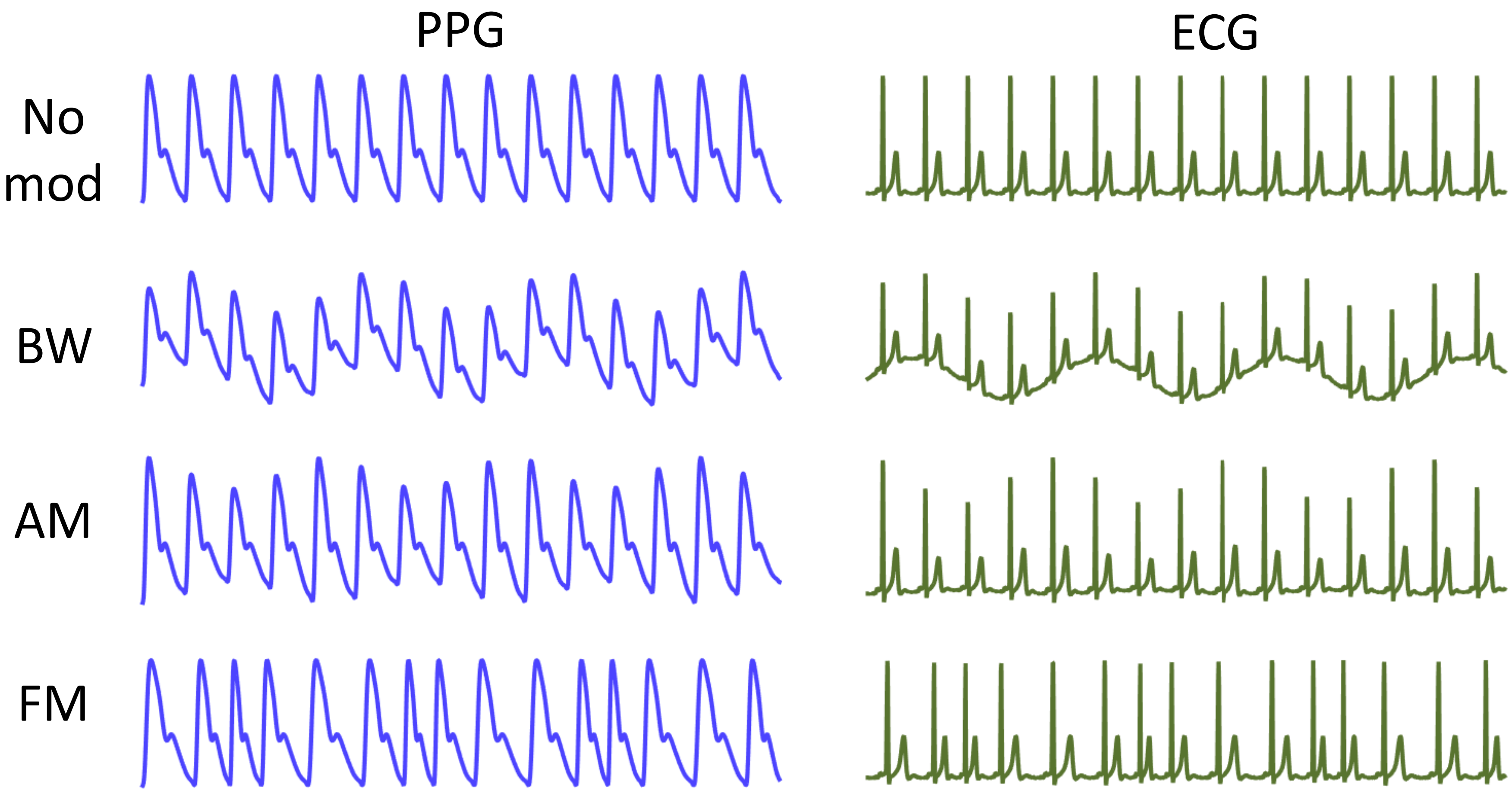


Further details at DOI: [10.1109/RBME.2017.2763681](https://doi.org/10.1109/RBME.2017.2763681) , Section 1.B

Physiological Basis



Physiological Basis

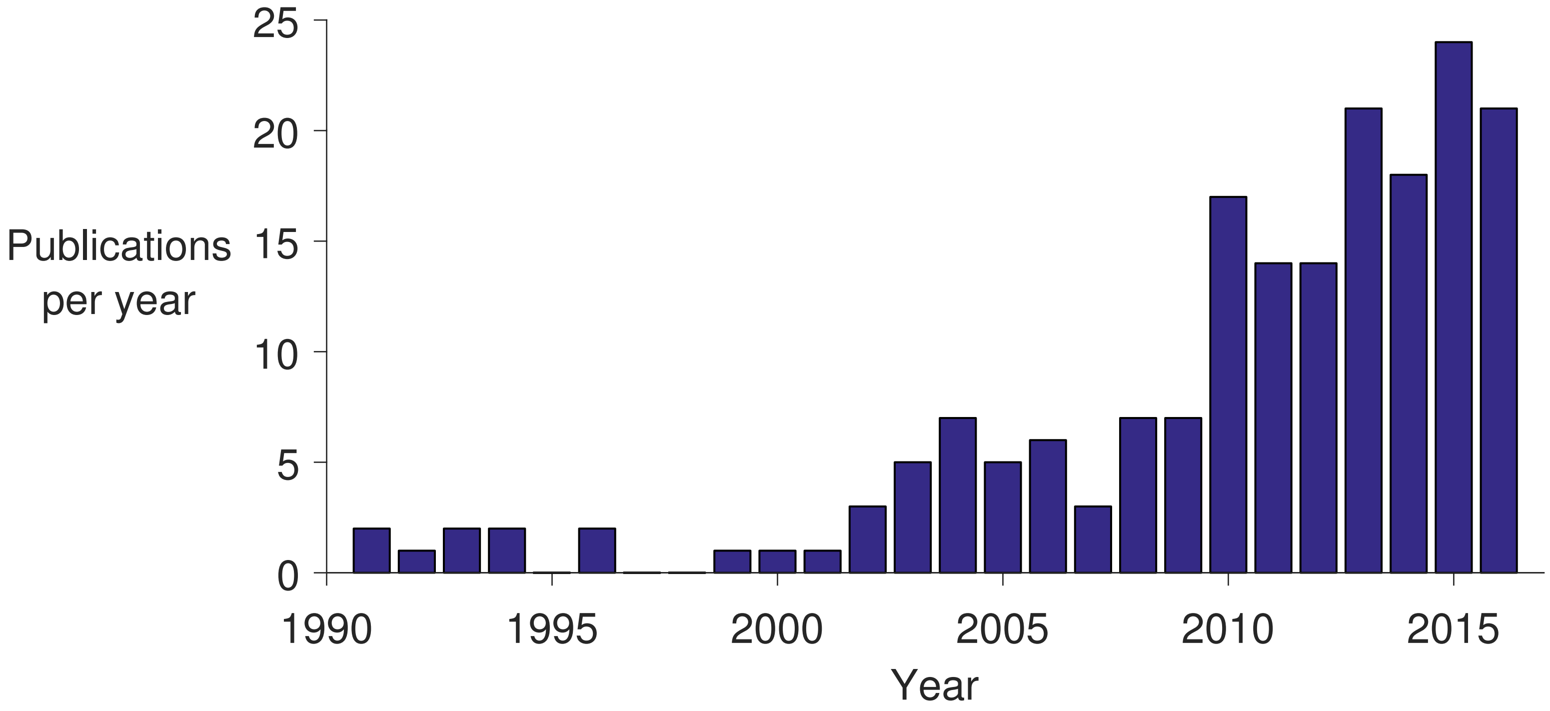


Further details at DOI: 10.1109/RBME.2017.2763681 , Section 1.C

Literature

RR algorithms described in

> 196 publications



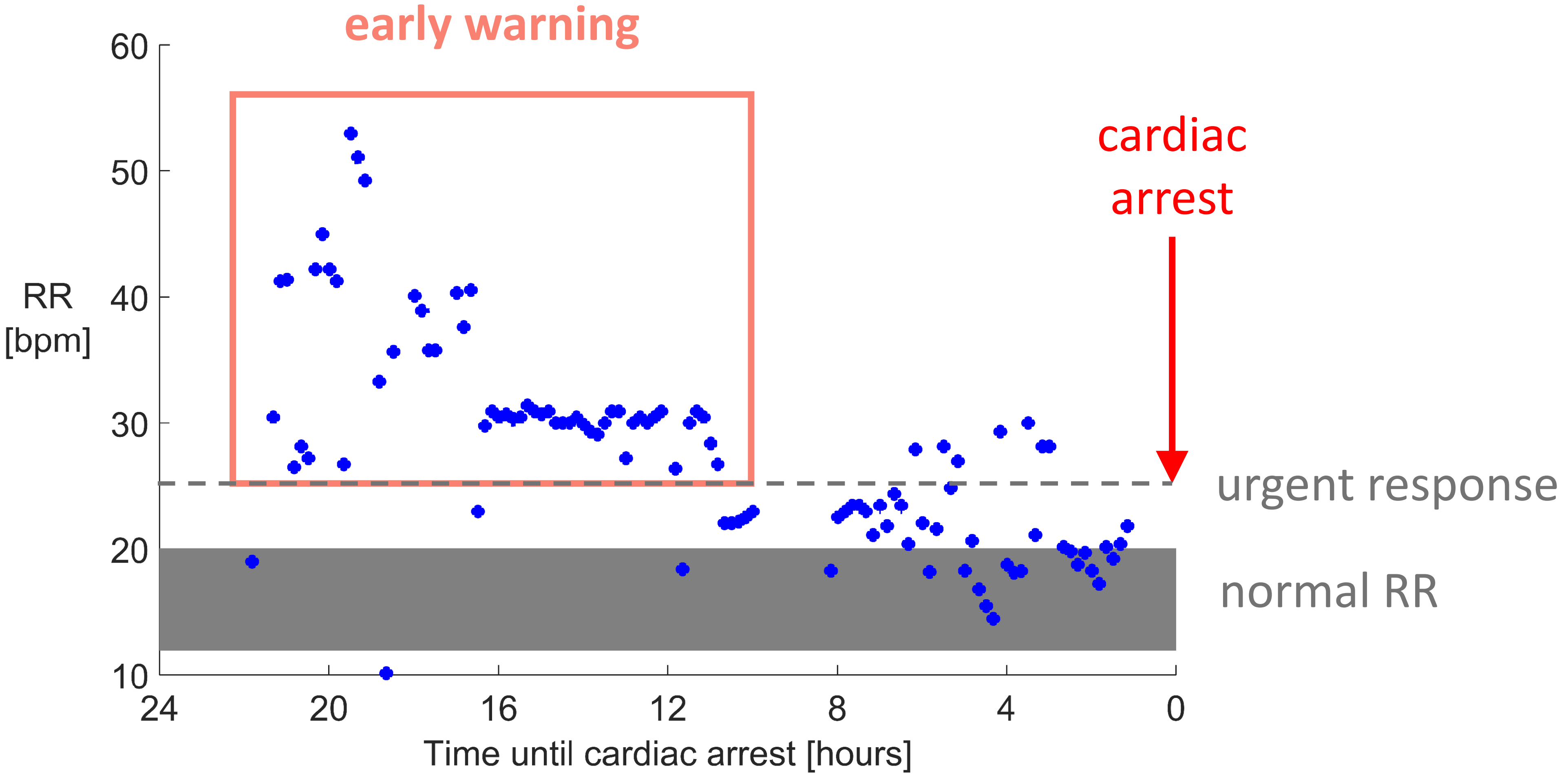
Further details at DOI: [10.1109/RBME.2017.2763681](https://doi.org/10.1109/RBME.2017.2763681) , Section 2

Outline

- Background
  - ***Case Study 1: Elevated RR prior to cardiac arrest***
- RR algorithms
  - *Case Study 2: Unobtrusive RR monitoring*
- Performance assessment
  - *Case Study 3: Predicting adverse events*
- Implementation
- Conclusion

Case Study 1

ECG-derived RRs every 10 mins on hospital ward



Outline

- Background
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- **RR algorithms**
  - *Case Study 2: Unobtrusive RR monitoring*
- Performance assessment
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- Implementation
- Conclusion

Implementation

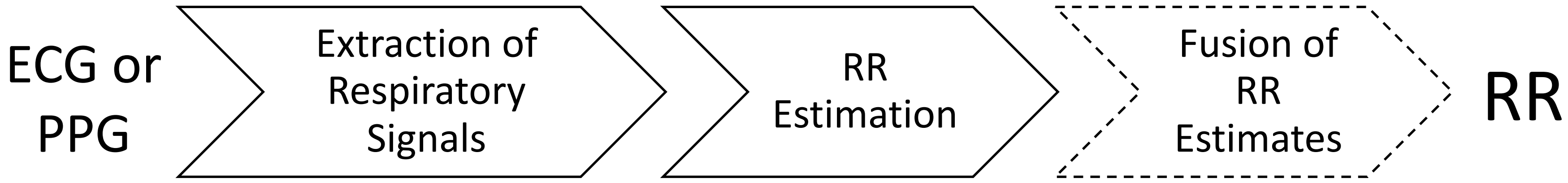
Charlton P.H. *et al.*

Breathing rate estimation from the electrocardiogram and photoplethysmogram: a review,

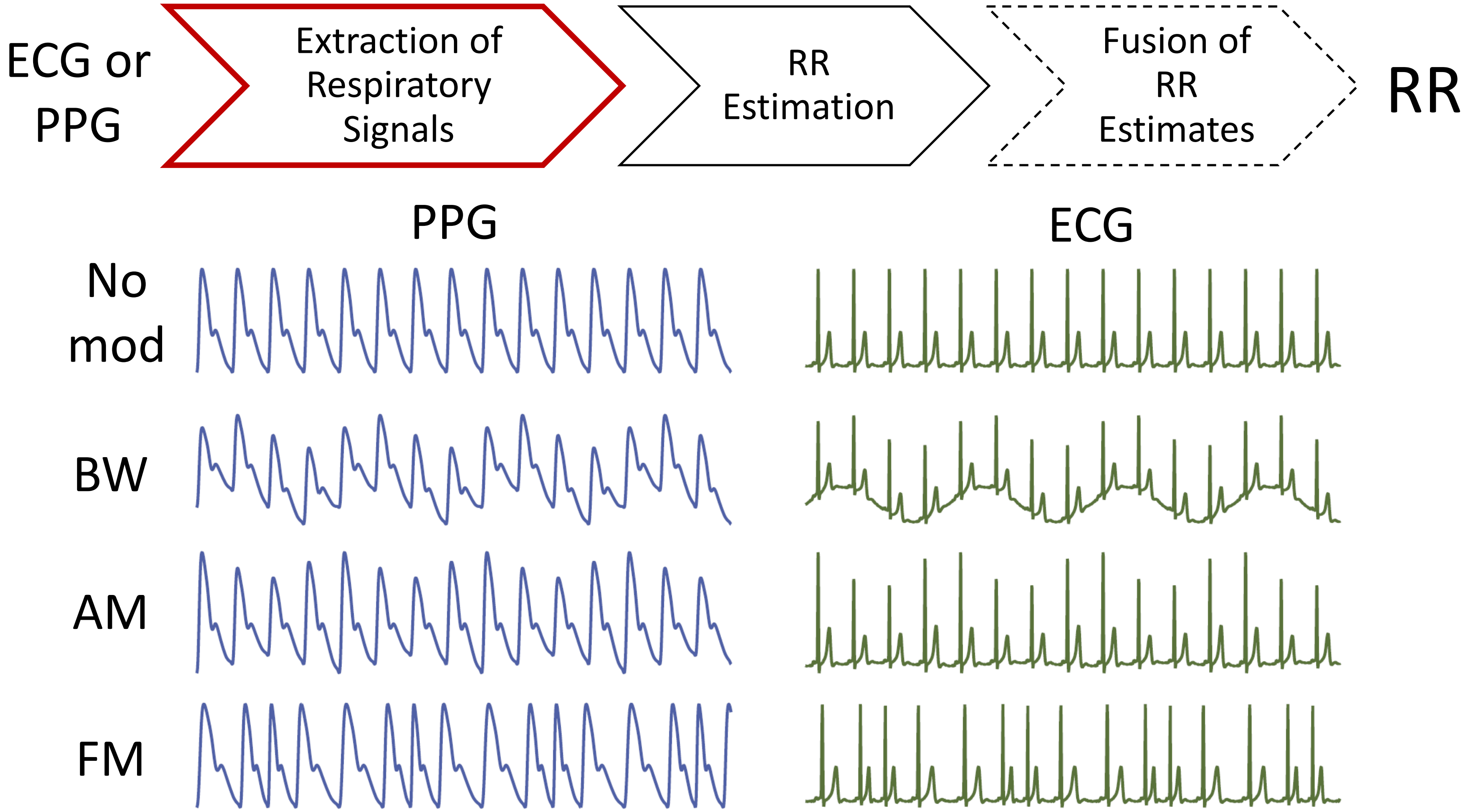
IEEE Reviews in Biomedical Engineering, In Press, 2017.

DOI: 10.1109/RBME.2017.2763681 . [CC BY 3.0 Licence]()

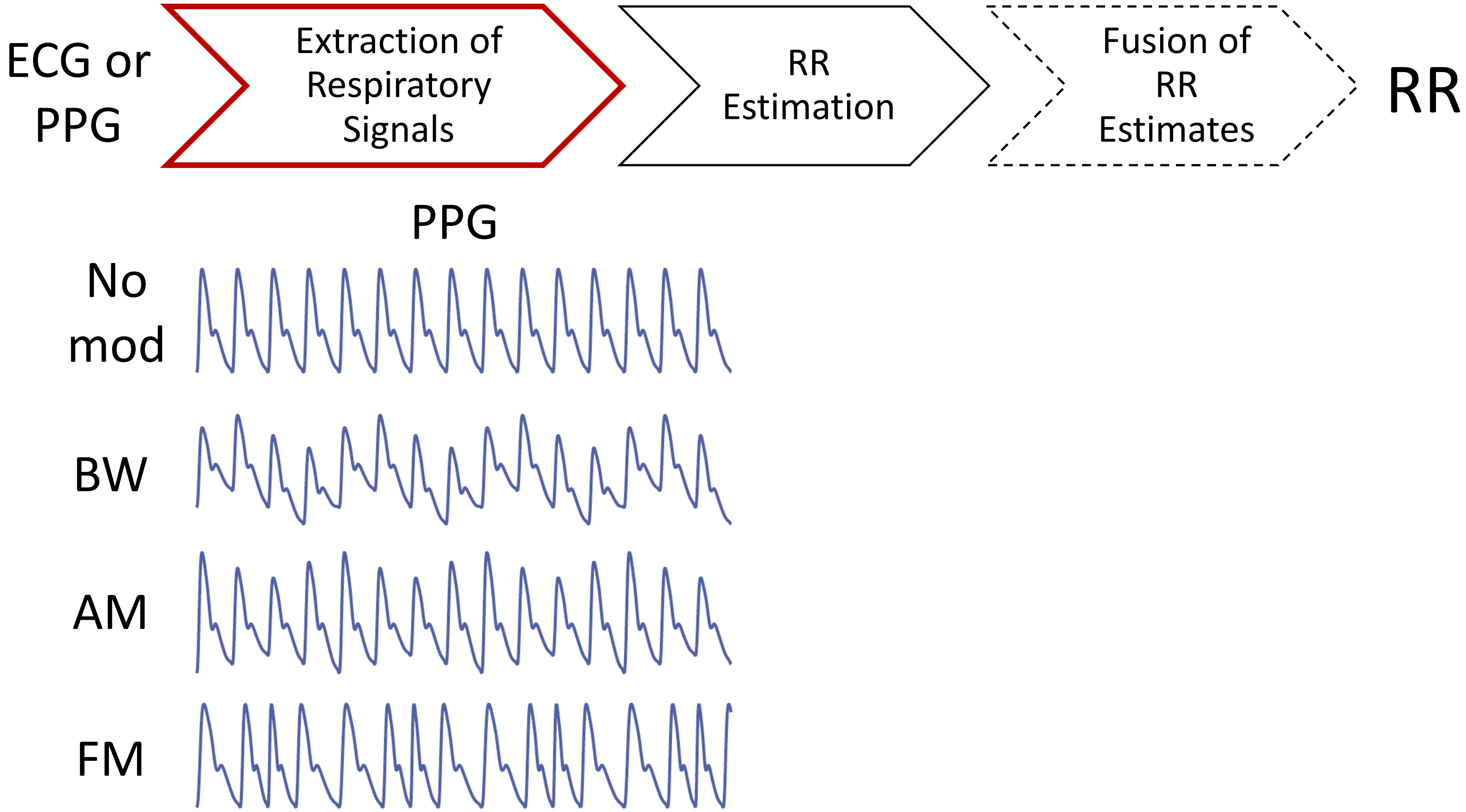
Structure of Algorithms



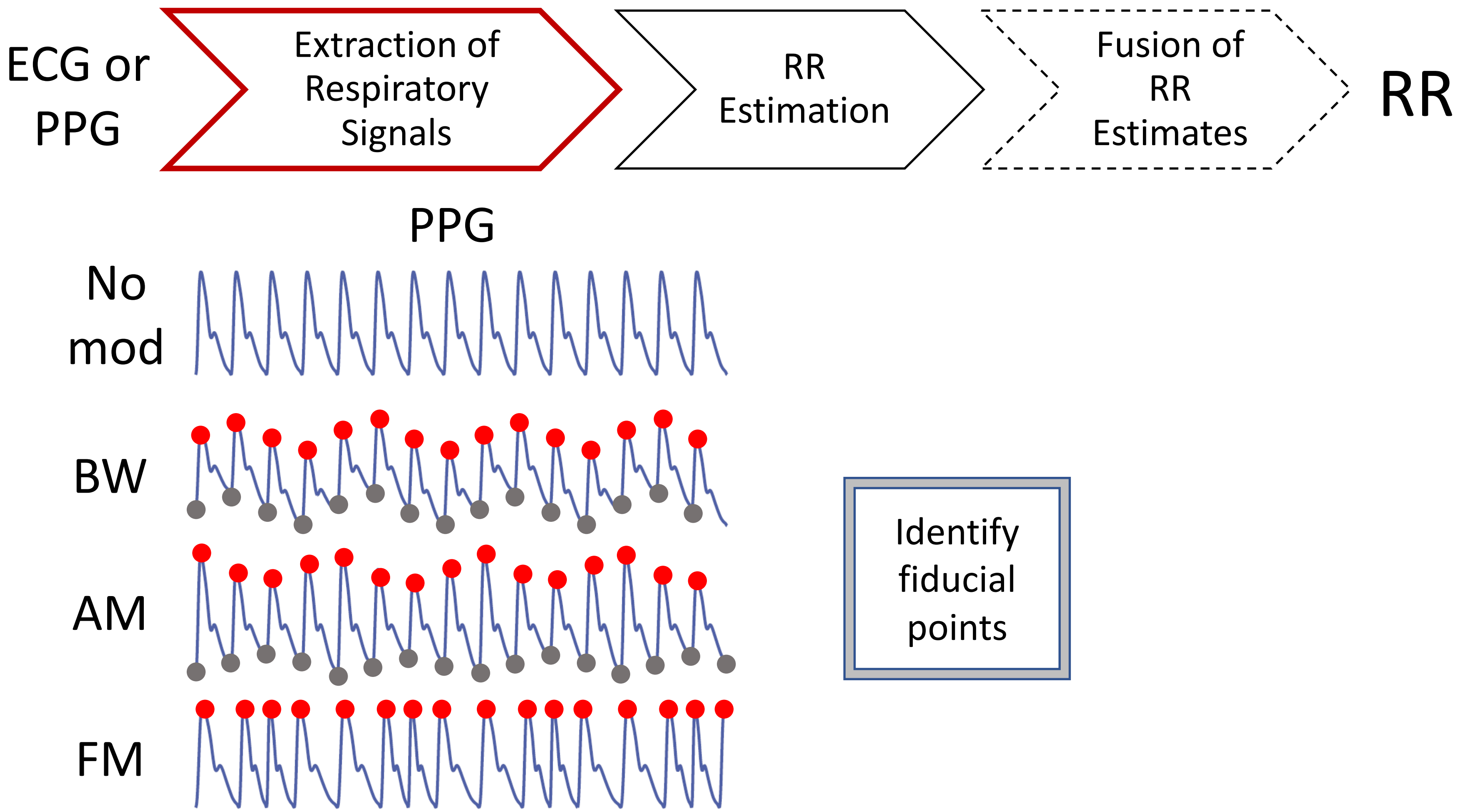
Structure of Algorithms



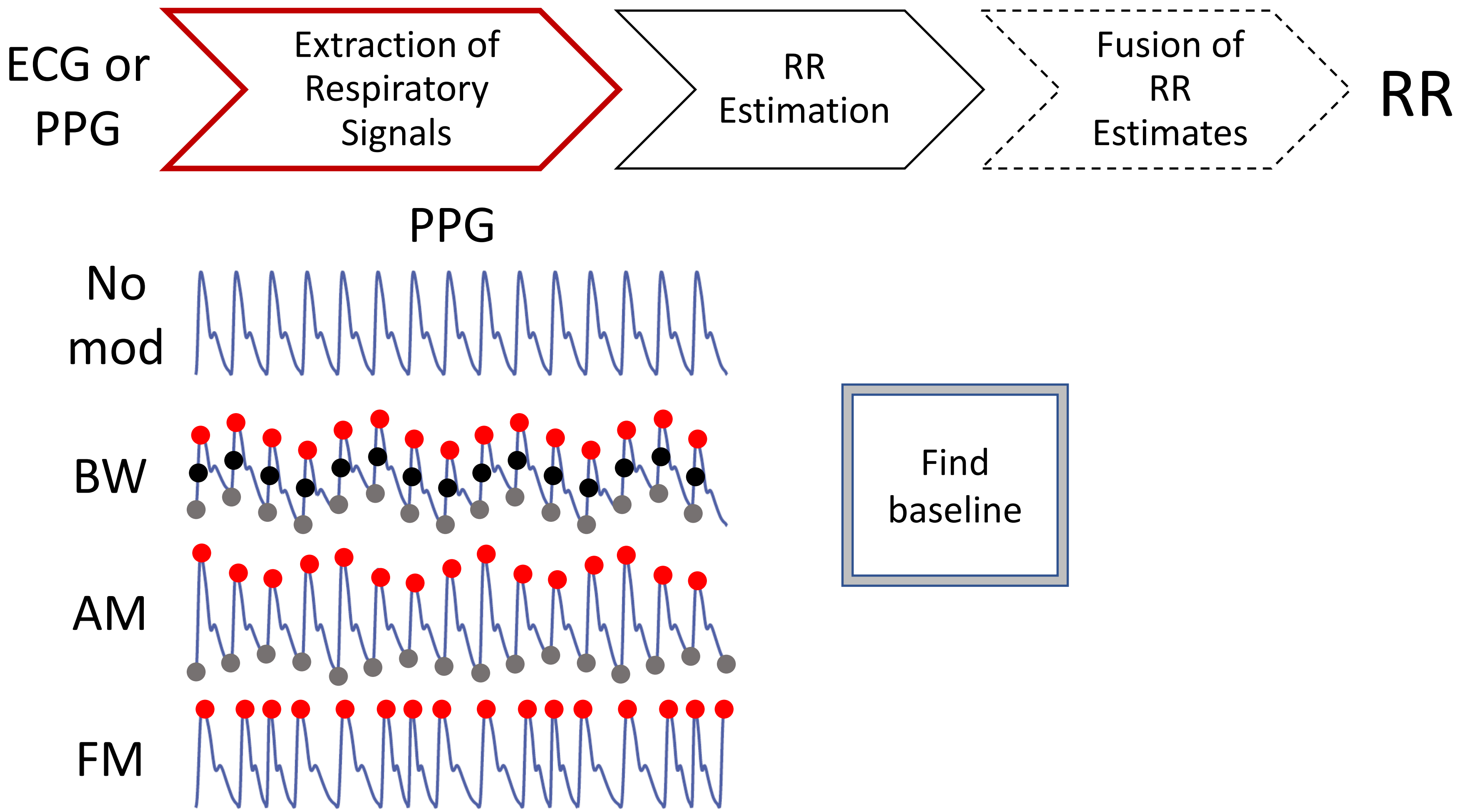
Structure of Algorithms



Structure of Algorithms

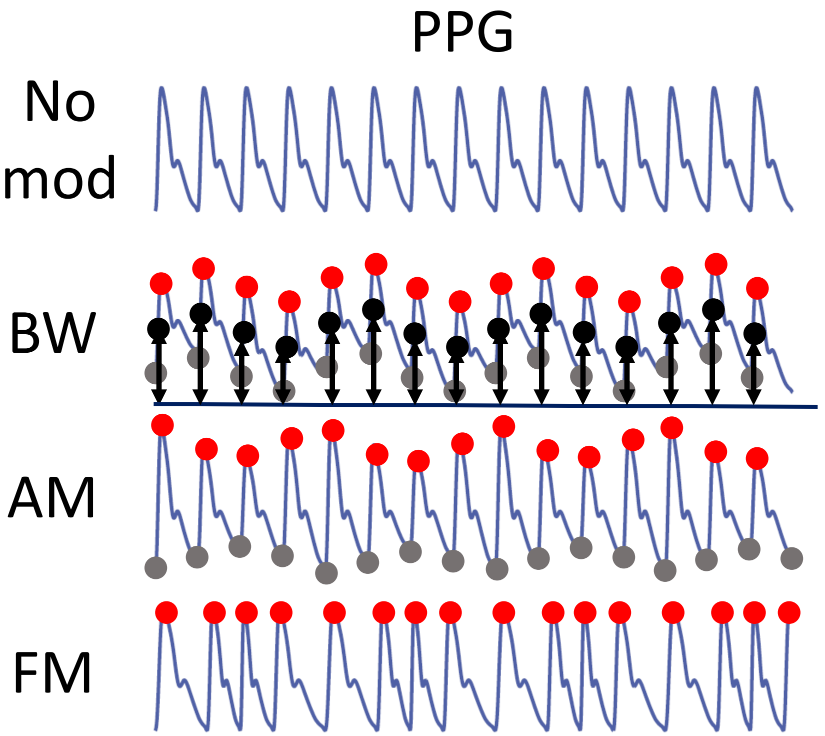


Structure of Algorithms



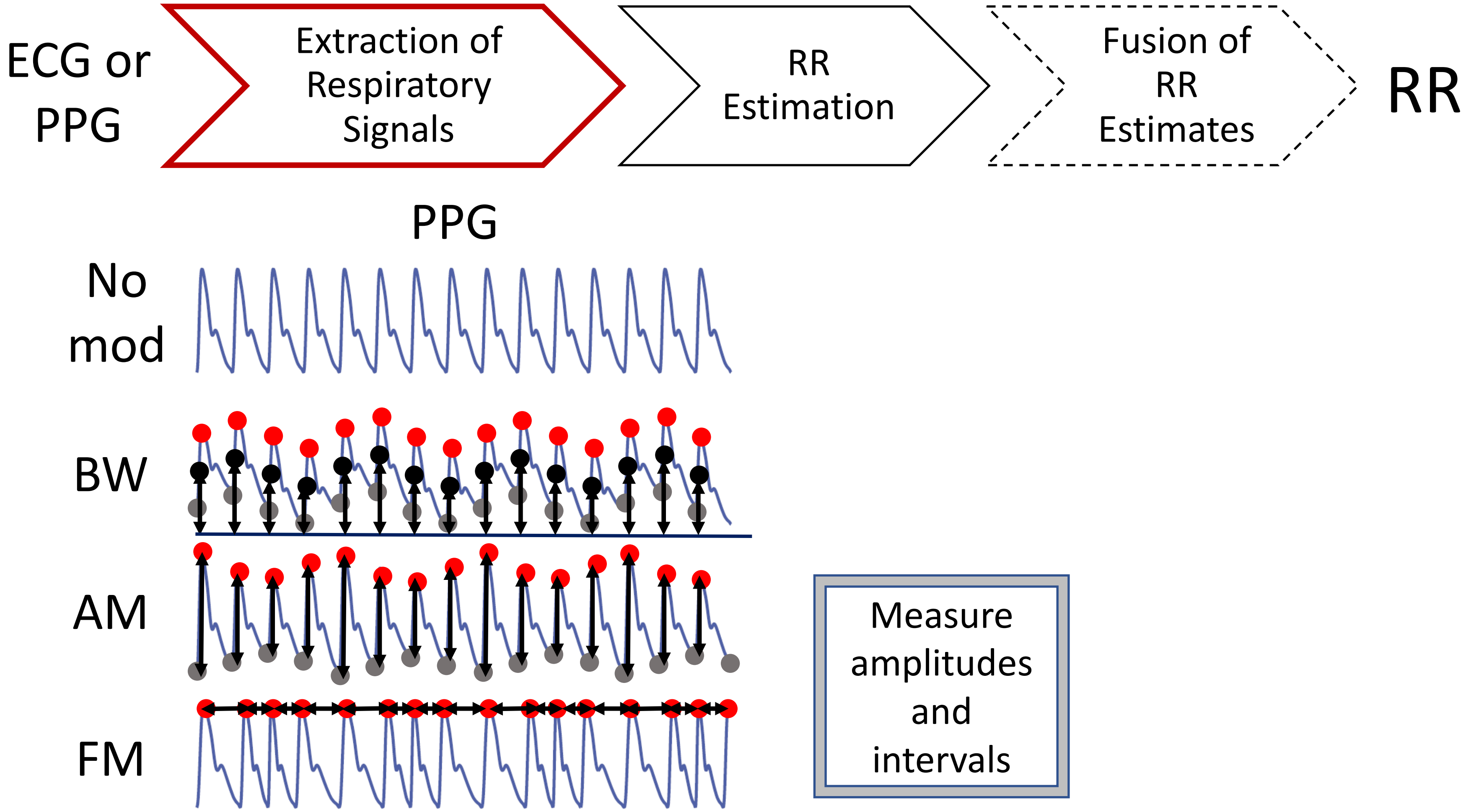
Structure of Algorithms

ECG or PPG → Extraction of Respiratory Signals → RR Estimation → Fusion of RR Estimates → RR

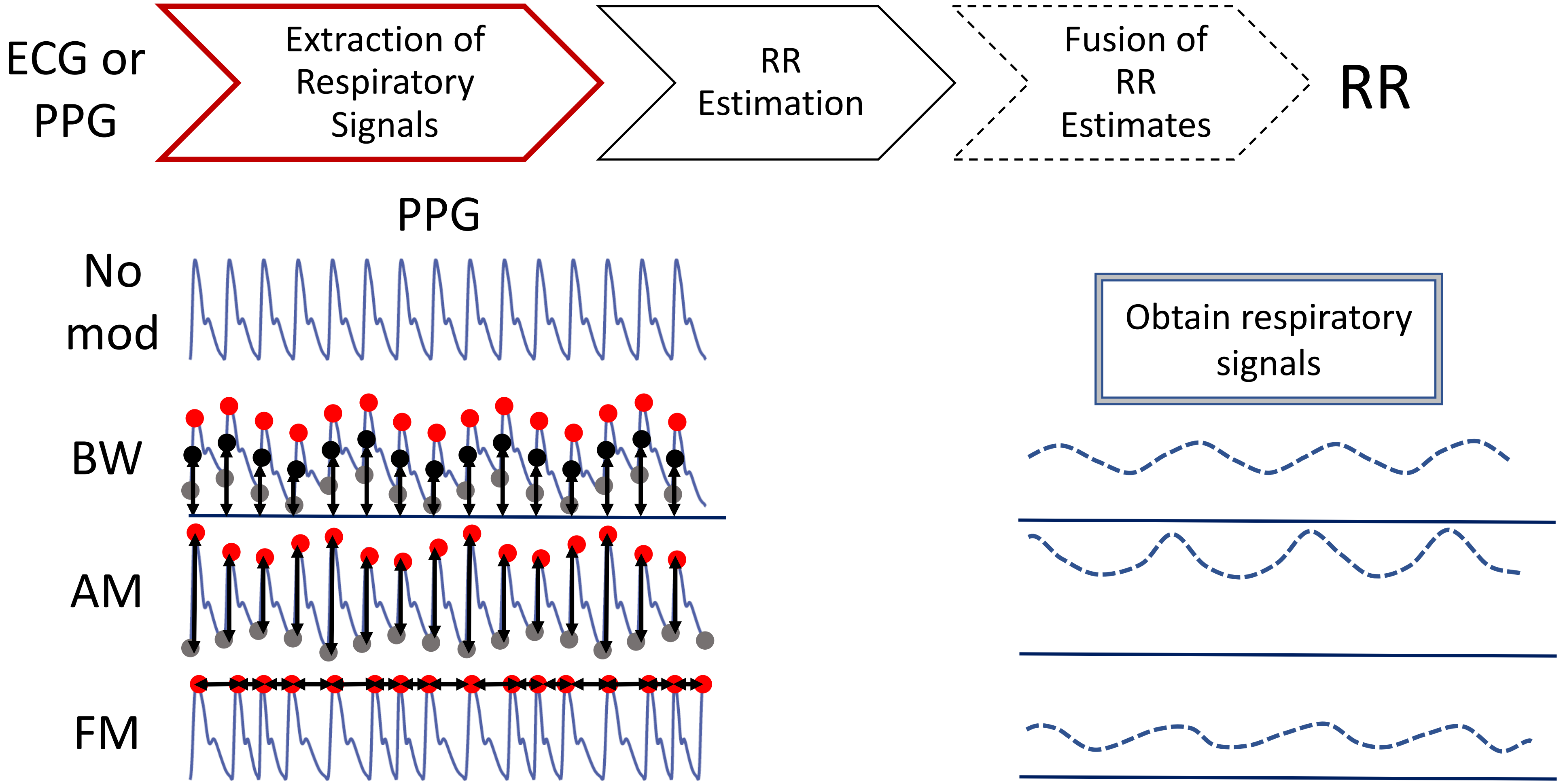


Find baseline

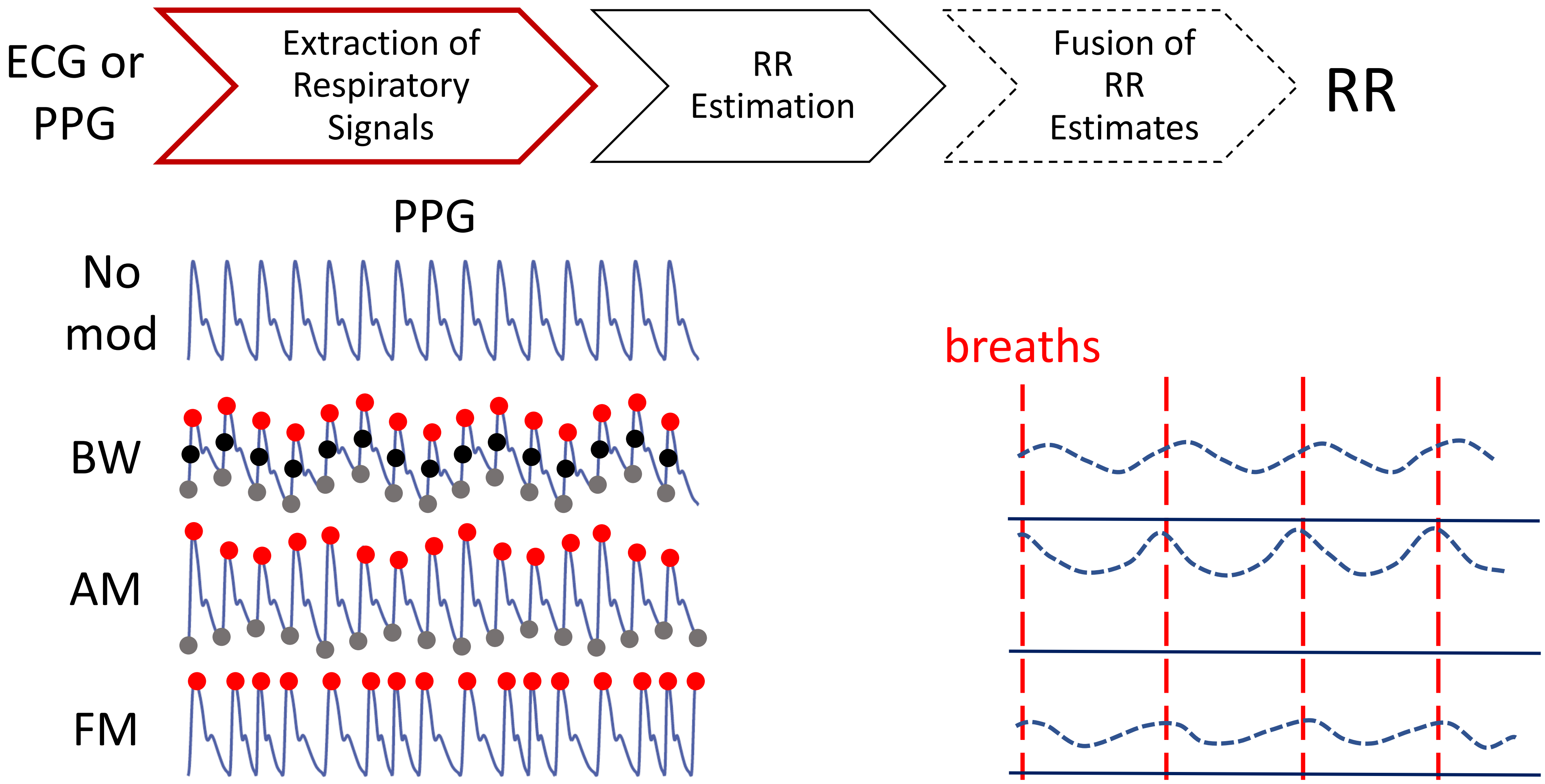
Structure of Algorithms



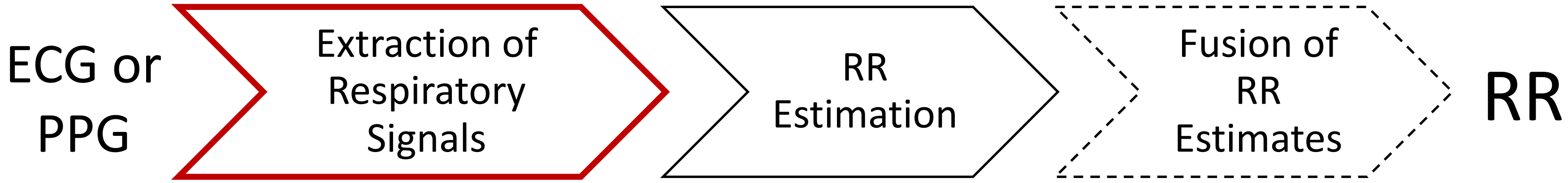
Structure of Algorithms

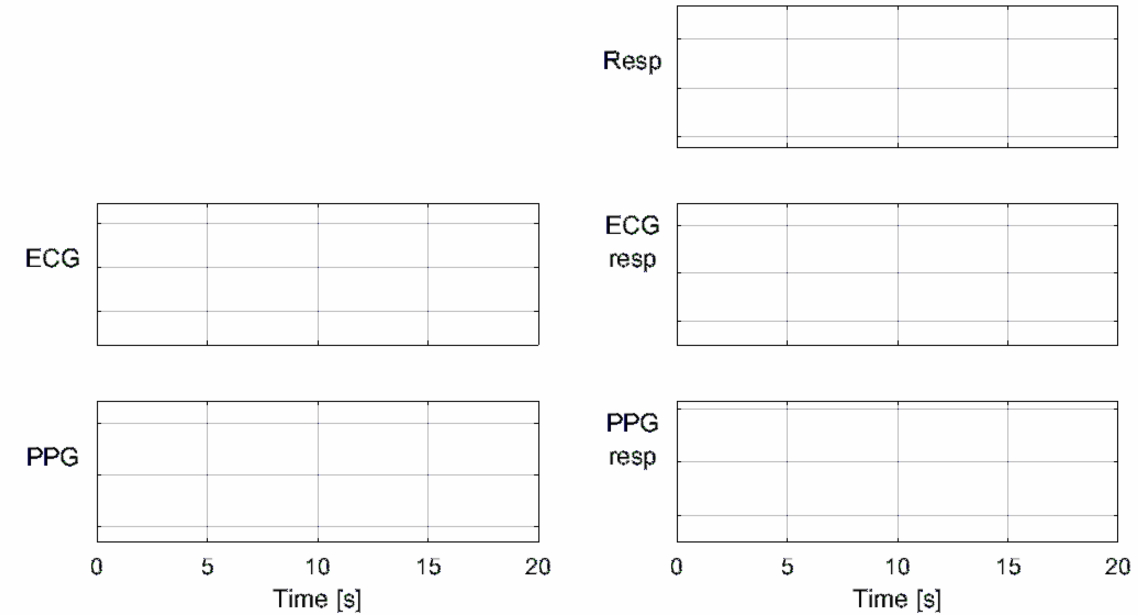


Structure of Algorithms

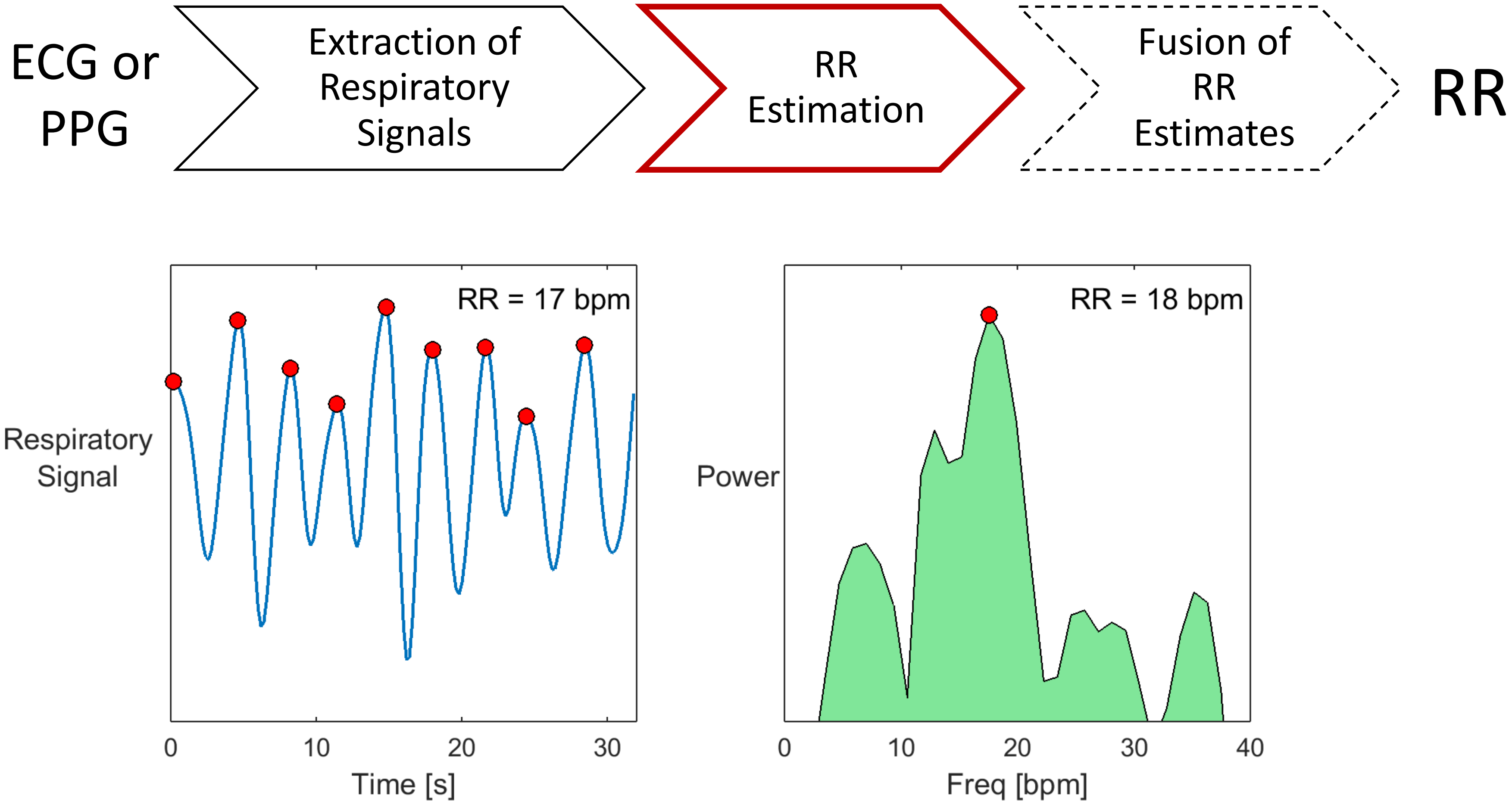


Structure of Algorithms

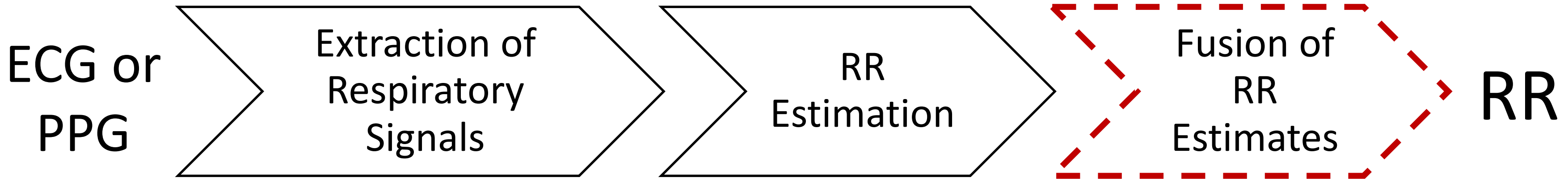


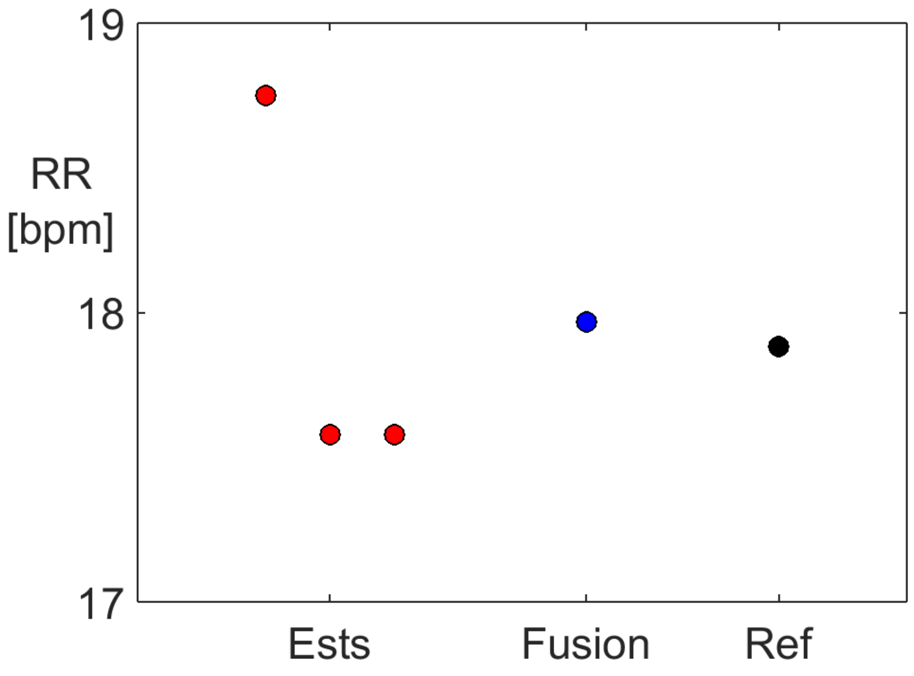


Structure of Algorithms

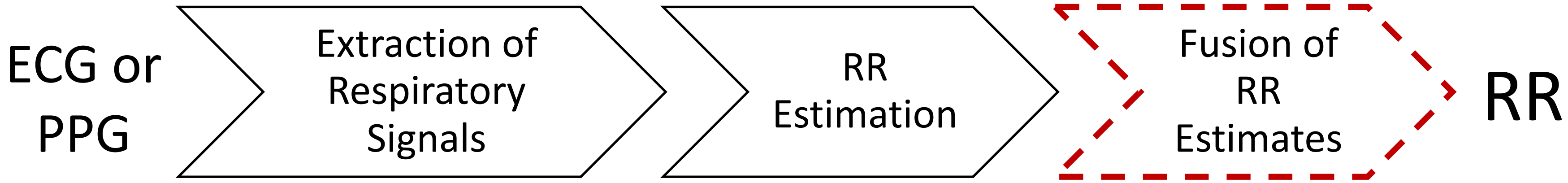


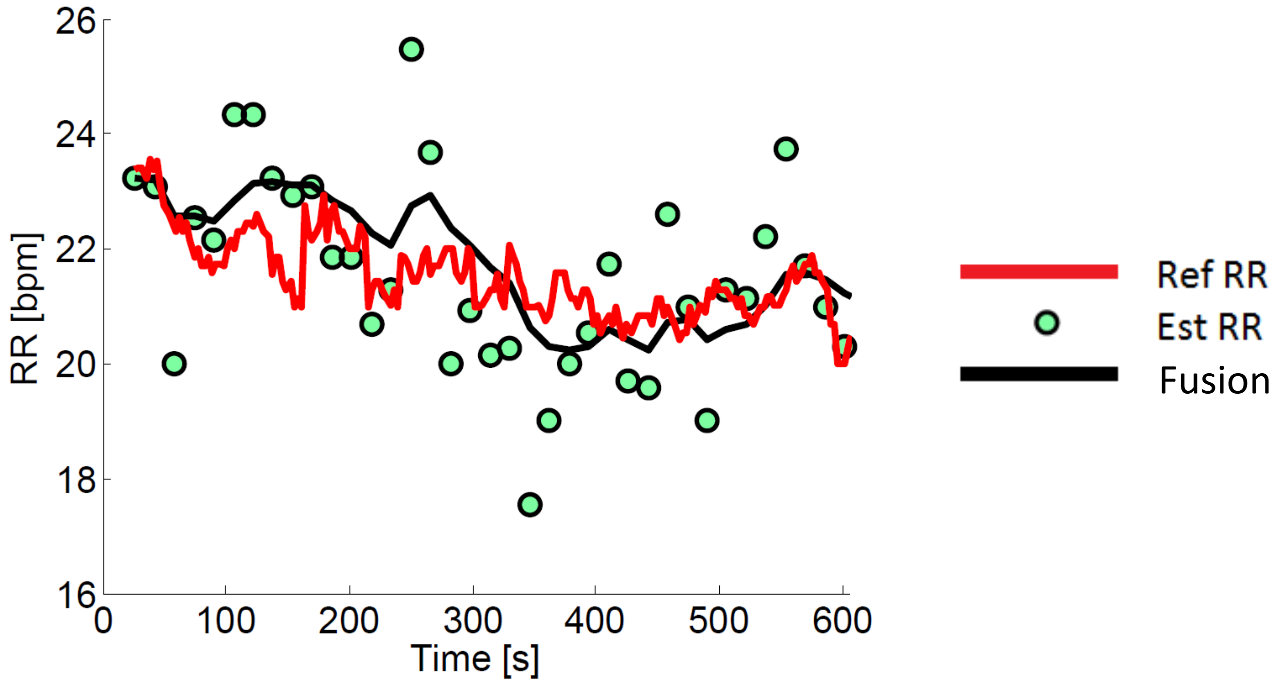
Structure of Algorithms





Structure of Algorithms





Structure of Algorithms

ECG or PPG → Extraction of Respiratory Signals → RR Estimation → Fusion of RR Estimates → RR

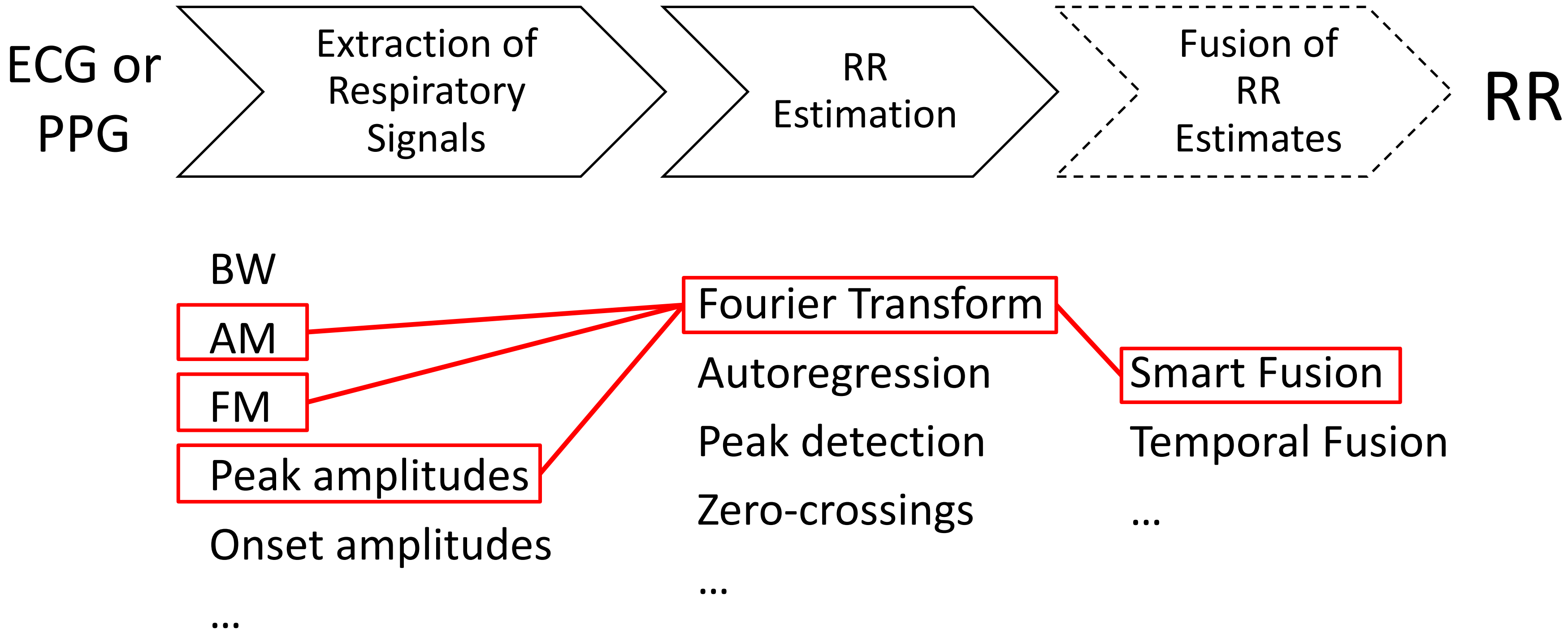
Extraction of Respiratory Signals	RR Estimation	Fusion of RR Estimates
BW	Fourier Transform	Smart Fusion
AM	Autoregression	Temporal Fusion
FM	Peak detection	…
Peak amplitudes	Zero-crossings	
Onset amplitudes	…	
…		

Structure of Algorithms

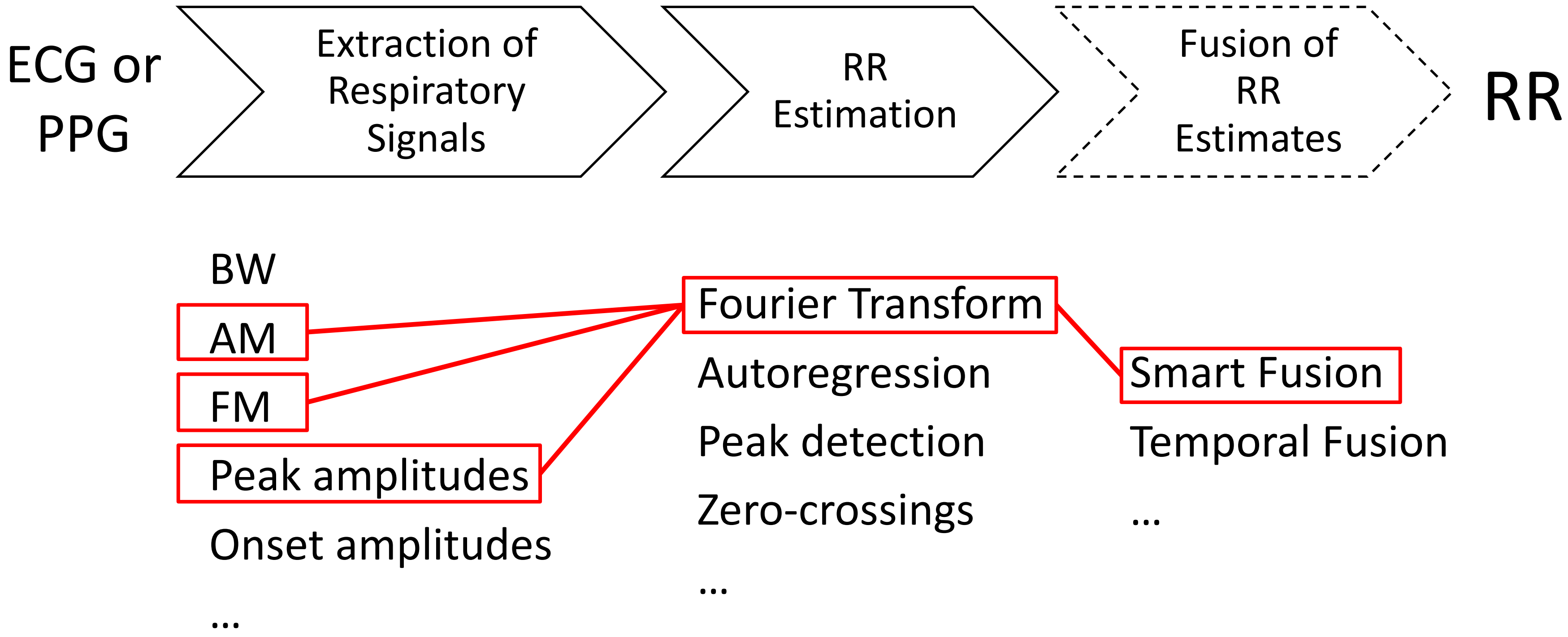
ECG or PPG → Extraction of Respiratory Signals → RR Estimation → Fusion of RR Estimates → RR

Extraction of Respiratory Signals	RR Estimation	Fusion of RR Estimates
BW	Fourier Transform	Smart Fusion
AM	$\boxed{\text{Autoregression}}$	Temporal Fusion
$\boxed{\text{FM}}$	Peak detection	…
Peak amplitudes	Zero-crossings	
Onset amplitudes	…	
…		

Structure of Algorithms



Structure of Algorithms



Further details of the structure of algorithms and possible mathematical techniques:
DOI: [10.1109/RBME.2017.2763681](https://doi.org/10.1109/RBME.2017.2763681) , Section 3

Outline

- Background
  - *Case Study 1: Elevated RR prior to cardiac arrest*
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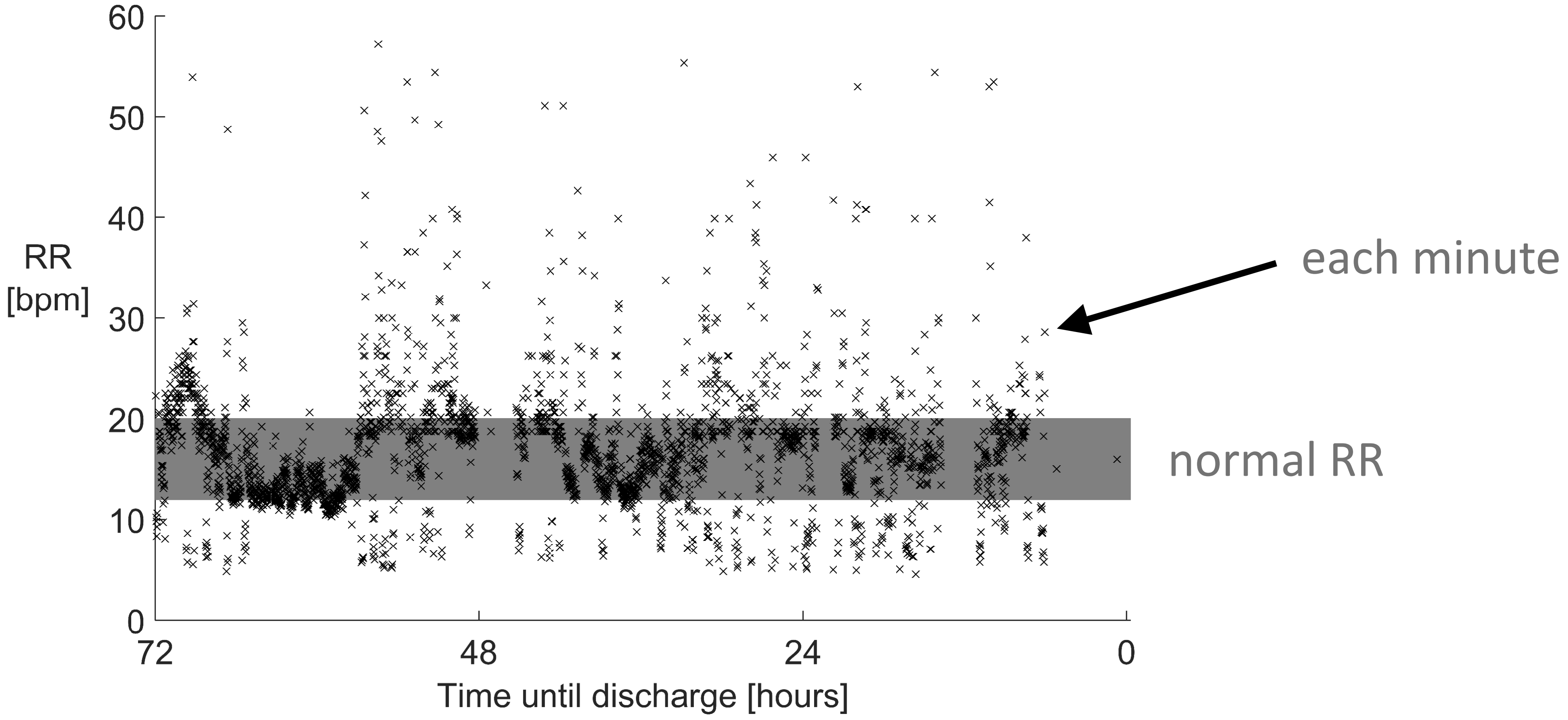
  - *Case Study 3: Predicting adverse events*
- Implementation
- Conclusion

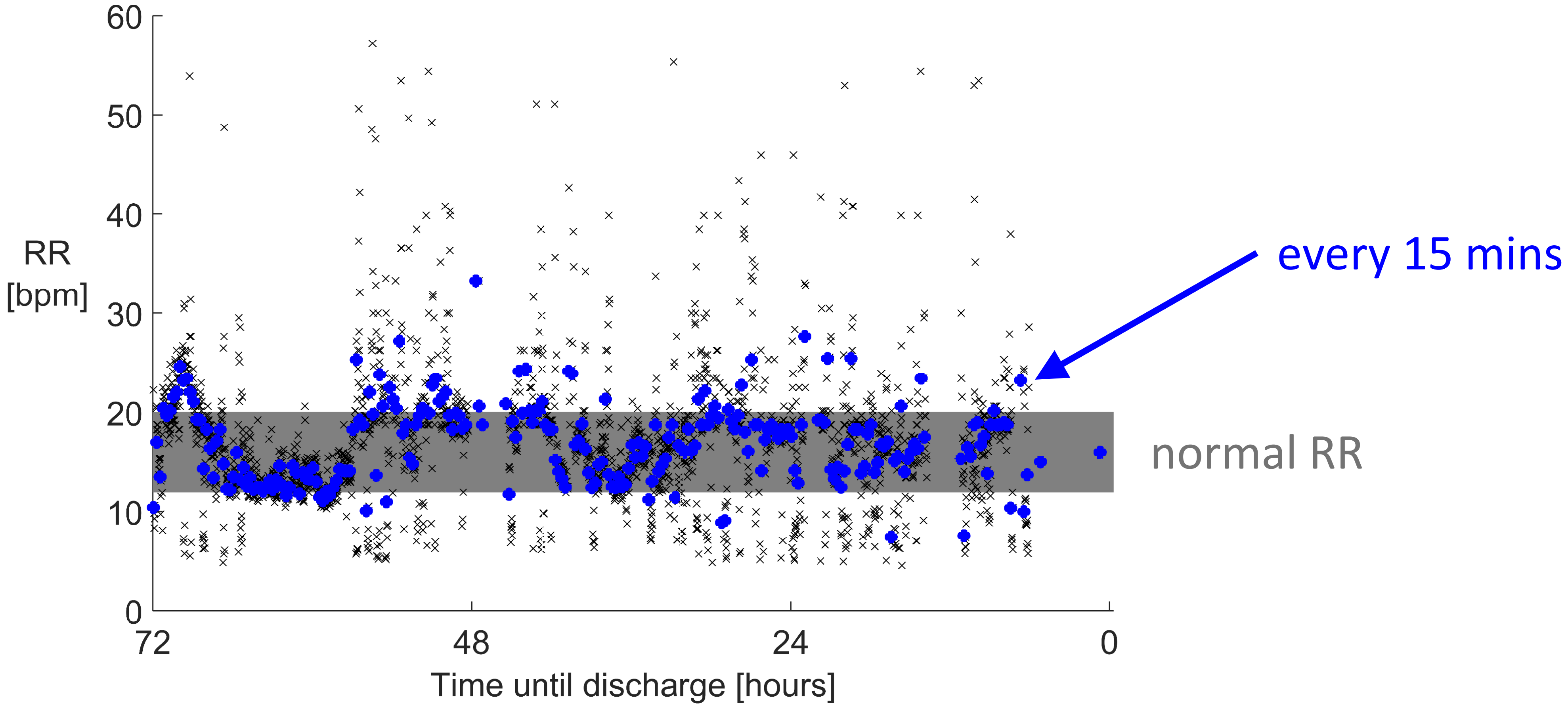
Case Study 2

ECG-derived RRs every minute throughout 3-day stay on hospital ward



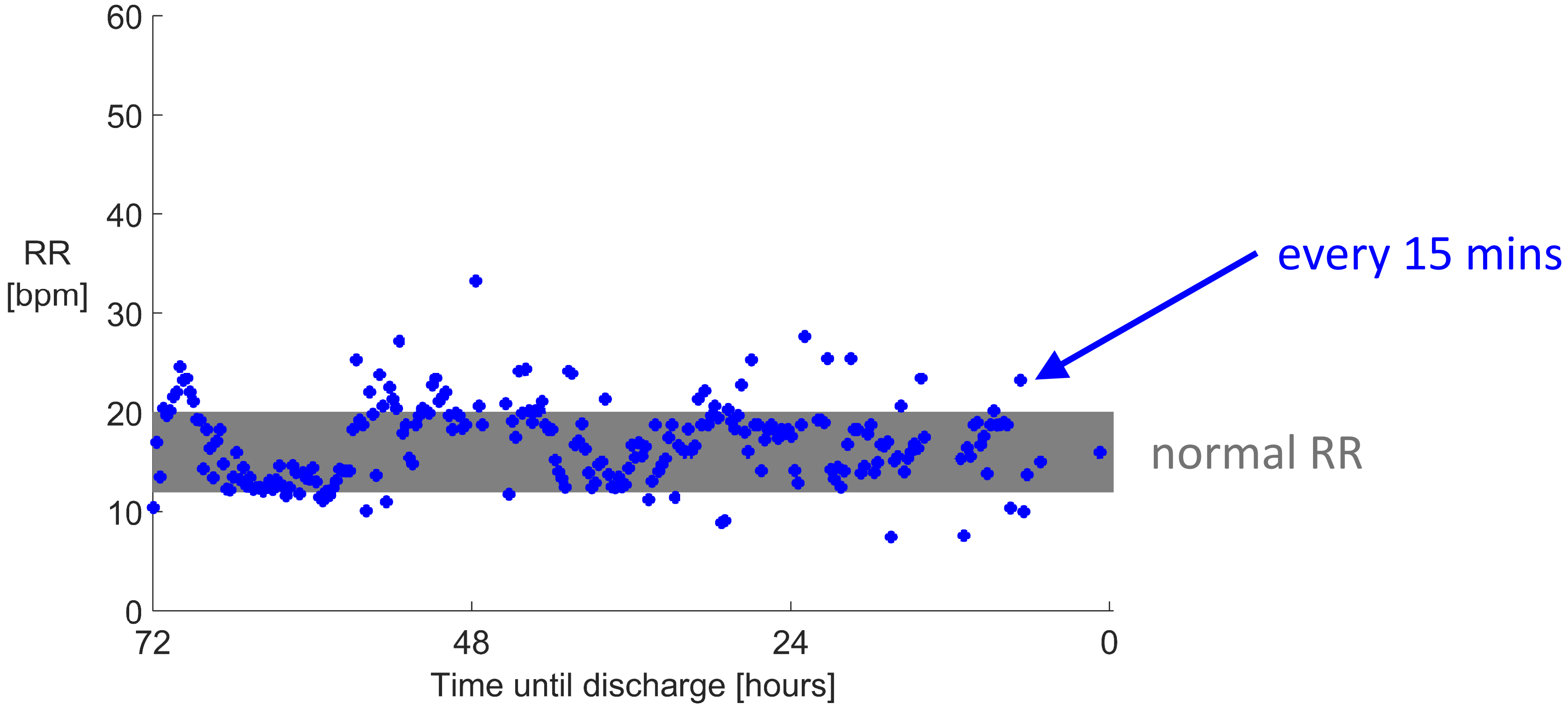
Case Study 2

ECG-derived RRs every 15 mins throughout 3-day stay on hospital ward



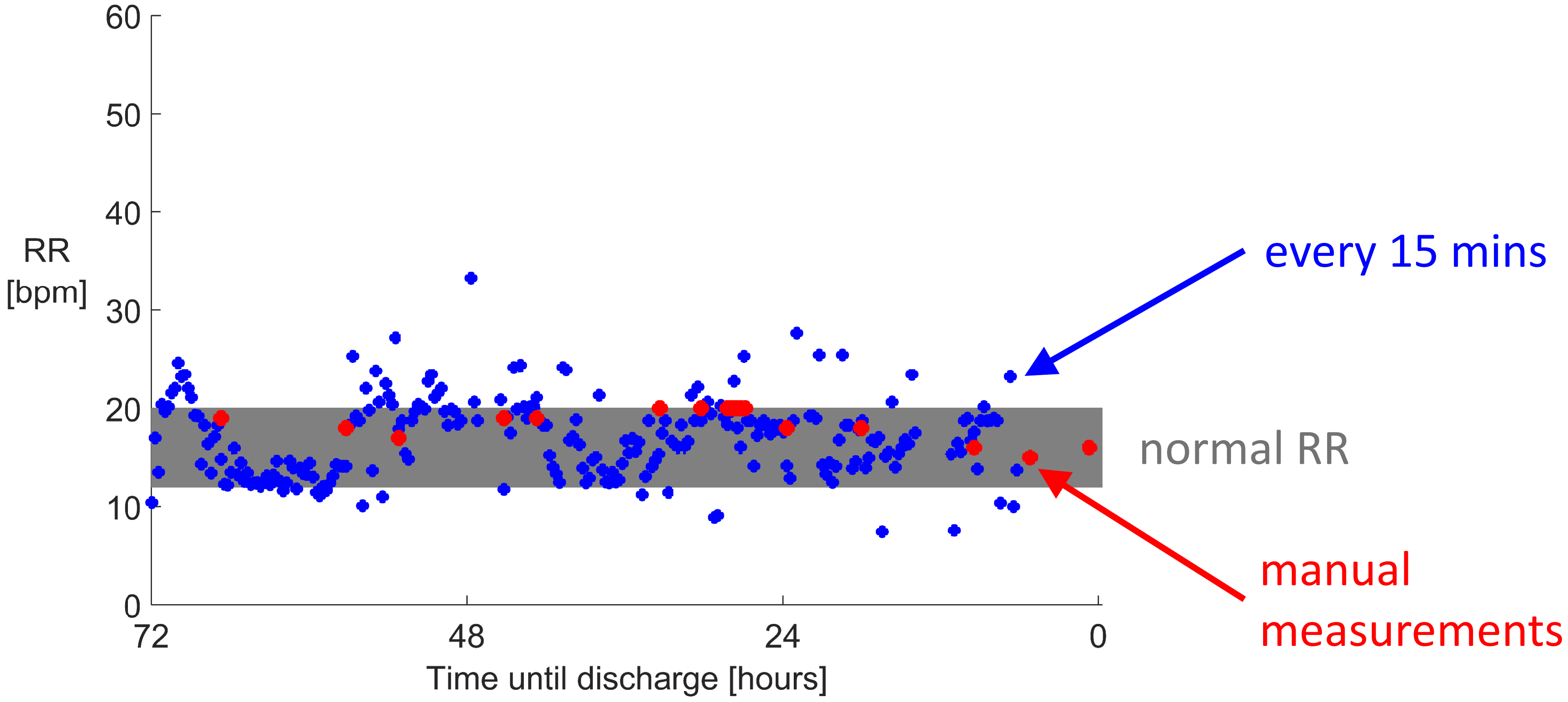
Case Study 2

ECG-derived RRs every 15 mins throughout 3-day stay on hospital ward



Case Study 2

ECG-derived RRs every 15 mins throughout 3-day stay on hospital ward



Outline

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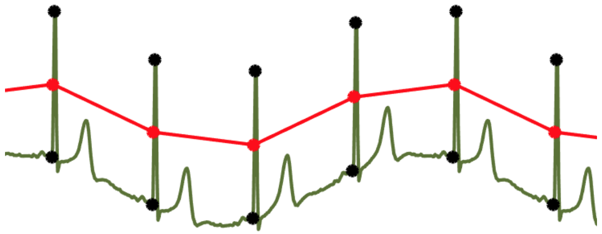
Algorithm Assessments

Difficult to determine which algorithm, if any, is suitable:

RR algorithms described in

> 196 publications

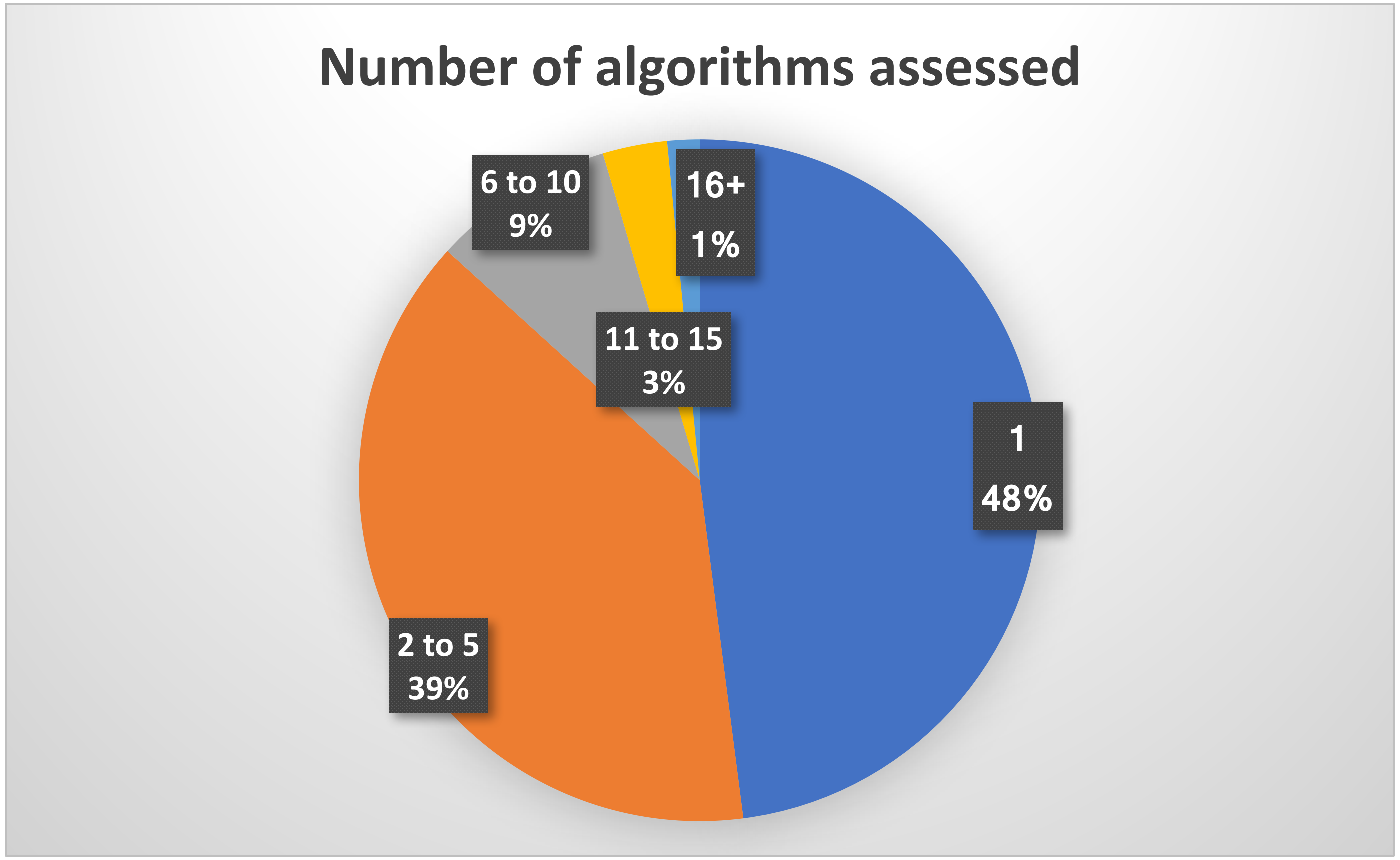


> 100 algorithms

Several potential applications

Previous Algorithm Assessments

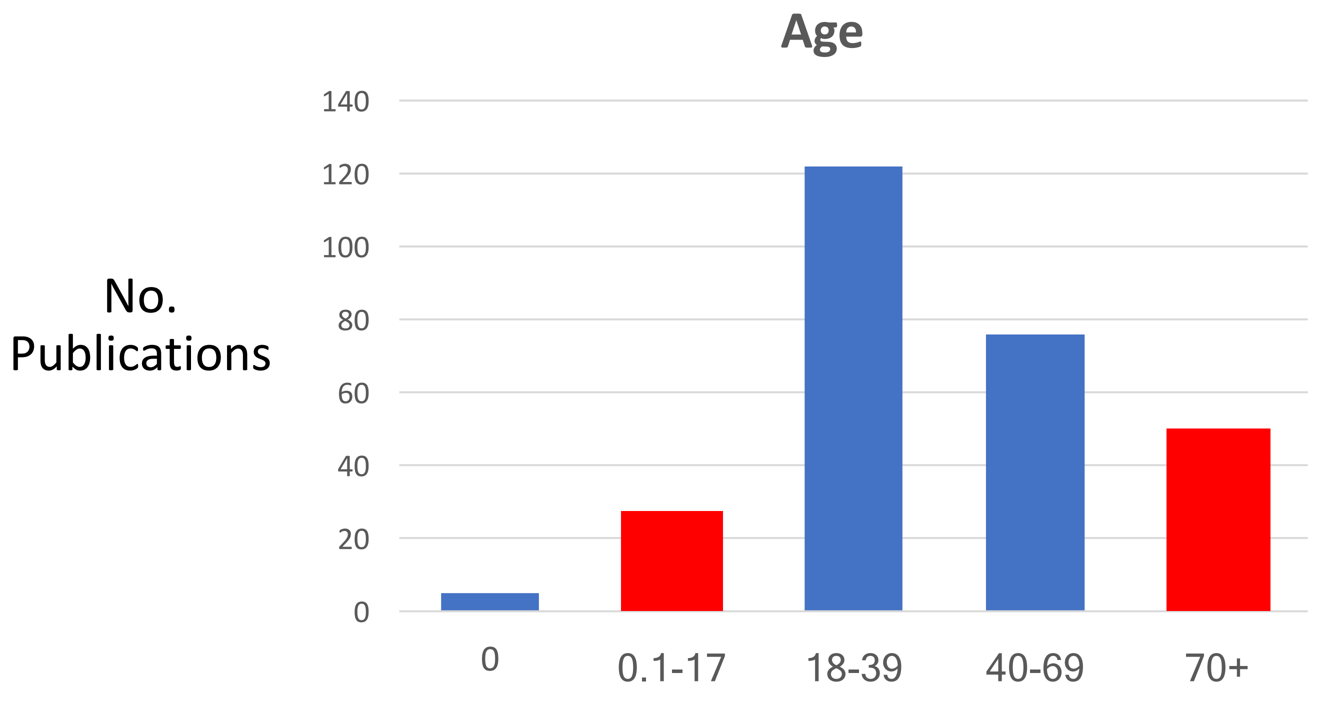
Focused on developing novel algorithms:

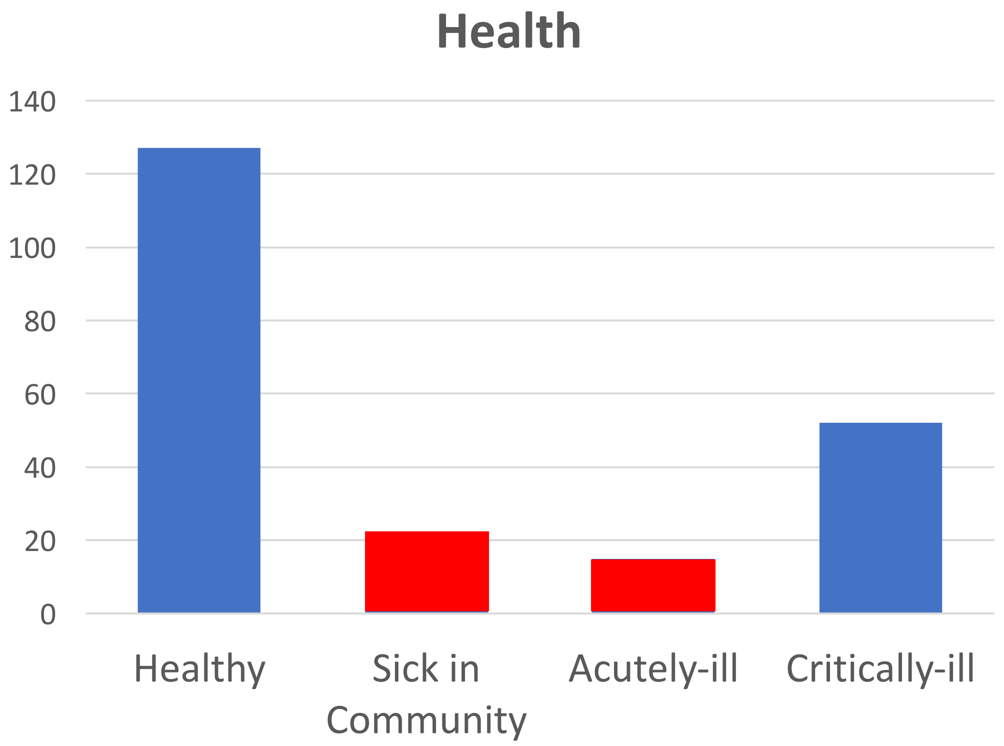


(out of 196 publications)

Previous Algorithm Assessments

Primarily used data from young adults, and healthy subjects:





of greatest interest

Previous Algorithm Assessments

Many used publicly available datasets:

Dataset	No. subjects	Age	ECG	PPG	Level of Illness
CapnoBase	42	paediatric, adult	✓	✓	surgery, anaesthesia
MIMIC-II	23,180	paediatric, adult	✓	✓	critically-ill
MGH/MF	250	paediatric, adult	✓		critically-ill
MIMIC	72	adult	✓	✓	critically-ill
VORTAL	57	adult	✓	✓	healthy
Fantasia	40	adult	✓		healthy
UCD Sleep Apnea	25	adult	✓		healthy, apnea
CEBS	20	adult	✓		healthy
ECG and Resp	20	adult	✓		healthy
MIT-BIH Polysomnographic	18	adult	✓		healthy, apnea
Apnea-ECG	8	adult	✓	✓	healthy, apnea
Portland State	1	paediatric	✓	✓	critically-ill

Previous Algorithm Assessments

Further details of previous algorithm assessments:

DOI: 10.1109/RBME.2017.2763681 , Section 4. A

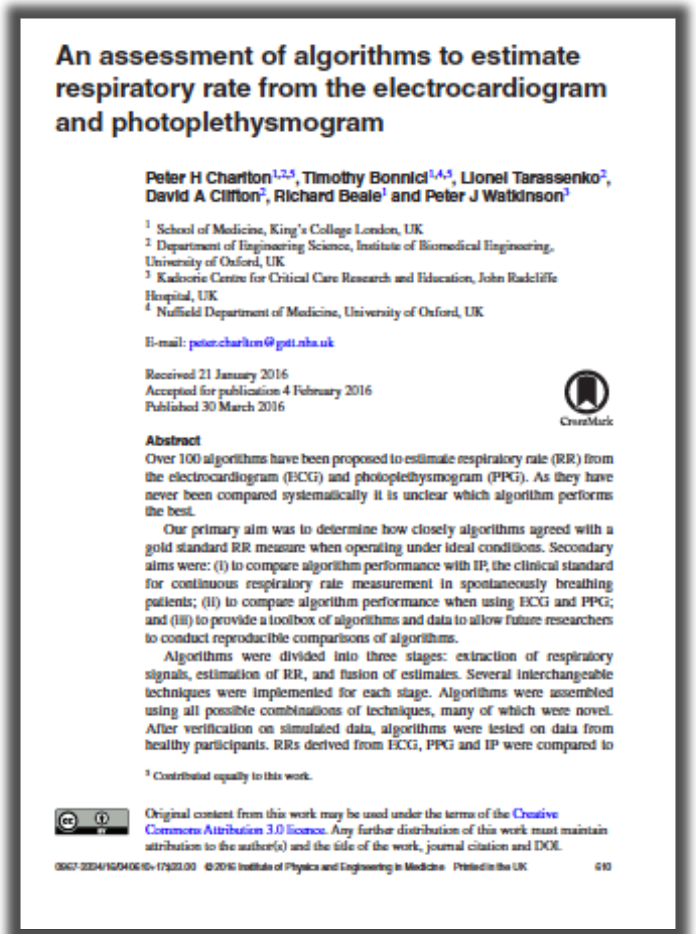
Example Assessment

Charlton P.H. and Bonnici T. *et al.*

An assessment of algorithms to estimate respiratory rate from the electrocardiogram and photoplethysmogram

Physiological Measurement, 37(4), 2016.

DOI: [10.1088/0967-3334/37/4/610](https://doi.org/10.1088/0967-3334/37/4/610) . [CC BY 3.0 Licence](https://creativecommons.org/licenses/by/3.0/)



An assessment of algorithms to estimate respiratory rate from the electrocardiogram and photoplethysmogram

Peter H Charlton[1,2,5], Timothy Bonnici[1,4,5], Lionel Tarassenko[2], David A Clifton[2], Richard Beale[1] and Peter J Watkinson[3]

[1] School of Medicine, King's College London, UK
[2] Department of Engineering Science, Institute of Biomedical Engineering, University of Oxford, UK
[3] Kadoorie Centre for Critical Care Research and Education, John Radcliffe Hospital, UK
[4] Nuffield Department of Medicine, University of Oxford, UK

E-mail: peter.charlton@gstt.nhs.uk

Received 21 January 2016
Accepted for publication 4 February 2016
Published 30 March 2016

Abstract

Over 100 algorithms have been proposed to estimate respiratory rate (RR) from the electrocardiogram (ECG) and photoplethysmogram (PPG). As they have never been compared systematically it is unclear which algorithm performs the best.

Our primary aim was to determine how closely algorithms agreed with a gold standard RR measure when operating under ideal conditions. Secondary aims were: (i) to compare algorithm performance with IP, the clinical standard for continuous respiratory rate measurement in spontaneously breathing patients; (ii) to compare algorithm performance when using ECG and PPG; and (iii) to provide a toolbox of algorithms and data to allow future researchers to conduct reproducible comparisons of algorithms.

Algorithms were divided into three stages: extraction of respiratory signals, estimation of RR, and fusion of estimates. Several interchangeable techniques were implemented for each stage. Algorithms were assembled using all possible combinations of techniques, many of which were novel. After verification on simulated data, algorithms were tested on data from healthy participants. RRs derived from ECG, PPG and IP were compared to

[5] Contributed equally to this work.

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Example Assessment

Primary aim:

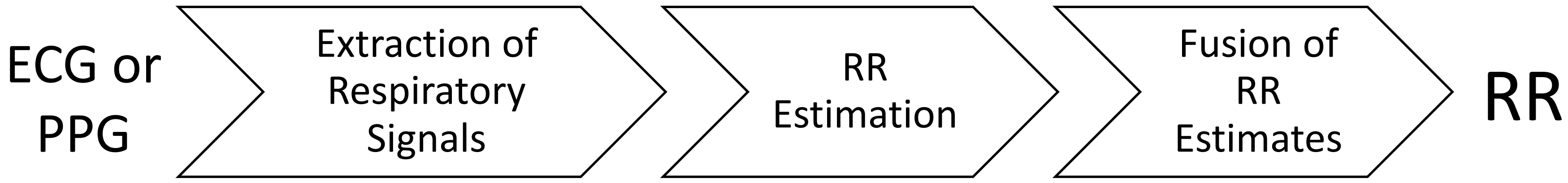
- Determine how closely algorithms agree with a gold standard reference RR under ideal conditions

Secondary aims:

- Compare performance to impedance pneumography
- Compare performance when using ECG or PPG

Example Assessment

Implementing RR algorithms:



BW
AM
FM
Peak amplitudes
Onset amplitudes
…

Fourier Transform
Autoregression
Peak detection
Zero-crossings
…

Smart Fusion
Temporal Fusion
…

Example Assessment

Implementing RR algorithms:

ECG or PPG → Extraction of Respiratory Signals → RR Estimation → Fusion of RR Estimates → RR

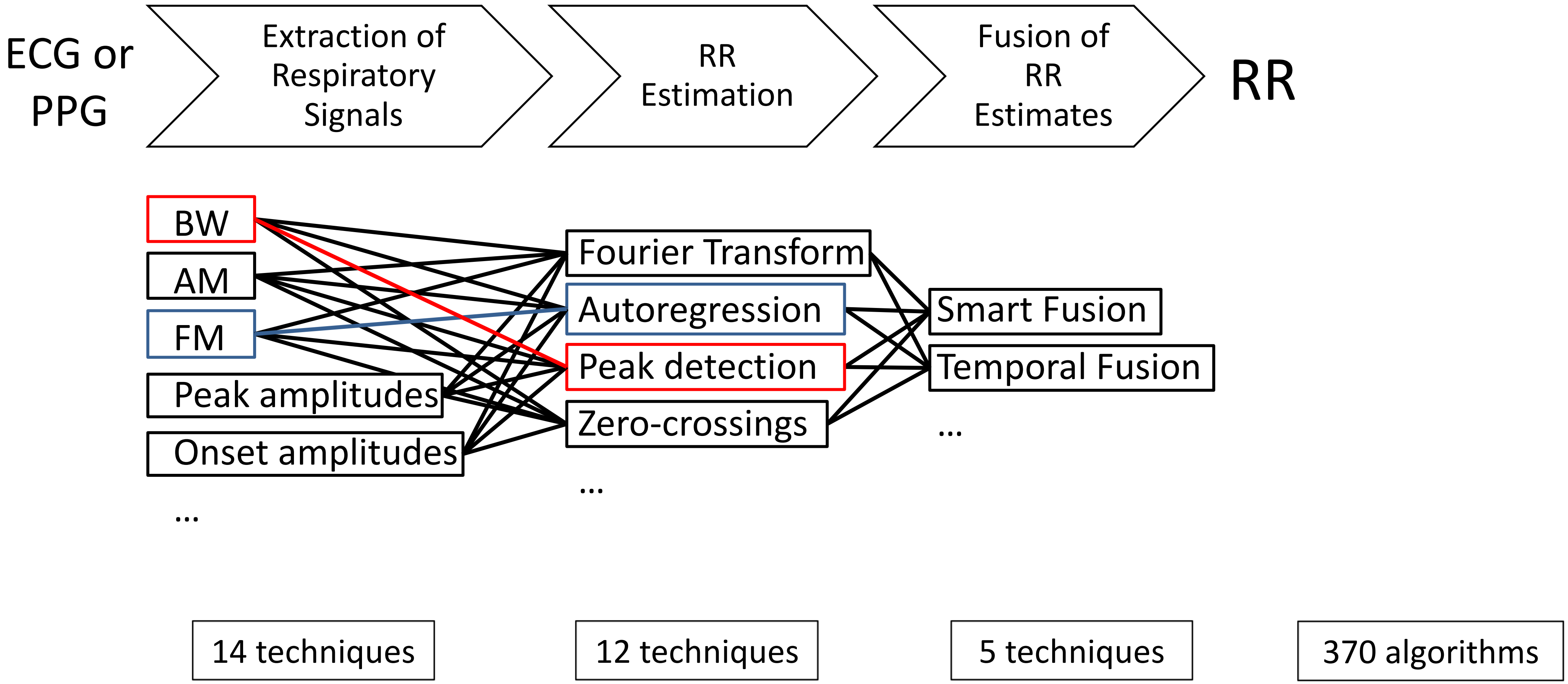
BW
AM
FM
Peak amplitudes
Onset amplitudes
…

Fourier Transform
Autoregression
Peak detection
Zero-crossings
…

Smart Fusion
Temporal Fusion
…

Example Assessment

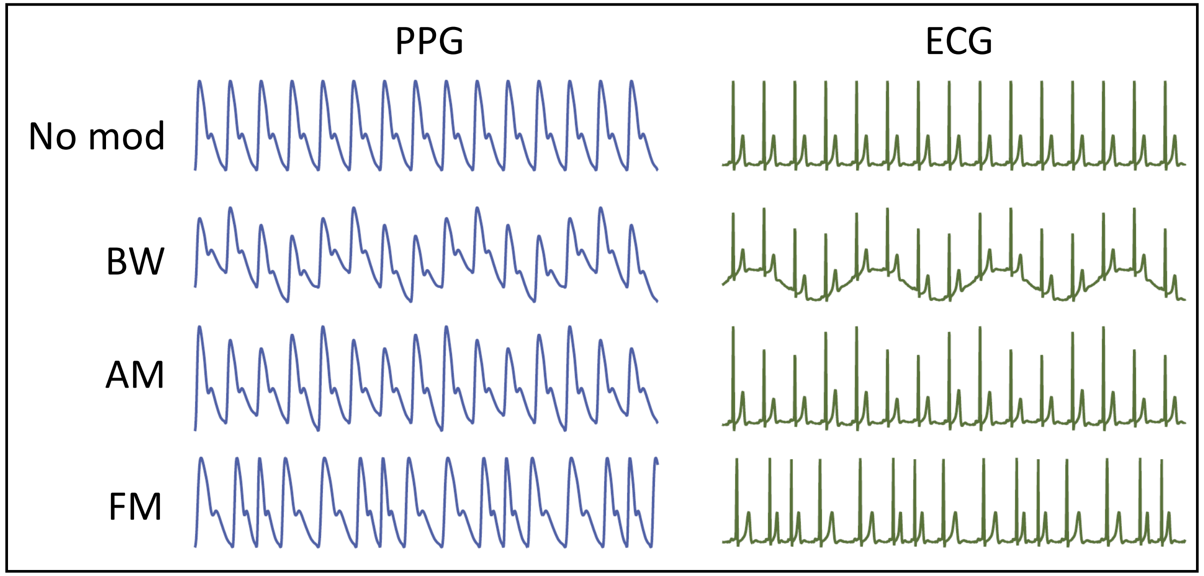
Implementing RR algorithms:



Example Assessment

Verifying algorithm implementations:

- Simulated data
- RR = 18 bpm, HR = 30:5:200 bpm
- HR = 80 bpm, RR = 4:2:60 bpm
- 314 (85%) of algorithms accurate, two techniques removed



Example Assessment

VORTAL dataset:

- 39 subjects, aged 18 to 39
- Healthy

Rest	Walk	Run	Recover
10 min	2 min	~ 5 min	10 min

[National Clinical Trial 01472133]

Example Assessment

VORTAL dataset:

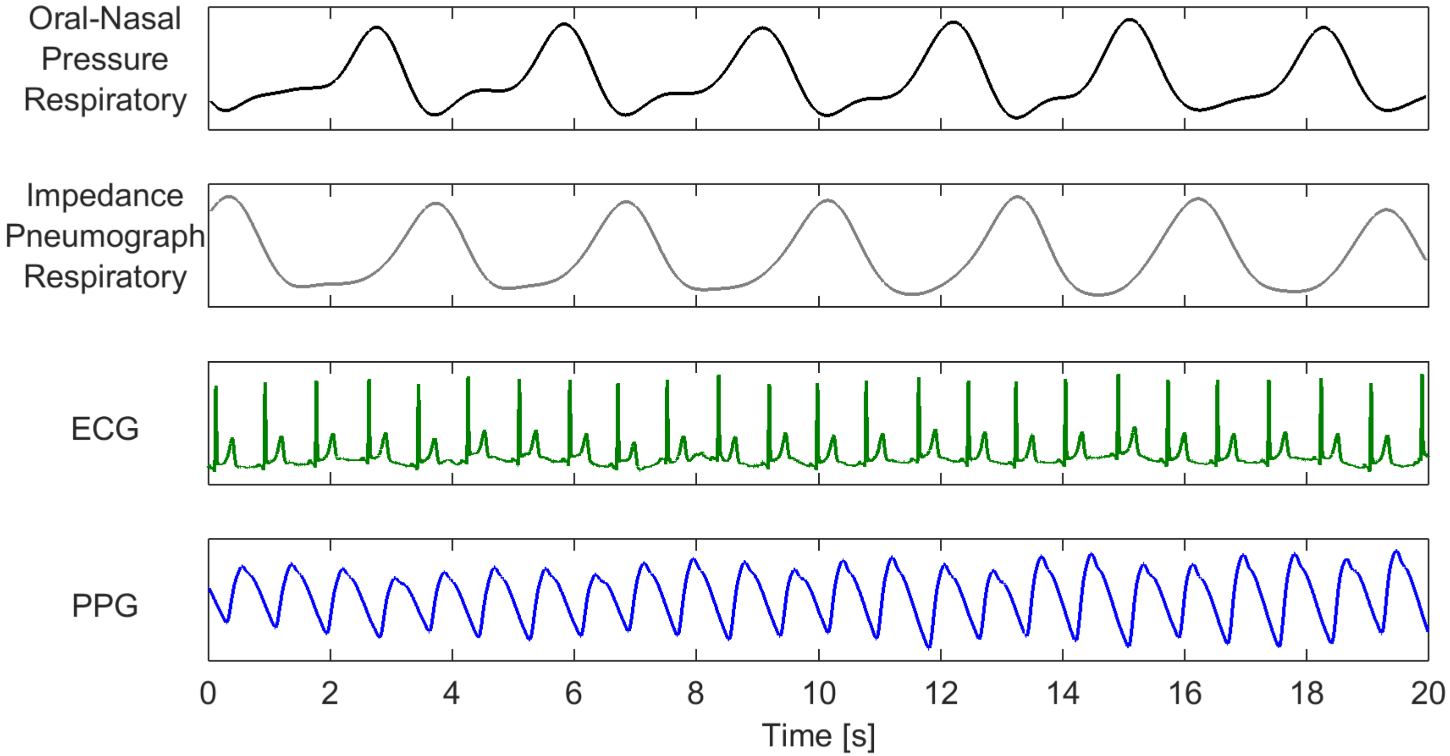
- 39 subjects, aged 18 to 39
- Healthy

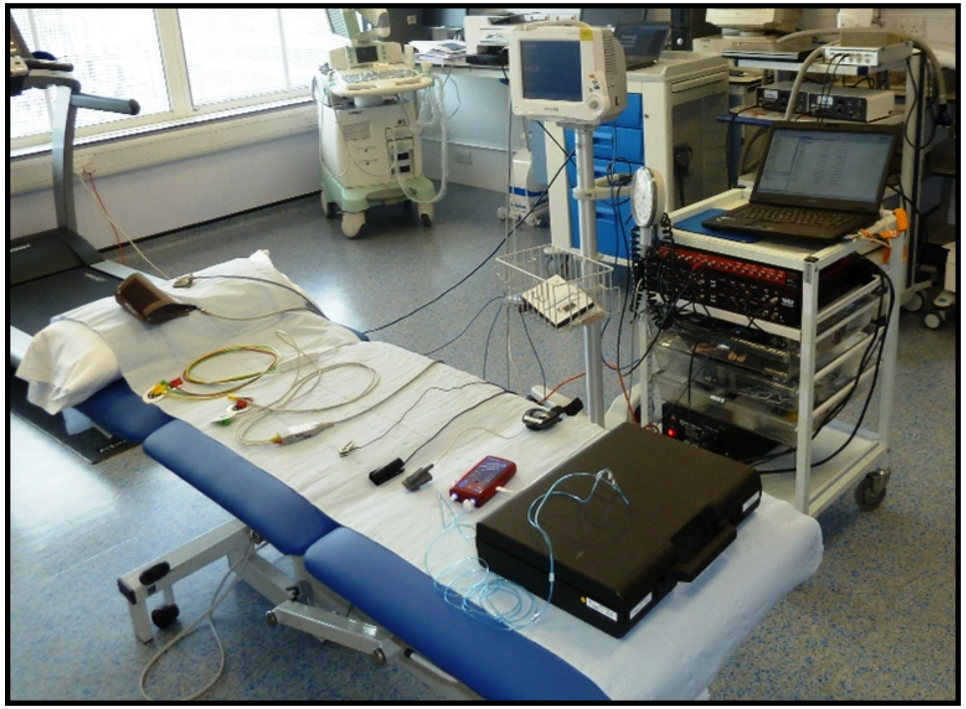
Rest	Walk	Run	Recover
10 min	2 min	~ 5 min	10 min

National Clinical Trial 01472133

Example Assessment

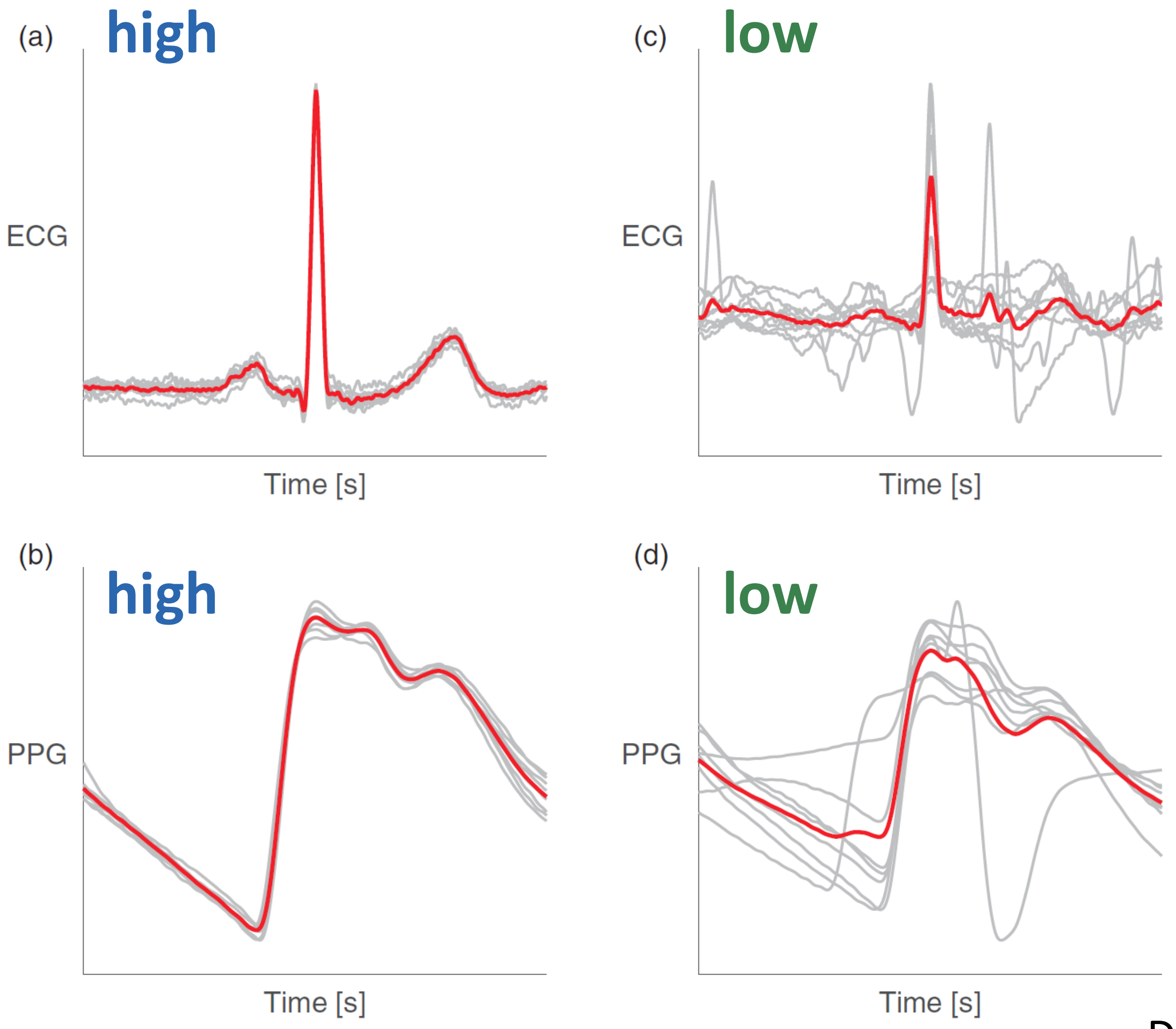
Signals:





Example Assessment

Signal quality:

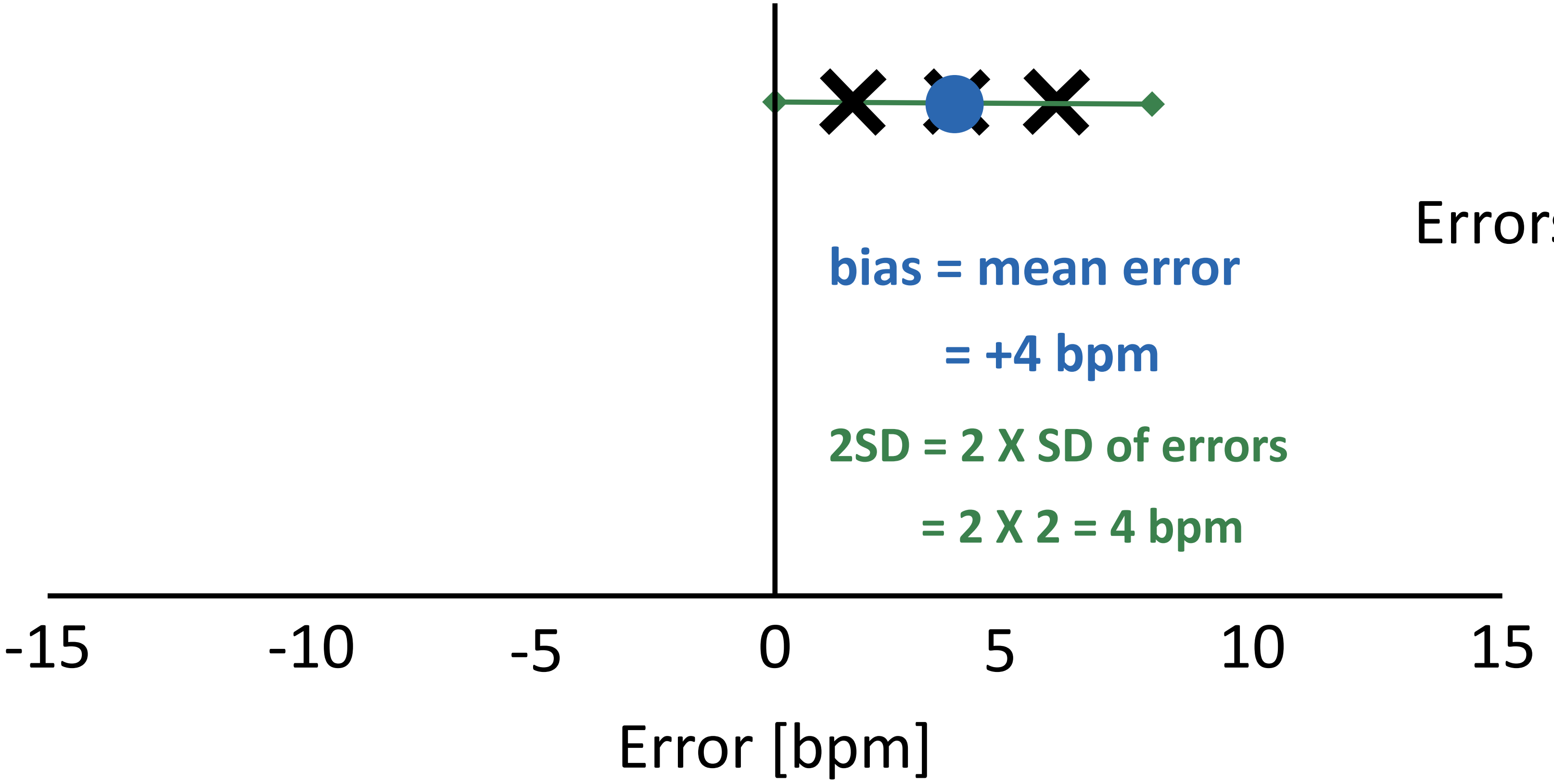


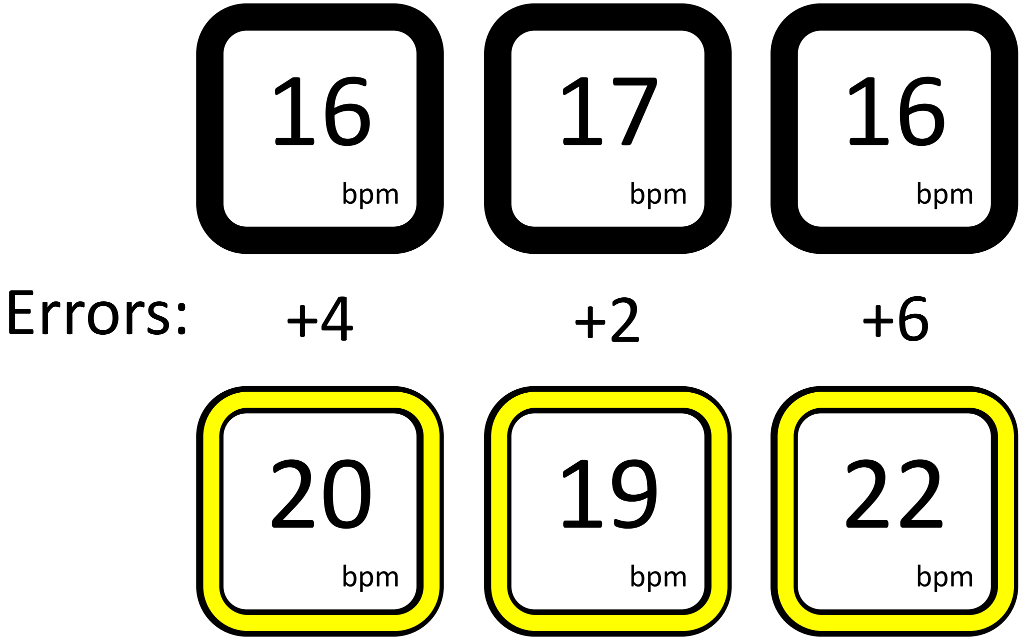
Further details:

DOI: [10.1109/JBHI.2014.2338351](https://doi.org/10.1109/JBHI.2014.2338351)

Example Assessment

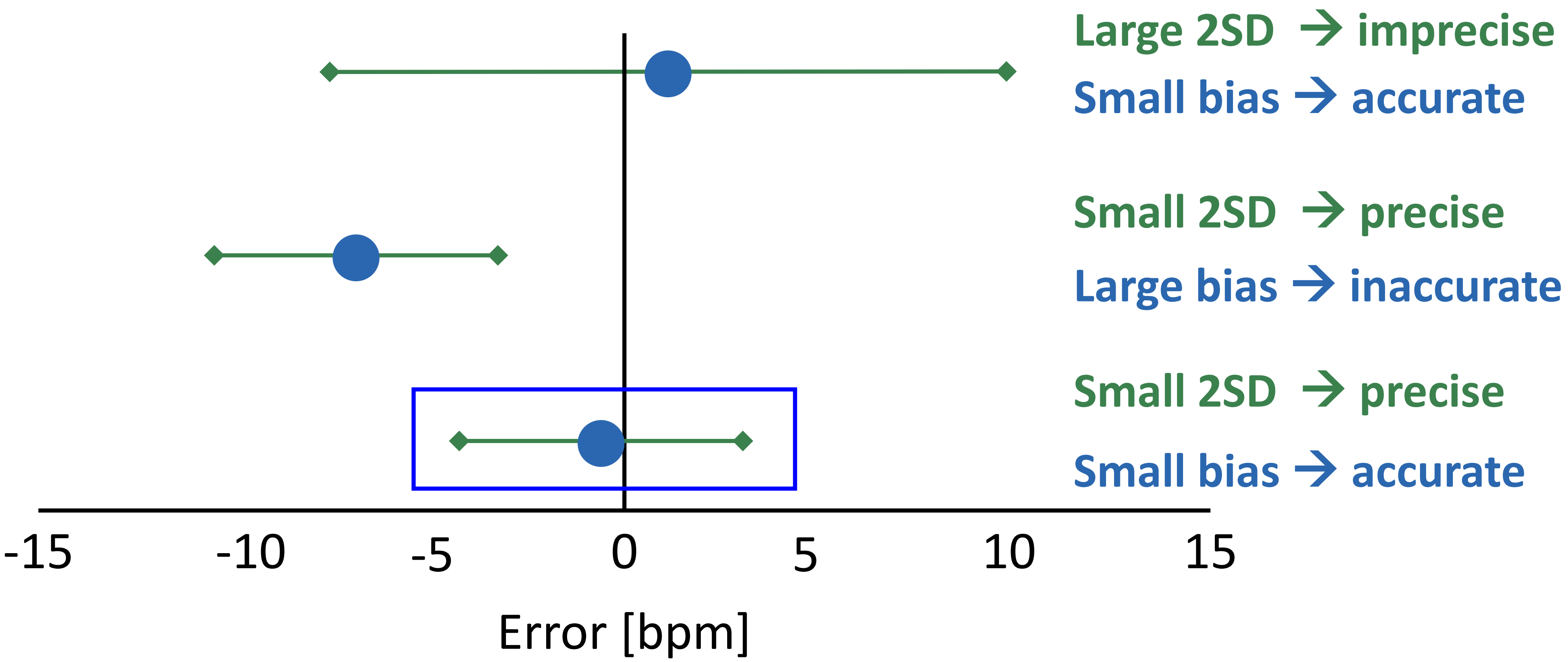
Statistics: Limits of agreement: **bias**, **2SD** (95% CIs)





Example Assessment

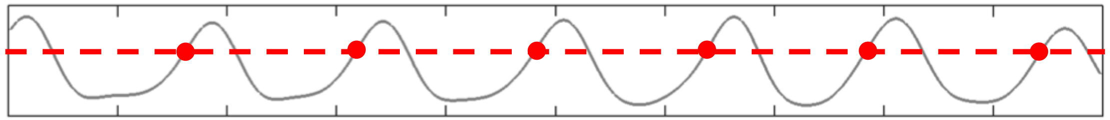
Statistics: Limits of agreement: (i) bias, (ii) 2SD (95% CIs)



Example Assessment

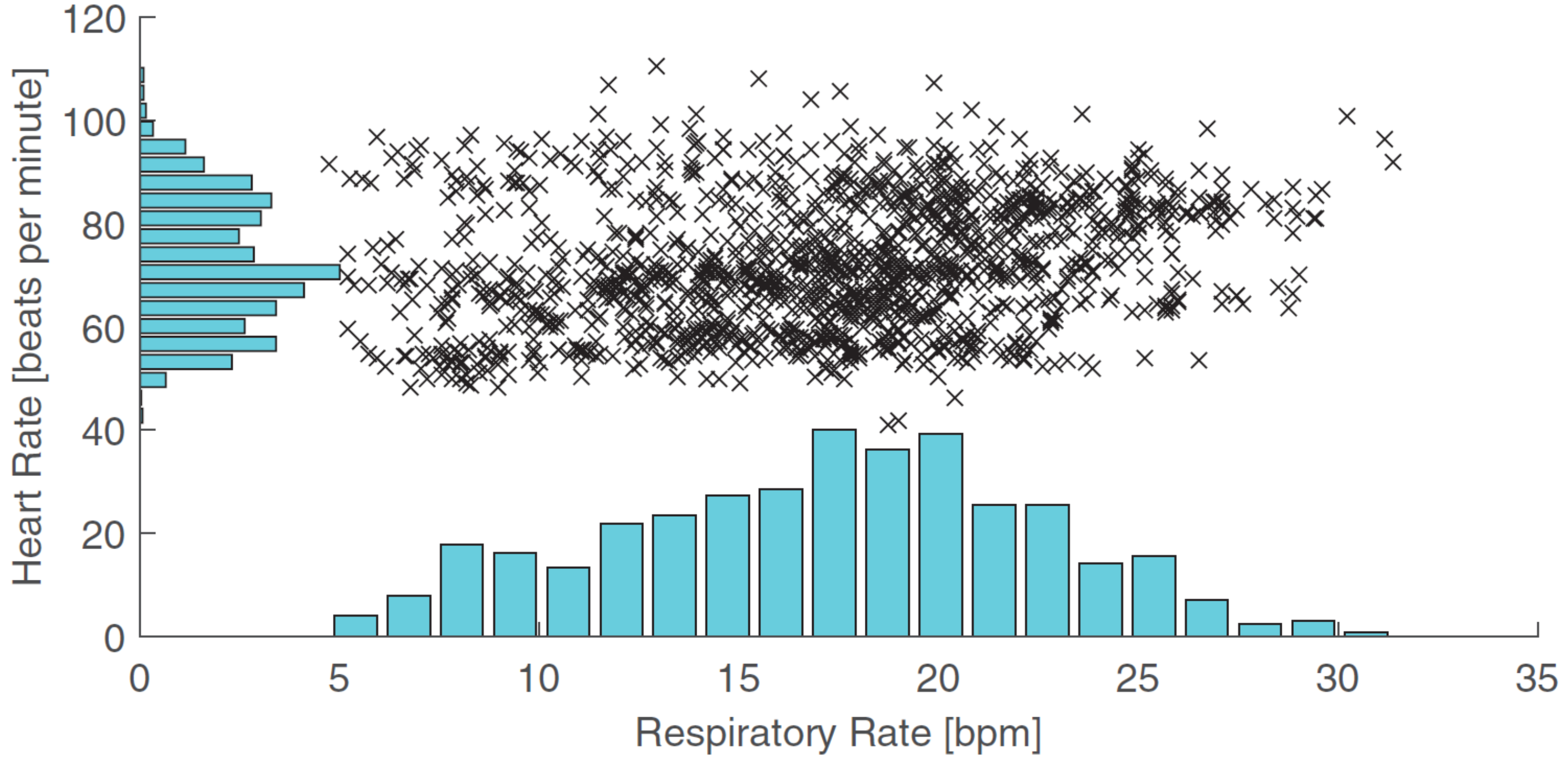
Reference RRs:

- Oral-nasal pressure
- Positive-gradient crossings
- Threshold determined using annotated breaths
- Performance:
  - Bias: 0.0 bpm
  - 2SD: 1.3 bpm



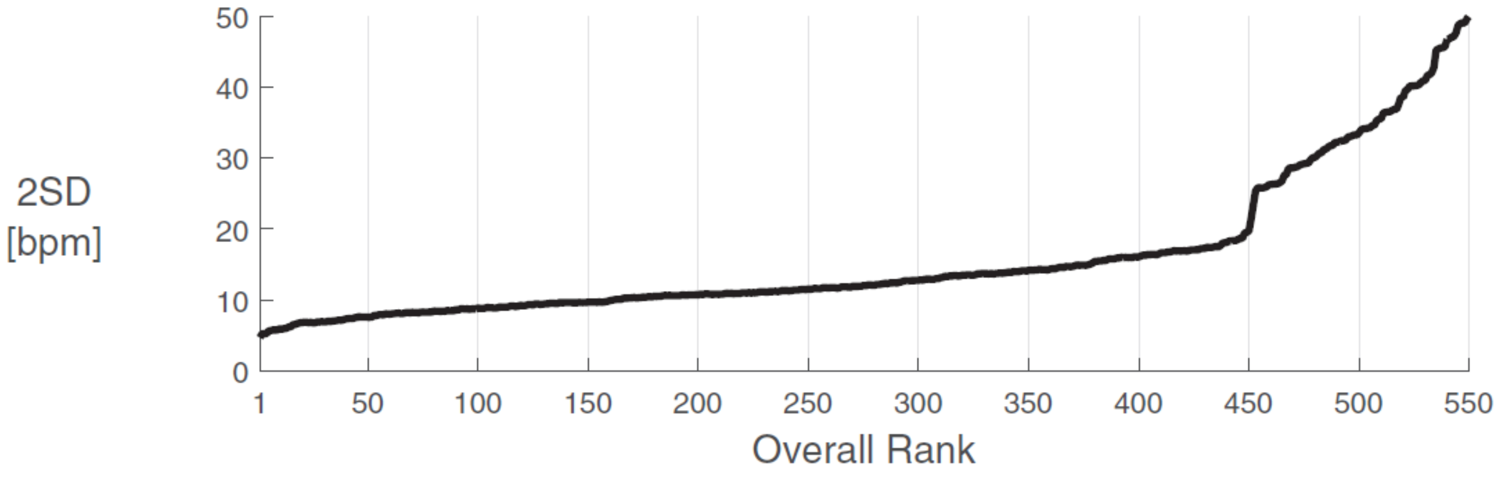
i.e. 95% of errors in reference RRs would be expected to be smaller than 0.0 ± 1.3 bpm

Example Assessment

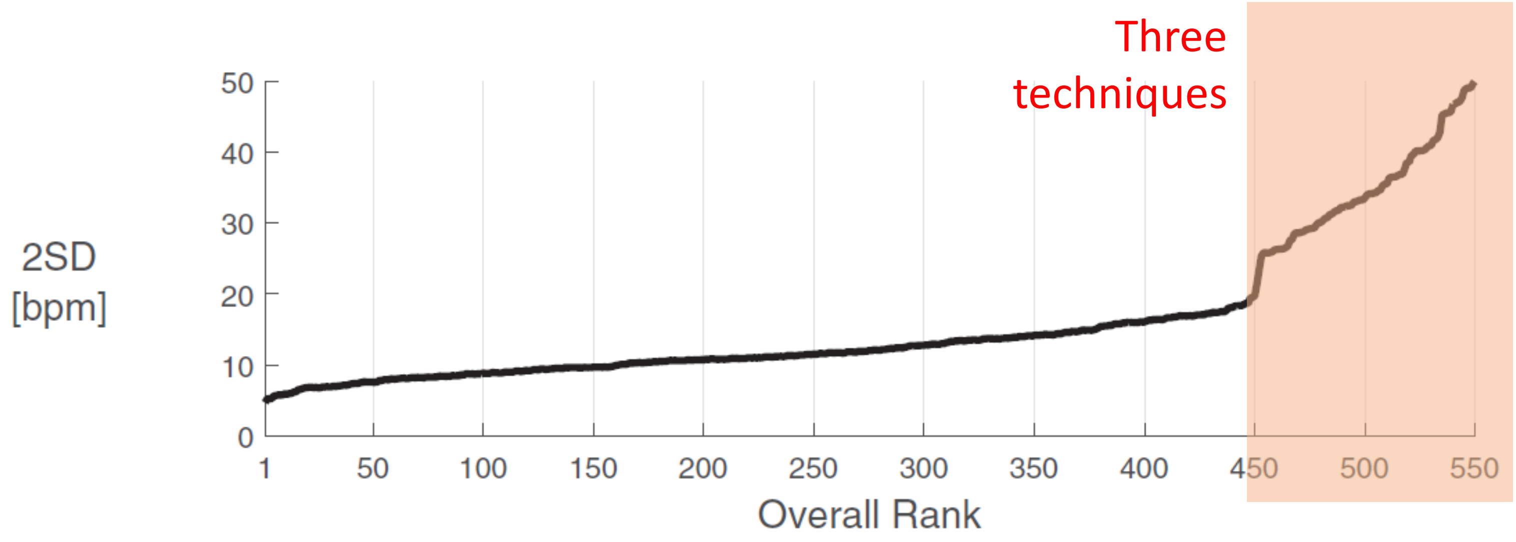


RR: 5-32 bpm
HR: 41 – 111 bpm

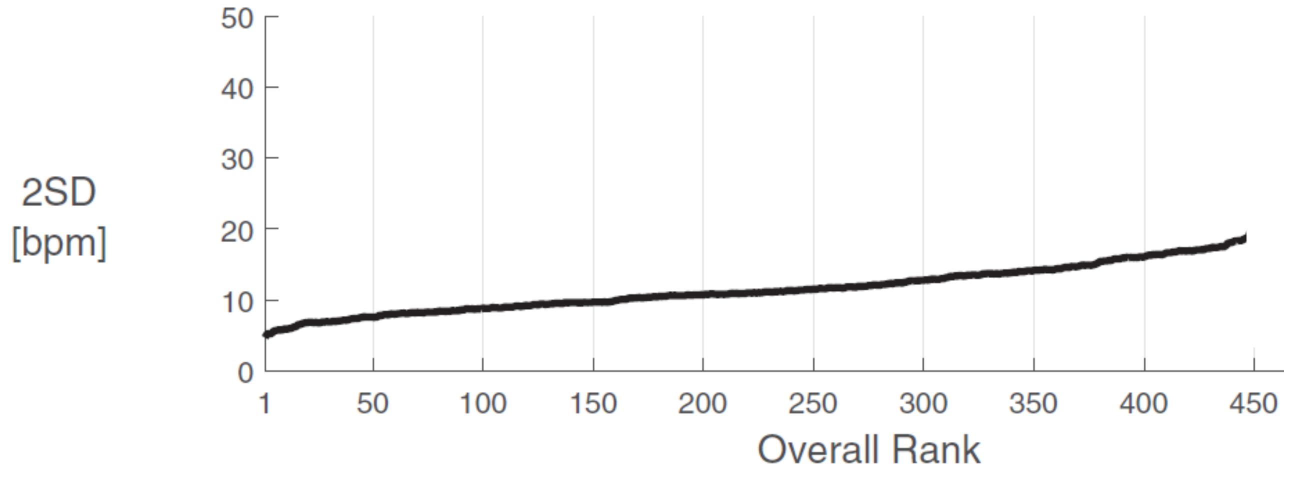
Example Assessment



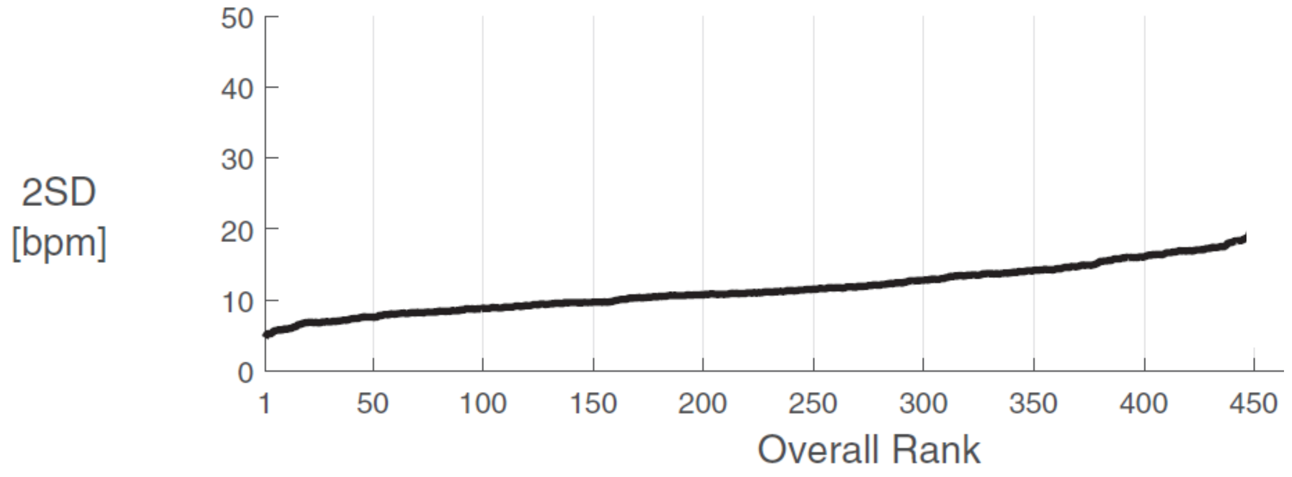
Example Assessment

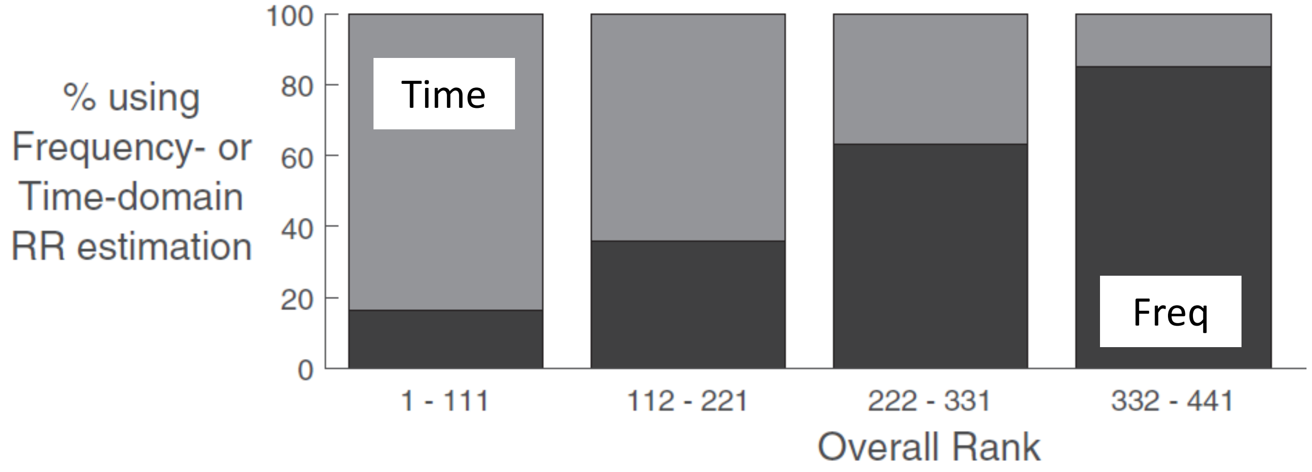


Example Assessment



Example Assessment





Example Assessment

Signal	Rank	2SD [bpm]	RR Estimation	Modulation Fusion?	Temporal Fusion?
Clinical (IP)	5	5.4			
ECG	1	4.7	Time	✓	
	2	5.2	Time	✓	
	3	5.2	Time	✓	
	4	5.3	Time	✓	
	6	5.6	Time		
PPG	15	6.2	Time	✓	
	17	6.5	Time	✓	
	35	7.0	Time	✓	✓
	46	7.5	Time		✓
	48	7.6	Time		✓

Same Algorithm

Example Assessment

ECG vs PPG:

- 2SD significantly lower when using ECG
- 64% of algorithms more precise on ECG
- Different physiological mechanisms

Example Assessment

Conclusions:

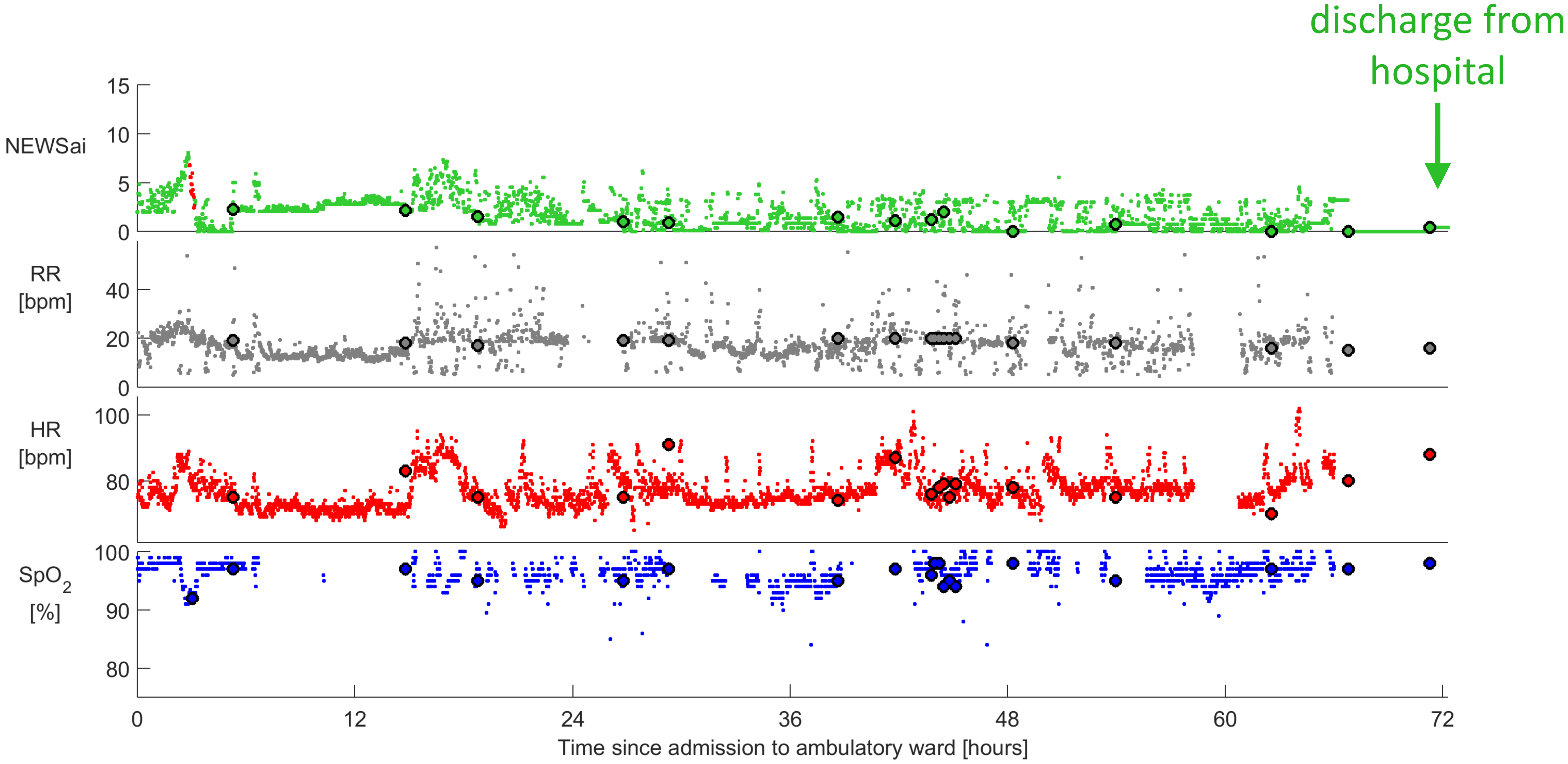
- 314 algorithms assessed under ideal conditions
- According to these results …
    - time-domain RR estimation, and
    - fusion of estimates

  … resulted in superior performance.
- Four ECG-based algorithms comparable to clinical standard
- ECG preferable to PPG

Outline

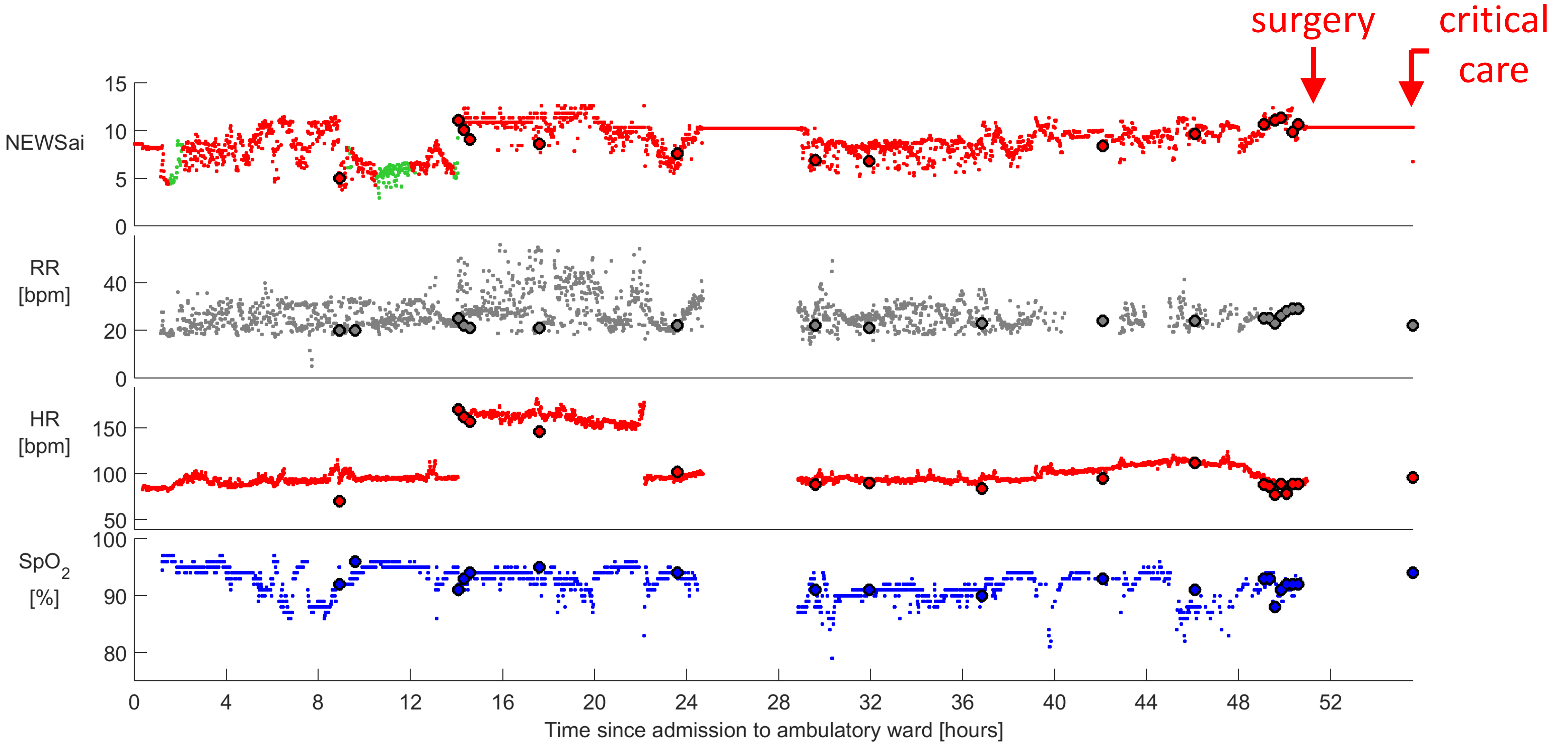
- Background
  - *Case Study 1: Elevated RR prior to cardiac arrest*
- RR algorithms
  - *Case Study 2: Unobtrusive RR monitoring*
- Performance assessment
  - ***Case Study 3: Predicting adverse events***
- Implementation
- Conclusion

Case Study 3



discharge from hospital
NEWSai
15
10
5
0
RR [bpm]
40
20
0
HR [bpm]
100
80
SpO_2 [%]
100
90
80
0
12
24
36
48
60
72
Time since admission to ambulatory ward [hours]

Case Study 3



surgery
critical care
NEWSai
15
10
5
0
RR [bpm]
40
20
0
HR [bpm]
150
100
50
SpO_2 [%]
100
90
80
0
4
8
12
16
20
24
28
32
36
40
44
48
52
Time since admission to ambulatory ward [hours]

Outline

- Background
  - *Case Study 1: Elevated RR prior to cardiac arrest*
- RR algorithms
  - *Case Study 2: Unobtrusive RR monitoring*
- Performance assessment
  - *Case Study 3: Predicting adverse events*
- **Implementation**
- Conclusion

Implementation

Charlton P.H. *et al.*

Extraction of respiratory signals from the electrocardiogram and photoplethysmogram: technical and physiological determinants,

Physiological Measurement, 37(4), 2016.

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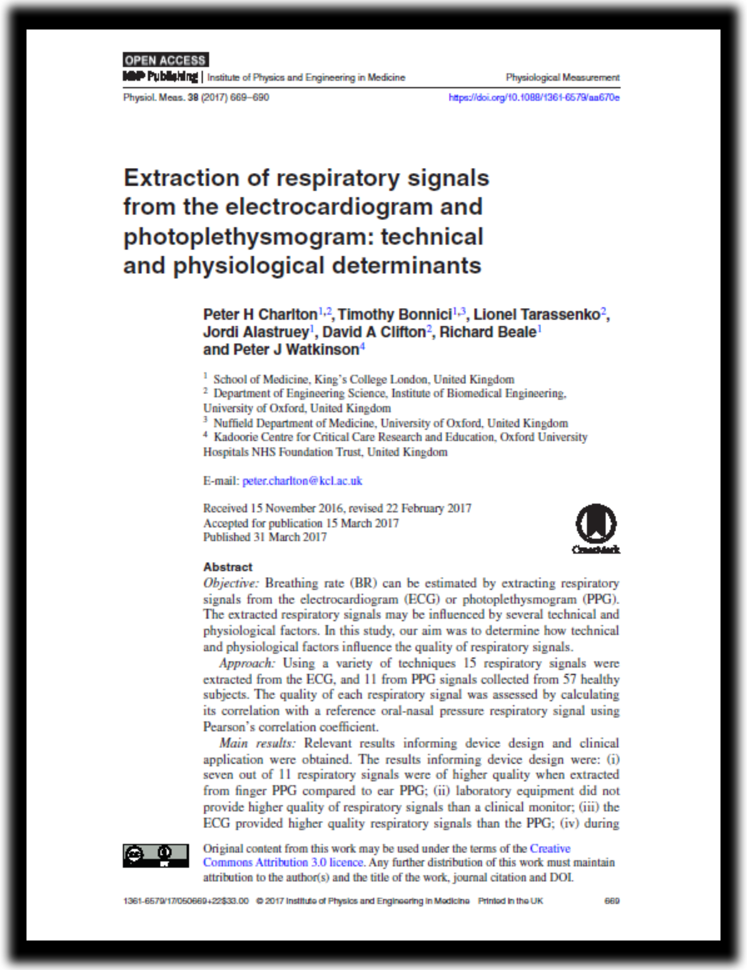

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Physiol. Meas. 38 (2017) 669–690 — https://doi.org/10.1088/1361-6579/aa670e

Extraction of respiratory signals from the electrocardiogram and photoplethysmogram: technical and physiological determinants

Peter H Charlton[1,2], Timothy Bonnici[1,3], Lionel Tarassenko[2], Jordi Alastruey[1], David A Clifton[2], Richard Beale[1] and Peter J Watkinson[4]

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[3] Nuffield Department of Medicine, University of Oxford, United Kingdom
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Abstract

Objective: Breathing rate (BR) can be estimated by extracting respiratory signals from the electrocardiogram (ECG) or photoplethysmogram (PPG). The extracted respiratory signals may be influenced by several technical and physiological factors. In this study, our aim was to determine how technical and physiological factors influence the quality of respiratory signals.

Approach: Using a variety of techniques 15 respiratory signals were extracted from the ECG, and 11 from PPG signals collected from 57 healthy subjects. The quality of each respiratory signal was assessed by calculating its correlation with a reference oral-nasal pressure respiratory signal using Pearson's correlation coefficient.

Main results: Relevant results informing device design and clinical application were obtained. The results informing device design were: (i) seven out of 11 respiratory signals were of higher quality when extracted from finger PPG compared to ear PPG; (ii) laboratory equipment did not provide higher quality of respiratory signals than a clinical monitor; (iii) the ECG provided higher quality respiratory signals than the PPG; (iv) during

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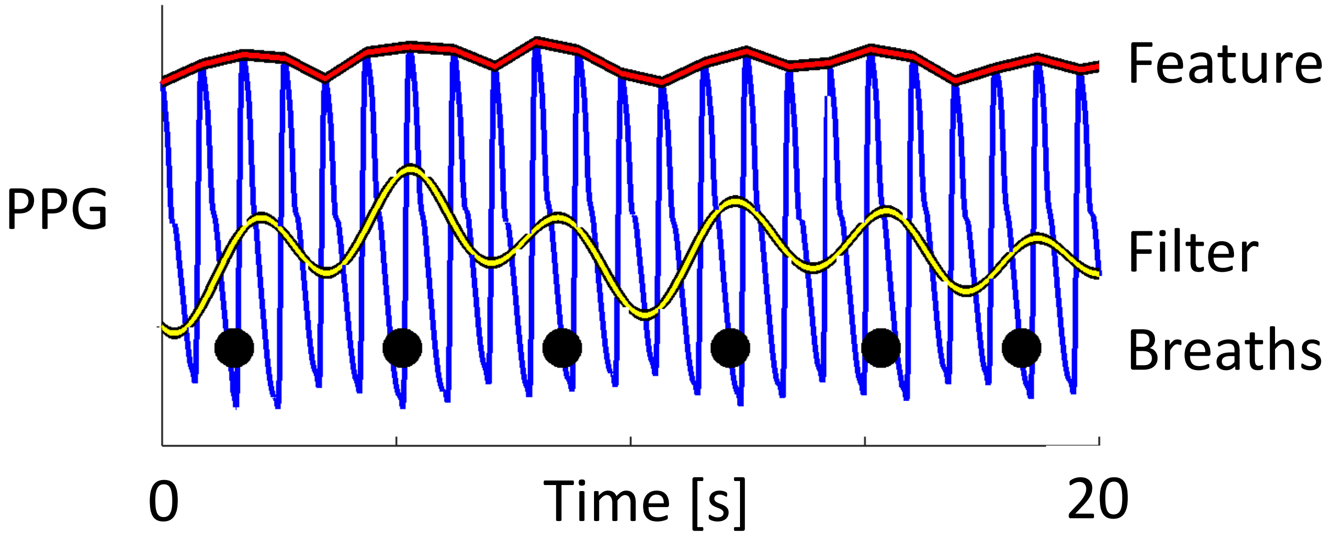
Implementation

- RR can be estimated from ECG and PPG in young, healthy subjects using laboratory equipment.
- Respiratory modulations must be of sufficient quality
- Several factors may affect quality in clinical setting



Implementation

Aim: Determine the influences of technical and physiological factors on respiratory modulations

Technical	Physiological
PPG measurement site: finger or ear	Age
Signal acquisition equipment: laboratory or clinical	Gender
Input signal: ECG or PPG	Respiratory rate (RR)
Sampling frequency	

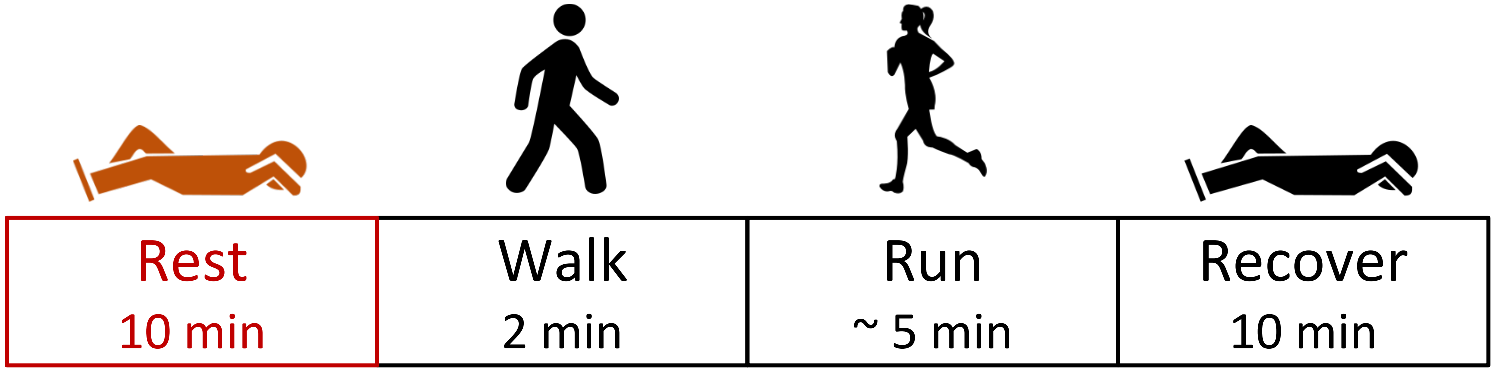
inform device design

determine clinical acceptability

Implementation

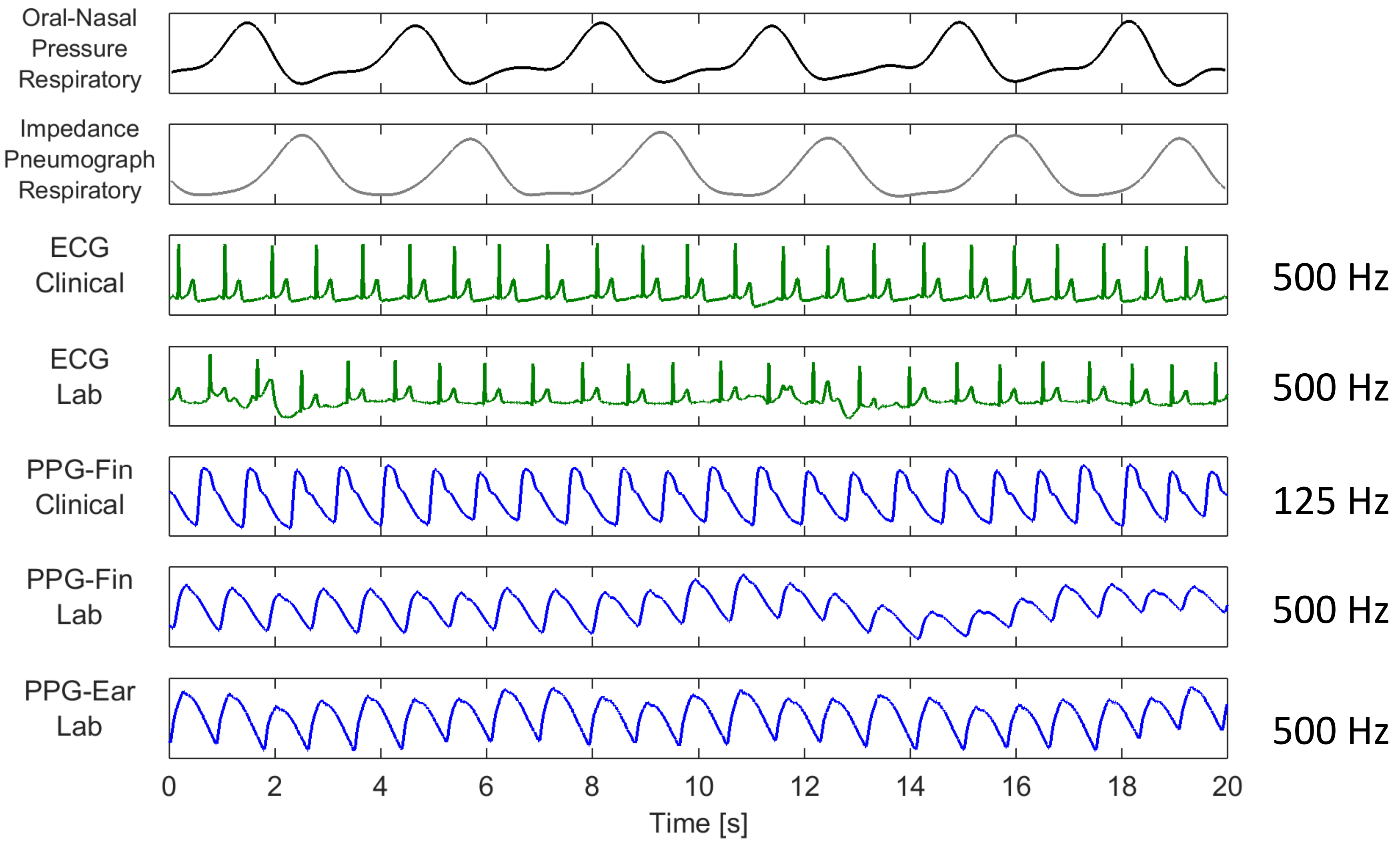
VORTAL dataset:

- 41 young subjects aged 18 to 39
- 16 elderly subjects aged > 70
- Healthy



[National Clinical Trial 01472133]

Signals


Oral-Nasal Pressure Respiratory
Impedance Pneumograph Respiratory
ECG Clinical
500 Hz
ECG Lab
500 Hz
PPG-Fin Clinical
125 Hz
PPG-Fin Lab
500 Hz
PPG-Ear Lab
500 Hz
0
2
4
6
8
10
12
14
16
18
20
Time [s]

Signal Processing

- 32 s windows
- Exclude low quality windows using SQIs
- Extract respiratory modulations

Signal Processing

Filter-based	Feature-based
BW: Band-pass filter	BW: mean amplitude of troughs and proceeding peaks
AM: Continuous Wavelet Transform	AM: Difference between amplitudes of troughs and proceeding peaks
FM: Continuous Wavelet Transform	FM: time interval between consecutive peaks
	BW: mean signal value between consecutive troughs
	BW, AM: peak amplitude
	BW, AM: trough amplitude
	FM: QRS duration
	AM, FM: QRS area
	BW: Principal component analysis

Signal Processing

- 32 s windows
- Exclude low quality windows using SQIs
- Extract respiratory modulations
- Modulation quality: correlation with oral-nasal pressure

Signal Processing

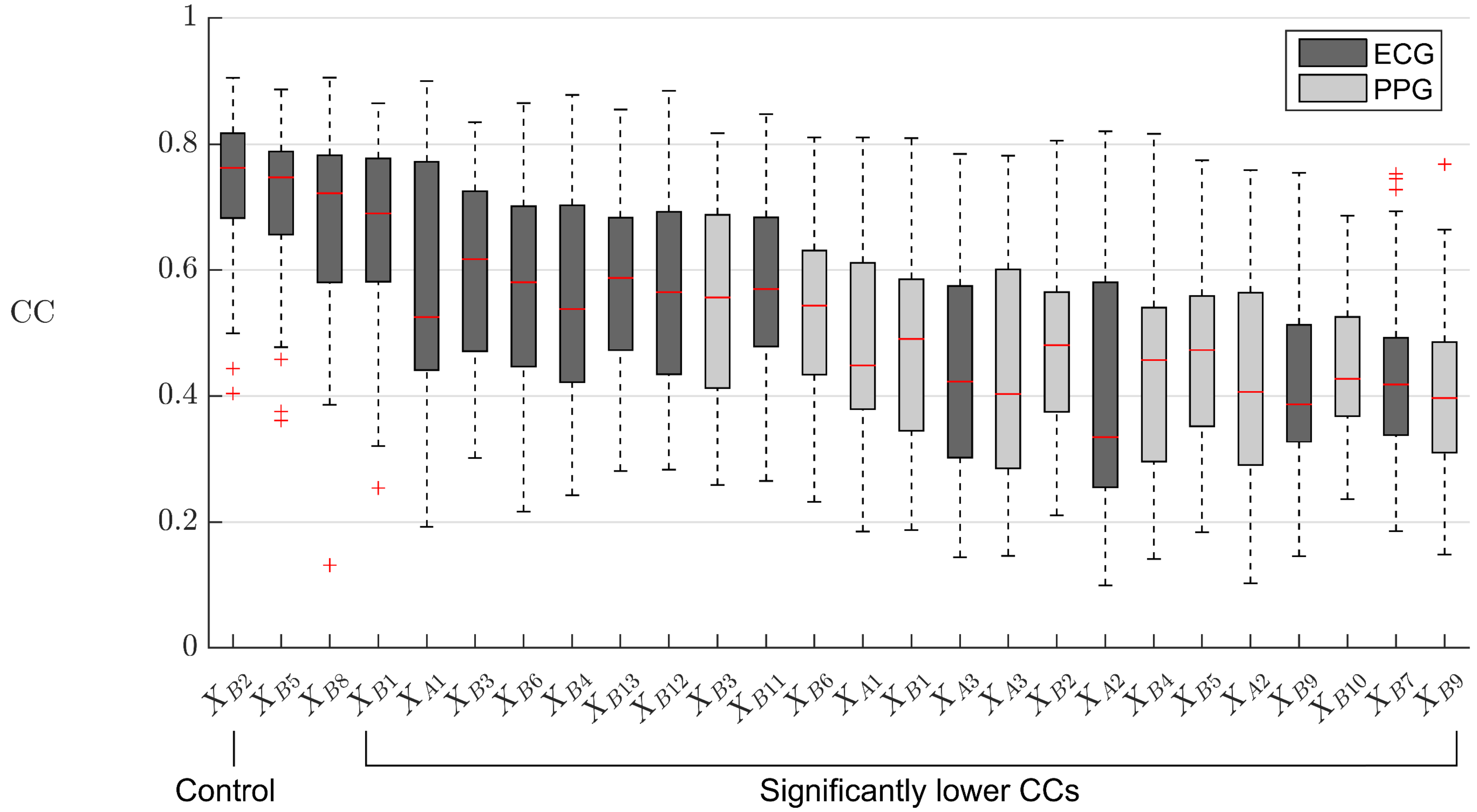
- 32 s windows
- Exclude low quality windows using SQIs
- Extract respiratory modulations
- Modulation quality: correlation with oral-nasal pressure
- Statistical tests for differences

Results

Technical:

Finger vs Ear:	Finger gave higher quality
Clinical vs Lab:	Similar quality
ECG vs PPG:	

Results



ECG
PPG
CC
1
0.8
0.6
0.4
0.2
0
X_{B2} X_{B5} X_{B8} X_{B1} X_{A1} X_{B3} X_{B6} X_{B4} X_{B13} X_{B12} X_{B3} X_{B11} X_{B6} X_{A1} X_{B1} X_{A3} X_{A3} X_{B2} X_{A2} X_{B4} X_{B5} X_{A2} X_{B9} X_{B10} X_{B7} X_{B9}
Control
Significantly lower CCs

Results

Technical:

Finger vs Ear:	Finger gave higher quality
Clinical vs Lab:	Similar quality
ECG vs PPG:	ECG
Sampling Freq:	

Results

Technical:

Finger vs Ear:	Finger gave higher quality
Clinical vs Lab:	Similar quality
ECG vs PPG:	ECG
Sampling Freq:	ECG ≥ 250 Hz; PPG ≥ 16 Hz

Results

Technical:

Finger vs Ear:	Finger gave higher quality
Clinical vs Lab:	Similar quality
ECG vs PPG:	ECG
Sampling Freq:	ECG ≥ 250 Hz; PPG ≥ 16 Hz

Physiological:

Age:	FM-based PPG of lower quality in elderly
Gender:	Similar quality
Respiratory Rate:	Lower quality at higher RRs

Recommendations

Technical:

Finger vs Ear:	Measure PPG at finger rather than ear
Clinical vs Lab:	Clinical equipment acceptable
ECG vs PPG:	ECG preferable
Sampling Freq:	ECG ≥ 250 Hz; PPG ≥ 16 Hz

Physiological:

Age:	Avoid FM-based respiratory signals in elderly
Gender:	No differences
Respiratory Rate:	Caution when detecting elevated RRs

Conclusion

- Assessed the impact of technical and physiological factors on respiratory modulations extracted from ECG and PPG
- Provided recommendations
- Ready for clinical assessment

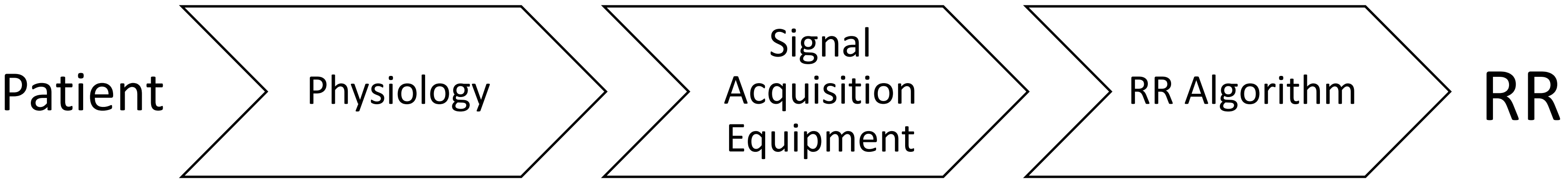
Outline

- Background
  - *Case Study 1: Elevated RR prior to cardiac arrest*
- RR algorithms
  - *Case Study 2: Unobtrusive RR monitoring*
- Performance assessment
  - *Case Study 3: Predicting adverse events*
- Implementation
- **Conclusion**

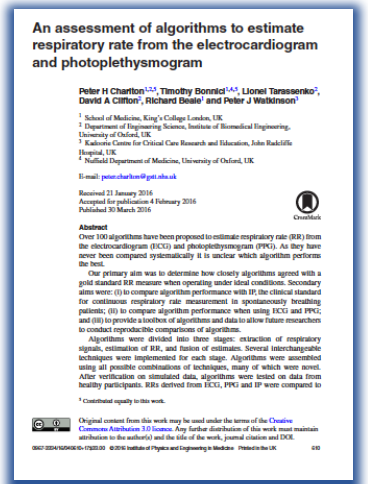
Conclusion

- Brief overview of estimating RR from ECG and PPG
- Case studies of clinical utility in unobtrusive hospital monitoring
- Assessed algorithm performance in ideal conditions
- Assessed impact of technical and physiological factors

Future Work



Physiology	Signal Acquisition Equipment	RR Algorithm
Age	Signal Fidelity	*Input Signal*
Disease	Filtering	*Techniques*
Arrhythmias	Noise	*Fusion*



An assessment of algorithms to estimate respiratory rate from the electrocardiogram and photoplethysmogram

Peter H Charlton[1,2,5], Timothy Bonnici[1,4,5], Lionel Tarassenko[2], David A Clifton[2], Richard Beale[1] and Peter J Watkinson[3]

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Abstract

Over 100 algorithms have been proposed to estimate respiratory rate (RR) from the electrocardiogram (ECG) and photoplethysmogram (PPG). As they have never been compared systematically it is unclear which algorithm performs the best.

Our primary aim was to determine how closely algorithms agreed with a gold standard RR measure when operating under ideal conditions. Secondary aims were: (i) to compare algorithm performance with IP, the clinical standard for continuous respiratory rate measurement in spontaneously breathing patients; (ii) to compare algorithm performance when using ECG and PPG; and (iii) to provide a toolbox of algorithms and data to allow future researchers to conduct reproducible comparisons of algorithms.

Algorithms were divided into three stages: extraction of respiratory signals, estimation of RR, and fusion of estimates. Several interchangeable techniques were implemented for each stage. Algorithms were assembled using all possible combinations of techniques, many of which were novel. After verification on simulated data, algorithms were tested on data from healthy participants. RRs derived from ECG, PPG and IP were compared to

[5] Contributed equally to this work.

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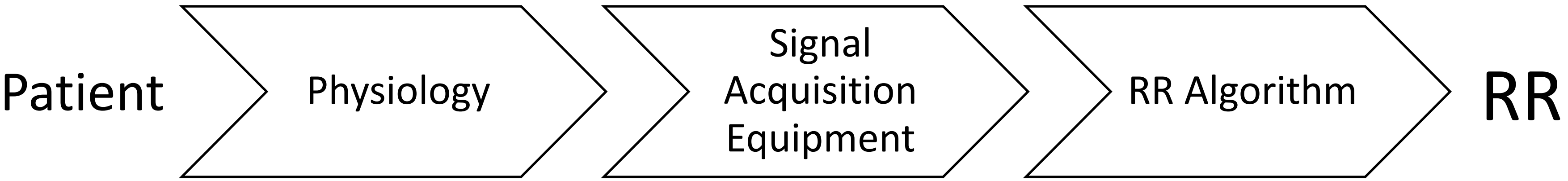
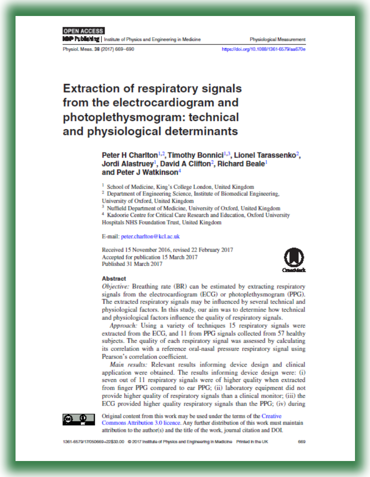
Charlton P.H. and Bonnici T. *et al.* **An assessment of algorithms to estimate respiratory rate from the electrocardiogram and photoplethysmogram**, *Physiological Measurement*, 37(4), 2016. DOI: 10.1088/0967-3334/37/4/610 . CC BY 3.0 Licence

Future Work



Physiology	Signal Acquisition Equipment	RR Algorithm
Age	Signal Fidelity	*Input Signal*
Disease	Filtering	*Techniques*
Arrhythmias	Noise	*Fusion*

Charlton P.H. *et al.* **Extraction of respiratory signals from the electrocardiogram and photoplethysmogram: technical and physiological determinants**, *Physiological Measurement*, 37(4), 2016. DOI: [10.1088/1361-6579/aa670e](https://doi.org/10.1088/1361-6579/aa670e) . [CC BY 3.0 Licence]


Extraction of respiratory signals from the electrocardiogram and photoplethysmogram: technical and physiological determinants

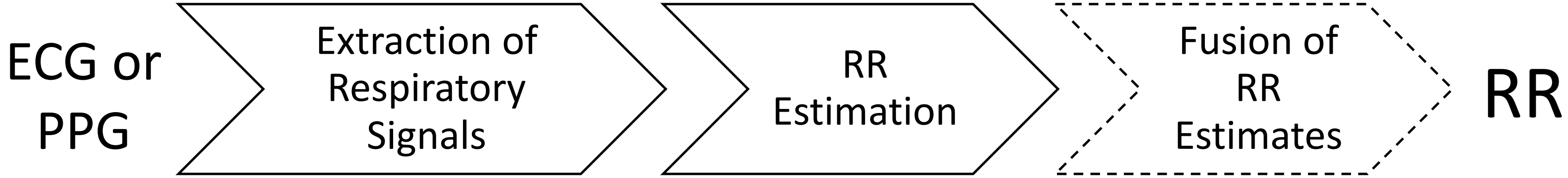
Future Work

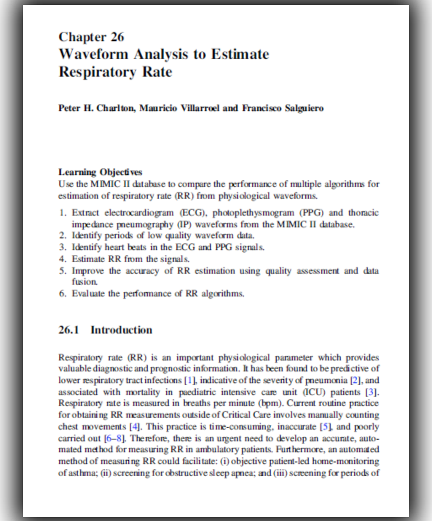
Patient → Physiology → Signal Acquisition Equipment → RR Algorithm → RR

Physiology	Signal Acquisition Equipment	RR Algorithm
Age	Signal Fidelity	*Input Signal*
Disease	Filtering	*Techniques*
Arrhythmias	Noise	*Fusion*

Resources

Matlab® Toolbox of algorithms:




Chapter 26
Waveform Analysis to Estimate Respiratory Rate

Peter H. Charlton, Mauricio Villarroel and Francisco Salguiero

Learning Objectives
Use the MIMIC II database to compare the performance of multiple algorithms for estimation of respiratory rate (RR) from physiological waveforms.

1. Extract electrocardiogram (ECG), photoplethysmogram (PPG) and thoracic impedance pneumography (IP) waveforms from the MIMIC II database.
2. Identify periods of low quality waveform data.
3. Identify heart beats in the ECG and PPG signals.
4. Estimate RR from the signals.
5. Improve the accuracy of RR estimation using quality assessment and data fusion.
6. Evaluate the performance of RR algorithms.

26.1 Introduction

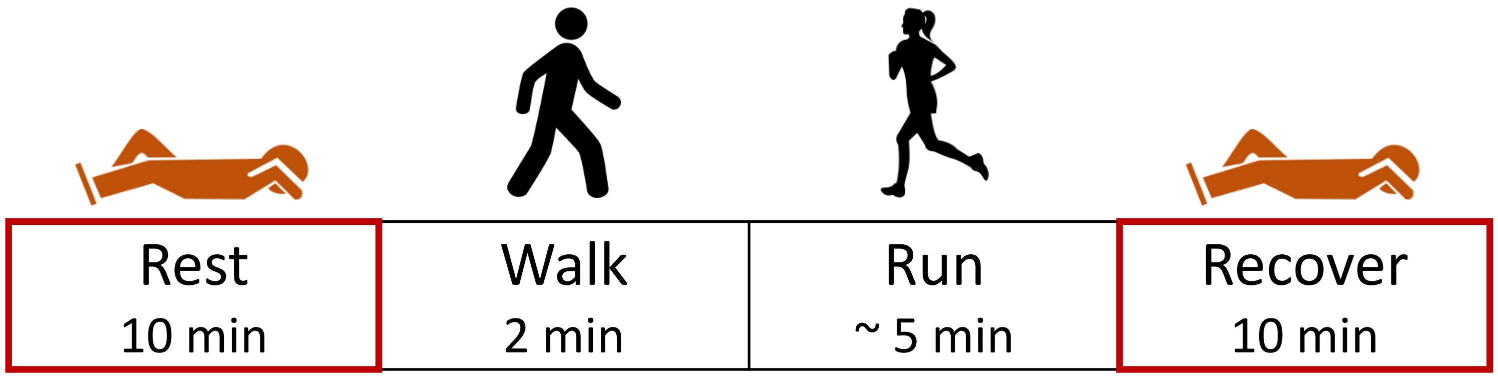
Respiratory rate (RR) is an important physiological parameter which provides valuable diagnostic and prognostic information. It has been found to be predictive of lower respiratory tract infections [1], indicative of the severity of pneumonia [2], and associated with mortality in paediatric intensive care unit (ICU) patients [3]. Respiratory rate is measured in breaths per minute (bpm). Current routine practice for obtaining RR measurements outside of Critical Care involves manually counting chest movements [4]. This practice is time-consuming, inaccurate [5], and poorly carried out [6–8]. Therefore, there is an urgent need to develop an accurate, automated method for measuring RR in ambulatory patients. Furthermore, an automated method of measuring RR could facilitate: (i) objective patient-led home-monitoring of asthma; (ii) screening for obstructive sleep apnea; and (iii) screening for periods of

Charlton P.H. *et al.* **Waveform analysis to estimate respiratory rate**, in *Secondary Analysis of Electronic Health Records*, Springer, pp.377-390, 2016.
DOI: 10.1007/978-3-319-43742-2_26 . CC BY-NC 4.0 Licence

Publicly available here

Resources

Vortal benchmark dataset:



41 Young

16 Elderly

39 Young

Available [here]

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Engineers:

Jordi Alastruey, David Clifton, Lionel Tarassenko, Marco Pimentel

Funders:

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The views expressed are those of the authors and not necessarily those of the EPSRC, NHS, NIHR, Department of Health, or Wellcome Trust.

A complete list of acknowledgments is available here.

Acknowledgment

Sources of content:

- Open ClipArt
- Peter H Charlton. (2016). The Processes and Benefits of Sharing Clinical Data. Zenodo. DOI: 10.5281/zenodo.166546
- Peter H Charlton. (2016). Wireless Wrist Pulse Oximeter Photo. Zenodo. DOI: 10.5281/zenodo.569814
- Peter H Charlton. (2017). Continuous monitoring of respiratory rate to detect clinical deteriorations using wearable sensors. PhD Thesis, King's College London.
- Peter H Charlton. (2016). Presentation of: An assessment of algorithms to estimate respiratory rate from the electrocardiogram and photoplethysmogram. Zenodo. DOI: 10.5281/zenodo.166525
- Peter H Charlton. (2017). Presentation of: Extraction of respiratory signals from the electrocardiogram and photoplethysmogram: technical and physiological determinants. Zenodo. DOI: 10.5281/zenodo.400255
- Peter H Charlton, & Timothy Bonnici. (2017). Martin Black Prize Presentation. Zenodo. DOI: 10.5281/zenodo.891179

… and the following references:

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Charlton P.H. and Bonnici T. *et al.* **An assessment of algorithms to estimate respiratory rate from the electrocardiogram and photoplethysmogram**, *Physiological Measurement*, 37(4), 2016.
DOI: 10.1088/0967-3334/37/4/610 . CC BY 3.0 Licence

Implementation

Charlton P.H. *et al.* **Extraction of respiratory signals from the electrocardiogram and photoplethysmogram: technical and physiological determinants**, *Physiological Measurement*, 38(5), 2017.
DOI: 10.1088/1361-6579/aa670e . CC BY 3.0 Licence

Tutorial on RRest Toolbox

Charlton P.H. *et al.* **Waveform analysis to estimate respiratory rate**, in *Secondary Analysis of Electronic Health Records*, Springer, 2016.
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Literature Review

Charlton P.H. *et al.* **Breathing Rate Estimation from the Electrocardiogram and Photoplethysmogram: A Review**, IEEE Reviews in Biomedical Engineering, in press, 2017.
DOI: 10.1109/RBME.2017.2763681 . CC BY 3.0 Licence

inc. references to 196 publications describing RR algorithms

This presentation is part of the **Respiratory Rate Estimation Project** at:

http://peterhcharlton.github.io/RRest/