# Respiratory rate monitoring to detect deteriorations using

# wearable sensors

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> Continuous Intermittent

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# Guy's and St Thomas' **NHS Foundation Trust**

Cardiovascular HEALTHCARE TECHNOLOGY CO-OPERATIVE

# 1. Continuous respiratory rate (RR) monitoring using wearable sensors

**Continuous monitoring may provide** early warning of deteriorations

It is difficult to monitor RR in ambulatory patients

Continuous RR monitoring often relies on cumbersome sensors, such as the chest band, facemask and oral-nasal cannula shown below. These are not suitable for monitoring ambulatory patients for several days.

# **RR could be estimated from** ECG or PPG signals

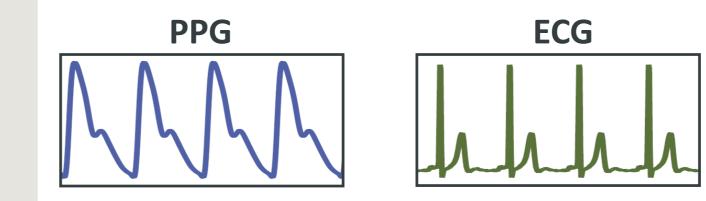
# The ECG and PPG are modulated by respiration

Respiratory rate (RR, number of breaths per minute) often increases in the hours before acute deteriorations such as cardiac arrests and sepsis. RR is currently measured by hand every 4 – 6 hours in hospitalised patients. Consequently, changes in RR can go unrecognised between measurements.

Unrecognised change

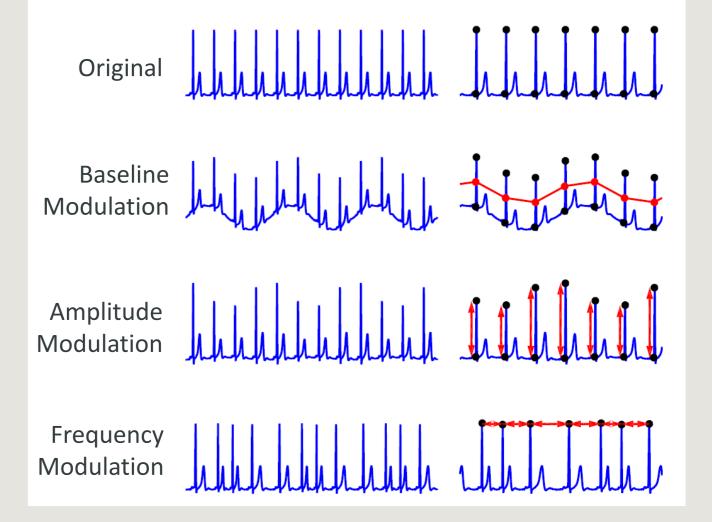
Time [hours]

Both the electrocardiogram (ECG) and pulse oximetry (photoplethysmogram, PPG) signals can be continuously monitored using wearable sensors.





The ECG and PPG are influenced by respiration in three ways. This provides opportunity to estimate RR from the signals.



# 2. Development of an algorithm to estimate RR from the ECG

## **RR** algorithms in the literature

A systematic review of the literature identified 140 publications containing evaluations of RR algorithms. A total of 95 candidate algorithms were implemented for

# Assessment of RR algorithms

The performances of RR algorithms were assessed on the four datasets using the limits of agreement statistics: the bias (*i.e.* mean error) and the limits of agreement (LoAs, within which 95% of errors are expected to lie). The results are shown in the table (bias ± LOAs in breaths per min).

Dataset	Best algorithm in literature		Novel RR algorithm	
	ECG	PPG	ECG	PPG
	Healthy subjects			
Vortal	-1.8 ± 7.9	-5.0 ± 10.2	-0.2 ± 3.1	$-0.9 \pm 4.5$
Fantasia	-1.8 ± 7.8	n/a	$-0.2 \pm 2.5$	n/a
	Hospitalised patients			
CapnoBase	-0.1 ± 3.6	$0.2 \pm 4.9$	0.4 ± 1.5	$0.8 \pm 3.3$
MIMIC-II	-1.2 ± 8.6	-1.8 ± 10.0	0.0 ± 3.2	-0.2 ± 9.0

### testing.

 $\mathsf{RR}$ 

[bpm]

25

## Publicly available datasets

Four datasets were identified with which to assess RR algorithms. Two datasets (Vortal and Fantasia) were acquired from healthy subjects, and two (MIMIC-II and CapnoBase) were collected from hospital patients.

The best algorithm in the literature demonstrated high levels of inaccuracy. The high LoAs of  $\pm$  8.6 and  $\pm$  10.0 bpm on the MIMIC-II dataset showed that the algorithm was too imprecise for continuous monitoring.

Results shown as bias ± limits of agreement [bpm]

## **Refinement for continuous monitoring**

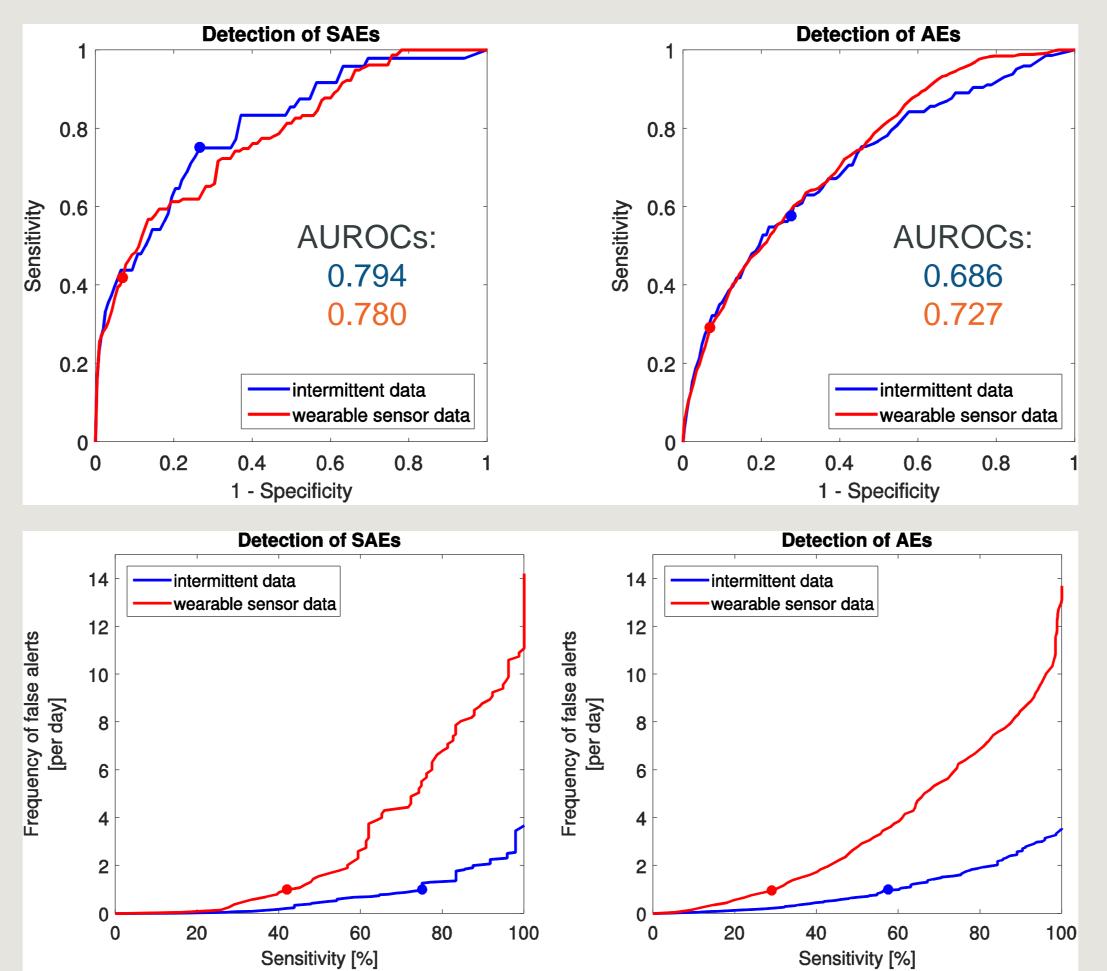
A novel RR algorithm was designed to provide more precise RR estimates (results in table). It achieved lower LOAs of  $\pm 3.2$  bpm when using the ECG.

# 3. Detection of deteriorations in real-time

# Application to clinical data

184 patients recovering from cardiac surgery in hospital were monitored using wearable sensors whilst staying on an ambulatory ward. The novel RR algorithm was used to estimate RRs from ECG signals. In addition, heart rate and blood oxygen saturation measurements were obtained from the wearable sensor.

### **Detection of deteriorations**



## Performance of continuous early warning scores

The performances of continuous early warning scores for predicting whether there would be a clinical event in the next 48 hours were assessed. Clinical events were separated into adverse events (AEs) and severe AEs (SAEs).

Upper plots: The AUROCs were similar when using continuous (wearable sensor) data, or manual intermittent data. This demonstrates the feasibility of using continuous RR estimates to calculate early warning scores.

Lower plots: The false alert rate was greatly increased when using wearable sensor data. This was due to the increased (continuous) rate of wearable sensor measurements, compared to 4 - 6 hourly intermittent measurements. Further work

A continuous early warning score was calculated by fusing the three wearable sensor parameters with intermittent measurements of blood pressure, temperature and the use of supplementary oxygen. Deterioration alerts were generated when  $\geq 80$  % of scores in the previous 30 mins were elevated.

The false alert rate associated with continuous early warning scoring was too high. Therefore, further work is required to improve the performance of algorithms to detect deteriorations from wearable sensor data.

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