Machine Learning Data Analytics

Friedrich-Alexander-Universität Technische Fakultät

Comparison of Algorithms for Respiratory Information Extraction from Wearable Sensors

Bachelor's Thesis in Medical Engineering

submitted
by

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Übersicht

Die Atemfrequenz RR ist ein wichtiges Vitalzeichen, das zur Beurteilung der Atemfunktion und der allgemeinen Gesundheit benutzt wird. Die Atemfrequenz variiert von Person zu Person und kann durch Faktoren wie Alter, körperliche Aktivität und medizinische Bedingungen beeinflusst werden. Die Forschung hat gezeigt, dass Veränderungen der Atemfrequenz zur Diagnose und Überwachung von Atemwegserkrankungen wie Asthma und chronisch obstruktiver Lungenerkrankung (COPD) beitragen können. Ein Ansatz zur automatischen, nicht invasiven und weniger zeitaufwändigen Überwachung ist die Extraktion der Atemfrequenz aus anderen physiologischen Parametern wie dem Elektrokardiogramm (EKG) oder inertial measurement unit (IMU) Sensoren. Es gibt zwar verschiedene Publikationen, die unterschiedliche Ansätze zur Rekonstruktion von Atemsignalen aus EKG- und IMU-Signalen untersuchen, allerdings fehlt bisher sowohl ein systematischer Vergleich beider Ansätze, als auch Forschungsarbeiten, welche untersuchen ob Kombination beider Modalitäten die Signalqualität verbessern würde. Das Ziel dieser Arbeit war daher die Implementierung verschiedener Algorithmen zur Extraktion von Atemsignalen, als auch zur Schätzung der Atemfrequenz aus EKG- und IMU-Signalen zu implementieren und die verschiedenen Methoden systematisch zu vergleichen. Um diese Algorithmen in einer realen Umgebung zu evaluieren, wurde ein neuer Datensatz bestehend aus IMU- und EKG-Daten, sowie einem Referenzsignal aufgenommen. Dabei wurde festgestellt, dass die EKG-basierten Algorithmen die IMU-basierten Algorithmen in Bezug auf die Korrelation mit dem Atemsignal als auch bei der Atemfrequenz Schätzung übertreffen. Während der beste EKG basierte Algorithmus einen mittleren absoluten Fehler (MAF) von 7,52 Atemzügen pro Minute erreichte, wies der beste IMU basierte Algorithmus einen MAF von 8,35 Atemzügen pro Minute auf. Außerdem konnte die Leistung der Atemfrequenz Schätzung weiter verbessert werden, indem die besten Algorithmen für jede Sensormodalität mit Hilfe eines Fusionsalgorithmus kombiniert wurden. Die Ergebnisse dieser Arbeit zeigen, dass die EKG-basierten Algorithmen besser abschneiden als IMU-basierte Algorithmen, und durch die Kombination beider Modalitäten konnte die Qualität weiter gesteigert werden. Allerdings sind die Unterschiede zwischen der Schätzung und der tatsächlichen Atemfrequenz immer noch zu groß. Aus diesem Grund sollte in weiteren Forschungsarbeiten untersucht werden, welche Verbesserungen das Hinzufügen zusätzlicher IMU-Sensoren bewirkt um atmungsbedingte und normale Körperbewegungen zu trennen, um die IMU-basierte Atmungsextraktion weiter zu verbessern.

Abstract

Respiration rate (RR), also known as breathing rate, is an important vital sign that is used to assess an individual's respiratory function and overall health. Normal RR varies among individuals and can be influenced by factors such as age, physical activity, and medical conditions. Research has shown, that changes in respiration rate can be used to diagnose and monitor respiratory disorders, such as asthma and chronic obstructive pulmonary disease (COPD). However, evidence suggests that RR is often not recorded, due to need for obtrusive sensor systems. A promising approach to automatically monitor RR, in an unobtrusive, and less time-consuming way is by extracting RR from other physiological parameters such as electrocardiogram (ECG) or IMU signals.

Although there are various publications that investigated different approaches to unobtrusively extract respiratory information from ECG or IMU signals, there is a lack of systematic comparison of both approaches, or whether combining both modalities would improve the signal quality. The aim of this work was therefore to implement different algorithms to extract respiration signals, as well as RRs, from ECG and IMU signals and to systematically compare the different methods. Additionally the impact of combining the IMU and ECG-based approaches should be investigated.

To evaluate these algorithms in a real-world environment, a new dataset containing IMU and ECG data as well as a ground truth signal from a respiration belt, was recorded. Thereby, the ECG-based algorithms outperformed the IMU based ones in terms of correlation with the ground truth respiration signal, as well as in RR estimation. While the best algorithm using an ECG signal achieved a Mean absolute error (MAE) of 7.52 the best algorithm using an IMU signal had a MAE of 8.35. Furthermore, the performance of RR estimation could be further improved, by combining the best algorithms for each sensor modality, by using a fusion algorithm.

The results of this thesis show that the ECG-based algorithms in general perform better than IMU-based ones and by combining both modalities the performance can be further increased. However, the differences between the estimation and the ground truth RR are still too large. For that reason, further research should examine the benefit of adding additional IMU sensors, for separating respiration induced and regular body movement, in order to further improve IMU-based respiration extraction.

Contents

Chapter 1

Introduction

In a hospital environment the recording of a patients vital signs, such as heart rate, blood pressure and temperature at least daily is considered standard [Cre08]. However there is evidence from previous studies that some vital signs such as RR are apparently regarded as less important [Rol19]. Although, especially RR, which is a early indicator for various diseases [Con18], is often not taken into account because of obtrusive sensor systems like nasal flow devices [Ott16], or impedance pneumography [Mły12]. In particular in an home monitoring environment those devices are often not applicable or just too expensive. Therefore, reliable and unobtrusive methods to collect real-world respiratory information might lead to a broader assessment of respiratory information, thus potentially allowing to develop better diagnostic approaches.

Over the past decades, several methods and algorithms were developed to derive respiratory information from other, less obtrusive sensor modalities. Inhalation and Exhalation are primarily caused by the contraction of the diaphragm and intercostal muscles, which consequently leads to a movement of the upper body. This movement can be measured, by for example IMU sensors and further processed to estimate the respiration rate [Ces18]. Another approach is to extract respiratory information from an ECG, also known as ECG-derived respiration (EDR). Since breathing modulates the ECG signal through several biological mechanisms. respiratory sinus arrhythmia (RSA) leads to shorter RR-Intervals during inspiration and longer ones during expiration due to an increased and decreased vagal tone respectively [Yas04]. The rotation of the cardiac vector is also influenced by respiration, leading to changes in the ECG waveform [Pal89]. Moreover the relative position of the electrodes to the heart changes during inhalation and exhalation, which also contributes as a modulation [OBr07].

Although the two approaches (IMU,ECG) have each been well studied, there is a lack of systematic comparison between both, or whether combining both modalities would improve the quality of the extracted information

The goal of this bachelor's thesis is therefore, to systematically compare the different kinds of respiration estimation algorithms and to investigate further possibilities of improving the estimation quality by combining both modalities. In order to compare the algorithms, a study was conducted where ECG, IMU data as well as a ground truth respiration signal using a thoracic respiratory belt via respiratory induction plethysmography. were recorded. As a part of this study the participants went through several phases where they were instructed to speak, stay in different postures and to follow different breathing patterns.

The structure of this thesis is organized as follows: Chapter 2 presents relevant related work of recent research in the field of respiration estimation, while Chapter 3 explains relevant medical background information. In Chapter 4 the methods for data aquisition and data processing are introduced. The results are presented in Chapter 5 and further discussed in Chapter 7. Chapter 8 concludes this thesis and provides an outlook on possible future research issues.

Chapter 2

Related Work

Respiratory information has been shown to be an early indicator for changes in a persons physiological state [Rol19]. Especially respiratory disorders such as COPD, Sudden Infant Death Syndrome (SIDS) and sleep breathing disorders can be diagnosed. [Ces18]. While manual counting of breaths per minute is still common in some hospitals [Cre08], finding and improving reliable and unobstrusive ways of continuous RR monitoring or automated longitudinal RR monitoring is an ongoing research task [Liu19].

2.1 EDR Algorithms and Methods

Previous work showed that it is possible to extract respiratory information reliably from the ECG. Moody et al. showed that interpolating the area of each detected QRS complex of an ECG results in a smooth EDR signal, which highly correlates with a reference pneumatic respiration transducer (PRT) recording [Moo85].

Over the last decades more algorithms have been developed utilizing different kinds of physiological modulations of respiration on the cardiac cycle [Maz03; Sch08; Boy09; Wid10] which will be explained later in this thesis. However, the first large systematic comparison of those algorithms was carried out by Charlton et al. who divided the process of estimating RR in three main steps: extraction of the respiration signal, estimation of the RR based on that signal and optionally fuse multiple RR estimations together. In their work, 14 extraction algorithms, 12 RR estimation algorithms and five fusion algorithms were used, which were usable in custom combinations. The combinations of algorithms were then ranked first by two standard deviations (SDs) from the ground truth labels and then by absolute bias. Four combinations were even better than a clinical impedance pneumograph (IP) device. A reference RR estimation was calculated using a oral-nasal pressure signal and expert annotations [Cha16].

2.2 IMU-derived Respiration

Apart from ECG based approaches, several other studies investigated RR estimation based on IMU sensor data. The main advantage of IMU sensors is that they are unobstrusive and inexpensive. Thus, they have the potential to help monitoring respiration on an ambulatory basis. Although, some studies suggest that using multiple IMU sensors results in a higher quality respiration extraction [Ces18], this thesis focuses on a single-IMU approach as it is easier to set up and less expensive.

Additionally, recent evidence suggests that using a single sensor produces sufficient results. An example for this is the study carried out by Rahman and Morshed, who used one IMU to detect the respiration signal. They achieved promising results by only using a moving average filter and normalization on the accelerometer data of the IMU sensor [Rah21].

A similar approach was carried out by Skoric et al. who conducted a study with 17 young, healthy and stationary participants. They processed the x-axis acceleration or the y-axis gyration with a Savitsky-Golay and a moving average filter. The generated two signals showed good reliability because they were highly correlated to the respiration signal, with a correlation coefficient of 0.895 for acceleration and 0.828 for gyration [Sko20].

Chapter 3

Medical Background

3.1 Clinical Measurement of Respiration

Respiratory disorders or lung diseases were one of the leading causes of death in 2019 according to the WHO [1] and with the recent global COVID pandemic more and more attention has focused on respiratory health. Especially RR is a vital sign which has been shown to be an important indicator of serious clinical events and illnesses, when deviating from the normal range of around 6-24 breaths per minute [Fle17]. These include for example intensive care unit (ICU) readmission [Car14], chronic heart failure [Pon01], pneumonia [Ram15], and cardiopulmonary arrest [Hod02]. Despite the fact that RR is clinically a strong indicator of deterioration, the measurement of RR is still often performed by manually counting the taken breaths per minute or even neglected, because of a lack of clinical resources or nurses and doctors not being aware of the importance of RR [Fle17]. However, manual counting can be very time consuming for the medical staff and also leads to inaccurate results [Kel11] due to counting for less than 60 seconds or just estimating the RR [Rol19].

Apart from manually counting there are three mainstream methods for clinically measuring RR. The first one being a spirometer which monitors the volume of air inspired and expired by the lungs through a mouthpiece. This can even be used for accurately measuring multiple respiratory parameters apart from only RR. However, due to the obstrusive mouthpiece this interferes with natural breathing and is also not suitable for continous monitoring. The second one is capnometry, which measures partial pressure of carbon dioxide in the exhaled air

[1] https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death

through a mouthpiece. Due to the carbon dioxide partial pressure peaking during exhalation this can also be used to accurately measure RR, but also has the same disadvantages as the spirometer. The third one is an impedance pneumograph (IP) which works by putting two or more electrodes on the chest, injecting a low-amplitude high-frequency into the thorax and measuring the impedance change due to the respiration cycle. Unlike the spirometer and the capnometer IP is suited for continous monitoring of RR, but it also requires special devices and is very error prone to motion and posture changes [Liu19].

3.2 Electrocardiogram (ECG)

An ECG records the electrical signals caused by the hearts polarization and depolarization. The basic segments of an ECG signal are illustrated in Figure 3.1[Taw12]. The ECG consists of the following three recurring waves:

P wave: corresponds to atrial depolarization

QRS complex: corresponds to ventricular depolarization

T wave: corresponds to ventricle repolarization

Together they form one single heart beat. Additionally the interval between two successive R peaks is often referred as RR-interval. But in order to avoid confusion with the respiration rate RR we will refer to it as NN-intervals, which emphasizes that only normalized RR-intervals are considered [Gou15].

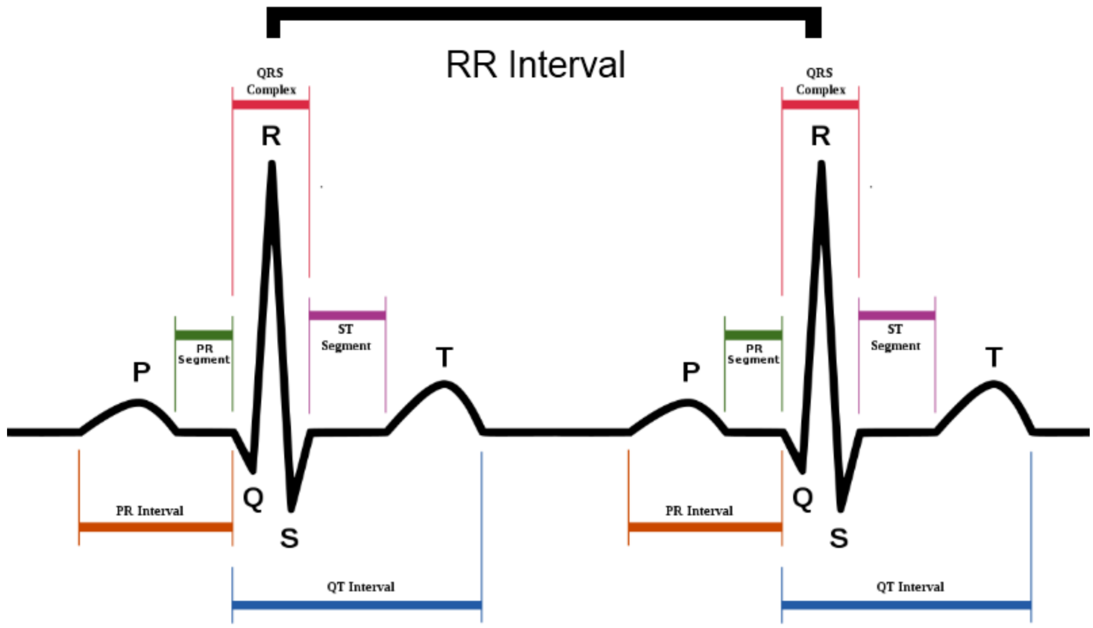

Figure 3.1: Illustration of the ECG segments [Taw12]

3.3 ECG Modulations

Previous research seperated the influence of respiration on the ECG in three categories, as illustrated in 3.2[Cha16]: baseline wander (BW), amplitude modulation (AM) and frequency modulation (FM) [Bai06; Mer12].

3.3.1 Beat Modulation

During inspiration the absolute peak values of the hearts electrical activity are decreased (AM). Moreover the general baseline of the signal is also shifted downwards during inspiration (BW). There are three suggested mechanisms for this behaviour. Probably the highest impact is caused by body movement during respiration which changes (1) the electrodes position relative to the heart [Fla67] and (2) the electrical axis of the heart [Bai06]. Moreover changes in the pattern of ventricular excitation, caused by variations in hemodynamics associated with respiration, could also be a reason for the modulation [Fla67] Another suggestion is that changes in thorax impedance, caused by filling and emptying of the lungs, could contribute

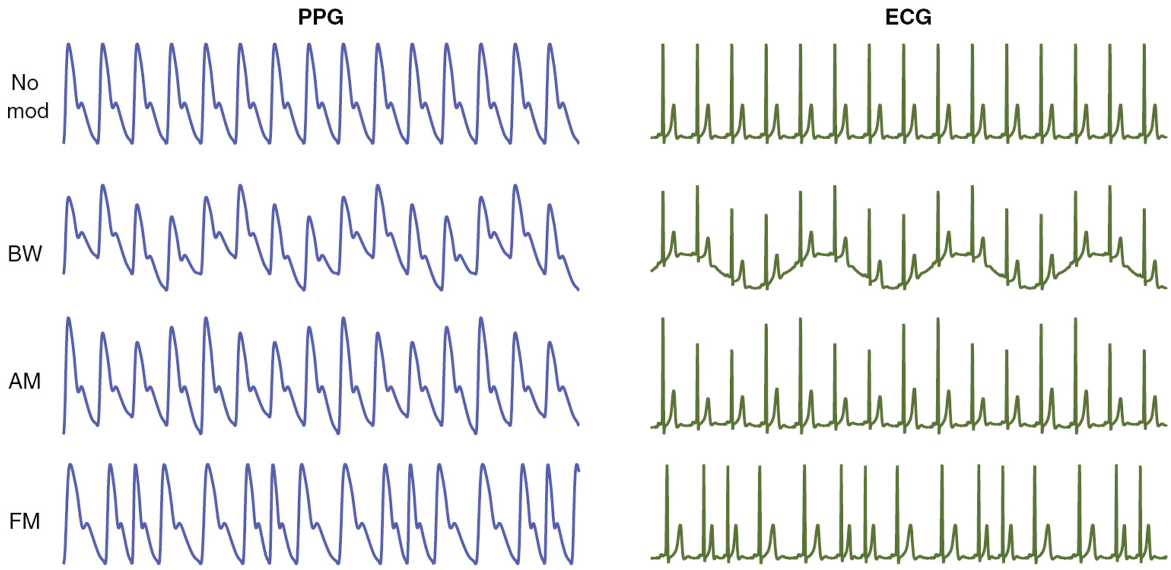

Figure 3.2: Illustration of respiration induced modulations on the ECG and PPG signal [Cha16]

to the modulation. However, the impact of this is assumed to be rather small [Fla67; Bai06].

3.3.2 Frequency Modulation

Respiratory Sinus Arrythmia also known as RSA, is one of the modulations the respiration has on the cardiac system. According to Grossman et al. RSA is *"a cardiorespiratory phenomenon characterized in mammals by heart rate (HR) or R-R interval (RRI) fluctuations that are in phase with inhalation and exhalation"* [Gro07]. More specifically Heart rate increases during inhalation and decreases during exhalation as shown in 3.2[Cha16]. RSA is believed to be a caused by increased vagal tone during inspiration. However, recent research suggests that there are limitations to that correlation [Gro07]. Furthermore the effect of RSA is not equal in every human. According to Meersmann there seems to be an age-related loss of vagal-cardiac activity and thus a decreased impact ofRSA on the ECG [De 93].

Chapter 4

Methods

4.1 Data Aquisition

To assess the impact of combining IMU and ECG based algorithms a study was conducted at the *Machine Learning and Data Analytics Lab (Erlangen, Germany)* from September to October 2022. Participants were asked to perform different breathing and movement patterns in order to assess various algorithms under different circumstances.

4.1.1 Study Population

In total 16 participants (10 male, 6 female) took part in the study after giving informed consent. An overview of demographic and anthropometric data of the participants can be found in Table 4.1.

	Participants	Age [years]	Height [cm]	Weight [kg]	BMI [kg/m^2]
female	6	24.12 ± 1.36	165.50 ± 3.01	58.37 ± 5.38	21.35 ± 2.58
male	10	25.10 ± 1.85	183.40 ± 8.43	83.10 ± 13.13	24.61 ± 2.78
total	16	24.81 ± 1.68	176.68 ± 11.21	74.00 ± 16.13	23.46 ± 3.04

Table 4.1: Demographic and anthropometric characteristics of the participants; Mean $\pm$ SD

Before the study started, participants filled out a questionnaire in order to ensure that no participant with insufficent physical condition took part. Exclusion criteria included an age under 18 and above 30, an extreme under- or overweight, physical or mental illness, intake of any heart medication, asthma or a recent COVID-19 infection within the last four weeks.

4.1.2 Experimental Setup

For recording ECG and respiration signals a *MP160* [1] data acquisition workstation together with the software tool *AcqKnowledge* [2] , both developed by *BIOPAC Systems Inc.[Goleta, USA]*, were used. The *MP160* is a 16-Channel data acquisition and analysis system which can record multiple Channels with different sampling rates up to 400 kHz. There are various modules for measuring different biosignals which can be connected to the base station. For this study the modules *ECG100C* and *r100C* were used for recording a Lead I ECG according to the Einthoven triangle, and a respiration signal as a reference for the ECG and IMU derived signals. The respiration was measured using a thoracic respiratory belt which's mechanism is based on respiratory induction plethysmography. The sampling rate for both was set to 250 Hz. For dividing the recordings in different phases the *AcqKnowledge* software was used to manually place event markers for each beginning of a phase during the recording. To record chest movement via IMU data another chest-worn wearable sensor *(Portabiles NilsPod, Portabiles GmbH, Erlangen, Germany)* was used. This sensor recorded 3D acceleration (range +-16g) as well as 3D angular rate (range +-2000°/s) at a sampling rate of 256 Hz. Furhtermore, it has a built-in ECG Sensor, which could also be used for extracting respiratory information. Figure 4.1 shows the sensor placement of both systems. Both devices were synchronised using a custom made syncboard.

[1] https://www.biopac.com/product/mp150-data-acquisition-systems/
[2] https://www.biopac.com/product-category/research/software/

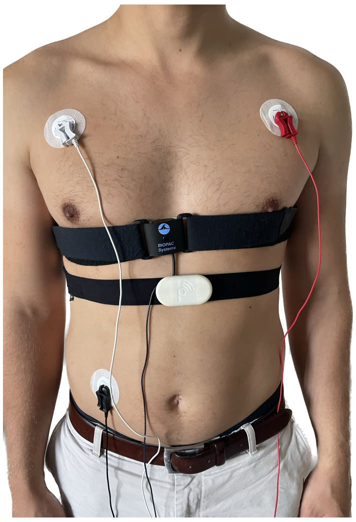

Figure 4.1: Electrode, respiratory belt and IMU placement

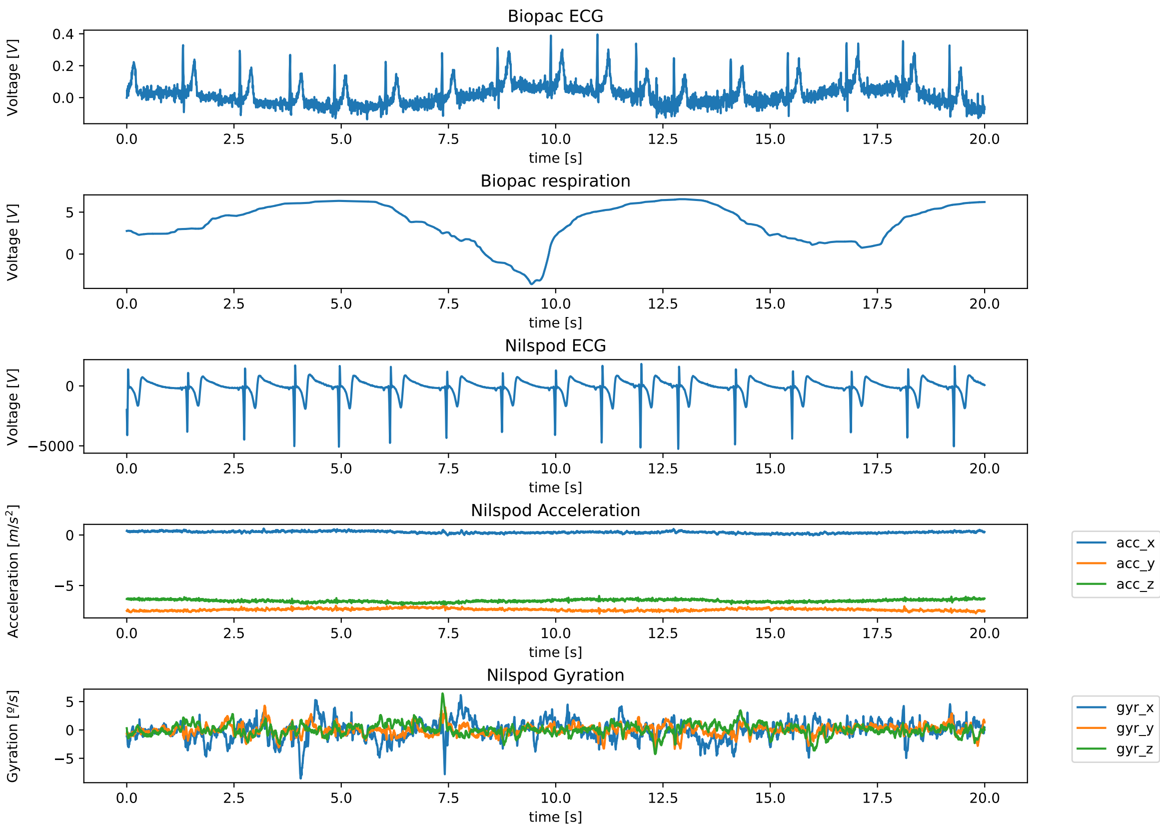

Figure 4.2: Recorded datastreams

4.1.3 Study Protocol

The study protocol which is also schematically shown in 4.3 consisted of the following tasks:

Initialization and synchronization: At the start of the recording the participants were asked to sit on a chair at rest, while data aquisition of the Biopac and the Portabiles sensors was started. To synchronize the two datastreams, a synchronisation signal was induced on one channel of both recording systems.

Baseline 1 (3 min): The participants were instructed to keep sitting on the chair at rest for a total of three minutes.

Speaking (2 min): The participants were asked to read out loud a text from a book of non-fiction, while continuing to sit on the chair in order to assess the algorithms performance in a real world situation.

Baseline 2 (1 min): In order to recover from the speaking phase a baseline phase of one minute was inserted in the study protocol.

Standing and rest (3 min): The participants were instructed to stand up and keep an upright position for three minutes.

Sitting and rest (2 min): Afterwards the participants were asked to sit down again. In order to allow the orthostatic response to wear off, the participant remaines in a sitting position for two more minutes.

4-7-8 Breathing (1 min): The participants were instructed to follow a breathing pattern from a smartphone app. Each cycle of this so called ”4-7-8 Breathing” consists of a four second inhalation interval, a seven second interval of holding the breath and an eight second exhalation interval.

Baseline 3 (1 min): In order to recover from the 4-7-8 Breathing phase another baseline phase of one minute was inserted in the study protocol.

Metronome Breathing (1 min): The participants were instructed to follow a breathing pattern from a smartphone app. This time, it was a regular breathing with a four second inhalation and a four second exhalation interval.

Baseline 4 (1 min): Another baseline for recovery before the last phases.

Inhalation and hold (3 min): The participants were instructed to inhale and hold their breath for 30 seconds. Afterwards, they were instructed to breath normally for 30 seconds in order to recover. This was repeated a total of three times.

Exhaltation and hold (2 min): The participants were asked to exhale deeply and then hold their breath for ten seconds. Like in the previous phase they were instructed to breath normally for 30 seconds in order to recover. This was also repeated three times.

Hyperventilation (1 min): Within the final breathing pattern an additional hyperventilation phase was performed where the participants were instructed to breath as quickly and briefly as they could, in order to simulate a highly increased RR. The participants should perform this for a maximum of one minute and in case they feel any dizziness they were instructed to stop prematurely.

Baseline 5 (1 min): A final baseline in which the data aquisition was ended.

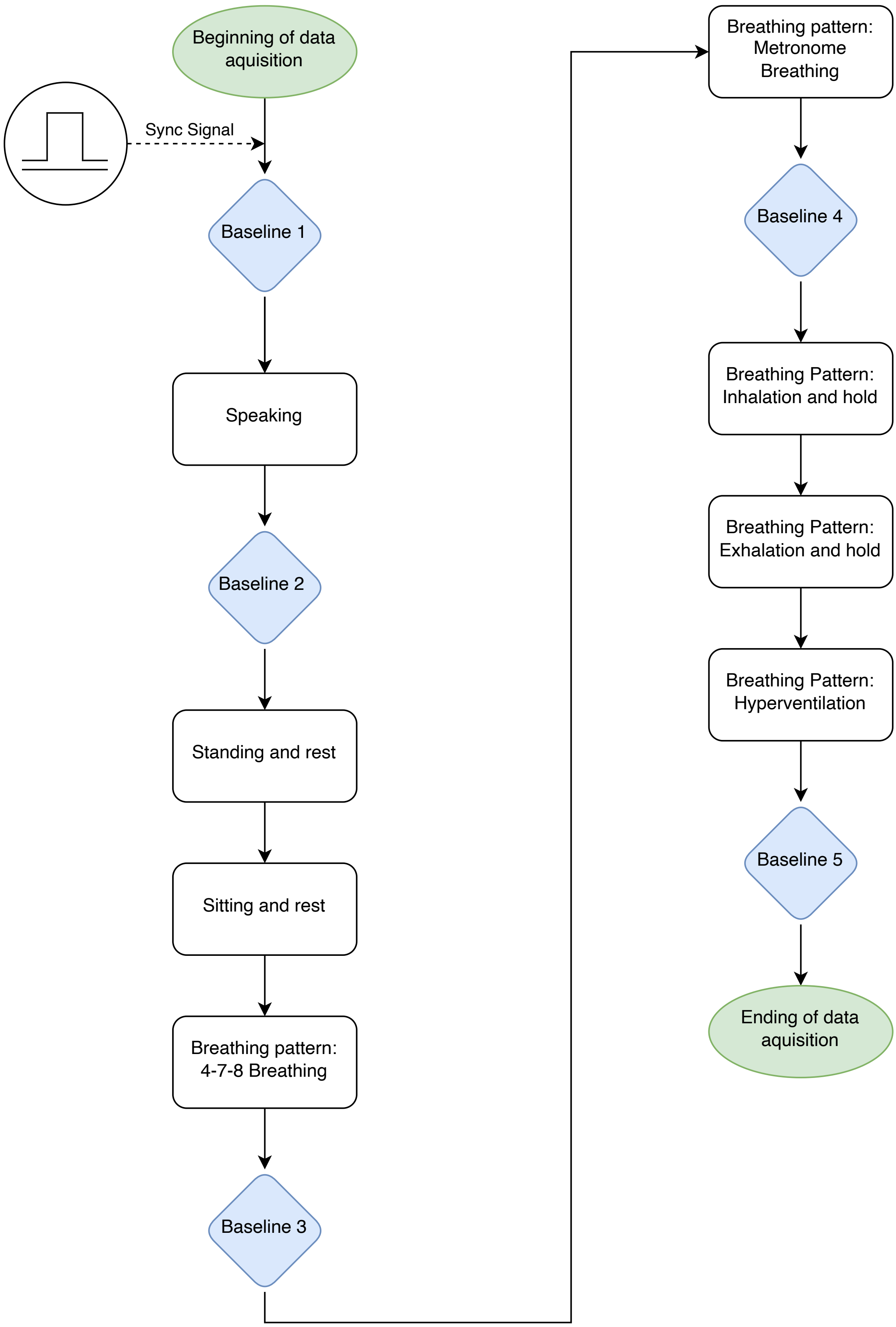

Figure 4.3: Visualization of the study protocol

4.2 Data Processing

In the following the pipeline for data processing is presented. Inspired from Charlton et al. [Cha16] the pipeline is divided into three parts (Figure 4.4). Each step consists of several interchangable algorithms. The first step consists of algorithms with either ECG or IMU data as input, and extract a respiratory signal. The second part are algorithms which take these extracted respiratory signals and estimate a RR based on them. As a last step an optional fusion algorithm can be added to further improve the RR estimation.

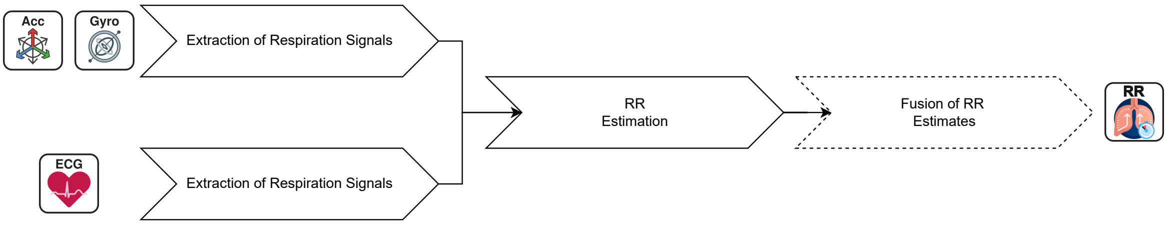

Figure 4.4: Data processing pipeline for extracting RR from either ECG or IMU. The dashed stage is optional. Design adapted from Charlton et al. [Cha16]

4.2.1 Respiratory Signal Extraction Algorithms

Each of the extraction algorithms computes an respiratory-like signal, which was then normalized using the following equation:

$$r_{normalized} = \frac{r_{raw} - r_{min}}{r_{max} - r_{min}} \tag{4.1}$$

Where r_{raw} are the extracted respiratory-like signal values and r_{min} and r_{max} are the global minimum and maximum respectively.

ECG-derived respiration

1. **ExtractionLindeberg**: Bandpass filter according to Lindeberg et al. [Lin92]

   The ECG signal is first bandpass filtered with a 10^{th} order Butterworth bandpass filter with a lower cutoff frequency of 0.066 Hz and an upper cutoff frequency of 1.0 Hz.

2. **ExtractionKarlen**: Amplitude differences of troughs and proceeding peaks according to Karlen et al. [Kar13]

The 'peak-trough-diff' method implemented in version 0.7.1 of the BioPsykit package [Ric21] was used for this. First all R-peaks are detected. Then the proceeding Q-waves within a 0.1 second interval before the R-peaks are detected. The difference between each Q-wave and R-peak pair is calculated and interpolated to the length of the raw ECG signal. Afterwards, this raw respiration signal is then filtered with a 10^{th} order Butterworth bandpass filter, with a lower cutoff freqency of 0.1 Hz and an upper cutoff frequency of 0.5 Hz.

3. **ExtractionOrphandiou**: Time between R-peaks according to Orphiandou et al. [Orp13]

   The 'peak-peak-interval' method implemented in version 0.7.1 of the BioPsykit package [Ric21] was used for this. First all R-peaks are detected. Afterwards, the difference between each peak and its successor is calculated. This Signal of NN-intervals is then interpolated to the length of the raw ECG signal and then filtered with a 10^{th} order Butterworth bandpass filter, with a lower cutoff freqency of 0.1 Hz and an upper cutoff frequency of 0.5 Hz.

4. **ExtractionCharlton**: Mean amplitude of troughs and proceeding peaks according to Charlton et al. [Cha16]

   The 'peak-trough-mean' method implemented in version 0.7.1 of the BioPsykit package [Ric21] was used for this. First all R-peaks are detected. Then the proceeding Q-waves within a 0.1 second interval before the R-peaks are detected. The mean for each Q-wave and R-peak pair is calculated and interpolated to the length of the raw ECG signal. Afterwards, this raw respiration signal is then filtered with a 10^{th} order Butterworth bandpass filter, with a lower cutoff freqency of 0.1 Hz and an upper cutoff frequency of 0.5 Hz.

5. **ExtractionAddisonAM**: The maximum amplitudes of the continuous wavelet transform (CWT) according to Addison and Watson [Add04]

   The advantage of CWT when used for analysing ECG data is that information about time and frequency can be extracted, opposed to for example the fast fourier transform (FFT) where only frequency information can be extracted. In a CWT of a raw ECG signal two ridges can be seen (Figure 4.5) [Add04]. One is induced by the beating heart and one from the respiration.

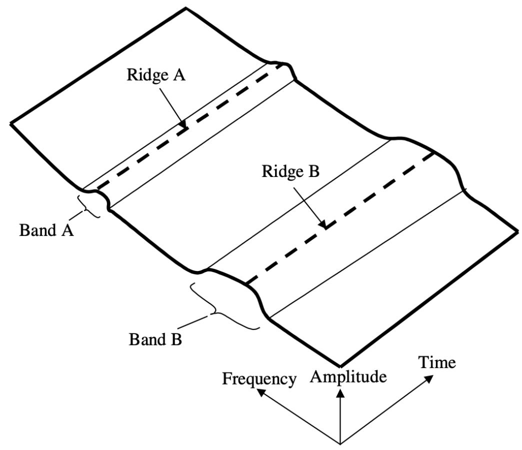

Figure 4.5: Visualization of the CWT of a signal with two ridges [Add04]

The algorithm consists of the following steps:

(a) Calculate the CWT of the ECG signal.

(b) Extract the region of plausible cardiac frequencies from 30-220 bpm

(c) Find the maximum magnitude for each time sampling point

(d) Create a ridge amplitude perturbation (RAP) signal [Add04] by projecting the found maxima onto the amplitude-time plane.

6. **ExtractionAddisonFM**: The frequency corresponding to the maximum amplitude of the CWT according to Addison and Watson [Add04].

   As in the previous method the CWT of the signal is calculated and maximum magnitudes within plausible cardiac frequencies are calculated. But instead of creating the RAP signal, a ridge amplitude perturbation (RFP) signal is created by projecting the maxima onto the frequency-time plane.

7. **ExtractionVangent2019**: Interpolating NN-intervals according to [Gen19]

   For this algorithm, the implementation of version 0.2.2 of the Neurokit2 Package was used [Mak21]. It is based on FM and creates a respiration signal by interpolating the NN-interval values. Afterwards an additional second order buttwerworth bandpass filter is applied, with a lower cutoff frequency of 0.1 Hz and an upper cutoff frequency of 0.4 Hz.

8. **ExtractionSoni2019**: Interpolating NN-intervals according to [Son19]

   For this algorithm, the implementation of version 0.2.2 of the Neurokit2 Package was used [Mak21]. It is based on FM and creates a respiration signal by interpolating the NN-interval values. Afterwards an additional lowpass filter is applied, with a cutoff frequency of 0.5 Hz.

9. **ExtractionSarkar2015**: Interpolating NN-intervals according to [Sar15]

   For this algorithm, the implementation of version 0.2.2 of the Neurokit2 Package was used [Mak21]. It is based on FM and creates a respiration signal by interpolating the NN-interval values. Afterwards an additional 6^{th} order butterworth bandpassfilter is applied, with a lower cutoff frequency of 0.1 Hz. and a higher cutoff frequency of 0.7 Hz.

IMU-derived respiration

1. **PositionalVectorExtraction**: Moving average filter the acceleration according to Rahman and Morshed [Rah21]

   For this algorithm the x,y and z-axis acceleration signals are first filtered by using a moving average filter of size 256 according to Equation 4.2.

$$a_{filtered}[n] = \frac{1}{256} \sum_{i=0}^{255} a[n-i] \tag{4.2}$$

   Where $a_{filtered}$ is the filtered acceleration vector and a is the vector containing the raw acceleration in all three axes. Afterwards, the signals of the three axes are each normalized according to Equation 4.3.

$$a_{norm}[n] = \frac{a_{filtered}[n] - a_{min}}{a_{max} - a_{min}} \tag{4.3}$$

   Where a_{min} is the minimum and a_{max} is the maximum of the normalized axis. The acceleration is then filtered again, using a moving average filter, this time with a window size of 384 Hz. As a last step, the amplitude values are calculated using Equation 4.4 and used as estimated respiration signal.

$$a_{amplitude}[n] = \sqrt[3]{a_x[n] + a_y[n] + a_z[n]} \tag{4.4}$$

Where $a_{amplitude}$ is the calculated amplitude value and a_x, a_y, and a_z are the signal values of the three axes.

2. **SavGolExtractionGyr/Acc**: Savitsky-Golay filter according to Skoric et al. [Sko20]

According to Skoric et al. the best two modalities for estimating respiration from IMU were found in x-axis acceleration and y-axis gyration, which are shown in 4.6 [Sko20]. The two corresponding axes of the Nilspod sensor were used, which were

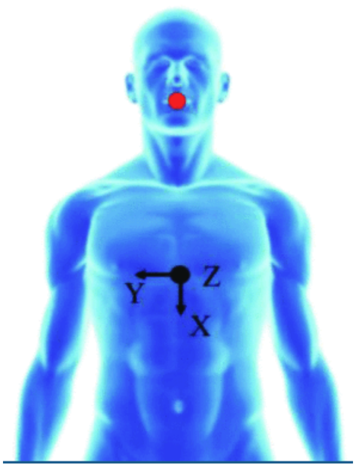

Figure 4.6: Coordinate system of Skoric et al. [Sko20]

the acceleration of the y-axis and the gyration of the x-axis which is refered to as signal in the following. First, the size of the filter window is determined. For this the summed power spectrum of all six acceleration and gyration axes is calculated. Then the frequency with the highest amplitude between 0.001 Hz and 2.0 Hz in the spectrum is assumed to be the respiration frequency. Thereby, the window size of the filter is then set to the corresponding respiration period. Afterwards, a 4^{th} order Savitsky-Golay filter with the calculated window size is applied to the signal.

4.2.2 RR Estimation

1. **PeakDetection**: Basic peak detection according to Shah [Sha12]

   On the respiration signal a simple 7-point peak detection was applied. If a point was greater or equal to the next three points to the left and right, it is considered a peak. The estimated respiration rate was calculated according to Equation 4.5.

   $$RR = \frac{n_{peaks}}{s/60} \frac{Breaths}{Minutes} \tag{4.5}$$

   Where RR is the estimated respiration rate, n_{peaks} the number of detected peaks and s length of the signal in seconds.

2. **GradiantDetection**: Zero crossing algorithm according to Johannson [Joh03]

   First, the normalized respiration signal is shifted downwards to have a a range of values from -0.5 to 0.5. Then all zero crossings with a positive gradiant are detected and counted. The respiration rate was then calculated according to Equation 4.6.

   $$RR = \frac{n_{ZeroCross}}{t_0 - t_N} \tag{4.6}$$

   Where $n_{ZeroCross}$ is the number of detected zero crossings and t_0 is the time of first and t_N the time of the last zero crossing.

3. **PeakThroughDetection**: Simple breath detection according to Fleming [Fle]

   Inspired from Schäfer et al. [Sch08] a 10^{th} order butterworth bandpass filter was applied to the respiration signal before counting peaks and troughs. The lower cutoff frequency was 0.1 Hz and the higher cutoff frequency 0.5 Hz.

   Then, all peaks and troughs were detected by checking the gradient. A change from positive to negative is regarded as a peak and a change from negative to positive as a trough.

   The mean of the signal was then calculated, whereas all minima above and maxima blow were deleted, while assuring that minima and maxima are still alternating. This was achieved by also deleting the closest other maximum for minima and the closest other minimum for maxima.

Then, all pairs of extrema are deleted, if their distance is smaller than 0.5 seconds. However, it is very rare for this to happen as Fleming already stated in his work [Fle].

4. **CountOrig**: Breath detection via 'Count-orig' according to Schäfer et al. [Sch08]

   The Original Counting Method (Count-orig) from Schäfer et al. consists of the following steps:

   1) Filter the respiration signal with a 10^{th} order butterworth bandpass filter was applied to the respiration signal. The lower cutoff frequency was 0.1 Hz and the higher cutoff frequency 0.5 Hz.
   2) Locate all peaks and troughs of the filtered curve.
   3) Take the third quartile Q_3 of all local maxima values and define $0.2 \cdot Q_3$ as a threshold.
   4) A breathing cycle begins and ends at a local maxima above the threshold level. A part of the signal between two of those extrema is regarded as a valid respiratory cycle if it contains exactly one minimum under 0
   5) The average length of all valid respiratory cycles is calculated and interpreted as the reciprocal respiration frequency.

5. **CountAdv**: Breath detection via 'Count-adv' according to Schäfer et al. [Sch08]

   The Advanced Counting Method (Count-adv) from Schäfer et al. consists of the first two steps of 'Count-orig' followed by:

   3) Calculate the absolute vertical differences of subsequent local extrema. Then determine the third quartile Q_3 of these and define $0.3 \cdot Q_3$ as a threshold.
   4) Find and remove all pairs of subsequent extrema, where their difference is below the threshold level. The remaining extrema are thought to originate all from breathing thus defining the all respiratory cycles.
   5) The RR is calculated as the reciprocal mean length of all detected respiratory cycles

4.2.3 Fusion of RR Estimates

There are many possibilities for fusing RR estimates, such as temporal smoothing or different spectral analysis methods [Orp09; Orp13; Láz13; Pla]. However, according to Charlton et al. [Cha16] the Smart Fusion algorithm proposed by Karlen et al. [Kar13] produced by far the best result. For that reason, this thesis only considers this fusion algorithm.

1. **SmartFusion**: Fusion based on calculating the mean according to Karlent et al. [Kar13]

   This algorithm takes three estimated RR values from three extraction methods, each one should be either be based on a different physiological modulation of the ECG or on the IMU signal. The fused respiration rate is defined as:

$$RR_{fused} = \begin{cases} \frac{RR_1+RR_2+RR_3}{3}, & \text{if } \sigma \leq 4 \\ NaN, & \text{otherwise} \end{cases}$$

   Where RR_1, RR_2 and RR_3 are the three RR estimates and σ is their SD. If their SD is greater than 4 breaths per minute the estimation is assumed to be of low quality and no value is returned to indicate that.

Chapter 5

Evaluation

5.1 Respiration Signal

5.1.1 Correlation

For the evaluation of the extracted respiration signals the Pearson correlation coefficient (PCC) of the ground truth signal and the extracted signal was calculated for each phase presented in Section 4.1.3. The PCC implementation of the SciPy Package was used for this[Vir20]. The Pearson correlation coefficient of two signals x and y is calculated as follows:

$$r_{xy} = \frac{\sum(x - m_x)(y - m_y)}{\sqrt{\sum(x - m_x)^2 \sum(y - m_y)^2}} \tag{5.1}$$

Where m_x and m_y are the mean values of the signals x and y respectively. The mean and SD of the PCC for each algorithm combination was calculated as:

$$\mu_{xy} = \frac{1}{N} \sum_{i=0}^{N-1} r_{xy_i} \tag{5.2}$$

$$\sigma_{xy} = \frac{1}{N} \sum_{i=0}^{N-1} (r_{xy_i} - \mu_{xy})^2 \tag{5.3}$$

5.2 Respiration Rate

For the evaluation of the estimated respiratory rate, the MAE for each algorithm combination was calculated according to Equation 5.4.

$$MAE = \frac{\sum_{i=0}^{n} \left| RR_{GroundTruth_i} - RR_{Estimated_i} \right|}{n} \tag{5.4}$$

Where $RR_{GroundTruth_i}$ is the ground truth RR for one phase, $RR_{Estimated_i}$ is the estimated RR for one phase and n is the number of estimated RRs. $RR_{GroundTruth_i}$ was calculated by using methods from the Neurokit2 Python package. The code can be found in the Appendix B.1.

Chapter 6

Results

6.1 Respiration Signal Extraction

Overall Perfomance

As shown in Table 6.1 the extraction algorithm with the highest absolute mean PCC over all participants and phases, was *ExtractionKarlen* 2 with a mean value of -0.31 and a SD of ± 0.24.

Extraction Algorithm	Sensor	Mean PCC	± SD
ExtractionKarlen	Biopac ECG	-0.31	0.24
ExtractionOrphandiou	Biopac ECG	-0.26	0.21
ExtractionCharlton	Biopac ECG	-0.25	0.22
ExtractionVangent2019	NilsPod ECG	0.23	0.25
ExtractionSarkar2015	NilsPod ECG	0.23	0.25
ExtractionOrphandiou	NilsPod ECG	-0.23	0.22
ExtractionAddisonAM	BioPac ECG	-0.20	0.34
ExtractionVangent2019	Biopac ECG	0.17	0.22
ExtractionSarkar2015	BioPac ECG	0.17	0.21
ExtractionSoni2019	NilsPod ECG	0.13	0.28

Table 6.1: Performances of the ten highest ranked algorithms for extracting respiration signals; ranked by the absolute value of the mean PCC

Performance based on raw signal

As shown in Figure 6.1 the Sensor modalities all have a mean PCC of approximately zero, mostly due to the fact that positive and negative coefficients cancel each other out and also because many phases contain irregular breathing patterns, which most extraction algorithms fail to replicate. However, compared to the NilsPod ECG and the NilsPod IMU the algorithms generally achieve higher correlation coefficients of around ± 0.8 when using the Biopac ECG signal.

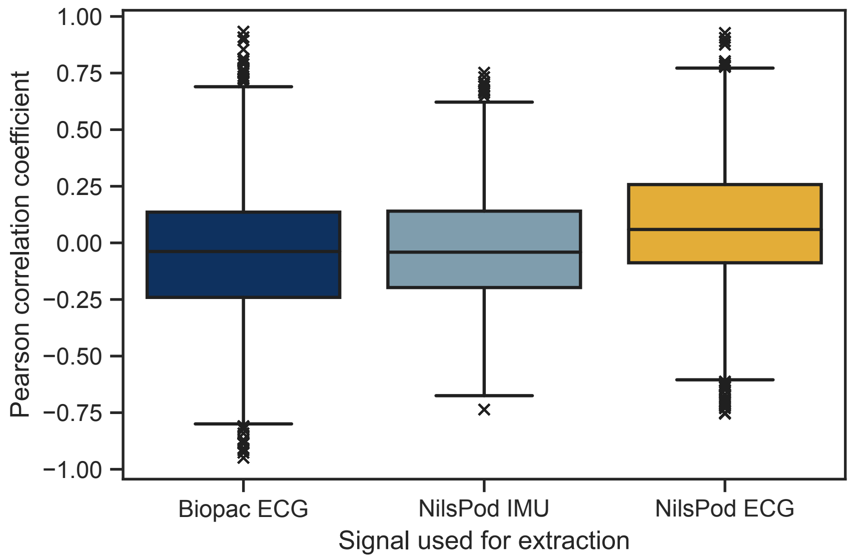

Figure 6.1: Boxplot to visualize the quality for respiration signal extraction using Biopac ECG (9 algorithms), NilsPod IMU (3 algorithms) and NilsPod ECG (9 algorithms)

Performance based on phases

As shown in Table 6.1 *ExtractionKarlen* achieved the highest absolute mean PCC, thus it will be used to demonstrate algorithms performance based on the phase they were applied. As shown in Figure 6.2 algorithms generally performed better on regular breathing patterns like the *Metronome Breathing* phase. In contrast to that, phases with irregular breathing like *Hyperventilation* and *4-7-8 breathing* were especially bad with almost all coefficients around zero. Whereas Phases with no prescribed breathing pattern like *Sitting and rest* and *Standing* *and rest* performed slightly better with several coefficients above 0.5 and under -0.5.

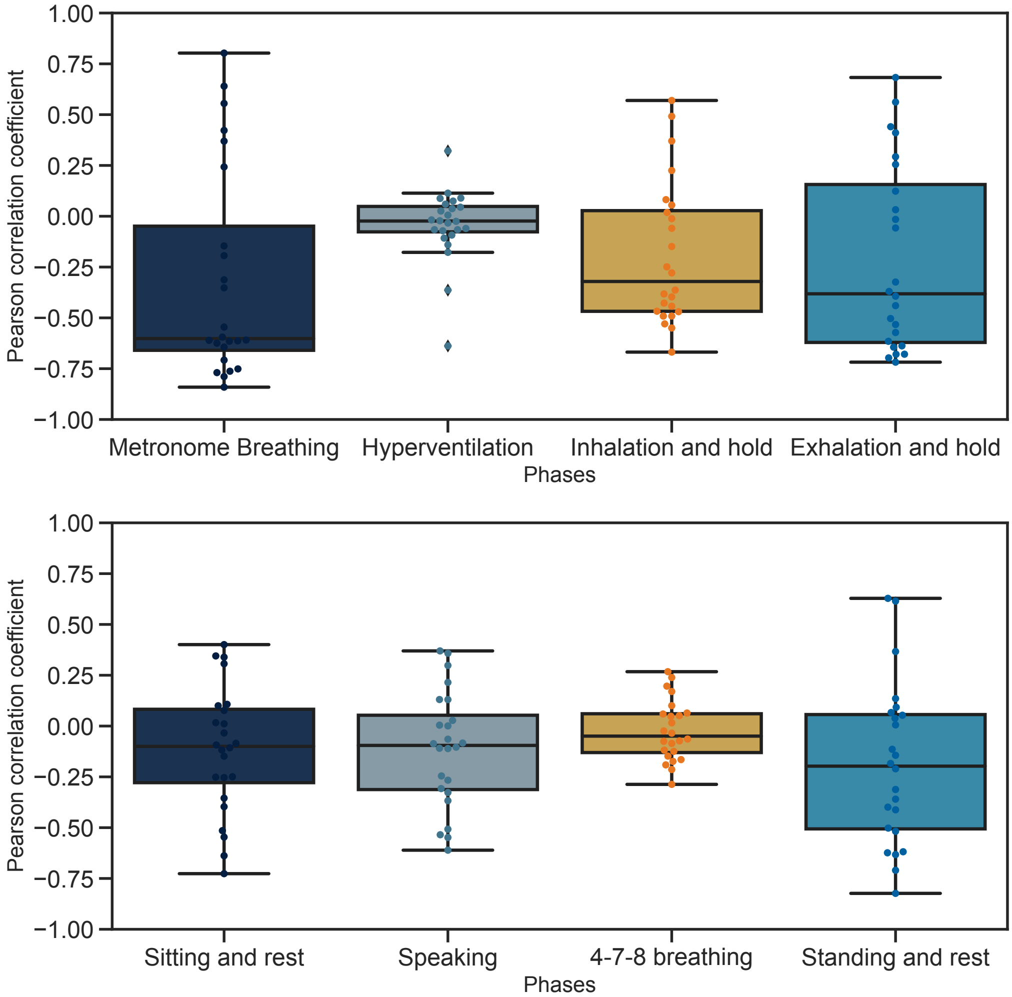

Figure 6.2: Performance of *ExtractionKarlen* algorithm depending on the used phase

6.2 RR Estimation

Overall Performance

As shown in Table 6.2 the best algorithm combination for estimating RR was *ExtractionSoni2019* for the signal extraction and *CountOrig* for the RR estimation. It has a MAE of 7.526957 breaths per minute over all participants and all phases. The best IMU based approach was the combination of *PositionalVectorExtraction* and *CountOrig* with a MAE of 8.357204.

Extraction Algorithm	Estimation Algorithm	Sensor	Mean Absolute Error [BPM]
ExtractionSoni2019	CountOrig	Biopac ECG	7.526957
ExtractionSarkar2015	CountOrig	Biopac ECG	7.527760
ExtractionCharlton	CountOrig	NilsPod ECG	7.571070
ExtractionSarkar2015	CountOrig	NilsPod ECG	7.656179
ExtractionSoni2019	CountOrig	NilsPod ECG	7.719700
ExtractionOrphandiou	CountOrig	Biopac ECG	7.750569
ExtractionKarlen	CountOrig	NilsPod ECG	7.777508
ExtractionOrphandiou	CountOrig	NilsPod ECG	7.786824
ExtractionSoni2019	PeakDetection	NilsPod ECG	7.859076
ExtractionKarlen	CountOrig	BioPac ECG	7.869668

Table 6.2: Performances of the ten highest ranked algorithm combinations for estimating respiratory rate based on the used Sensor; ranked by the MAE in breaths per minute (BPM).

In total 105 different combinations of algorithms were tested. Some combinations showed very large errors, such as the *ExtractionAddissonFM* extraction with the *PeakDetection* algorithm, which had a MAE of 14247.76 [BPM] over all participants and phases. A complete listing can be found in the Appendix.

Performance based on phases

Figure 6.3 presents the residual plot for the best algorithm combination shown in Table 6.2. It can be seen that even the ground truth RR has high outliers which were not all caused by the *Hyperventilation* phase. In Figure 6.4 the residual plot is further divided into the different phases.

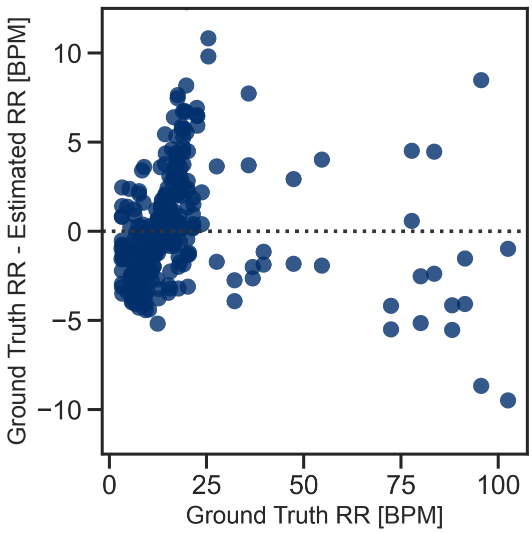

Figure 6.3: RRs of the best algorithm combination

6.3 Fusion Algorithm Performance

For further optimizing the estimated RR the *SmartFusion* algorithm was applied on the RRs of the best algorithm combination for Biopac ECG, NilsPod ECG and NilsPod IMU. Figure 6.5 shows the residual plot for the fused RRs of all participants and subjects. In Figure 6.6 a more detailed view over the different phases is given.

It can be seen, that compared with Figure 6.3 the differences between the ground truth and the estimated RRs has strongly decreased. There were almost no datapoints with a difference greater than five breaths per minute. From 156 datapoints 12 were discarded. Seven of them were discarded because of the *Initialization* phase, which was too short for the ground truth estimation algorithm to calculate a reference value. Only five of the 156 datapoints (2.5%) were discarded due to a SD greater than four breaths per minute.

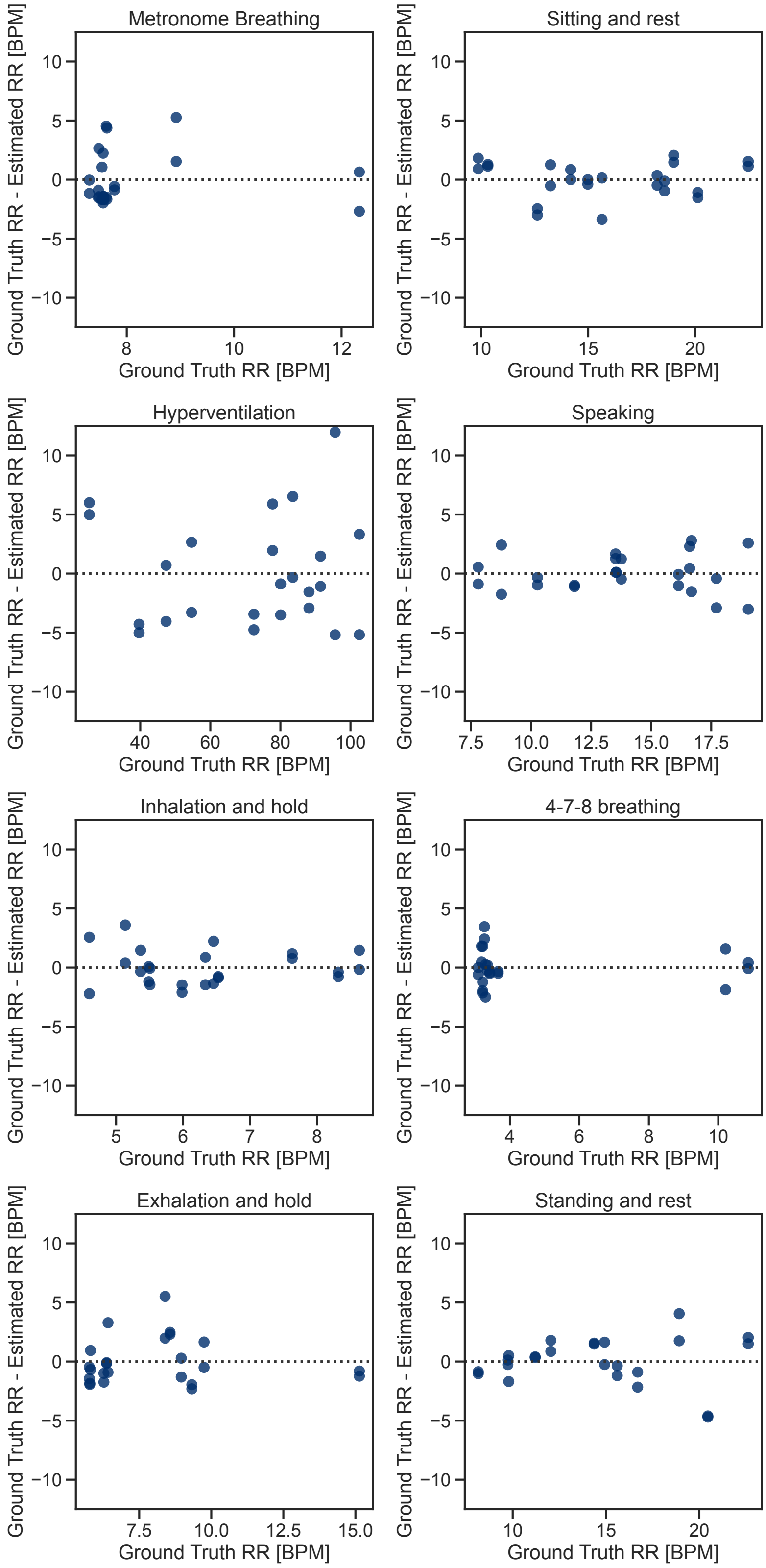

Figure 6.4: Performance of the *(ExtractionSoni2019, CountOrig)* algorithm combination depending on the used phase; using both NilsPod ECG and Biopac ECG

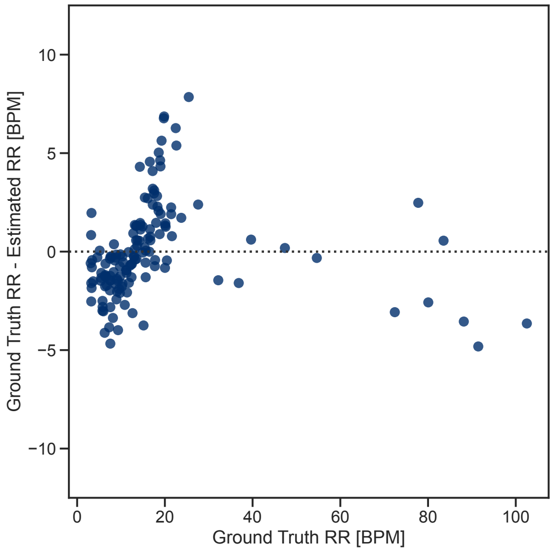

Figure 6.5: Fused RRs of the best algorithms

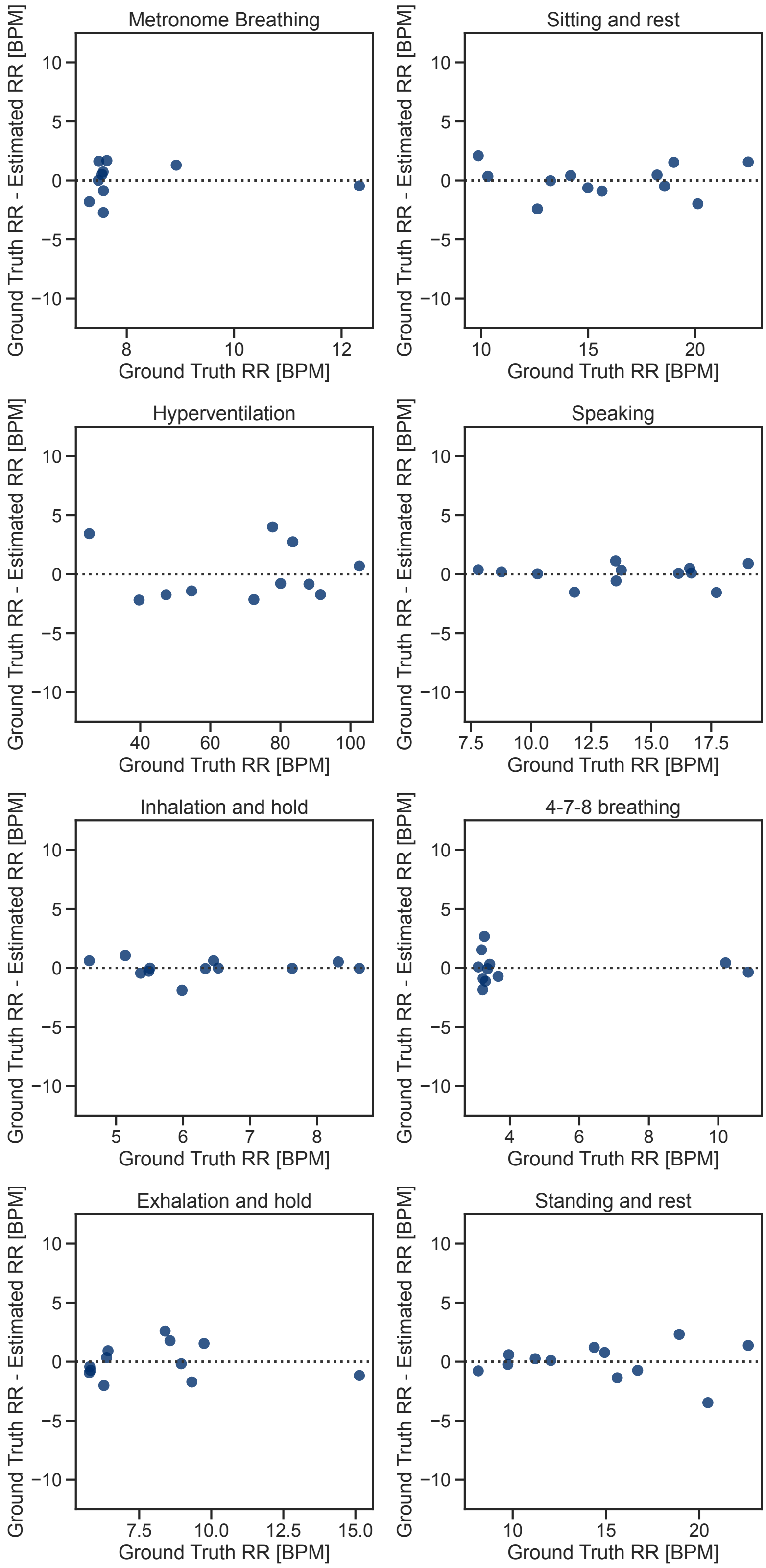

Figure 6.6: Performance of the fusion of the best three algorithm combination depending on the used phase

Chapter 7

Discussion

One main objective of this thesis was to systematically compare methods for RR estimation, by using different combinations of algorithms with different input modalities on a medium sized dataset. The following Chapter discusses the presented methods for data aquisition, the study design, the methods for data processing and their corresponding results according to their suitability for a continous RR monitoring.

7.1 Data Aquisition

7.1.1 Sensor Placement

For recording the dataset a chest-worn IMU sensor was used, which was easy to attach with a chest belt because there was nothing special to watch out for. However, the respiration belt for recording the ground truth respiration signal was more difficult to attach correctly. The main issue was that the respiration belt needed to be pulled tight while completely exhaling, otherwise it might happen that the respiration signal spikes downwards when the participants exhales deeply e.g. in the *Exhalation and hold* breathing pattern. Although the participants were instructed to do so, there were still a few occasions where this was notable in the respiration signal. A possible solution for that would be to let the study supervisor attach the respiration belt to make sure it is tight enough. However there is still be possibility for human error. A less error prone approach would be to test the signal quality during the *Initialization* phase, to assure a reliable ground truth signal. Another limitation is that in this dataset respiration was only recorded based on displacements of the rib cage, whereas abdominal or diaphragmatic breathing was not recorded at all. The signal quality of ground truth could therefor be further optimized by considering this additional measurement for further research.

7.1.2 Study Protocol

For evaluation of the presented algorithms the participants went through several phases, where they were instructed to speak, switch posture and to follow prescribed breathing patterns. Between phases there were multiple baselines for recovery, which were not further analysed. The results show that algorithms generally perform better on the phases with a regular and calm breathing pattern like *Metronome Breathing*, *Standing and rest* or *Sitting and rest*. Whereas phases with irregular breathing, like the *Hyperventilation* phase or the phases containing intervals where participants were instructed to hold their breath, were harder to estimate RR on. Most likely because extraction algorithms fail to replicate longer intervals of no breathing. In case of *Hyperventilation* its probably due to the fact that most participants had a very shallow breathing and some estimation algorithms either failed to detect peaks and/or discarded too much of them.

Another limitation was the algorithm from the Neurokit2 Python package [Mak21], used for estimating the RR of the ground truth signal. In Figure 6.4 it can clearly be seen that even during phases with a prescribed breathing pattern, like *Exhalation and hold*, the reference algorithm results in different RRs, although they should be almost the same for each participant. The reason for this could be too much noise in the respiration signal because of the high sampling rate of 250 Hz. In further research, a additional processing of the raw respiration signal could be investigated in order to remove noise and result in a more reliable ground truth signal.

The study procedure outlined in Section 4.1.3 provided enough different phases for an evaluation of the algorithms used in this work. However, one limitation is that all datasets were recorded in a controlled laboratory environment with a study supervisor present. This likely influenced the behavior and physical activity of the study participants. Furthermore, the use of multiple electrode leads and two chest belts may have restricted the subjects' body movements and breathing patterns. Without these measurement devices, physical and respiratory activity could be less restricted. Future studies should include recordings in everyday environments without supervision and with less restrictive methods for reference measurements.

7.1.3 Dataset Population

The recorded dataset originally consisted of 16 participants (10 male, 6 female), of which four (3 male, 1 female) were excluded because of corrupted IMU data. However, since this study only contained young and healthy participants, there is still need to validate the results on a bigger dataset. Therefore future work should include a wider range of participants, in order to properly evaluate the effectiveness of IMU and ECG derived RR. This should include individuals of different ages, ethnicities and also with different respiration related diseases in order to provide more profound results.

7.2 Data Processing

7.2.1 Signal Extraction

For extraction of respiration signals, 12 different algorithms were implemented. Nine were based on ECG signals and three on IMU signals. As reported in Section 6, the algorithms based on the Biopac ECG signal achieved slightly higher correlation than the ones based on NilsPod ECG and NilsPod IMU signals. There are several possible explanations for these results. On the one hand the Biopac ECG signal is less preprocessed than the NilsPod ECG signal, which can also seen in Figure 4.2. Therefore respiration induced artifacts like BW,AM and FM could be less prominent. On the other hand the NilsPod IMU signals do not only contain acceleration or gyration induced from breathing, but also from regular upper body movement. This leads to large spikes, when for example sitting down or standing up. However, there are ways to compensate these effects. For example by using a reference IMU sensor which is placed on a body part that is not involved in respiratory movements (e.g., coccyx or anterior superior iliac crest). This can then be used for extracting only the respiration induced movements [Ces18].

Moreover, the IMU based approaches were still able to extract signals with a relatively high correlation to the ground truth signal of around 0.75. These findings support previous research from Skoric et al. [Sko20], which showed similar correlations by also using just one IMU node.

7.2.2 RR Estimation

For estimation of RR, five different algorithms were implemented, which calculated a respiration rate based on a extracted respiration signal. The algorithm *CountOrig* was by far the best-performing one. As shown in 6.2 nine of the ten best combinations used it as an estimation algorithm. This is somewhat surprising, because Schäfer et al. reported in his work that the *CountAdv* algorithm performed better than *CountOrig* [Sch08]. The discrepancy could be attributed to the noise in the respiration signals, because when many large spikes are present, its likely that the Q_3 threshold is influenced and more correct respiration peaks are excluded.

7.2.3 Fusion

After evaluation of all extraction and estimation combinations, the best combination for each sensor modality was selected to be combined in the fusion algorithm. These combinations were the *(ExtractionSoni2019, CountOrig)* for both ECGs and *(PositionalVectorExtraction, CountOrig)* for the IMU signals. By fusing the RR estimates the range of error significantly decreased, as apparent when comparing Figure 6.4 and Figure 6.6. There is abundant room for further optimising estimation of RRs. For example there are much more advanced fusion algorithms available using temporal smoothing or spectral analysis methods [Cha16].

Chapter 8

Conclusion and Outlook

This first research goal of this work was to implement and systematically compare different algorithms to derive respiratory information from ECG and IMU signals. For that purpose a set of interchangeable extraction and estimation algorithms was implemented. The resulting respiration signals and the estimated RRs , of a recorded dataset with 12 Participants, were then used for evaluation. The best algorithm for extraction of a respiration signal was ECG based, and achieved a mean PCC of $-0.3.14$ and a SD of ± 0.249254.

Moreover, the best algorithm combination for estimating RR with ECG signals was found to have a MAE of 7.526957 breaths per minute. Which first seems extraordinary high considering a range from 12 to 16 breaths per minute in an average adult person. But first of all that is the value for all phases. But it needs to be emphasized that phases, which were in general more difficult to estimate correctly, strongly contributed to this value. Secondly the algorithm for estimating RR with the ground truth signal also sometimes resulted in incorrect RRs due to noise and problems during data aquisition. The best algorithm combination when using IMU signals performed only slightly worse, with a MAE of 8.357204.

As the second research goal of this thesis, further potential of combining IMU and ECG data in order to improve signal and estimation quality. Therefore, the best performing algorithm combination for each sensor modality were combined in a fusion algorithm. The computed fused RRs showed a clear improvement in all evaluated phases.

In this thesis it was shown that combining IMU and ECG can improve quality of RR estimations. However the dataset was still recorded in a controlled laboratory environment. In order to make this approach suitable for home monitoring, more recordings in everyday environments need to be included in future studies. However, for that the used sensor systems would need to be even less obstrusive, for example by using the *NilsPod* ECG sensor instead of the *BioPac MP160*. Also in regards to signal quality there is still a long way to go, as the differences of multiple breaths per minute are still too large to make this method reliable for a home monitoring environment. Because of that, future research should focus on isolating respiration induced acceleration and gyration by using multiple nodes instead of just one, in order to further improve IMU based respiration extraction.

Appendix A

Glosary

DNN deep neural network

RR respiration rate

IMU inertial measurement unit

EDR ECG-derived respiration

RSA respiratory sinus arrhythmia

ECG electrocardiogram

PRT pneumatic respiration transducer

PPG photoplethysmogram

IP impedance pneumograph

SD standard deviation

COPD chronic obstructive pulmonary disease

SIDS Sudden Infant Death Syndrome

ICU intensive care unit

AM amplitude modulation

BW baseline wander

FM frequency modulation

CWT continuous wavelet transform

RAP ridge amplitude perturbation

RFP ridge amplitude perturbation

FFT fast fourier transform

MAE Mean absolute error

PCC Pearson correlation coefficient

Appendix B

Listings

B.1 Python code for RR ground truth calculation

```
class NeurokitDetection(BaseEstimationRR):

    """
    Algorithm used for calculating the reference respiration rate.
    Calculates RR signal and returns the mean of that signal.
    """

    def estimate(self, respiration_signal: pd.DataFrame,
                                     sampling_rate: float):

        """
        @param respiration_signal: respiratory_signal to extract
                                       respiration rate
        @param sampling_rate: sampling rate of the respiratory_signal
        @return: self, respiration rate is saved as a instance
                                       attribute self.
                                       respiration_rate (float
                                       if successful nan
        otherwise)
        """

        # Check if signal is too short
        minimum_seconds = 12
```

```
        threshold = sampling_rate * minimum_seconds
        if len(respiration_signal.index) < threshold:
            self.respiration_rate = np.nan
            return self

        # Cleaning signal
        cleaned = nk.rsp_clean(
            respiration_signal.iloc[:, 0], sampling_rate=
                                        sampling_rate
        )

        # Extract peaks
        _, peaks = nk.rsp_peaks(cleaned, sampling_rate=sampling_rate)
        rsp_rate = nk.rsp_rate(cleaned, sampling_rate=sampling_rate)

        self.respiration_rate = np.mean(rsp_rate)
        return self
```

Appendix C

Additional Statistics and Figures

C.1 Ranking of RR Estimations

	Extraction	Estimation	Sensor	RR Mean Absolute Error
22	ExtractionSoni2019	CountOrig	BioPac ECG	7.526957
42	ExtractionSarkar2015	CountOrig	BioPac ECG	7.52776
7	ExtractionCharlton	CountOrig	NilsPod ECG	7.57107
42	ExtractionSarkar2015	CountOrig	NilsPod ECG	7.656179
22	ExtractionSoni2019	CountOrig	NilsPod ECG	7.7197
37	ExtractionOrphandiou	CountOrig	BioPac ECG	7.750569
2	ExtractionKarlen	CountOrig	NilsPod ECG	7.777508
37	ExtractionOrphandiou	CountOrig	NilsPod ECG	7.786824
20	ExtractionSoni2019	PeakDetection	NilsPod ECG	7.859076
2	ExtractionKarlen	CountOrig	BioPac ECG	7.869668
8	ExtractionCharlton	CountAdvDetection	BioPac ECG	7.903433
10	ExtractionVangent2019	PeakDetection	NilsPod ECG	8.009535
10	ExtractionVangent2019	PeakDetection	BioPac ECG	8.018071
3	ExtractionKarlen	CountAdvDetection	BioPac ECG	8.04716
4	ExtractionKarlen	GradiantDetection	BioPac ECG	8.049854
35	ExtractionOrphandiou	PeakDetection	BioPac ECG	8.069058
35	ExtractionOrphandiou	PeakDetection	NilsPod ECG	8.140228
12	ExtractionVangent2019	CountOrig	BioPac ECG	8.159637
12	ExtractionVangent2019	CountOrig	NilsPod ECG	8.172626
20	ExtractionSoni2019	PeakDetection	BioPac ECG	8.206364
3	ExtractionKarlen	CountAdvDetection	NilsPod ECG	8.265588
8	ExtractionCharlton	CountAdvDetection	NilsPod ECG	8.28529
32	ExtractionAddisonFM	CountOrig	NilsPod ECG	8.305268
2	PositionalVectorExtraction	CountOrig	NilsPod IMU	8.357204
1	ExtractionKarlen	PeakThroughDetection	BioPac ECG	8.37099
1	ExtractionKarlen	PeakThroughDetection	NilsPod ECG	8.456003
6	ExtractionCharlton	PeakThroughDetection	NilsPod ECG	8.463781
6	ExtractionCharlton	PeakThroughDetection	BioPac ECG	8.557275
9	ExtractionCharlton	GradiantDetection	NilsPod ECG	8.652321
32	ExtractionAddisonFM	CountOrig	BioPac ECG	8.65773
13	SavGolExtractionAcc	CountAdvDetection	NilsPod IMU	8.705614
27	ExtractionAddisonAM	CountOrig	NilsPod ECG	8.717575
44	ExtractionSarkar2015	GradiantDetection	NilsPod ECG	8.726912
8	SavGolExtractionGyr	CountAdvDetection	NilsPod IMU	8.748673
17	ExtractionLindeberg	CountOrig	BioPac ECG	8.776838
27	ExtractionAddisonAM	CountOrig	BioPac ECG	8.868236
43	ExtractionSarkar2015	CountAdvDetection	BioPac ECG	8.968984
39	ExtractionOrphandiou	GradiantDetection	NilsPod ECG	8.981982
7	ExtractionCharlton	CountOrig	BioPac ECG	9.003326
12	SavGolExtractionAcc	CountOrig	NilsPod IMU	9.045418
5	ExtractionCharlton	PeakDetection	NilsPod ECG	9.057889
3	PositionalVectorExtraction	CountAdvDetection	NilsPod IMU	9.057994
18	ExtractionLindeberg	CountAdvDetection	NilsPod ECG	9.118871
9	ExtractionCharlton	GradiantDetection	BioPac ECG	9.127045
4	ExtractionKarlen	GradiantDetection	NilsPod ECG	9.164712

	Extraction	Estimation	Sensor	RR Mean Absolute Error
0	ExtractionKarlen	PeakDetection	NilsPod ECG	9.17467
14	ExtractionVangent2019	GradiantDetection	NilsPod ECG	9.215795
38	ExtractionOrphandiou	CountAdvDetection	NilsPod ECG	9.253925
43	ExtractionSarkar2015	CountAdvDetection	NilsPod ECG	9.279574
38	ExtractionOrphandiou	CountAdvDetection	BioPac ECG	9.3227
23	ExtractionSoni2019	CountAdvDetection	BioPac ECG	9.399044
23	ExtractionSoni2019	CountAdvDetection	NilsPod ECG	9.439697
13	ExtractionVangent2019	CountAdvDetection	NilsPod ECG	9.44772
40	ExtractionSarkar2015	PeakDetection	NilsPod ECG	9.564632
28	ExtractionAddisonAM	CountAdvDetection	BioPac ECG	9.611468
33	ExtractionAddisonFM	CountAdvDetection	BioPac ECG	9.618481
28	ExtractionAddisonAM	CountAdvDetection	NilsPod ECG	9.627963
33	ExtractionAddisonFM	CountAdvDetection	NilsPod ECG	9.631345
18	ExtractionLindeberg	CountAdvDetection	BioPac ECG	9.654608
36	ExtractionOrphandiou	PeakThroughDetection	NilsPod ECG	9.672455
13	ExtractionVangent2019	CountAdvDetection	BioPac ECG	9.738027
0	ExtractionKarlen	PeakDetection	BioPac ECG	9.84998
39	ExtractionOrphandiou	GradiantDetection	BioPac ECG	10.029961
36	ExtractionOrphandiou	PeakThroughDetection	BioPac ECG	10.033733
41	ExtractionSarkar2015	PeakThroughDetection	BioPac ECG	10.130162
11	ExtractionVangent2019	PeakThroughDetection	BioPac ECG	10.282571
40	ExtractionSarkar2015	PeakDetection	BioPac ECG	10.352067
11	SavGolExtractionAcc	PeakThroughDetection	NilsPod IMU	10.438534
21	ExtractionSoni2019	PeakThroughDetection	BioPac ECG	10.524512
11	ExtractionVangent2019	PeakThroughDetection	NilsPod ECG	10.559157
41	ExtractionSarkar2015	PeakThroughDetection	NilsPod ECG	10.569465
16	ExtractionLindeberg	PeakThroughDetection	BioPac ECG	10.639258
14	ExtractionVangent2019	GradiantDetection	BioPac ECG	10.866124
31	ExtractionAddisonFM	PeakThroughDetection	BioPac ECG	11.03218
21	ExtractionSoni2019	PeakThroughDetection	NilsPod ECG	11.038163
7	SavGolExtractionGyr	CountOrig	NilsPod IMU	11.055842
6	SavGolExtractionGyr	PeakThroughDetection	NilsPod IMU	11.176994
44	ExtractionSarkar2015	GradiantDetection	BioPac ECG	11.235589
31	ExtractionAddisonFM	PeakThroughDetection	NilsPod ECG	11.261452
5	ExtractionCharlton	PeakDetection	BioPac ECG	11.385997
17	ExtractionLindeberg	CountOrig	NilsPod ECG	11.508222
1	PositionalVectorExtraction	PeakThroughDetection	NilsPod IMU	11.643594
26	ExtractionAddisonAM	PeakThroughDetection	BioPac ECG	11.668878
29	ExtractionAddisonAM	GradiantDetection	BioPac ECG	11.677441
4	PositionalVectorExtraction	GradiantDetection	NilsPod IMU	11.808556
24	ExtractionSoni2019	GradiantDetection	NilsPod ECG	11.894221
24	ExtractionSoni2019	GradiantDetection	BioPac ECG	12.107589
14	SavGolExtractionAcc	GradiantDetection	NilsPod IMU	12.14389

	Extraction	Estimation	Sensor	RR Mean Absolute Error
16	ExtractionLindeberg	PeakThroughDetection	NilsPod ECG	13.195909
19	ExtractionLindeberg	GradiantDetection	BioPac ECG	13.316477
26	ExtractionAddisonAM	PeakThroughDetection	NilsPod ECG	14.686988
9	SavGolExtractionGyr	GradiantDetection	NilsPod IMU	14.851874
29	ExtractionAddisonAM	GradiantDetection	NilsPod ECG	16.794699
25	ExtractionAddisonAM	PeakDetection	BioPac ECG	18.744934
19	ExtractionLindeberg	GradiantDetection	NilsPod ECG	23.558622
25	ExtractionAddisonAM	PeakDetection	NilsPod ECG	25.50224
15	ExtractionLindeberg	PeakDetection	BioPac ECG	27.884567
15	ExtractionLindeberg	PeakDetection	NilsPod ECG	36.902604
5	SavGolExtractionGyr	PeakDetection	NilsPod IMU	47.143896
34	ExtractionAddisonFM	GradiantDetection	NilsPod ECG	50.02592
0	PositionalVectorExtraction	PeakDetection	NilsPod IMU	52.313423
34	ExtractionAddisonFM	GradiantDetection	BioPac ECG	62.227418
10	SavGolExtractionAcc	PeakDetection	NilsPod IMU	76.838792
30	ExtractionAddisonFM	PeakDetection	BioPac ECG	13902.387507
30	ExtractionAddisonFM	PeakDetection	NilsPod ECG	14247.765421

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Bibliography

[Add04] Paul S. Addison and James N. Watson. "Secondary transform decoupling of shifted nonstationary signal modulation components: application to photoplethysmography". In: *International Journal of Wavelets, Multiresolution and Information Processing* 02.1 (Mar. 2004). Publisher: World Scientific Publishing Co., pp. 43–57. ISSN: 0219-6913. DOI: 10.1142/S0219691304000329. URL: https://www.worldscientific.com/doi/abs/10.1142/S0219691304000329 (visited on 10/28/2022).

[Bai06] Raquel Bail. "ECG-Derived Respiratory Frequency Estimation". In: (2006), p. 30.

[Boy09] Justin Boyle, Niranjan Bidargaddi, Antti Sarela, and Mohan Karunanithi. "Automatic Detection of Respiration Rate From Ambulatory Single-Lead ECG". In: *IEEE Transactions on Information Technology in Biomedicine* 13.6 (Nov. 2009). Conference Name: IEEE Transactions on Information Technology in Biomedicine, pp. 890–896. ISSN: 1558-0032. DOI: 10.1109/TITB.2009.2031239.

[Car14] Filipe S. Cardoso, Constantine J. Karvellas, Norman M. Kneteman, Glenda Meeberg, Pedro Fidalgo, and Sean M. Bagshaw. "Respiratory rate at intensive care unit discharge after liver transplant is an independent risk factor for intensive care unit readmission within the same hospital stay: A nested case-control study". In: *Journal of Critical Care* 29.5 (Oct. 1, 2014), pp. 791–796. ISSN: 0883-9441. DOI: 10.1016/j.jcrc.2014.03.038. URL: https://www.sciencedirect.com/science/article/pii/S0883944114001440 (visited on 12/05/2022).

[Ces18] Ambra Cesareo, Ylenia Previtali, Emilia Biffi, and Andrea Aliverti. "Assessment of Breathing Parameters Using an Inertial Measurement Unit (IMU)-Based System". In: *Sensors* 19.1 (Dec. 27, 2018), p. 88. ISSN: 1424-8220. DOI: 10.3390/

s19010088. URL: http://www.mdpi.com/1424-8220/19/1/88 (visited on 04/26/2022).

[Cha16] Peter H. Charlton, Timothy Bonnici, Lionel Tarassenko, David A. Clifton, Richard Beale, and Peter J. Watkinson. "An assessment of algorithms to estimate respiratory rate from the electrocardiogram and photoplethysmogram". In: *Physiological Measurement* 37.4 (Apr. 1, 2016). Publisher: IOP Publishing, pp. 610–626. ISSN: 0967-3334. DOI: 10.1088/0967-3334/37/4/610. URL: http://dx.doi.org/10.1088/0967-3334/37/4/610.

[Con18] N. T. Contributor. *Respiratory rate 1: why measurement and recording are crucial*. Nursing Times. Mar. 26, 2018. URL: https://www.nursingtimes.net/clinical-archive/respiratory-clinical-archive/respiratory-rate-1-why-measurement-and-recording-are-crucial-26-03-2018/ (visited on 08/09/2022).

[Cre08] Michelle A Cretikos, Rinaldo Bellomo, Ken Hillman, Jack Chen, Simon Finfer, and Arthas Flabouris. "The Medical Journal of Australia". In: 188.11 (2008). tex.ids= Cretikos2008, p. 3.

[De 93] R. E. De Meersman. "Aging as a modulator of respiratory sinus arrhythmia". In: *Journal of Gerontology* 48.2 (Mar. 1993), B74–78. ISSN: 0022-1422. DOI: 10.1093/geronj/48.2.b74.

[Fla67] John T. Flaherty, Sarah D. Blumenschein, Ann W. Alexander, Richard D. Gentzler, Thomas M. Gallie, John P. Boineau, and Madison S. Spach. "Influence of respiration on recording cardiac potentials: Isopotential surface-mapping and vectorcardiographic studies∗". In: *The American Journal of Cardiology*. Symposium on The Pulmonary Heart and the Cardiac Lung 20.1 (July 1, 1967), pp. 21–28. ISSN: 0002-9149. DOI: 10.1016/0002-9149(67)90106-3. URL: https://www.sciencedirect.com/science/article/pii/0002914967901063 (visited on 12/05/2022).

[Fle] Susannah Fleming. "Measurement and fusion of non-invasive vital signs for routine triage of acute paediatric illness". In: (), p. 249.

[Fle17] Tracy Flenady, Trudy Dwyer, and Judith Applegarth. "Accurate respiratory rates count: So should you!" In: *Australasian emergency nursing journal: AENJ* 20.1 (Feb. 2017), pp. 45–47. ISSN: 1839-2776. DOI: 10.1016/j.aenj.2016.12.003.

[Gen19] Paul van Gent, Haneen Farah, Nicole van Nes, and Bart van Arem. "HeartPy: A novel heart rate algorithm for the analysis of noisy signals". In: *Transportation Research. Part F: Traffic Psychology and Behaviour* 66 (2019), pp. 368–378. ISSN: 1369-8478. DOI: 10.1016/j.trf.2019.09.015. URL: http://www.scopus.com/inward/record.url?scp=85072869351&partnerID=8YFLogxK (visited on 12/07/2022).

[Gou15] Robert M. Goulding, Nathan J. Stevenson, Deirdre M. Murray, Vicki Livingstone, Peter M. Filan, and Geraldine B. Boylan. "Heart rate variability in hypoxic ischemic encephalopathy: correlation with EEG grade and 2-y neurodevelopmental outcome". In: *Pediatric Research* 77.5 (May 2015). Number: 5 Publisher: Nature Publishing Group, pp. 681–687. ISSN: 1530-0447. DOI: 10.1038/pr.2015.28. URL: https://www.nature.com/articles/pr201528 (visited on 12/05/2022).

[Gro07] Paul Grossman and Edwin W. Taylor. "Toward understanding respiratory sinus arrhythmia: Relations to cardiac vagal tone, evolution and biobehavioral functions". In: *Biological Psychology*. Special Issue of Biological Psychology on Cardiac Vagal Control, Emotion, Psychopathology, and Health. 74.2 (Feb. 1, 2007), pp. 263–285. ISSN: 0301-0511. DOI: 10.1016/j.biopsycho.2005.11.014. URL: https://www.sciencedirect.com/science/article/pii/S0301051106001876 (visited on 12/05/2022).

[Hod02] Timothy J. Hodgetts, Gary Kenward, Ioannis G. Vlachonikolis, Susan Payne, and Nicolas Castle. "The identification of risk factors for cardiac arrest and formulation of activation criteria to alert a medical emergency team". In: *Resuscitation* 54.2 (Aug. 1, 2002), pp. 125–131. ISSN: 0300-9572. DOI: 10.1016/S0300-9572(02)00100-4. URL: https://www.sciencedirect.com/science/article/pii/S0300957202001004 (visited on 12/05/2022).

[Joh03] A. Johansson. "Neural network for photoplethysmographic respiratory rate monitoring". In: *Medical and Biological Engineering and Computing* 41.3 (May 1, 2003), pp. 242–248. ISSN: 1741-0444. DOI: 10.1007/BF02348427. URL: https://doi.org/10.1007/BF02348427 (visited on 12/07/2022).

[Kar13] Walter Karlen, Srinivas Raman, J. Mark Ansermino, and Guy A. Dumont. "Multiparameter Respiratory Rate Estimation From the Photoplethysmogram". In: *IEEE Transactions on Biomedical Engineering* 60.7 (July 2013). Publisher: IEEE, pp. 1946–1953. ISSN: 0018-9294. DOI: 10.1109/TBME.2013.2246160. URL: http://ieeexplore.ieee.org/document/6458992/.

[Kel11] John Kellett, Min Li, Shahzeb Rasool, Geoffrey C. Green, and Andrew Seely. "Comparison of the heart and breathing rate of acutely ill medical patients recorded by nursing staff with those measured over 5min by a piezoelectric belt and ECG monitor at the time of admission to hospital". In: *Resuscitation* 82.11 (Nov. 1, 2011), pp. 1381–1386. ISSN: 0300-9572. DOI: 10.1016/j.resuscitation.2011.07.013. URL: https://www.sciencedirect.com/science/article/pii/S0300957211004497 (visited on 12/05/2022).

[Láz13] Jesús Lázaro, Eduardo Gil, Raquel Bailón, Ana Mincholé, and Pablo Laguna. "Deriving respiration from photoplethysmographic pulse width". In: *Medical & Biological Engineering & Computing* 51.1 (Feb. 1, 2013), pp. 233–242. ISSN: 1741-0444. DOI: 10.1007/s11517-012-0954-0. URL: https://doi.org/10.1007/s11517-012-0954-0 (visited on 12/06/2022).

[Lin92] L. -G. Lindberg, H. Ugnell, and P. Å. Öberg. "Monitoring of respiratory and heart rates using a fibre-optic sensor". In: *Medical and Biological Engineering and Computing* 30.5 (Sept. 1, 1992), pp. 533–537. ISSN: 1741-0444. DOI: 10.1007/BF02457833. URL: https://doi.org/10.1007/BF02457833 (visited on 11/02/2022).

[Liu19] Haipeng Liu, John Allen, Dingchang Zheng, and Fei Chen. "Recent development of respiratory rate measurement technologies". In: *Physiological Measurement* 40.7 (July 2019). Publisher: IOP Publishing, 07TR01. ISSN: 0967-3334. DOI: 10.1088/1361-6579/ab299e. URL: https://doi.org/10.1088/1361-6579/ab299e (visited on 06/07/2022).

[Mak21] Dominique Makowski, Tam Pham, Zen J. Lau, Jan C. Brammer, François Lespinasse, Hung Pham, Christopher Schölzel, and S. H. Annabel Chen. "NeuroKit2: A Python toolbox for neurophysiological signal processing". In: *Behavior Research Methods* 53.4 (Aug. 2021), pp. 1689–1696. ISSN: 1554-3528. DOI: 10.3758/s13428-020-01516-y. URL: https://doi.org/10.3758/s13428-020-01516-y.

[Maz03] B. Mazzanti, C. Lamberti, and J. de Bie. "Validation of an ECG-derived respiration monitoring method". In: *Computers in Cardiology, 2003*. Computers in

Cardiology, 2003. ISSN: 0276-6547. Sept. 2003, pp. 613–616. DOI: 10.1109/CIC.2003.1291230.

[Mer12] D. J. Meredith, D. Clifton, P. Charlton, J. Brooks, C. W. Pugh, and L. Tarassenko. “Photoplethysmographic derivation of respiratory rate: a review of relevant physiology”. In: *Journal of Medical Engineering & Technology* 36.1 (Mar. 1, 2012). Publisher: Taylor & Francis _eprint: https://doi.org/10.3109/03091902.2011.638965, pp. 1–7. ISSN: 0309-1902. DOI: 10.3109/03091902.2011.638965. URL: https://doi.org/10.3109/03091902.2011.638965 (visited on 12/05/2022).

[Mły12] Marcel Młyńczak and Gerard Cybulski. “Impedance pneumography: Is it possible?” In: *Photonics Applications in Astronomy, Communications, Industry, and High-Energy Physics Experiments 2012*. Photonics Applications in Astronomy, Communications, Industry, and High-Energy Physics Experiments 2012. Vol. 8454. SPIE, Oct. 15, 2012, pp. 542–555. DOI: 10.1117/12.2000223. URL: https://www.spiedigitallibrary.org/conference-proceedings-of-spie/8454/84541T/Impedance-pneumography-Is-it-possible/10.1117/12.2000223.full (visited on 06/10/2022).

[Moo85] George Moody, Roger Mark, Andrea Zoccola, and Sara Mantero. “Derivation of Respiratory Signals from Multilead ECGs”. In: *Computers in Cardiology* 12 (Jan. 1, 1985).

[OBr07] Ciara O’Brien and Conor Heneghan. “A comparison of algorithms for estimation of a respiratory signal from the surface electrocardiogram”. In: *Computers in Biology and Medicine* 37.3 (Mar. 1, 2007), pp. 305–314. ISSN: 0010-4825. DOI: 10.1016/j.compbiomed.2006.02.002. URL: https://www.sciencedirect.com/science/article/pii/S0010482506000357 (visited on 11/30/2022).

[Orp09] Christina Orphanidou, Oliver Brain, Jacques Feldmar, Shahab Khan, James Price, and Lionel Tarassenko. “Spectral fusion for estimating respiratory rate from the ECG”. In: *2009 9th International Conference on Information Technology and Applications in Biomedicine*. 2009 9th International Conference on Information Technology and Applications in Biomedicine. ISSN: 2168-2208. Nov. 2009, pp. 1–4. DOI: 10.1109/ITAB.2009.5394435.

[Orp13] C. Orphanidou, S. Fleming, S. A. Shah, and L. Tarassenko. "Data fusion for estimating respiratory rate from a single-lead ECG". In: *Biomedical Signal Processing and Control* 8.1 (Jan. 1, 2013), pp. 98–105. ISSN: 1746-8094. DOI: 10.1016/j.bspc.2012.06.001. URL: https://www.sciencedirect.com/science/article/pii/S1746809412000699 (visited on 12/06/2022).

[Ott16] G. Ottaviano and W. J. Fokkens. "Measurements of nasal airflow and patency: a critical review with emphasis on the use of peak nasal inspiratory flow in daily practice". In: *Allergy* 71.2 (2016). _eprint: https://onlinelibrary.wiley.com/-doi/pdf/10.1111/all.12778, pp. 162–174. ISSN: 1398-9995. DOI: 10.1111/all.12778. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/all.12778 (visited on 06/07/2022).

[Pal89] R. Pallas-Areny, J. Colominas-Balague, and F.J. Rosell. "The effect of respiration-induced heart movements on the ECG". In: *IEEE Transactions on Biomedical Engineering* 36.6 (June 1989). Conference Name: IEEE Transactions on Biomedical Engineering, pp. 585–590. ISSN: 1558-2531. DOI: 10.1109/10.29452.

[Pla] Jesus Lazaro Plaza. "Non-invasive techniques for respiratory information extraction based on pulse photoplethysmogram and electrocardiogram". In: (), p. 142.

[Pon01] Piotr Ponikowski, Tuan Peng Chua, Stefan D. Anker, Darrel P. Francis, Wolfram Doehner, Waldemar Banasiak, Phillip A. Poole-Wilson, Massimo F. Piepoli, and Andrew J.S. Coats. "Peripheral Chemoreceptor Hypersensitivity". In: *Circulation* 104.5 (July 31, 2001). Publisher: American Heart Association, pp. 544–549. DOI: 10.1161/hc3101.093699. URL: https://www.ahajournals.org/doi/10.1161/hc3101.093699 (visited on 12/05/2022).

[Rah21] Mahfuzur Rahman and Bashir I. Morshed. "Estimation of Respiration Rate using an Inertial Measurement Unit Placed on Thorax-Abdomen". In: *2021 IEEE International Conference on Electro Information Technology (EIT)*. 2021 IEEE International Conference on Electro Information Technology (EIT). ISSN: 2154-0373. May 2021, pp. 1–5. DOI: 10.1109/EIT51626.2021.9491900.

[Ram15] Clotilde Rambaud-Althaus, Fabrice Althaus, Blaise Genton, and Valérie D'Acremont. "Clinical features for diagnosis of pneumonia in children younger than 5 years: a systematic review and meta-analysis". In: *The Lancet Infectious Dis-*

eases 15.4 (Apr. 1, 2015), pp. 439–450. ISSN: 1473-3099. DOI: 10.1016/S1473-3099(15)70017-4. URL: https://www.sciencedirect.com/science/article/pii/S1473309915700174 (visited on 12/05/2022).

[Ric21] Robert Richer, Arne Küderle, Martin Ullrich, Nicolas Rohleder, and Bjoern M. Eskofier. "BioPsyKit: A Python package for the analysis of biopsychological data". In: *Journal of Open Source Software* 6.66 (Oct. 12, 2021), p. 3702. ISSN: 2475-9066. DOI: 10.21105/joss.03702. URL: https://joss.theoj.org/papers/10.21105/joss.03702 (visited on 12/06/2022).

[Rol19] Sandy Rolfe. "The importance of respiratory rate monitoring". In: *British Journal of Nursing* 28.8 (Apr. 25, 2019). Publisher: Mark Allen Group, pp. 504–508. ISSN: 0966-0461. DOI: 10.12968/bjon.2019.28.8.504. URL: https://www.magonlinelibrary.com/doi/full/10.12968/bjon.2019.28.8.504 (visited on 08/09/2022).

[Sar15] Surita Sarkar, Saptak Bhattacherjee, and Saurabh Pal. "Extraction of respiration signal from ECG for respiratory rate estimation". In: *Michael Faraday IET International Summit 2015*. Michael Faraday IET International Summit 2015. Sept. 2015, pp. 336–340. DOI: 10.1049/cp.2015.1654.

[Sch08] Axel Schäfer and Karl W. Kratky. "Estimation of Breathing Rate from Respiratory Sinus Arrhythmia: Comparison of Various Methods". In: *Annals of Biomedical Engineering* 36.3 (Jan. 11, 2008). tex.ids= Schafer2008, p. 476. ISSN: 1573-9686. DOI: 10.1007/s10439-007-9428-1. URL: https://doi.org/10.1007/s10439-007-9428-1 (visited on 06/10/2022).

[Sha12] S. Shah. "Vital sign monitoring and data fusion for paediatric triage". http://purl.org/dc/dcmitype/Text. Oxford University, UK, 2012. URL: https://ora.ox.ac.uk/objects/uuid:80ae66e3-849b-4df1-b064-f9eb7530200d (visited on 11/09/2022).

[Sko20] James Skoric, Yannick D'Mello, Ezz Aboulezz, Siddiqui Hakim, Nathan Clairmonte, Michel Lortie, and David V. Plant. "Relationship of the Respiration Waveform to a Chest Worn Inertial Sensor". In: *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. 2020 42nd Annual International Conference of the IEEE Engineering in Medicine &

Biology Society (EMBC). ISSN: 2694-0604. July 2020, pp. 2732–2735. DOI: 10.1109/EMBC44109.2020.9176245.

[Son19] Rahul Soni and Manivannan Muniyandi. "Breath Rate Variability: A Novel Measure to Study the Meditation Effects". In: *International Journal of Yoga* 12.1 (2019), pp. 45–54. ISSN: 0973-6131. DOI: 10.4103/ijoy.IJOY_27_17. URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6329220/ (visited on 12/07/2022).

[Taw12] M Iqbal Tawakal, M Eka Suryana, Ari Noviyanto, I Putu Satwika, M Sakti Alvissalim, Indra Hermawan, Sani M. Isa, and Wisnu Jatmiko. "Analysis of multi codebook GLVQ versus standard GLVQ in discriminating sleep stages". In: *2012 International Conference on Advanced Computer Science and Information Systems (ICACSIS)*. 2012 International Conference on Advanced Computer Science and Information Systems (ICACSIS). Dec. 2012, pp. 197–202.

[Vir20] Pauli Virtanen, Ralf Gommers, Travis E. Oliphant, Matt Haberland, Tyler Reddy, David Cournapeau, Evgeni Burovski, Pearu Peterson, Warren Weckesser, Jonathan Bright, Stéfan J. van der Walt, Matthew Brett, Joshua Wilson, K. Jarrod Millman, Nikolay Mayorov, Andrew R. J. Nelson, Eric Jones, Robert Kern, Eric Larson, C. J. Carey, İlhan Polat, Yu Feng, Eric W. Moore, Jake VanderPlas, Denis Laxalde, Josef Perktold, Robert Cimrman, Ian Henriksen, E. A. Quintero, Charles R. Harris, Anne M. Archibald, Antônio H. Ribeiro, Fabian Pedregosa, and Paul van Mulbregt. "SciPy 1.0: fundamental algorithms for scientific computing in Python". In: *Nature Methods* 17.3 (Mar. 2020). Number: 3 Publisher: Nature Publishing Group, pp. 261–272. ISSN: 1548-7105. DOI: 10.1038/s41592-019-0686-2. URL: https://www.nature.com/articles/s41592-019-0686-2 (visited on 12/08/2022).

[Wid10] Devy Widjaja, Joachim Taelman, Steven Vandeput, Marijke AKA Braeken, Rénee A Otte, Bea RH Van den Bergh, and Sabine Van Huffel. "ECG-derived respiration: Comparison and new measures for respiratory variability". In: *2010 Computing in Cardiology*. 2010 Computing in Cardiology. ISSN: 2325-8853. Sept. 2010, pp. 149–152.

[Yas04] Fumihiko Yasuma and Jun-Ichiro Hayano. "Respiratory sinus arrhythmia: why does the heartbeat synchronize with respiratory rhythm?" In: *Chest* 125.2 (Feb. 2004), pp. 683–690. ISSN: 0012-3692. DOI: 10.1378/chest.125.2.683.