

# **Non-contact assessment of pneumonia in low and middle income countries**



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# Abstract

Pneumonia is an illness usually caused by an acute respiratory tract infection in which lungs become inflamed and congested, limiting oxygen intake and leading to breathlessness. Despite the reduction in cases among children under the age of 5, pneumonia is still the main cause of childhood death in low income countries in Asia and Africa. The global community has therefore committed to ending preventable mortality and morbidity caused by pneumonia by 2025. To achieve this goal, the World Health Organisation (WHO) developed a pneumonia control strategy which provides clinical case management guidelines to offer a basic standard for appropriate assessment and treatment of sick children in Low and Middle Class-Income Countries (LMIC). However, due to factors such as inadequate training and supervision, as well as a shortage of skilled health professionals, adherence to these strategies remain poor in many settings. This failure in guideline implementation is further compounded by large numbers of seriously ill children in need of care.

The WHO recommends the use of raised respiratory rate (RR) and chest wall in-drawing to help health workers in developing countries to diagnose pneumonia. A particular problem, however, is the accuracy and reliability of identification of these key clinical features of pneumonia by junior clinicians. Guidelines on diagnosis, hospital admission and ultimately treatment require clinicians to measure respiratory rate by counting chest wall movements and assess the degree of respiratory distress by physical examination. Studies have shown poor inter-observer agreement for assessing clinical signs, thus technologies that can accurately identify and standardise assessment of respiratory distress would be a major advance towards improving the efficiency and quality of clinical assessment and, ultimately, clinical outcomes for pneumonia.

Smartphones offer a platform for developing these technologies to help healthcare professionals consistently identify clinical signs of severe illness, improve diagnosis of pneumonia and assess its severity. Smart phone cameras have the potential to enable standardised recognition of clinical signs of respiratory distress based on image processing and machine learning algorithms. These advances, combined with low-cost sensors (e.g. for oxygen saturation or temperature measurement), could result in a new generation of decision support tools. The same technology may also contribute towards refining existing WHO clinical algorithms amid growing concerns of diminished specificity of current guidelines for reliably identifying bacterial pneumonia in the post-pneumococcal and Haemophilus I vaccine era.

This transfer report covers the development of algorithms for estimation of heart rate (HR) and RR across two clinical datasets. In chapter 3, red and near-infrared signals from a wrist-worn photoplethysmography (PPG) device were used to estimate HR ( $r = 0.99$ , MAE 1.2 = beats/minute) and RR ( $r = 0.67$ , MAE = 1.6 breaths/minute) during periods of induced hypoxia in a clinical study involving healthy volunteers. In chapter 4, video data from an observational neonatal intensive care unit (NICU) study was used to estimate HR ( $r = 0.83$ , MAE = 3.2 ) and RR ( $r = 0.71$ , MAE = 5.3). These results show that the algorithms developed are applicable in realistic scenarios using data from both wearables and video cameras.



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# List of abbreviations

**$SpO_2$**  Peripheral oxygen saturation, as measured by a pulse oximeter.

**CHW** Community Health Worker.

**DC** non-pulsatile component of the plethysmograph signal.

**HR** Heart rate.

**LMIC** Low and Middle Income Countries.

**MAD** Mean Absolute Deviation.

**MAE** Mean Absolute Error.

**PPG** Photoplethysmography.

**RMSE** Root Mean Square Error.

**ROI** Regions of Interest.

**RR** Respiratory rate.

**SQI** Signal Quality Index.



# Chapter 1

## Introduction

### 1.1 Motivation

Despite a general improvement in living conditions, improved nutrition, introduction of vaccines and greater access to healthcare, pneumonia remains the biggest cause of mortality in children under the age of 5, accounting for more than 15% of childhood deaths globally [55]. In 2011, there were an estimated 120 million episodes of childhood pneumonia globally, of which 14 million advanced to severe disease, leading to 1.3 million deceased cases. Most deaths (81%) occurred in children under 2 years of age. The highest incidences of severe cases were in Southeast Asia (39%) and Africa (30%) [62]. Hospitalisation of children with pneumonia in Low and Middle Income Countries (LMIC) increased from 7% to 50% between 2000 and 2015 [32].

Shortage of clinical expertise, high-quality treatment facilities and availability of adequate medical equipment in LMIC prevents early detection and treatment of pneumonia in children. Timely and accurate diagnosis that facilitates appropriate treatment could reduce mortality by as much as 42% [61]. While high-income countries remain at the forefront of developing the latest mobile technologies used in healthcare, the rate of penetration of such technologies in LMICs has recently exceeded that of their wealthier neighbours [6]. My research therefore aims to develop and implement low-cost, user friendly smart phone algorithms to assist the existing clinical staff in the diagnosis of childhood pneumonia in LMIC areas.

### 1.2 Pneumonia

Pneumonia is a highly prevalent acute respiratory infection. The disease is caused by pathogens such as bacteria, viruses or fungi causing an inflammation in the lungs. The alveoli (the microscopic air sacks in the lungs where oxygen and carbon dioxide exchange occurs) get filled up with fluid and pus, decreasing lung compliance (the change in volume per unit change in pressure). This leads to reduced volume for gas exchange and difficulty in breathing, affecting oxygen supply to the bloodstream [2].

#### 1.2.1 Symptoms and causes

Children diagnosed with pneumonia often present symptoms of fast breathing, classified by the World Health Organisation (WHO) as having a respiratory rate (RR)  $\geq 50$  breaths/min in a child aged 2-11 months and  $\geq 40$  breaths/min in a child aged 1-5 years [41]. In most cases, illness begins as an upper respiratory tract infection and progresses gradually over several days, with increasing severity of cough and respiratory distress. To maintain an adequate supply of air in the lungs during the respiratory cycle with the decreased lung compliance caused by pneumonia, greater inspiratory force is needed. Consequently, the subcostal tissue on the chest is pulled inward during inspiration, producing what the WHO Integrated Management of Childhood Illness (IMCI) guidelines define as chest in-drawing [33]. Children with a cough, difficulty

breathing and chest in-drawing are considered to have severe pneumonia. Very severe pneumonia can be detected from the presence of central cyanosis (blue colour tint in skin, hips or mucus membranes), a peripheral oxygen saturation ( $SpO_2$ ) < 90%, severe respiratory distress or the inability to breastfeed [3].

In severely ill infants and toddlers with a rapid onset and progression of symptoms of pneumonia, the bacteria *Streptococcus pneumoniae* is often the predominant cause of infection. It is estimated to cause 18% of severe cases and 33% of deaths. In 2016, *Streptococcus pneumoniae* was the leading cause of lower respiratory infection morbidity and mortality globally, contributing to more deaths than all other aetiologies combined [56]. Other important pathogens include *Haemophilus influenzae type b* (*Hib*), estimated to account for 4% of severe episodes and 16% of deaths; and *influenza virus*, which is associated with approximately 7% of severe episodes and 11% of deaths. Stagno *et al* [48] found that the presence of more than one pathogen was significantly associated with more frequent requirements for oxygen and mechanical ventilation. These pathogens can infect a child either through air droplets (e.g. from a cough) or through contaminated blood (especially during and shortly after birth) and contribute to the progression of illness.

### 1.2.2 Diagnosis

Even though there are guidelines on recognising pneumonia, diagnosis can often be challenging because the clinical manifestation of pneumonia in children is variable [47]. X-rays, in combination with arterial blood gas tests (ABGs), auscultation of the lungs using a stethoscope, heart rate,  $SpO_2$ , temperature and respiratory rate count are typically used as diagnostic mechanisms [12]. Signs of chronic airflow obstruction, hyperinflation and various abnormalities of chest wall motion are also used to diagnose pneumonia. The WHO recommends that community health workers treat pneumonia in children according to specific case-management algorithms and use respiratory rate (RR) and chest in-drawing for diagnosis [42].

The measurement of other vital signs such as  $SpO_2$ , heart rate (HR) and temperature allows clinicians to have a more complete view of the child's physiology. These vital signs help guide the hospital admission decisions for pneumonia as well as the treatment of other accompanying diseases or complications [31]. RR, HR, and  $SpO_2$  are monitored in those with severe pneumonia or requiring regular oxygen therapy. The gold standard for assessing oxygen saturation is arterial blood gas measurement. However, it is time consuming and invasive. Pulse oximetry is therefore commonly used in hospital settings to monitor pneumonia patients and has also been recommended for use in the community [24].

The most common methods to measure RR and HR are counting breaths using observation and auscultation of the heart respectively. However, it can be difficult to identify breaths and maintain a count when estimating RR by manually counting breaths. Clinically, RR is computed using electrodes attached to the patient's chest, a technique called impedance pneumography (IP) [5]. This technique often requires expensive devices and therefore is not commonly used in LMICs. HR auscultation has similar challenges to counting breaths.

### 1.2.3 Treatment

IMCI guidelines indicate when referral for pneumonia treatment is needed and specify the appropriate antimicrobial agents when referral is not needed. The guidelines state that treatment should target the bacterial causes most likely to lead to severe disease, including *streptococcus pneumoniae* and *Haemophilus influenzae*. Identification of the causative pathogen of pneumonia is however challenging as few children

develop bacteraemic illness, where bacteria is present in the blood stream and detected through blood cultures [62]. Furthermore, only a third of pneumonia cases can be attributed to a certain aetiology via culture, antigen detection or clinically available serological techniques [34]. Most diagnostic tests for pneumonia pathogens have suboptimal diagnostic sensitivity. Blood cultures are frequently performed for hospitalised pneumonia patients but are positive only in <10% of cases [36].

A 2005 technical update of the WHO IMCI guidelines recommended the administration of amoxicillin (50 mg/kg per dose, in two divided doses), with co-trimoxazole as an alternative in the treatment of non-severe pneumonia in some settings. Treatment failure was defined in a child who develops pneumonia signs warranting immediate referral or who did not have a decrease in respiratory rate after 48 – 72 hours of therapy [22]. Suitable recommended treatments include the administration of a high-dose antibiotic (i.e. amoxicillin-clavulanic acid) for children over 3 years of age.

Between 2010 and 2013, more than 54 countries supported by the Global Alliance for Vaccines and Immunisation (GAVI) issued recommendations for paediatric pneumonia treatment, implementing the pneumococcal conjugate vaccine protocols[45]. These recommendations were primarily intended for high to middle-income nations. However, new information on antimicrobial resistance, the changing epidemiology of pneumonia and the availability of a broader range of antimicrobial agents prompted the need to update the guidelines. With improved vaccine uptake, the prevalence of vaccine-targeted pathogens may diminish, while a greater proportion of cases may occur due to *Staphylococcus aureus*, *Klebsiella pneumoniae* and *Mycobacterium tuberculosis* in tuberculosis (TB) endemic areas such as Sub-Saharan Africa. [62]. New guidelines are needed for antimicrobial treatment of non-severe pneumonia among children assessed by first-level health providers, often with basic health training.

### 1.3 Challenges in LMIC

Strategies for prevention, diagnosis and treatment of pneumonia are well documented and are mostly effective in resource-rich settings. However, the accuracy and viability of most diagnostic tools for pneumonia have not been assessed or validated in LMIC. The reference standard for the diagnosis of pneumonia is the extraction of fluid or tissue samples from the lower respiratory tract. Such invasive measures are reserved for patients with severe or life-threatening pneumonia who do not respond to first-line therapies. In general practice, a chest radiograph is considered a clinical reference standard for pneumonia given it is well studied in the literature, is readily available in low-resource settings and is less invasive.

Because of limited resources in LMIC, timely diagnosis of pneumonia is a challenge. The WHO recommendations rely on simple clinical signs: tachypnoea or respiratory distress in a child with cough or difficulty breathing. Community health workers are trained to count the respiratory rate of a child with cough and/or difficulty breathing. The health workers determine whether the child has fast breathing or not based on how the child's respiratory rate relates to generic cut-off thresholds. Counting the number of breaths is typically performed manually with the aid of watches or timers [16], [40]. However, even with these counting aids, measuring a child's respiratory rate through visual observation requires focused concentration and can be challenging in a child who may be moving, crying or breathing rapidly. Inaccurate or imprecise measurements can stem from factors including poor visibility of the start or end of a breath, an irritable or moving child, or difficulty counting or remembering the count [19]. Until now, there has been limited evidence on the efficacy of technology and other affordable tools to help community health workers in resource-poor settings improve the classification of fast breathing or other breathing patterns for the

diagnosis of pneumonia.

The uncertainty surrounding the diagnosis of pneumonia has therefore contributed to antibiotic overuse in children with viral respiratory tract infections. Thus, there is an urgent need to rethink existing practises of using manual breath counts for RR estimation as a stand-alone criteria for diagnosing pneumonia. Cost effective, portable, non-contact methods can be useful in diagnosing pneumonia, particularly in LMIC. If diagnosed early, targeted antibiotic therapy can be initiated to effectively treat the disease.

Recent advances have shown that estimation of vital signs such as HR and RR through non-contact means is viable. This estimation can even be achieved using typical smart phone cameras. Such an approach would allow for the accurate estimation of these vital signs without requiring expensive specialised equipment and clinical expertise. These vital signs estimates, if made available in LMIC, may aid in the early detection and diagnosis of childhood pneumonia.

#### **1.4 Objectives**

The main aim of my DPhil is to develop non-contact video based algorithms to identify breathing patterns and signs of respiratory distress in children diagnosed with pneumonia in LMIC using the video cameras available in smartphones. The algorithms will be implemented as a smartphone-based decision tool that will improve admission and referral decision making, reduce the use of broad-spectrum antibiotics (reserving these only for severe pneumonia cases in line with WHO guidelines) and help reduce the problem of antimicrobial resistance (AMR). In order to do so, the two main areas of research are:

1. The development of algorithms that can accurately estimate vital signs using a smartphone camera.
2. The development of machine learning algorithms for the classification of respiratory patterns in children diagnosed with pneumonia.

#### **1.5 Contributions**

The major contributions made during my first year of DPhil are:

1. Development of signal processing algorithms to assess the quality of the information recorded by wearable devices and estimate vital signs such as HR, RR and  $SpO_2$ .
2. Development of image and video processing algorithms to extract respiratory and cardiac image plethysmography (PPGi) signals from video data recorded from infants in the Neonatal Intensive Care Unit (NICU). From the physiological signal extracted, I developed algorithms to estimate HR and RR.

#### **1.6 Outline of the report**

This report is composed of 5 chapters. Chapter 1 discusses the motivation and objectives of this research. Chapter 2 reviews the background literature and current state-of-the-art technology to diagnose pneumonia. Chapter 3 describes signal processing methods used to compute physiological parameters from wearable devices. Chapter 4 discusses methods used to estimate vital signs from video cameras. Finally, chapter 5 concludes the report and discusses areas of future research work.

# Chapter 2

## Literature review

### 2.1 Introduction

Pneumonia is responsible for approximately 18% of deaths in children under the age of five (see figure 2.1). More than 95% of the childhood pneumonia cases and 99% of subsequent deaths occur in low and middle income countries (LMIC)[44]. However, only 3% of global infectious disease research spending is currently allocated to pneumonia [54], such studies being very rare in LMICs due to their resource-intensiveness.

Accurate and timely diagnosis of pneumonia is essential for the prevention of hospitalisation and reduction of mortality rates however, access to high-quality healthcare is often limited in LMICs. Appropriate diagnostic assessment of childhood pneumonia typically relies on the use of advanced tools (such as X-rays and blood culture) by a clinical expert who assesses and interprets a combination of clinical measurements [21]. This chapter reviews existing diagnostic innovations for childhood pneumonia. These approaches include image based technologies that can accurately identify abnormal breathing patterns and data-driven machine learning algorithms for interpretation of symptoms.

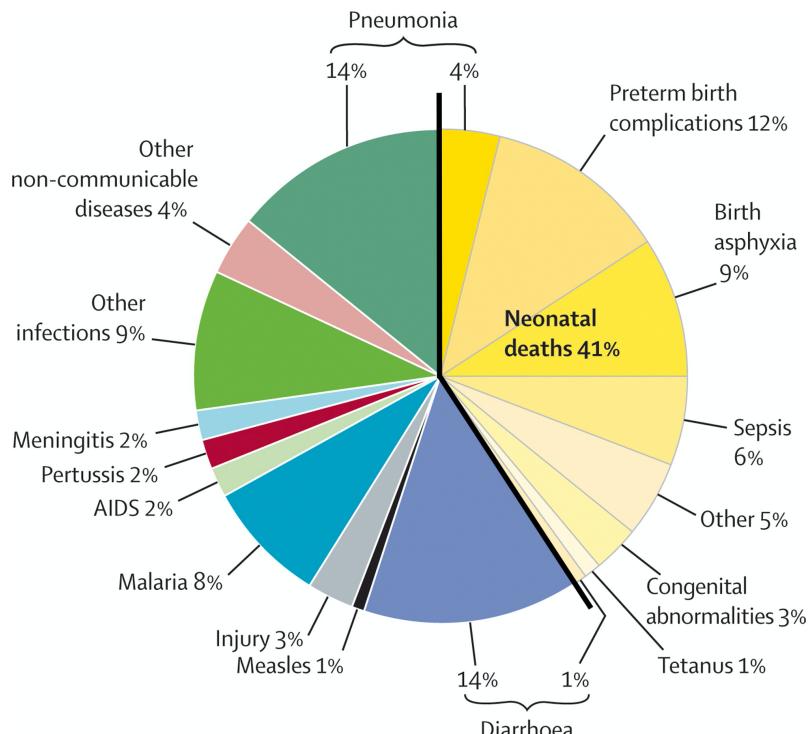


Figure 2.1: Global causes of childhood deaths. Yellow colour represents deaths of neonates aged 0 - 27 days and the rest correspond to children aged 1 month to 5 years [7].

## 2.2 Diagnostic Innovations

### 2.2.1 Pulse oximetry

Pulse oximetry is a low-cost technology, widely accepted as the standard for detection of hypoxaemia, an often fatal complication of pneumonia. It has been used to reliably measure hypoxaemia, identifying 20–30% more cases than clinical signs alone [13]. Pulse oximeters are devices that non-invasively measure peripheral oxygen saturation  $SpO_2$ . They are inexpensive, portable and, with adequate training and supervision, can be reliably used with children at all levels of the health system in low-resource settings, including by lay community health workers at the household level [20]. Oxygen saturation estimates may lead to detection of changes in patient conditions that could otherwise be missed, such as a lower  $SpO_2 (<95\%)$  which indicates hypoxia and insufficient oxygen supply to the human body. Children with hypoxaemic pneumonia therefore need to be identified, admitted to hospital, given supplemental oxygen and be monitored closely. This necessitates a heightened awareness of the prevalence and the risk of hypoxaemia among children presenting to health-care facilities and robust mechanisms to detect it [49].

### 2.2.2 Lung auscultation

Lung auscultation is the use of a stethoscope to acoustically assess airflow through the trachea-bronchial tree and remains an important component of pneumonia diagnosis, with more predictive accuracy than an initial clinical assessment alone [43]. The addition of lung auscultation as a diagnostic tool improved the classification of radiographically confirmed clinical pneumonia in cases with decreased breath sounds, absence of wheezes, but presence of crackles [43]. Crackles are discontinuous, explosive, and non musical adventitious lung sounds normally heard in inspiration and sometimes during expiration. Crackles are usually classified as fine or coarse based on their duration, loudness, pitch, timing in the respiratory cycle, and relationship to coughing and changing body position[46]. Although traditional acoustic stethoscopes are inexpensive and portable, the implementation of lung auscultation in low-resource settings is limited by challenges including the training required to recognise the specific signals necessary to make a diagnosis. Computerised analysis of lung sounds has been suggested and explored as a tool for automated classification of acoustic patterns and different respiratory conditions.

### 2.2.3 Other innovations

Other diagnostic innovations being developed include automated respiratory rate counters with a variety of technologies such as accelerometers and bioimpedance among others). The combination of several diagnostic and prognostic innovations into an integrated instrument could improve identification of pneumonia and its severity [17]. Table 2.1 summarises some of the recent devices proposed.

## 2.3 Vital sign acquisition and estimation

Respiratory rate can be difficult to measure in a standardised way. It is typically counted manually in low-resource settings, using timers or counting beads. Manual measurement, although often the reference standard, can be imprecise and is affected by intra-observer variation as it requires focused concentration. It is often required to be measured from a crying, irritable and moving child. Automated devices to compute RR are more commonly available in well-resourced settings. These include extracting respiration from the photoplethysmography (PPG) signal from a pulse oximeter, or remotely using a modern camera.

Table 2.1: Summary of diagnostic innovations that have been recently developed, or are currently under development in the context of childhood pneumonia. sources (UNICEF 2013) and personal research.

<b>Diagnostic Innovation</b>		<b>Description</b>
mPneumonia		An Android mobile application which automates the WHO IMCI protocol. The app paired with a software-based breath counter and a pediatric pulse oximeter to facilitate rapid identification of fast breathing [18].
WHO timer and Counting Beads	ARI	Designed as a simple and cheap way to help community health workers count breaths. The counting beads comprise of one strand of beads, non-specific for children ages 0–5 years. The strand is necklace shaped and has a protruding start/end bead. The health worker count breaths by moving a bead for each breath. When 1 minute has passed the CHW counts back the beads to determine the RR. Counting beads should be used in conjunction with the ARI Timer.
RRate mobile application		RRate measures RR by recording the time interval in between breaths as the user taps on a touch sensitive screen of a mobile device in time with inspiration. Once a consistent set of taps has been achieved, a chime noise is played and the result displayed [28].
Amplified stethoscopes e.g ThinkLabs & Ekuore		Digital stethoscopes that can transmit lung signals (auscultation) onto a smart phone [38].
The HealthPatch MD		Consists of two ECG electrodes, a tri-axial accelerometer, micro-controller and transceiver within a patch that straps like a bandage over the heart. The device measures HR, RR, steps and posture and connects wirelessly to a smartphone via bluetooth [9].

### 2.3.1 Pulse oximetry

One of the earliest light-based continuous vital-sign monitoring methods developed was pulse oximetry, first explored in the 1930s [14]. Pulse oximetry is a non-invasive technology that uses a light source and a photo detector at the surface of skin to measure the volumetric variations of blood circulation. The light source illuminates the tissue, and the photo detector measures the small variations in the reflected or transmitted light intensity associated with changes in perfusion. The fundamental principle of pulse oximetry relies on the differences in absorption of blood and other tissue components at different wavelengths[57]. When the heart pumps blood to the body and the lungs during systole, the amount of blood that reaches the capillaries in the skin surface increases, resulting in more light absorption. The blood then travels back to the heart through the venous network, leading to a decrease of blood volume in the capillaries and less light absorption[50]. These changes can be recorded as the PPG waveform, comprising a pulsatile signal from which oxygen saturation ( $SpO_2$ ) and other vital signs such as heart rate (HR) and respiratory rate (RR) can be computed.

The pulsatile changes of the PPG waveform is often called the "AC" component, it is synchronous with the beating heart. In contrast, the non-pulsating component "DC" is a function of the basic blood volume, respiration, the sympathetic nervous system, and thermo-regulation. As shown schematically in figure 2.2, most of the signal is static (DC) and represents the light that has not been modulated by arterial blood [35].

### 2.3.2 Wearable technology

There is a growing interest in continuous monitoring of vital signs outside of traditional settings such as the clinic or hospital. The development of wearable technology that unobtrusively and reliably monitors vital

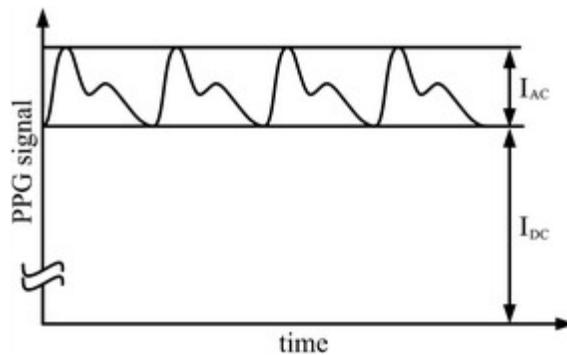


Figure 2.2: A typical PPG waveform showing the AC component and DC component [23]

signs has allowed the evaluation of patient recovery after discharge and the monitoring of those deemed at risk or suffering from chronic illness [8]. Wearable devices can incorporate a range of sensors such as PPG, accelerometer and gyroscopes. These devices can be worn in a variety of different locations, including finger, ear lobe and wrist to provide measurements from these sensors.

### 2.3.3 PPG imaging

Despite conventional PPG's wide range of applications, there are several significant limitations to the usefulness. Current monitoring systems available to track changes in the vital signs of patients require contact with the subject by using adhesive electrodes or sensors [60]. These can however damage the fragile skin of young infants or cause stress and discomfort. The introduction of fast digital cameras into clinical imaging monitoring and diagnosis systems, the desire to reduce the physical restrictions, and the possible new insights that might come from perfusion imaging and mapping inspired the evolution of conventional PPG technology to photoplethysmographic imaging (PPGi) [50]. Video-based vital sign monitoring extends the concepts of traditional PPG, using the multiple photosites present in an imaging sensor to record the blood volume changes associated with the cardiac cycle. These physiological changes result in a signal from which vital signs such as HR, RR, oxygen saturation  $SpO_2$  and others can be estimated [53, 59].

In 2008, Verkruyse *et al* [58] showed for the first time, that PPG signals could be remotely acquired from the human face with a simple, digital, consumer-level camera as the detector more than 1 m away. The study conducted used daylight as the illumination source in combination with normal artificial fluorescent light. Regions of interest (ROIs) were selected in images of the faces from human volunteers. The authors presented evidence that the reflectance signals were pulsatile cardiac signals by showing that signals corresponding to movement of facial areas with no exposed skin (edge of the face and hair above the ear) were not predominantly at the heart rate frequency. The green channel was found to provide the strongest plethysmographic signal amplitude, corresponding to an absorption peak by oxyhaemoglobin, but the red and blue channels were also shown to contain plethysmographic information. The paper showed how heart rate could be extracted from the frequency content of these images using the fast Fourier transform (FFT) for 10s windows, and hinted at how respiratory rate might be computed using an ROI which encompasses the entire face.

In 2010, Tan *et al* presented a real-time vision based respiration monitoring system. The method involved image and signal processing techniques to extract chest and abdominal movement information from a sequence of video images recorded using a single video camera. The system provided a real-time respiration signal from which RR was computed [52]. In the same year, Bai *et al*[4] designed an embedded

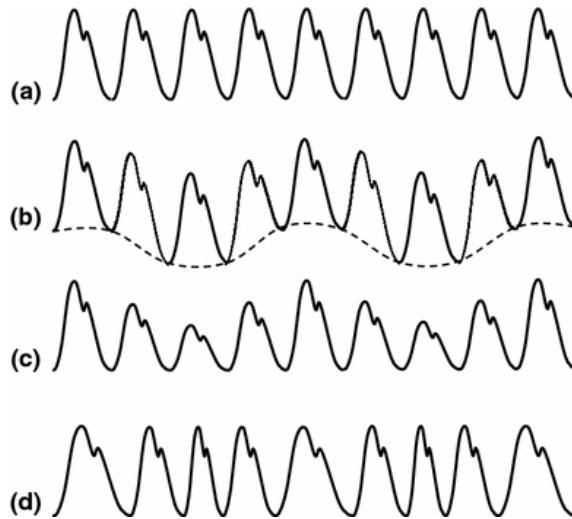


Figure 2.3: Modulation of the PPG signal due to respiration; a) Unmodulated PPG showing cardiac pulse waveforms; b) Baseline modulation (cardiac pulses riding on top of baseline shown dashed); c) Amplitude modulation (cardiac pulse amplitudes varying over the respiratory cycle); d) RSA (pulse period varying over the respiratory cycle). Figure reproduced from [1].

monitoring system for body breath detection using a webcam. Their design employed a temporal differencing algorithm, which subtracts subsequent frames to detect moving objects [30]. This was used to identify chest movement and determine the respiratory rate. The developed system estimated the respiration rate of sleeping or stationary subjects with a static background, which poses a limitation for monitoring children or infants.

Jorge *et al* proposed a new method for use in neonates in 2017, which was incorporated into a Cessation Of Breathing Events (COBE) detection system. For this method, skin pixels were identified first in each frame using a skin classifier and the ROI for motion analysis selected. Motion analysis was done to detect breathing movements and estimate their frequency. A binary signal quality index (SQL) was produced for these estimates based on the level of activity on the video sequence. In contrast to the previous methods discussed, this approach is able to account for subject motion and changes in background lighting [27].

## 2.4 Respiratory signal processing

### 2.4.1 Respiratory signal extraction

Extracting a respiratory signal from PPG requires the identification of respiratory modulation components driven by the fluctuation of blood volume in the peripheral vascular bed. These modulation components are pulse amplitude, baseline and respiratory sinus arrhythmia (RSA).

- **Baseline modulation:** A baseline modulation of the PPG signal is caused by changes in venous return secondary to changes in intra-thoracic pressure throughout the respiratory cycle. During inspiration, decreases in intra-thoracic pressure result in a small decrease in central venous pressure increasing venous return. The opposite occurs during expiration. As more blood is averted from the low pressure venous system and the venous bed cyclically fills and drains, the baseline PPG is modulated accordingly [1]. This effect is shown in figure 2.3b.

- **Amplitude modulation:** Amplitude modulation is caused directly by changes in intra-thoracic pressure during the respiratory cycle. These changes result in respiratory oscillations in the amplitude of the signal, and this effect is shown in figure 2.3c.
- **RSA:** Respiratory sinus arrhythmia is a variation in heart rate that occurs throughout the respiratory cycle. It is well documented that heart rate increases during inspiration and decreases during expiration. While the precise mechanisms of RSA remain disputed, it is a result of autonomic nervous system activity fluctuation during respiration. This effect is shown in figure 2.3d.

The extraction of respiratory components is particularly challenging as the three aforementioned respiratory modulations may be present to varying degrees across the patient population. A further challenge for algorithms to extract respiratory signals is that respiratory components often appear concurrently with a range of other low frequency artefacts due, for example, to voluntary or involuntary movements of the patients or blood pressure changes [1]. Appropriate signal processing techniques must therefore be implemented to accurately extract this information.

### 2.4.2 Signal processing techniques

From the presence of the respiratory response in a PPG waveform, many researchers have been motivated to develop or utilise methods for RR estimation, such as digital filters, auto-regressive (AR) models, variable frequency complex demodulation and particle filters.

#### Digital filtering

In their 2000 study, Nilsson *et al* [39] extracted the respiratory synchronous part of the PPG signal using a band pass filter. A 3<sup>rd</sup> order Butterworth band-pass filter with a pass-band from  $f = 0.1 - 0.3$  Hz (6 to 18 breaths/min) was used. Detection of breaths in the filtered PPG signals was done both visually and by using an automated algorithm. In 2009, Nakajima *et al.* developed a technique that used digital filters to estimate HR and RR from a PPG signal. The cut-off frequency of the respiratory signal filter was selected automatically depending on the heart rate so that a higher cut-off frequency was used at higher heart rates [37]. Despite the complexity of the algorithm, it did not perform as well as the method proposed by Nilsson *et al*, and had an average error of over 3 breaths per minute when compared to the reference rate.

#### Auto-regressive modelling

Auto-regressive (AR) modelling looks for regular frequencies in a signal which is deemed to be stationary over the period of analysis. It models this periodic behaviour by comparing the signal with its own past values at various time lags [51]. In 2007, Fleming and Tarassenko developed a method to estimate RR from a PPG signal using an AR model. This method was shown to perform better than both the digital filtering and wavelet decomposition methods [15]. An AR method involving factorising the estimated AR parameters into multiple pole terms was later presented by Lee *et al* [29]. The pole with the highest magnitude was chosen to represent the respiratory rate. The method showed accurate respiratory rate extraction, especially for high respiratory rates (36 – 48 breaths/min). To mitigate a previously described limitation of AR models, particle filtering was introduced to track moving targets. Recent efforts have been made to develop efficient algorithms for real-time implementation [26].

HR and RR estimation using AR modelling has also been proposed for video-based vital sign monitoring by Tarassenko *et al.* [53]. This method also cancels out aliased frequency components caused by artificial light flicker using AR modelling and pole cancellation.

## **Chapter 3**

# **Vital sign estimation using wearable devices**

### **3.1 Introduction**

Wearable devices such as wristbands and smart watches are increasingly being used to monitor the physiological parameters of individuals to track changes in heart rate, oxygen saturation and respiratory rate [10]. Data can be acquired without imposing a disruption to a subject's daily schedule, providing a more informed assessment of the subject's well-being and helping detect health problems that might have otherwise been missed. The availability and low cost of wearables could therefore provide new ways to monitor children's health in LMICs. The aim of the chapter is to compute HR, RR and changes in  $SpO_2$  from data recorded from a wearable device in a clinical study involving healthy volunteers undergoing a hypoxia protocol.

### **3.2 Data set**

The clinical study took place at the Cardiovascular Clinical Research Facility, John Radcliffe Hospital, Oxford, UK. It was a collaboration between the Institute of Biomedical Engineering and clinicians from the Nuffield Department of Clinical Neurosciences at the University of Oxford. The study received ethical approval by the East of Scotland Research Ethics Service REC 2 (19/ES/0008). The study was carried out to test the performance of wearable devices in a simulated clinical setting during hypoxia exposure (low oxygen levels).

#### **3.2.1 Participant recruitment and assessment**

43 healthy volunteers were recruited for the study. Written consent was obtained for each study participant. The screening assessment for the study was completed by an appropriately qualified, medically trained member of the research team, who confirmed the volunteers' eligibility. Participants were excluded if incomplete data were collected for any one device during the duration of the study, or if hypoxia was not achieved.

Demographics data including age, sex, height, weight, skin type (Fitzpatrick scale [25]), heart rate and  $SaO_2$  (from arterial blood gas (ABG)) were collected for each participant, at the start of their sessions and recorded in a Case Report Form (CRF). All data from participants were identified using a study number. Four participants presented adverse clinical conditions (three anaemia cases - evaluated from the first ABG - and one sickle cell trait). Therefore, 39 complete data sets were acquired in total. The summary of the demographic information of the study volunteers is presented in table 3.1.

#### **3.2.2 Study set-up**

The study participants lied comfortably on a bed in a semi-horizontal, supine position. A tight-fitting silicone face mask was placed and connected to a hypoxic unit (Everest Summit Hypoxic Generator). If required, additional 7% oxygen in nitrogen from a cylinder was added into the hypoxic unit circuit to ensure tight

Table 3.1: Summary of the population in the clinical study.

Description	Value
Total number of complete recording sessions	39
Average length of a recording session (minutes)	$18.4 \pm 2.9^1$
<b>Gender</b>	
Females	21 (53.8%) <sup>2</sup>
Male	18 (46.2%) <sup>2</sup>
Age	$32.6 \pm 10.4^1$
Weight	$71.2 \pm 13.4^1$
Height(m)	$1.71 \pm 0.10^1$
<b>Fitzpatrick Skin type</b>	
Type I	10 (25.6 %) <sup>2</sup>
Type II	18 (46.2 %) <sup>2</sup>
Type III	2 (5.1 %) <sup>2</sup>
Type IV	9 (23.1 %) <sup>2</sup>

<sup>1</sup> mean  $\pm$  standard deviation<sup>2</sup> Total number (percentage)

control of fraction of inspired oxygen ( $FiO_2$ ) provided to the participant.  $SaO_2$  readings were taken for the 100%, 95%, 90%, 87%, 85%, 83% and 80%  $SpO_2$  target values, with the corresponding output of the blood gas analyser then taken as the reference value.  $SpO_2$  stability was subjective for each target  $SaO_2$  window, i.e. a senior anaesthetist decided when a stable oxygen level was achieved in order to take the ABG, based on the clinical values shown by the standard  $SpO_2$  monitor.  $SpO_2$  measurements of greater than or equal to 90% were considered normoxia, while levels between 85% and 89% were considered mild hypoxia. Oxygen saturation levels below 85% were regarded as severe hypoxia.

### 3.2.3 Instrumentation

Participants wore several ambulatory monitoring devices (AMD) including a purely wrist worn device (Wavelet Health, USA) and up to three wrist-worn devices with finger probes. In this chapter, data from the Wavelet wristband, wearable device using reflectance PPG to measure pulse rate was used. The device records 1 minute red and near-infrared (NIR) time series data with 1 minute gaps in between at a sampling rate of 79Hz. Other sensors in the Wavelet Health include 3-axis accelerometer sensor (recorded at 10Hz) and gyroscope.

The Philips Monitor MX450 was used as the reference clinical standard device, recording  $SpO_2$  values and HR at a sample rate of 1Hz. Figure 3.1 shows a 30-minute window of vital signs measured using the Philips monitor, as well as the red/NIR signals recorded from the Wavelet Health device.

### 3.2.4 Data selection

39 complete data sets were acquired. 28 sessions with data that was greater than 20 minutes in length were selected; to allow 2 minutes for recovery to normal oxygen saturation (>90%). 19 sessions were subsequently selected because these data sets were not corrupted by motion. Finally 10 sessions were selected for analysis in this report. Figure 3.2 shows a summary of the data collection criteria.

Figure 3.3 shows the distribution of HR,  $SpO_2$  and RR values from the 10 chosen volunteers. Mean  $SpO_2 = 91.2\%$ , Median  $SpO_2 = 90.9\%$ , Inter-quartile range = 13.9. The mean HR was 66.3 beats/minutes.

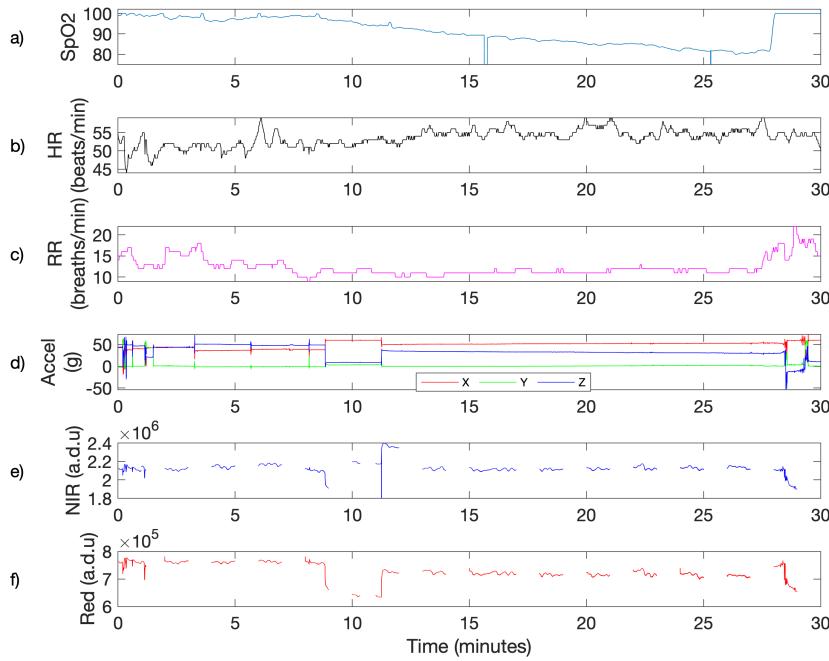


Figure 3.1: Physiological parameters recorded by the Phillips monitor and the Wavelet Health device. a)  $SpO_2$  from the Phillips monitor. Lowest recorded Oxygen saturation was 80% as per protocol. b) Heart rate and c) Respiratory rate from the Philips monitor. d) Accelerometer data recorded by Wavelet Health. e) Raw NIR signal and f) Red signal from the Wavelet Health device. The device records 1 minute data on and off.

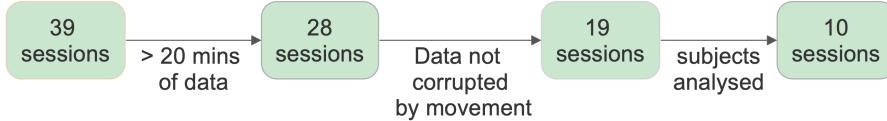


Figure 3.2: Flow diagram outlining the patient selection process.

Median HR = 65 beats/minutes, inter-quartile range = 12. Mean RR = 14.1 breaths/minutes, Median RR = 14 breaths/minutes, Inter-quartile range = 55.

### 3.3 Heart rate estimation

#### 3.3.1 Overview of the process

HR is used frequently in healthcare and easily extractable from a PPG signal, as pulsatile blood flow from the heart modifies the absorption of NIR light. The NIR signal was detrended and filtered to remove noise. The filtered signal was then split into 10s windows, and the peaks of the pulsatile signal were detected for each of these windows. These peaks were counted to estimate HR. A motion SQL was then applied using accelerometer data from the Wavelet Health device, which discarded HR estimates where the NIR signal was corrupted by motion. Figure 3.4 presents an overview of the process of estimating HR using the Wavelet Health device.

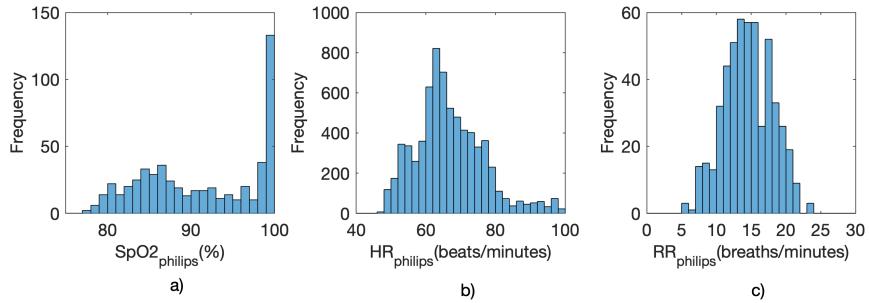


Figure 3.3: Distribution of vital signs recorded by the Philips monitor for the 10 sessions selected for analysis.  
a) $SpO_2$ ; b) HR and c) RR

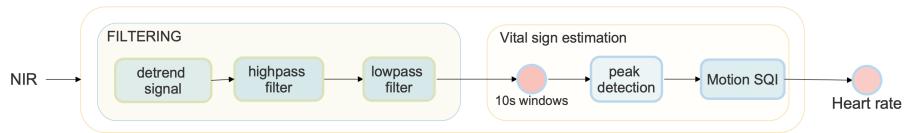


Figure 3.4: Flow diagram outlining the process of computing heart rate from the NIR signal from the Wavelet Health device.

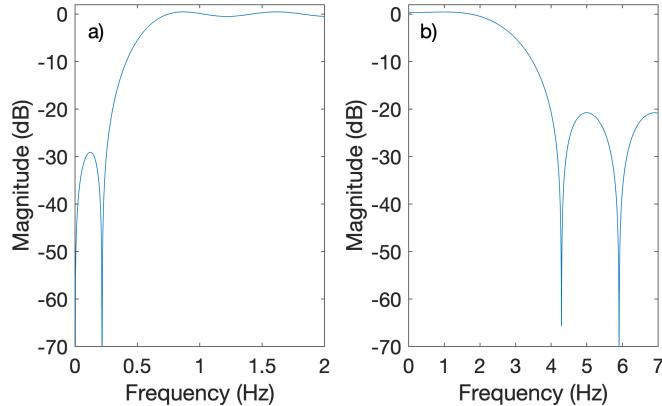


Figure 3.5: Magnitude responses for a) High-pass filter b) low-pass filter.

### 3.3.2 Filtering

The NIR signal was first detrended to remove the DC component. The de-trended signal was further processed by designing two zero-phase FIR filters, shown in figure 3.5, to remove low and high frequency noise from the signal respectively. A 181<sub>st</sub> order high-pass filter was designed with a passband frequency of 0.7Hz (42 beats/min) and a stop-band frequency of 0.3Hz (18 beats/min). A 36<sub>th</sub> order low-pass filter was subsequently applied with a passband frequency of 2Hz (120 beats/min) and a stop-band frequency of 4Hz (240 beats/min). Both filters were designed with a passband ripple of 1dB and stop band attenuation of 20dB.

Figure 3.6 shows an example plot of the NIR signal before and after de-trending and filtering. The Fast Fourier Transform (FFT) plots shown in figure 3.6c and figure 3.6d show a clear peak at 0.9 Hz corresponding to a HR of approximately 54 beats/minute. The reference HR recorded by the Philips monitor was 55 beats/minute.

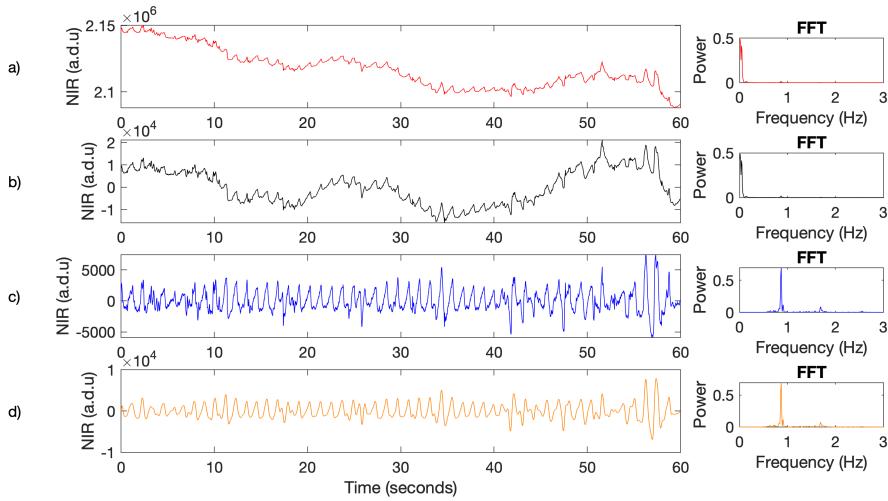


Figure 3.6: 60-second sample time series from the NIR waveform. a) Input signal; b) de-trended. Signal after the c) high-pass and d) low-pass filter were applied. The FFT panels show a peak at 0.9Hz corresponding to a HR of approximately 54 beats/minute. The reference HR recorded by the Philips monitor was 55 beats/minute.

### 3.3.3 Peak detection

Peak-to-trough analysis was performed on the filtered signal. This process identified prominent maximum and minimum points in the signal to measure changes in signal amplitude. The algorithm used for peak detection first identified a peak as the  $i_{th}$  sample in a time series  $ts$  if:

$$ts(i) > ts(i - 1) \text{ and } ts(i) > ts(i + 1) \quad (3.1)$$

To avoid reporting erroneous peaks due to noise, identified peaks were kept if:

$$ts(i_{peak}) > MinPeakHeight \quad (3.2)$$

where  $MinPeakHeight$  was set to a signal intensity of 100, based on manually observing the minimum height of waveform peaks in low intensity segments of the recording. Remaining peaks were retained if:

$$i_{peak_n} - i_{peak_{n-1}} > MinPeakDistance \quad (3.3)$$

where  $MinPeakDistance$  was set to give a refractory period (a recovery time after each peak) of 40 samples (corresponding to 84 beats/minute) based on the histogram of reference vital-sign data for the session in figure 3.3. Finally, peaks were selected as:

$$prom(i_{peak}) > MinPeakProminence \quad (3.4)$$

where  $prom$  was the prominence of a peak, defined as the height of the peak relative to neighbouring troughs. Here,  $MinPeakProminence$  was set to a value of 58 based on manually observing peak prominences

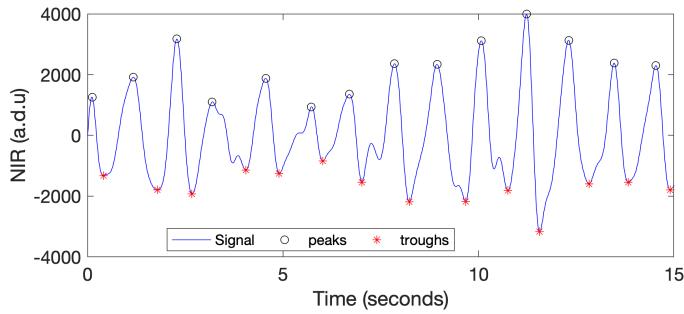


Figure 3.7: Detection of peaks and troughs on the NIR signal over a 15-second sample window.

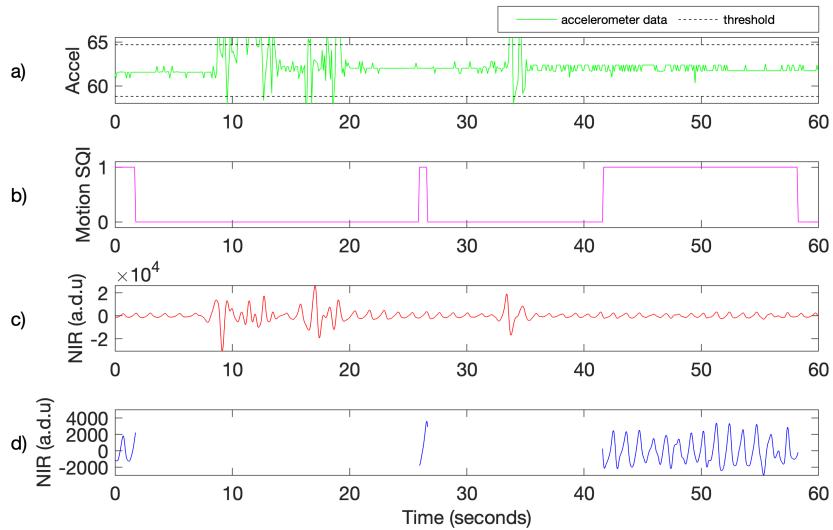


Figure 3.8: Using motion SQI to discard time periods corresponding to motion artefacts. a) Accelerometer data, b) computed SQI, data is discarded at  $\text{SQI} = 0$ . c) NIR signal before motion SQI, d) NIR signal after motion SQI was applied.

in several example recording segments. The algorithm then returned a vector containing the location and magnitude of each peak as shown in figure 3.7.

### 3.3.4 Motion SQI

Motion analysis was used to compute a signal quality index (SQI) designed to exclude time periods during which significant movement artefacts occurred. The accelerometer data recorded by the Wavelet health device was first split into 5-minute non-overlapping windows. Subsequently, the mean and standard deviation were calculated for each window. Data points for which the acceleration was greater than  $\pm 2$  standard deviations from the mean for that window were considered to have an SQI of 0, corresponding to time periods of motion; otherwise an SQI of 1 was assigned, corresponding to time periods of good quality. Finally, the NIR signal within  $\pm 3$  s of any accelerometer data with an SQI of 0 were discarded. An example of this process is shown in figure 3.8.

### 3.3.5 Heart rate computation

Beat-to-beat time intervals were computed by subtracting the time value of each peak from the time value of a succeeding peak. From the peak-to-peak intervals, HR was computed using a window length of 10 seconds sliding by 1 second. The averaged values of HR were then calculated using the equation below:

$$HR = \frac{60}{\text{median}(\text{peak\_time\_interval})} \quad (3.5)$$

### 3.3.6 Time alignment between heart rate from Philips and HR estimated from the Wavelet Health device

The Wavelet Health and Phillips devices have separate clocks, which could not be synchronised. The time delay between devices varied session to session. To compare vital signs estimated from the Wavelet Health device to reference values from the Phillips monitor, the time delay between these devices need to be estimated and accounted for. This was accomplished by comparing the estimated HR values from the Wavelet device with the reference HR signal from the Phillips monitor, similar to Chaichulee [11]. The cross correlation between the two HR signals was calculated for time lags from -30 s to 30 s.

Given that  $f$  and  $g$  are vectors containing a time series signal, the cross-correlation measures the similarity between  $f$  and a shifted version of  $g$ . The cross-correlation at a time lag  $t$  is defined as:

$$R_{xy}(t) = \frac{\sum_{i=1}^N (f_i - \mu_f)(g_{i-t} - \mu_g)}{(N-1)\sigma_f\sigma_g} \quad (3.6)$$

where  $\mu_f$  and  $\mu_g$  are the means of  $f$  and  $g$  respectively,  $\sigma_f$  and  $\sigma_g$  are the variances of  $f$  and  $g$  respectively. The maximum of the cross-correlation indicated the time delay for which the two signals are best aligned. The time delay is defined as

$$T = \text{argmax} R_{xy}(t) \quad (3.7)$$

The time delay indicates how much  $g$  is shifted, along the x-axis (time axis), with respect to  $f$ . Computed heart rates were then plotted and comparisons were made with the reference heart rate from the Philips monitor.

## 3.4 Respiratory rate estimation

### 3.4.1 Overview of the process

The estimation of respiratory rate is possible because the NIR signal recorded by the Wavelet device presents respiratory driven blood volume changes. Modulation of the NIR signal due to respiration is used to estimate RR. Two methods were used to extract a respiratory signal and compute RR from the raw NIR PPG signal. Amplitude modulation, caused by changes in intra-thoracic pressure during the respiratory cycle, resulted in respiratory oscillations in the amplitude of the signal from which RR could be estimated. The second method, frequency modulation, used the variation in the instantaneous heart rate during the respiratory cycle, also known as respiratory-sinus arrhythmia. The extracted respiratory signals were filtered using two zero-phase Infinite Impulse Response (IIR) filters. The mean of the two filtered respiratory signals was taken as the final estimate of RR.

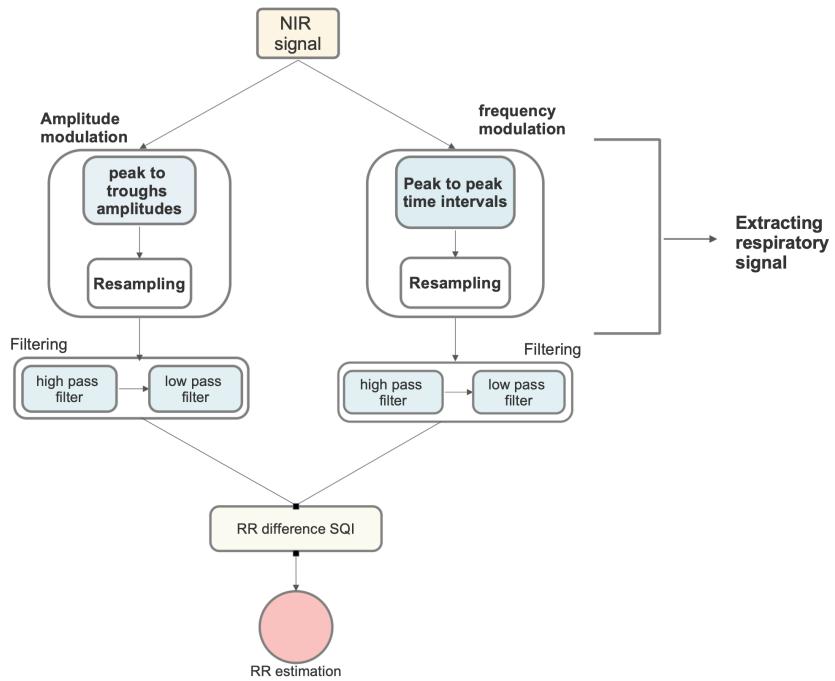


Figure 3.9: Flow diagram outlining the process of computing respiratory rate from the NIR signal recorded by the Wavelet Health wearable device.

### 3.4.2 Extracting respiratory signal

#### Amplitude modulation

Amplitude modulation is defined as the difference in peak amplitudes of consecutive peaks and troughs, effectively resulting in a time-series of the amplitude of each PPG pulse. It is caused directly by changes in intra-thoracic pressure during the respiratory cycle. These changes result in respiratory oscillations in the amplitude of the signal, from which RR can be estimated.

For this method, the peaks and troughs of the NIR signal were computed using the algorithm described in section 3.9, as shown in figure 3.10a. The amplitude of each beat was computed by subtracting the trough values from each respective peak. Outliers, defined as values more than three standard deviations from the mean, were removed from the peak-trough amplitudes to discard noisy periods. The signal was then re-sampled at 25 Hz (using a cubic spline), and de-trended as shown 3.10b and 3.10c.

Two Butterworth IIR filters shown in figure 3.11, were designed to remove low and high frequency noise from the signal. An  $8_{th}$  order low-pass filter was designed with a cut-off frequency of 0.60 Hz (36 breaths/min) and a passband frequency of 0.40 Hz (24 breaths/min). A high-pass filter of order 17 with a passband frequency of 0.12 Hz (7.2 breaths/min) and a cut-off frequency of 0.10 Hz (6 breaths/min) was then applied to the signal. Both filters were designed with a passband ripple of 1 dB and stop band attenuation of 20 dB. Figure 3.10 shows an example plot of the NIR signal before and after de-trending and filtering. The designed filters were used to remove low and high frequency noise from the signal as shown in figure 3.10d and 3.10e.

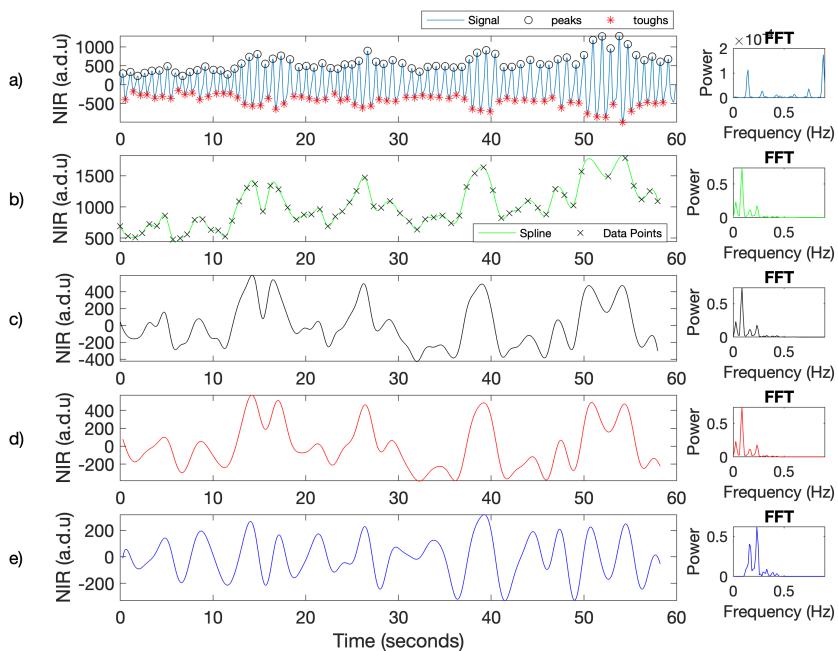


Figure 3.10: 60-second example of the amplitude modulation method being used to estimate RR from the NIR signal. a) Peak-to-trough detection; b) signal amplitude; c) de-trended; d) low-pass filtered signal; e) high-pass filtered signal. The FFT panels show a peak at 0.23Hz, corresponding to a RR of approximately 13.8 breaths/minute. The reference RR recorded by the Philips monitor was 15 breaths/minute.

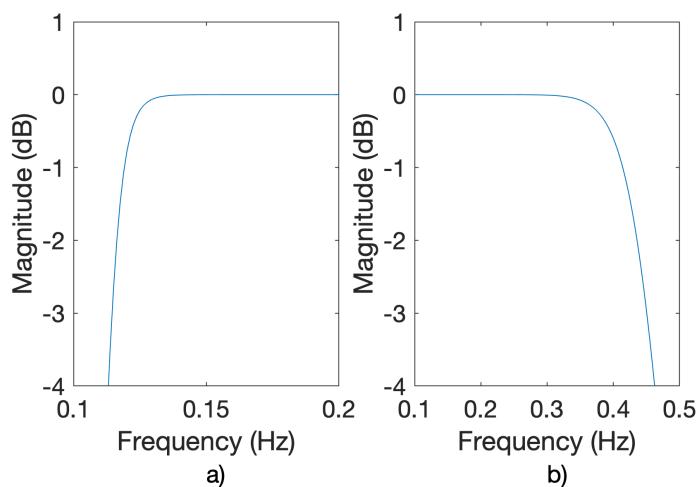


Figure 3.11: Filter magnitude responses for a) high-pass filter b) low-pass filter.

### Frequency modulation

Frequency modulation, also known as respiratory sinus arrhythmia, is a variation in heart rate that occurs throughout the respiratory cycle. It is well documented that heart rate increases during inspiration and decreases during expiration. While the precise mechanisms of frequency modulation remain disputed, it is a result of autonomic nervous system activity fluctuation during respiration.

To compute RR using this method, peak to peak time intervals were computed by subtracting the peak time point from a succeeding peak. The peak-to-peak time intervals for each breath pulse from the NIR signal were extracted to construct a respiratory signal. The signal was re-sampled at 25Hz (using a cubic spline). Subsequently, the detrended signal was filtered using similar filters designed for the amplitude modulation method. The peak-to-peak time intervals were then used to compute RR. An example from this process is shown in figure 3.12. The FFT panels show a peak at 0.24Hz, corresponding to a RR of 14.4 breaths/minute. The reference RR recorded by the Philips monitor was 15 breaths/minute.

#### 3.4.3 RR estimation

To compute RR, similar algorithms described in section 3.3.3 were used to perform peak to peak analysis on the respiratory signals extracted from the NIR waveform using both of the proposed methods. This analysis was done using MinPeakDistance of 1.2 s (50 breaths/min) and MinPeakProminence of 0.02. RR was computed as the average peak-to-peak time interval over a window of 30 seconds sliding by 5 seconds. The agreement between the estimated RR from the two methods (amplitude and frequency modulation) was used to compute an SQI. This SQI was set to 1, corresponding to periods of good quality estimates, if the two estimates were within 5 breaths/min; conversely, it was set to 0 otherwise, corresponding to time periods of poor-quality estimates. The mean of the two respiratory rates was taken as the final estimate of RR for periods of good-quality signal.

## 3.5 Oxygen saturation

### 3.5.1 Overview of the process

The Wavelet Health device, although it provided estimates of HR, also recorded the red and NIR signals. These signals were split into windows, and then detrended and filtered to remove noise. Subsequently, a motion SQI was applied using accelerometer data to remove data where the red and NIR signals were corrupted by motion. After this, the peaks and troughs in the red and NIR signals were detected, and the signal amplitude computed. The ratio between the red and NIR signal amplitudes were then compared to the reference  $SpO_2$  estimates from the Philips monitor. This process is shown in figure 3.13.

### 3.5.2 Filtering

The NIR and Red signals were de-trended and subsequently filtered using two zero-phase FIR filters with a passband ripple of 1dB and stop band attenuation of 20dB to remove low and high frequency noises from the signal respectively. The high-pass filter was designed with a passband frequency of 0.7Hz (42 beats/min) and a stop-band frequency of 0.3Hz (18 beats/min)). The low-pass filter was designed with a passband frequency of 2Hz (120 beats/min) and a stop-band frequency of 4Hz (240 beats/min)). Thresholds were selected based on the population distribution of data shown in figure 3.3. The magnitude response of the resulting filters is shown in figure 3.14.

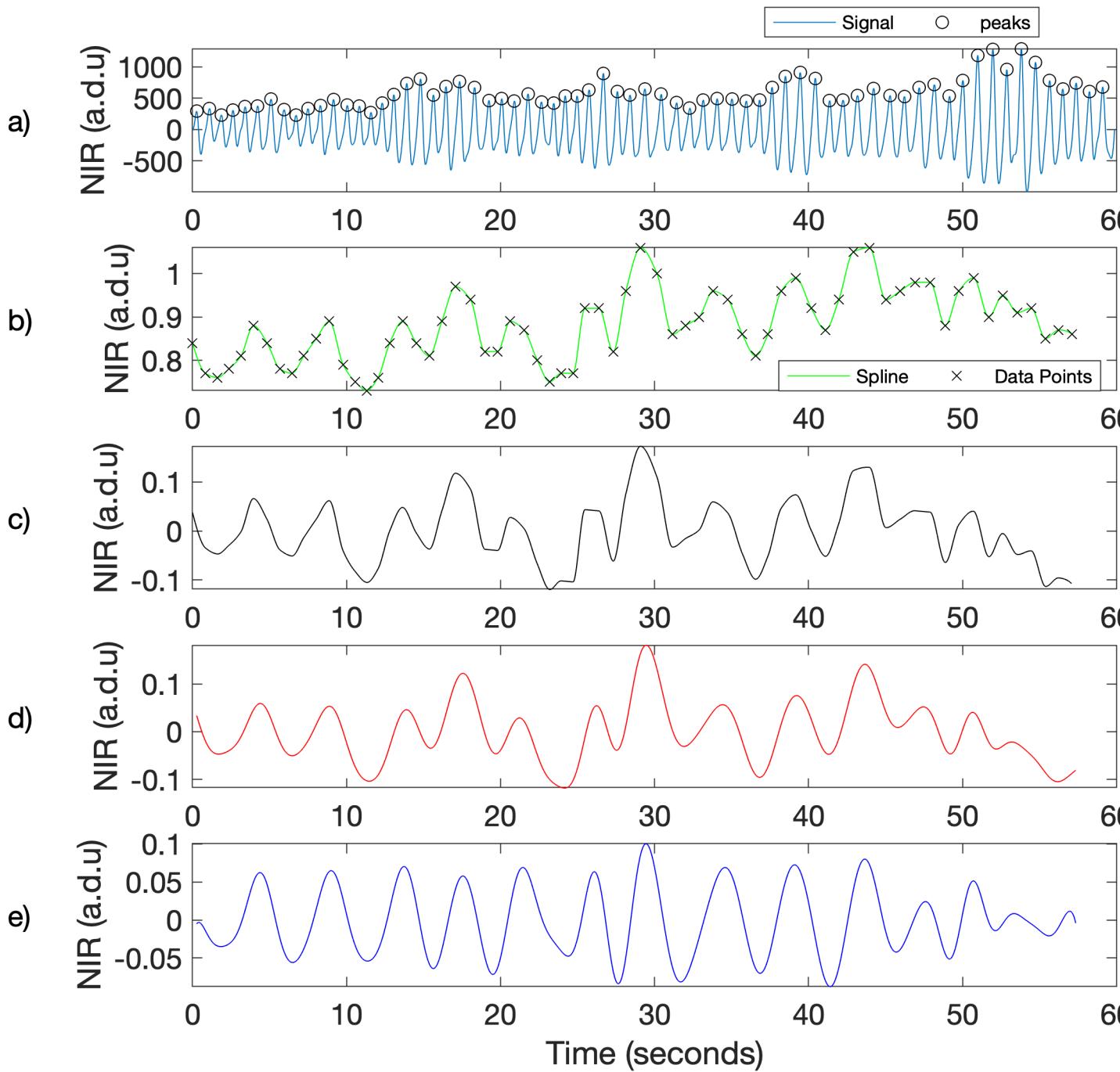


Figure 3.12: 60-second example of the frequency modulation method used to estimate RR from the NIR signal. a) Peak to peak time intervals; b) peak to peak time intervals; c) de-trended; d) low-pass filtered signal; e) high-pass filtered signal. The FFT panels show a peak at 0.24Hz, corresponding to a RR of 14.4 breaths/minute. The reference RR recorded by the Philips monitor was 15 breaths/minute.

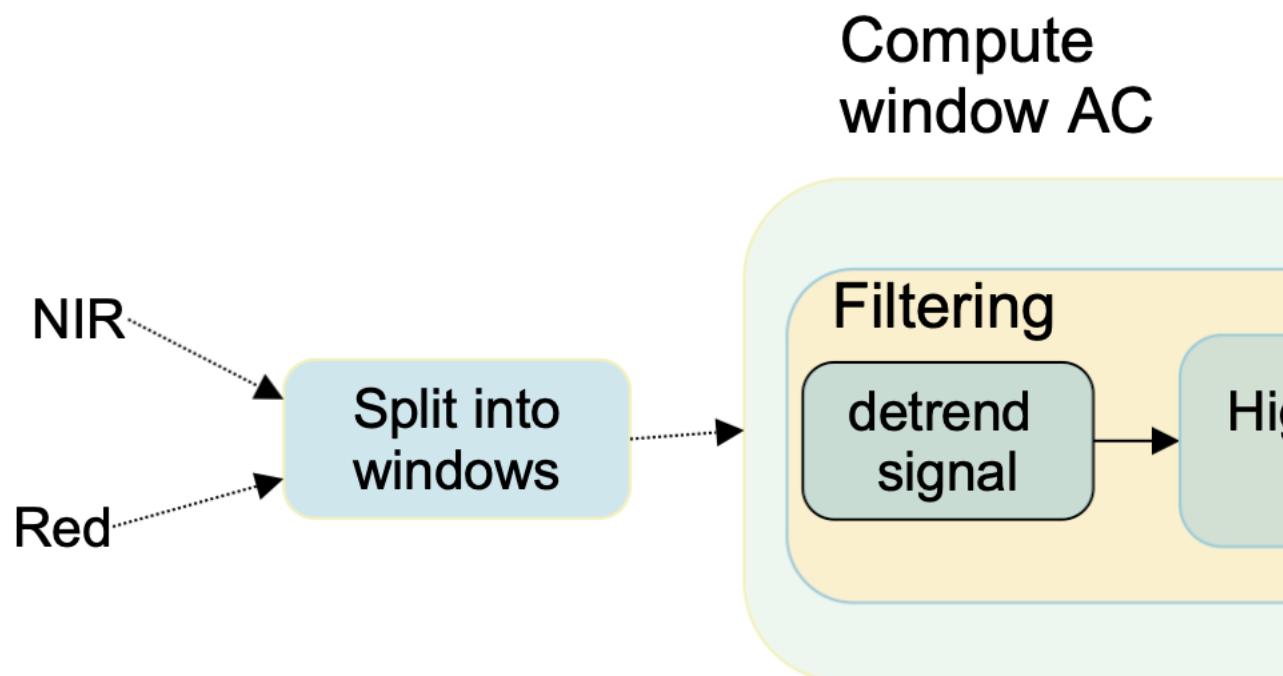


Figure 3.13: Flow diagram outlining the process of computing the relationship between the ratio of ratios of the red and NIR signals recorded by the Wavelet Health device and the reference  $SpO_2$  from the Philips monitor.

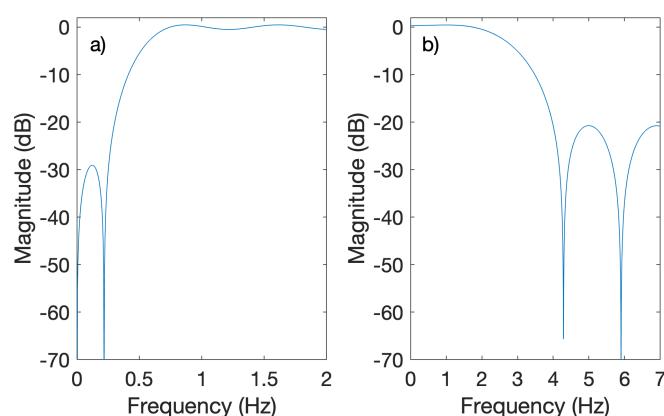


Figure 3.14: Magnitude responses for the a) High-pass filter and b) low-pass filter designed.

Motion SQI and peak detection algorithms similar to those used in section 3.3 were then applied to the filtered data.

### 3.5.3 Signal amplitude

The detected peaks and troughs used for HR were used to compute the amplitude of the red and NIR PPG signals. Amplitudes were determined by consistently subtracting the value of a trough from the value of a preceeding peak.

### 3.5.4 Computing Red/NIR Ratios

Median values of the red and NIR PPG amplitudes were computed for non-overlapping windows of length 15 second and with 15 second step size. The ratio between the red and NIR PPG amplitudes was then applied. For comparison, the median of 15 second non-overlapping windows were also computed from the reference  $SpO_2$  values recorded by the Philips monitor data. The computed Red/NIR ratios were then compared to the median  $SpO_2$  values to assess the correlation.

## 3.6 Results

### 3.6.1 Error metrics

The comparison between the reference values from the Philips monitor and the estimated vital signs from the Red and NIR signals for all recordings in the study were performed using Bland-Altman analysis, the mean absolute error (MAE), the mean absolute deviation (MAD) and Pearson's correlation coefficients. The Bland-Altman plot was designed to assess the agreement between two clinical measurements. It was constructed by plotting the mean of the estimates from the devices against their differences.

Given two time series  $x$  and  $y$  of length  $N$ , the MAE was defined as:

$$MAE = \frac{1}{N} \sum_{i=1}^N |y - x| \quad (3.8)$$

Given  $z$  is the difference between the two time series  $x$  and  $y$ , and  $\mu$  is the mean of  $z$ , the MAD was defined as:

$$MAD = \frac{1}{N} \sum_{i=1}^N |z - u| \quad (3.9)$$

The Root Mean square error (RMSE) was calculated using the equation

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y - x)^2} \quad (3.10)$$

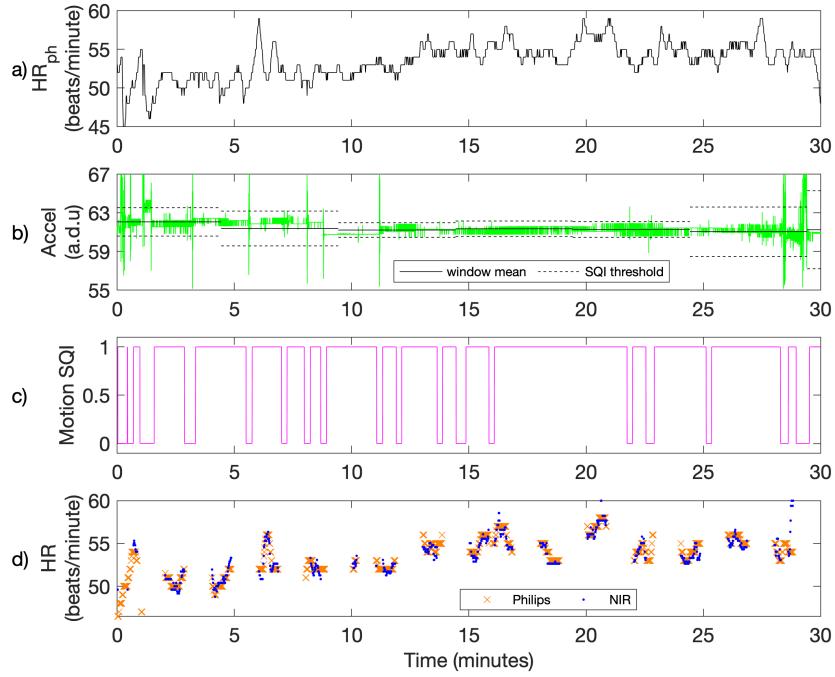


Figure 3.15: Comparison between HR provided by the Philips monitor and the HR estimates computed by the proposed algorithms. a) HR from Philips monitor. b) Accelerometer data recorded by the Wavelet Health device. c) Motion SQI. Values of 1 correspond to periods of good-quality signal; Conversely values of 0 correspond to periods of poor quality signal. d) Estimated HR from NIR signal compared to reference HR.

The Pearson's correlation coefficient measures the linear correlation between two time series using the following equation:

$$R = \frac{\text{cov}(x, y)}{\sigma_x \times \sigma_y} \quad (3.11)$$

where  $\text{cov}(x, y)$  is the covariance,  $\sigma_x$  and  $\sigma_y$  are the standard deviation of x and y time series respectively.

### 3.6.2 Heart rate

Figure 3.15 compares the reference HR from the Philips monitor with the estimated HR from the Wavelet Health device. Table 3.2 shows MAE, MAD, RMSE values and the correlation values computed across the 10 subjects selected for analysis.

Figure 3.16 (a) shows the Bland- Altman plot comparing the Philips and estimated heart rate values for all 10 patients. The plot shows a mean bias of 0.16 beats/min, 95% of the differences fall within [-3.4, 3.1] beats/min, the correlation coefficient is 0.99. The MAE between both heart rate measurements was 1.2 beats/min with a MAD of 1.2 beats/min.

### 3.6.3 Respiratory rate

Figure 3.17 shows a comparison between the reference RR from the Philips monitor and the estimated RR computed from the Wavelet Health device by the proposed algorithms. Table 3.3 shows MAE, MAD and

Table 3.2: Summary of results for the proposed algorithms to estimate HR from the NIR signals for the 10 patients analysed.

Patient Number	MAE*	MAD*	RMSE*	r
001	0.6	0.6	0.9	0.92
002	1.6	1.6	2.0	0.94
003	0.6	0.6	0.8	0.99
004	1.0	1.0	1.3	0.98
005	0.7	0.7	1.0	0.98
006	1.9	1.9	2.9	0.89
007	1.2	1.2	1.8	0.97
008	2.3	2.2	3.1	0.9
009	0.7	0.7	1.0	0.96
010	1.2	1.2	1.5	0.97
Overall	1.2	1.2	1.8	0.99

\*Values in beats/minute

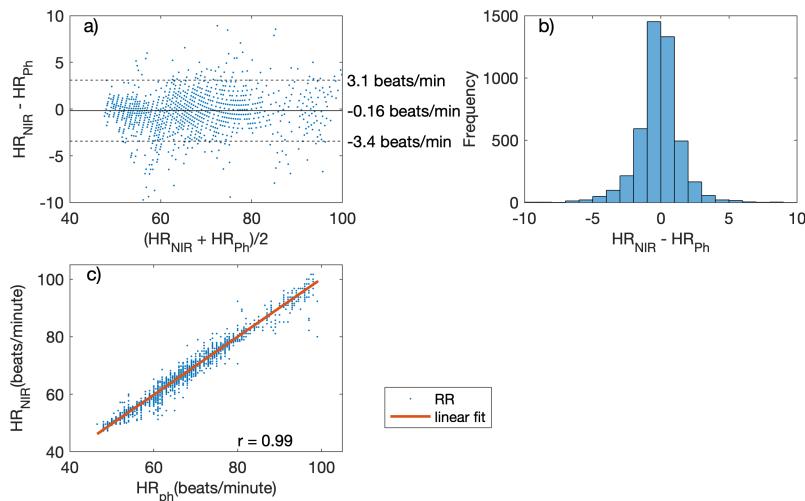


Figure 3.16: Comparison between the reference and estimated heart rate for the 10 patients analysed. a) Bland-Altman plot, b) histogram of the differences between the two heart rate estimates. c) Correlation plot showing a positive correlation between the two measurements, the red line represents the linear fit.

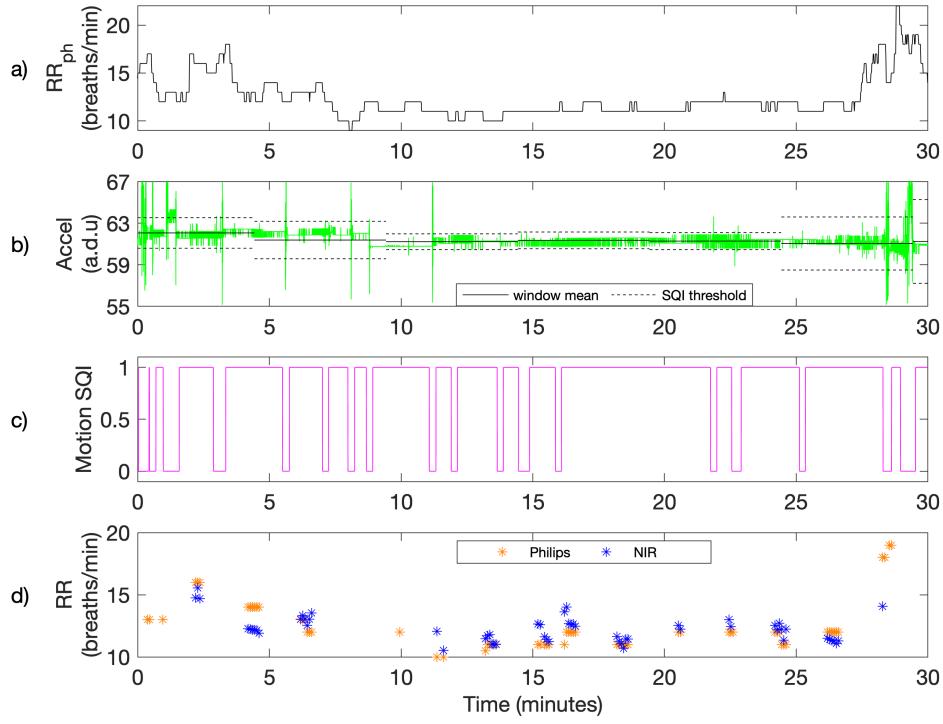


Figure 3.17: Comparison between the reference RR provided by the Philips monitor and the estimated respiratory rates a) RR from Philips monitor; b) Acceleration data from the Wavelet Health device; c) Motion SQI. Values of 1 correspond to periods of good-quality signal; Conversely values of 0 correspond to periods of poor quality signal; d) RR medians computed from reference respiratory rate and computed respiratory rate from the NIR signal.

RMSE values, correlation values and the error distribution computed across 10 subjects in the dataset.

Figure 3.18(a) shows the Bland- Altman plot comparing the Philips and estimated respiratory rate values for all 10 patients. The plot shows a mean bias of 0.18 breaths/min, most of the differences falling within [-4.3, 4.6] breaths/min, the correlation coefficient is 0.74. The MAE between both respiratory rate measurements was 1.6 breaths/min with a MAD of 1.6 breaths/min.

### 3.6.4 $SpO_2$

Figure 3.19 shows the relationship between the ratio of ratios computed using the Red/NIR signals from the Wavelet Health wearable device, compared with the reference  $SpO_2$  provided by the Philips monitor for a sample recorded session. An inverse correlation between  $SpO_2$  and the Red/NIR ratio can be seen. Figure 3.20 shows the scatter plots comparing the red/NIR ratio obtained from the Wavelet Health to the Philips  $SpO_2$  values for all 10 patients. The plots shows correlation coefficient ranging from  $r = 0.62$  to  $r = 0.98$ .

## 3.7 Discussion

Heart rate is a vital sign that can be estimated from a wearable device, which makes it a good candidate for validating the proposed signal processing algorithms. As can be seen in figure 3.16 and table 3.2, our HR

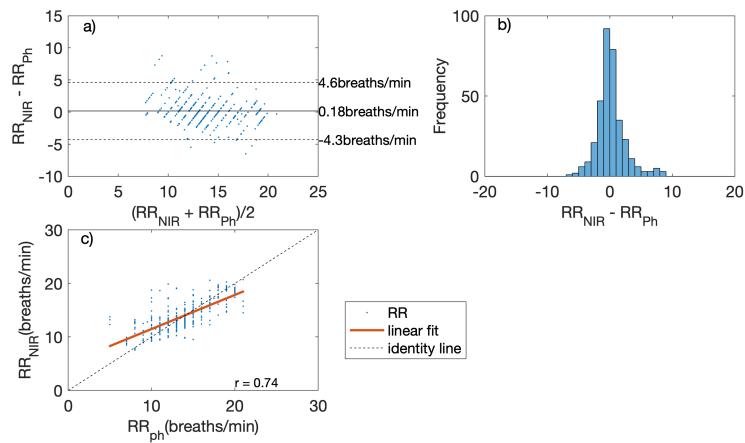


Figure 3.18: Comparison between the reference and estimated RR for the 10 patients in the dataset. a) Bland-Altman plot; b) histogram of the differences between the two RR estimates; c) Correlation plot shows a positive correlation between the two measurements, the red line represents the linear fit.

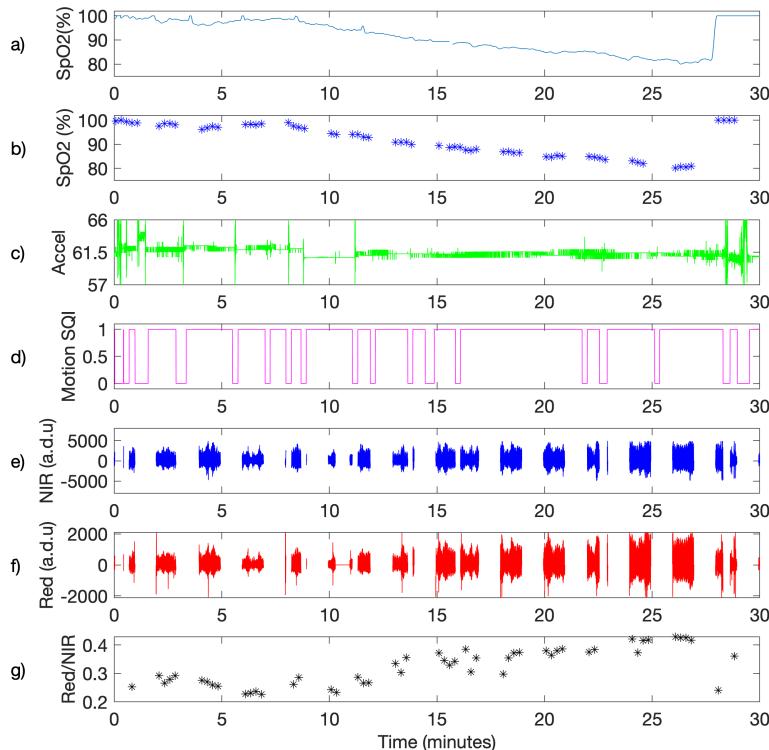


Figure 3.19: Comparison of the trend between the Red/NIR ratio and the reference  $SpO_2$ . a) Reference  $SpO_2$ ; b) Medians of the reference  $SpO_2$ ; c) Accelerometer data; d) Motion SQI; e) NIR signal amplitudes; f) Red signal amplitudes; g) Red/NIR amplitudes ratio.

Table 3.3: Summary of the results for the proposed algorithms to estimate respiratory rate.

Patient No.	Amplitude modulation				Frequency Modulation				Combined Method			
	MAE*	MAD*	RMSE*	r	MAE*	MAD*	RMSE*	r	MAE*	MAD*	RMSE*	r
001	1.4	1.4	2.0	0.33	1.4	1.4	2.0	0.60	0.9	0.9	1.2	0.61
002	2.7	2.0	3.6	0.45	2.2	1.9	2.9	0.54	1.7	1.3	2.2	0.74
003	2.5	2.2	3.5	0.27	3.0	2.8	4.5	0.09	1.0	1.0	1.5	0.79
004	1.9	1.8	2.5	0.19	1.4	1.4	1.9	0.51	1.5	1.4	2.0	0.42
005	1.4	1.3	1.7	0.55	2.4	1.8	3.0	0.53	1.4	1.2	1.8	0.57
006	4.0	2.9	5.0	-0.32	2.3	2.0	3.0	0.06	2.5	2.4	3.6	-0.17
007	3.7	2.8	4.5	-0.05	1.8	1.8	2.5	0.08	2.0	2.0	2.5	0.11
008	3.6	2.2	4.6	0.08	4.4	2.7	5.3	0.17	3.4	2.0	4.1	0.19
009	1.4	1.2	1.8	0.36	4.2	3.7	5.6	-0.16	0.8	0.8	1.0	0.46
010	2.6	3.2	4.2	0.34	1.2	1.3	3.3	-0.09	0.6	0.6	0.8	0.89
Overall	2.5	2.5	3.5	0.52	2.3	2.3	3.5	0.47	1.6	1.6	2.3	0.74

\*Values in breaths/minute

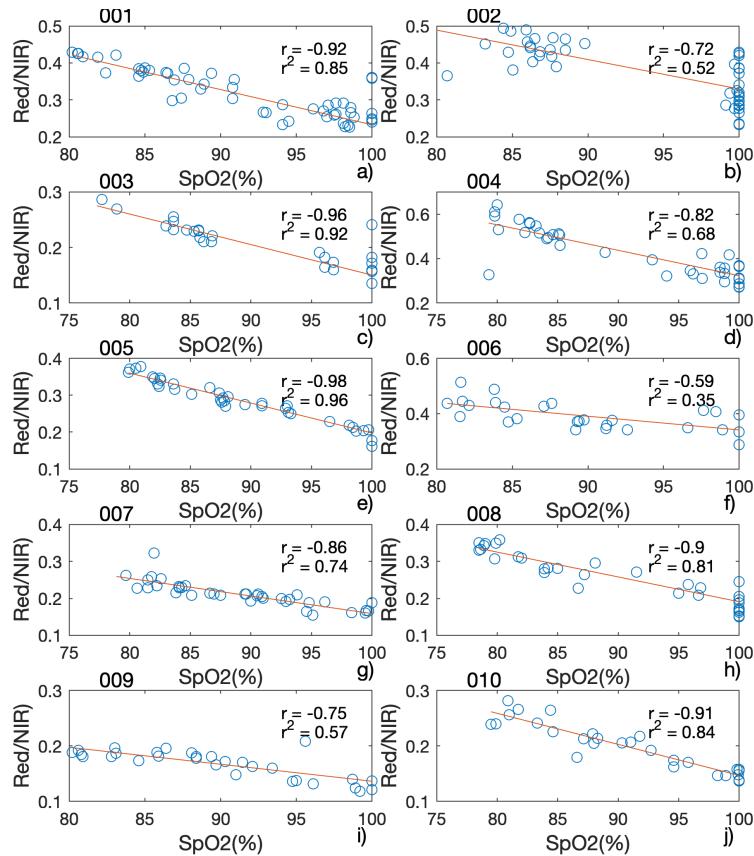


Figure 3.20: Correlation plots of the Red/NIR Ratio for the 10 patients in the dataset. Increased red light absorbance (increased Ratio) is associated with increased de-oxyhaemoglobin, i.e., lower  $SpO_2$ . The red line represents the linear fit.

estimates are comparable to the values computed by a reference medical device. The mean bias of 0.16 beats/min and correlation coefficient of 0.99 suggests that our proposed signal processing algorithms work adequately.

Respiratory rate is considerably more difficult to estimate from a wearable device. The lower correlation coefficient ( $r = 0.74$ ) and errors (MAE and MAD of 1.6 breaths/min) shown in figure 3.18 and table 3.3 respectively, are clear indication of this. By combining the two proposed methods using an additional SQI (respiratory difference) the estimation results were improved and there was a low bias and positive correlation present.

The Wavelet Health device is a novel wrist worn device. Comparisons between  $SpO_2$  from the Philips monitor and Wavelet Health device showed inconsistent performance showing that the device is not adequate to estimate  $SpO_2$  during desaturation periods.

### **3.8 Conclusion**

This chapter presented the algorithms for estimating vital signs (HR,RR and  $SpO_2$ ) from the Wavelet Health wearable device. The HR results had minimal errors with a positive correlation coefficient of 0.99. The other results (RR and  $SpO_2$ ) had errors greater than the WHO guidelines. New and improved methods are needed to design technologies that can estimate vital signs for the target population of this report

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