Detection of Sleep and Wake States Based on the Combined Use of Actigraphy and Ballistocardiography

by

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B.A.Sc., Simon Fraser University, 2016

Thesis Submitted in Partial Fulfillment of the
Requirements for the Degree of
Master of Applied Science

in the
School of Mechatronic Systems Engineering
Faculty of Applied Sciences

SIMON FRASER UNIVERSITY
Spring 2019

Approval

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Degree:	**Master of Applied Science**
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Date Defended/Approved:	April 30, 2019

Ethics Statement

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Abstract

Sleep is a vital part of every humans daily circadian rhythm. People can rest and recover their body and mind and live a more active and alert life with an appropriate amount of sleep. The current gold standard method for sleep analysis is polysomnography, but due to the complexity, it is not convenient to perform it regularly and it disrupts the normal sleep environment of the patient. This thesis presents a method of integrating two alternative measurements of sleep analysis for an improved analysis. Combining the motion detection of actigraphy and the cardiac parameters of ballistocardiography, a novel algorithm was developed to analyze sleep and wake states without interfering with the natural sleep cycle of the participant. Without interfering with the natural sleep environment, this system can be implemented for continuous monitoring and be used to evaluate daily sleep patterns to assess overall sleep quality and health over time. The experimental results demonstrate the effectiveness of the novel proposed algorithm in comparison with each device used separately in improving the sleep classification.

Keywords: Actigraphy; Polysomnography; Ballistocardiography; Sleep

Acknowledgements

I would like to express my gratitude towards my senior supervisor, Dr. Edward Park, for giving me the opportunity to develop this project and obtain my Master's degree. From when I first worked on my capstone project with him, he has been mentoring and guiding me through my academic career. I have learned valuable skills for conducting research and writing academic papers and especially for providing important feedback and recommendations for my research and associated works.

I would like to thank Dr. Yaser Roshan for guiding my on the initial phase of my research by setting some of the ground work that provided my focus on where I should take the next steps. Also, for reviewing my material and written works to provide an excellent feedback for further developments. I would like to thank and am very grateful for Dr. Carolyn Sparrey and Dr. Faranak Farzan for taking their time to examine my thesis work. In addition, I would like to thank Dr. Siamak Arzanpour for serving as the chairman of my defence.

I would like to thank all the members of the SFU Biomechatronics Systems Lab for providing valuable feedback throughout my studies. Each of them has provided relevant advice on the methods for preparing and accomplishing my academic works. I would like thank Dr. Osman Ipsiroglu of UBC and his team at the BC Childrens Hospital for providing me with some of the vital equipment required to complete my research work. Also, I would like to thank Professor Gerard Klosch who was introduced by Dr. Ipsiroglu. Professor Klosch is an expert in sleep and neurology and helped with verification with the data I have gathered and gave me advice on how I should proceed with my analysis.

I am very grateful to all the participants that agreed to help me collect data as I know the data collection would interfere with their sleep schedules. Collecting data from everyone was very beneficial to my research and without their help, I would not be able to complete my study.

Finally, I would like to thank my parents for supporting me throughout my studies. With their love and encouragement, I was able to complete my work.

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List of Acronyms

ADL	Activity of Daily Living
PSG	Polysomnography
AASM	American Academy of Sleep Medicine
REM	Rapid Eye Movement
NREM	Non-Rapid Eye Movement
ISR	Inter-Scorer Reliability
BCG	Ballistocardiography
ECG	Electrocardiogram
EEG	Electroencephalogram
EOG	Electro-oculogram
EMG	Electromyogram
HRV	Heart Rate Variability
IMU	Inertial Measurement Unit
R and K rules	Rechtschaffen and Kales Sleep Scoring Rules
ROC	Right Outer Canthus
LOC	Left Outer Canthus
PLM	Periodic Limb Movements
CO_2	Carbon Dioxide
SWS	Slow Wave Sleep
BPM	Beats Per Minute
PNS	Parasympathetic Nervous System
SNS	Sympathetic Nervous System
ULF	Ultra-Low-Frequency
VLF	Very-Low-Frequency
LF	Low-Frequency
HF	High-Frequency
SDNN	Standard Deviation of Normal Intervals
pNN50	Percent Difference of Adjacent Intervals by 50ms
RMSSD	Root Mean Square of Successive Differences
IMU	Inertial Measurement Unit
HFHRV	High Frequency Heart Rate Variability
LFHRV	Low Frequency Heart Rate Variability

RR	Respiration Rate
RRV	Respiration Rate Variability
Lp	Low Pass
SV	Stroke Volume
Rdepth	Respiration Depth
TST	Total Sleep Time
TWT	Total Wake Time
SE	Sleep Efficiency
IIR	Infinite Impulse Response

Glossary

naison	Between forehead and nose
inion	Ridge behind the skull
preauricular points	Indentations above the tragus cartilage
QRS-complex	Typical heart rate deflection signal for ECG
Sleep Inertia	Cognitive or physical impairment present immediately waking from sleep
Sleep Drunkenness	Sleep disorder of slow speech or confusion upon waking
Systole	Heart contracts and pushes blood into body, blood pressure increases
Diastole	Heart relaxes and blood fills heart chambers, blood pressure decreases
Sympathetic Nervous System	Part of nervous system that stimulates activity
Parasympathetic Nervous System	Part of nervous system that activates at rest
Sympothavagal balance	The balance between sympathetic and parasympathetic autonomic states
Fight or Flight	Autonomic response to regulate stress to direct reaction of potentially harmful event identified
Zero Sum System	Situation when one gains and another loses an equal amount or vice versa, final result always zero
LF/HF	Sympathovagal balance frequency ratio

Chapter 1.

Introduction

1.1. Overview

Sleep is an important part of a healthy human life and can make up a quarter of the total life span [1]. Sleep is vital for recovery and resting the brain and human body that benefits in an increased awareness and productivity throughout the day. Excessive lack of sleep can be the result of various sleep disorders such as obstructive sleep apnea syndrome, narcolepsy, idiopathic hypersomnia, and periodic limb movement disorder which can also be related to other medical, neurological and psychiatric disorders [2]. In addition, the U.S. National Highway Traffic Safety Administration estimates that a lack of sleep while driving has caused 100,000 car accidents resulting in over 1500 deaths, 70,000 injuries and 12 billion dollars in financial losses per year [2]. Maintaining the appropriate amount of quality sleep is very important for ones well being by promoting awareness and productivity throughout the day. As a result, it has become increasingly popular for the general public to monitor and measure their sleep quality [3].

As more people have access to smart phones and tablets, applications are being developed to track and log sleep cycles and create personal trends to manage one's sleep quality. As well as integrating wearable technology with the connectivity of smart devices, people can measure various parameters during activities of daily living (ADL) in addition to sleep quality [3]. Commercially available devices such as the FitBit wearable band and the Beddit sleep tracker, which is a sensor placed on the bed, are both devices that can measure sleep quality conveniently in a person's own home [4],[5]. However, most of these devices are not considered medical devices and are only used to help users be more mindful of their sleeping activity and adjusting their daily patterns accordingly. Therefore, the accuracy is not as good as medical devices designed to monitor sleep but can be used as a convenient way to have a rough idea of one's sleep quality. The alternative to measuring the sleep quality during a night cycle is to visit a sleep clinic and undergo professional medical assessment. This would establish the best assessment of sleep quality because professional medical grade equipment would gather related information accurately and the measurement will be monitored by a medical doctor or

technician trained in sleep scoring. The main drawbacks of a sleep clinic, however, are the financial expenses and the intrusiveness as the patient usually sleeps in the clinic (away from their natural sleeping environment) with multiple sensors directly attached to the body [6]. Therefore, users might prefer more convenient methods for measuring sleep quality and researchers are exploring alternatives for effectively measuring sleep quality without heavily impacting a person during the sleep cycle.

1.2. Literature Survey

The gold standard for measuring sleep quality is the sleep analysis system known as polysomnography (PSG) as it can measure many physiological signals such as brain waves, eye movements, heart rate and body position and diagnose sleep disorders [7]. Each sleep related parameter is measured by attaching electrodes directly to specific locations of the body [9]. A sleep study is usually performed by having the patient attend a sleep clinic to have the PSG device attached to the patient's body before sleeping. Usually, the patient would spend the night at the clinic to be monitored by medical professionals. For some instances, the patient is given the PSG device to take home and instructed on how to apply each of the sensors for the specific data collection and returned to the clinic for evaluation by trained sleep technologists or doctors [10]. Evaluating a patient's sleep quality through PSG has been criticized to be intrusive and disrupt the natural environment of the patient by relocating them to a new location and attaching many devices directly to their body [7]. As a result, the data collected may not represent the best data to diagnose the participant properly because of all the sensors and electrodes attached directly to their body. The American Academy of Sleep Medicine (AASM) considers PSG as the gold standard due to the sleep-related body functions that are measured and the combinations of these parameters can be observed to diagnose sleep disorders specifically [8].

Each signal collected from the PSG unit needs to be analyzed by trained personnel, which is typically done by visually inspecting the signal over the night cycle. The process of visually analyzing each signal and scoring sleep is time-consuming and can be inaccurate and expensive; and thus developments have begun on automated sleep scoring software packages [11]. In 1968, Alan Rechtschaffen and Anthony Kales had developed a manual for techniques, terminology and scoring system for sleep stages that has been well accepted and used throughout the world for analyzing sleep [12],[13]. This

manual defined sleep scores by separating sleep into 4 non rapid eye movement sleep (NREM) and rapid eye movement (REM) stages. Their technique included electrodes and measurement device placement on the patient's body and head to obtain vital physiological signals. The Rechtschaffen and Kales sleep staging criteria define stage 1 and stage 4 to be light and deep NREM sleep, respectively, and the REM sleep stage was defined when a person is dreaming with rapid eye movements as if the dream is being observed while sleeping [14]. However, over the years the AASM has released a comprehensive manual for scoring sleep stages and continually updates it based on numerous inquires and interpretations of the scoring rules [15]. As a result of the changes to the standards of scoring sleep stages, reliability among experienced sleep experts would vary when scoring the same sleep cycles. The AASM developed a program to measure inter-scorer reliability (ISR) to asses the validity of new updates and how each trained scorer interprets them [16]. The ISR in 2013 was 82.6% agreement for 9 sleep fragments and scored by roughly 2500 technologists and physicians [17].

As previously mentioned, PSG is considered the gold standard but inconvenient to use for the general public to measure sleep quality. Therefore, less intrusive methods such as actigraphy have been proposed to measure sleep quality continuously without interfering with the natural sleep environment. Actigraphy is the method of scoring sleep and wakefulness with a high degree of accuracy by using the motion data from a wrist-mounted device including an accelerometer as shown by Mullaney et al. [18]. This method was further expanded on in Cole et al. [19] and Kripke et al. [20] by developing automatic scoring systems for actigraphy and general algorithms that could be used with any actigraphic instruments. Based on published literature, the predicted values for sleep could be up to 90% when comparing actigraphy with PSG [21]. However, this high accuracy can be credited to overestimating sleep. During the night, people are usually sleeping more than being awake which leads to a higher accuracy for some instances. The convenience and inexpensiveness compared to PSG makes actigraphy very useful for researchers to obtain unobtrusive sleep measurements in many circumstances and locations over a period of days [22]. However, one drawback of actigraphy is being able to only focus on detecting sleep and wake states and not diagnosing some sleep disorders such as respiratory related disorders.

Balistocardiography (BCG) is a method of observing and measuring ballistic forces exerted on the human body by the equal but opposite forces of circulating blood [23]. This

phenomenon was first observed by Gordon, J.W. in 1877 by measuring small motions in sync with heart rate pulses described in [24]. The modern ballistocardiogram is based on the work present by Starr et al. [25] and started an era for investigating BCG and the benefits it could have [24]. One of the parameters that PSG measures to sleep stages is heart rate through electrocardiography (ECG) and BCG has therefore been used in place of an ECG in a nonintrusive manner. As PSG requires multiple electrodes attached to the body to gather signals, BCG on the other hand can gather similar signals through a sensor placed on the bed to measure vibrations throughout the night [26]. In addition to heart rate, heart rate variability (HRV) has become an important factor for measuring sleep stages as it relates to the autonomic nervous system whose regulation changes during sleep and transitions between sleep stages [27]. Heart rate is the number of heart beats in a minute while HRV is the fluctuations of time intervals between heartbeats [28]. The variability of heart rate is not perfectly on beat and can be chaotic to adjust for the constant changing environment that a human will experience, as can be witness between sound sleep and actively waking [29].

An initial investigation was performed in [46] to relate cardiorespiratory signals with actigraphy. This paper concluded that there is an improvement from a combination of both methods and a viable choice to detecting sleep states. However, they used a PSG with ECG leads and respiratory effort belts to collect cardiorespiratory signals to compare with actigraphy to analyze the sleep states. There was brief mention on using BCG for cardiorespiratory analysis with actigraphy to create a truly unobtrusive sleep state analysis method. Therefore, this thesis aims to observe the effects of a novel combination of BCG and actigraphy to measure sleep states with minimal disturbances to the participant.

1.3. Objective

The main objective of this thesis was to develop an algorithm combining a wrist-worn 3-axis accelerometer for actigraphy and a BCG bed sensor to properly score sleep/wake states compared to a full PSG device. Creating a sleep scoring system utilizing actigraphy and BCG only would be more convenient for researchers and patients by collecting vital sleep data over multiple sleep cycles without disturbing the regular sleep environment. This would provide more natural sleep data for scoring sleep stages and help diagnose sleep related problems. For example, older adults or people with a chronic illness that require constant monitoring may like to still have some independence by not

constantly being interrupted by a medical professional or caregiver checking up on them. A system like this could be monitored by a nurse remotely to observe their daily sleep quality and pattern for continuous assessment of their health. In addition, sleep disorders could potentially be diagnosed if they are not sleeping properly and would let the patient sleep naturally without physical nightly check ups.

In this work, PSG is to be used for verification purposes and should be scored properly to have a gold standard comparison for the developed algorithm. The accelerometer data from a 3-axis accelerometer designed for motion capture are to be used as an actigraphic device. The actigraphy algorithm could be deployed to a variety of commercially available smart watch devices and integrated into a wide variety of systems. In addition, the small size of the accelerometer would not only be convenient but simulate the size and weight of a wrist worn smart watch device. The BCG algorithm would take cardiologic measurements from a BCG bed sensor placed on the mattress while a person sleeps to score sleep stages. The sensors inside of the BCG device would be sensitive enough to detect accurately measure heart rate and heart rate variability. Also, the small size of the BCG sensor should be unobtrusive in the person's bed while they sleep. The combination of actigraphic and BCG devices together should not interrupt the natural sleep environment and the signals obtained and improve the sleep scoring overall as compared to being separate.

1.4. Contributions

The main contribution of this work is the proposed combination of actigraphy and BCG specifically to improve the detection of sleep/wake states. Each sensor individually can be used as a non-intrusive method for detecting states during the sleep cycle, and the hypothesis was that the combination would improve sleep scoring, while maintaining a comfortable sleep environment. A research grade 3-axis accelerometer in an inertial measurement unit (IMU) was used to create actigraphic analysis for accurate sleep/wake detection. A commercially-available BCG device was used gather cardiological signals and low pass filtering with Bollinger bands was applied; to output sleep/wake states as well. Once each sensor outputs their respective sleep states, the proposed algorithm would combine both results to output an improved sleep score over the night compared to the sensors individually. The sensors outputs were compared to the gold standard scores from PSG to validate the effectiveness. Experiments on human subjects showed improved

results with full sensor setup with PSG comparison. The experiment was performed over multiple days to have more verification from each participant by observing unique sets of sleeping data.

1.5. Thesis Overview

This thesis is divided into the following five chapters: 1) Introduction, 2) Background, 3) Experimental procedure and setup and 4) Results and Discussion and 5) Conclusion. In Chapter 2, fundamental information about each method and sensor is presented as well as describing how the PSG readings were scored, actigraphy was developed with the IMU and the cardiological signals measured from the BCG device were analyzed for sleep scoring. Chapter 3 describes the experimental setup including the participant selection, how the equipment was used and experimental procedure for data collection. Chapter 4 describes the results and discussion. Chapter 5 concludes the thesis and provides recommendations for future research related to sleep analysis with actigraphy and BCG.

Chapter 2.

Background

2.1. Polysomnography

2.1.1. Introduction

PSG is the gold standard when it comes to measuring the quality of sleep [7]. A PSG device measures sleep functions by directly attaching electrodes and sensors to the body such as: electroencephalography (EEG), electro-oculogram (EOG), electromyogram (EMG), nasal or mouth airflow, chest, abdominal and leg movements, snoring, body position and pulse oximetry [9], [30]. Over the last century, many studies investigated the related physiology of sleep. For example, Macwilliams demonstrated blood pressure fluctuations during sleep periods of sleep, Loomis et al. showed EEG changes in NREM stages and Aserinsky and Kleitman demonstrated REM sleep [9]. Rechtschaffen and Kales created a manual for which were known as the R and K rules and were used until 2007, when the AASM updated the sleep scoring rules known as the AASM scoring manual [31]. The former R and K rules segregated sleep into five stages, from stage 1 to stage 4 and a REM stage while the updated AASM rules combined stage 3 and 4 into a single stage for deep sleep. The sleep scoring rules are meant to be used as a guide for interpreting sleep stages and create uniform standards that can be referred to as opposed to a hard framework [31]. As a result, the AASM often verifies the ISR to measure how well the sleep score rules are being interpreted and revises them accordingly if problems arise [16], [17].

2.1.2. Polysomnography Parameters

The PSG device itself, houses many sensors that are attached directly to the human body via electrodes and can be customized to measure specific regions of the body for scoring sleep and diagnosing sleep disorders. As summarized in Table 1 obtained from [32] with permission, PSG assessment can be classified into four levels based on the intensity of data collection and patient observations. Level 1 is the standard PSG with the

Table 1. Assessment levels of PSG studies [32]

	Level 1 Standard Polysomnography	Level 2 Comprehensive Portable Polysomnography	Level 3 Modified Portable Sleep Apnea testing	Level 4 Continuous Single or Dual-bioparameter recording
Parameters	Minimum of seven, including EEG (C4-A1 or C3-A2), EOG, chin EMG, ECG, airflow, respiratory effort, oxygen saturation	Minimum of seven, including EEG (C4-A1 or C3-A2), EOG, chin EMG, ECG or heart rate, airflow, respiratory effort, oxygen saturation	Minimum of four, including ventilation (at least two channels of respiratory movement and airflow), heart rate or ECG, oxygen saturation	Minimum of one
Body Position	Documented or objectively measured	May be objectively measured	May be objectively measured	Not measured
Leg Movement	EMG or motion sensor desirable but optional	EMG or motion sensor desirable but optional	May be recorded	Not recorded
Personnel	In constant attendance	Not in attendance	Not in attendance	Not in attendance
Intervention	Possible	Not possible	Not possible	Not possible

Abbreviations: electroencephalogram – EEG, electro-oculogram – EOG, electromyogram – EMG, electrocardiogram – ECG

most sensors analyzed and usually done in a sleep clinic with observation from trained technicians, while levels 2 through 4 being less intrusive and portable to allow the patient to sleep outside of a clinic [32]. In addition, certain sleep disorders would only require specific sensors to diagnose and therefore, a higher level of PSG unit would be used for the specific analysis. EEG measures electrical activity from the brain by attaching sensor electrodes to the surface of the scalp. The internationally accepted method for electrode placement is known as the 10-20 system. The name refers to placing the electrodes 10-20% distance between landmarks on the head and the reason to use percentages instead of distances is to compensate for varying head sizes. The landmarks on the head are: indents between forehead and nose (naison), ridge behind the skull (inion) and two preauricular points that are indentations above the tragus cartilage or ear. In addition, each electrode site placement location is named with the following nomenclature: F = frontal, P = parietal, T = temporal, C = central, O = occipital and A = auricular; with

numerical subscripts given for locating the right (even) and left (odd) side of the head such as C_3/A_2 or C_4/A_1 which is one of the common electrode placement locations for sleep scoring. The voltages measured from the scalp are usually too small and need to be amplified, which is known as gain, for suitable interpretations [30]. EOG measures eye movements by placing an electrode around the eyes in the outer canthus area (ROC – right outer canthus and LOC – left outer canthus). Placing the electrodes above and below each eye can produce an out of phase deflection for eye movements and helps distinguish artifacts from the EOG from other channels on the PSG. The EOG measures the electro potential difference between the front and back of the eye such as, the recording will be a positive deflection when the eye moves towards the electrode and a negative deflection when the eye moves away [30]. EMG measures the chin muscles and some limbs, most commonly the legs or anterior tibialis muscles. The electrodes are placed about 1-2 cm apart on the left and right side of the chin and about 2-4 cm apart on any of the limbs. The measure is obtained bipolarly among the combinations of electrodes attached. If the electrodes are attached to any of the limbs, usually this is to diagnose periodic limb movements (PLM) during sleep [30]. ECG measures the electrical pulses around the heart to obtain heart rate and cardiological signals. The heart rate is represented by beats per minute where each beat obtained is from the QRS-complex in Figure 1, with R being the spike and beat pulse. Traditionally, heart rate is not used for scoring sleep stages but is useful for diagnosing health disorders related to the heart such as abnormal heart beats during sleep [33].

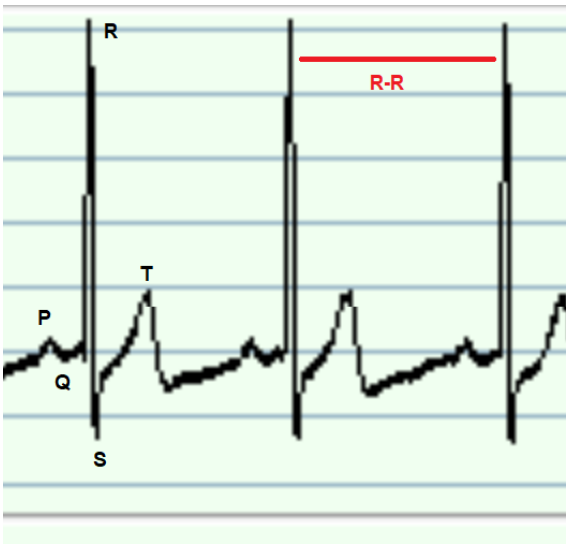


Figure 1: Heart rate QRS-complex obtained from ECG with R-R interval

Respiratory effort measures the airflow from a person breathing while they sleep. There are many methods to detect airflow such as thermistor or thermocouples, nasal cannulas and respiratory effort belts. Thermistors or thermocouples sense the temperature difference between breathes and is measured as a change of resistance and electromotive forces. Nasal cannulas detect pressure change with tubes inserted in the nose. Airflow estimates pressure decrease with inspiration and increase with expiration. An issue with nasal cannula is that it only detects airflow from the nose and does not detect oral airflow if the person breathes through their mouth however, newer cannulas have been designed to incorporate oral airflows [30].

Pulse oximetry measures oxygen levels by transmitting two wavelengths of light through the skin. Usually it is attached to the finger but can be attached to the ear lobe or nose as well. The infrared lights are used to measure the exchange of oxygen and CO_2 validate adequate ventilation. However, issues arise with pulse oximeter because the sensor depends on a clean connection to the skin and motion, skin pigment and fingernail discoloration can provide false reading. Also, the infrared light may heat the skin and become uncomfortable to the user [9].

2.1.3. Sleep Stages and Scoring

Each vital parameter measured with PSG is scored in accordance with the R and K rules developed by Rechtschaffen and Kales and further expanded on by the AASM over the years. Sleep scoring is primarily done by a trained sleep technician or doctor, visually examining the vital signals from the EEG, EMG and EOG outputs by the PSG [14]. The R and K rules recommended to view each epoch in 30 second intervals because at the time, the non digital polygraph paper speeds would output each trace at 10mm/s and 30 seconds was a convenient portion of time to observe [34]. Each epoch is viewed and given a score based on the scorer's interpretation of the R and K rules and if an epoch appears to have more than 1 potential stage it could be scored, the greatest portion of the score is assigned to the epoch [34]. As a result, this makes sleep scoring with automatic software difficult because many of the epochs exhibit mixed sleep stages and even if a small number of misclassified epochs can substantially affect the overall diagnosis. In addition, the electrodes attached directly to the body can produce artifacts and fragments from movement and electrodes coming off the body [34]. Table 3 summarizes the rules for manual scoring sleep [30], [33], [34] and Table 4 summarizes the differences from the

original sleep scoring rules developed by Rechtschaffen and Kales compared to the new scoring rules updated by the AASM described by [31] with permission. EEG is one of the main methods to measure sleep stages by observing the specific frequencies of brain waves with other vital parameters used to help further distinguish differences between stages throughout a sleeping cycle [9]. When scoring sleep, the observer should initially quickly scroll through the whole sleep cycle to see specific shapes of the waveforms as each person has a unique pattern to their brain waves, eye and body movements signals [30]. Table 2 shows each of the frequency rhythms in Hz acquired from the EEG parameter and a brief explanation (brief) of each stage is obtained from [30].

The wake stage is the first stage recorded as a person usually enters the bed and begins the process of falling asleep. The EEG will score more than 50% of each epoch as alpha waves with some mixed alpha and beta waves as the eyes are closing and opening throughout the wake stage. EMG will show high muscle activity as the person moves in the bed and adjusts to a comfortable sleeping position and EOG will show little eye movements unless responding to external stimuli before becoming drowsy from closed eyes. Muscle tones and eye movements will reduce as person comes closer to stage 1 sleep and may alternate between stage 1 and wake before fully entering stage 1 sleep [30].

Table 2: EEG Frequency Rhythms

Rhythms	Frequency (Hz)
β	≥ 14
α	8-13
θ	4-7
δ	< 4

Table 3: Summary of manual sleep scoring stages

Stage	EEG Readings	EOG Readings	EMG readings	ECG readings
Wake	Mixed beta and alpha waves with 50% alpha usually	Little eye movement unless stimulated or blinking	High muscle tones and contractions and movement artifacts	Heart rate like daily rate
Stage N1	More than 50% theta waves with mix of alpha and beta waves	Signs of slow eye movements	Less activity than wake usually	Heart rate regularizes and blood pressure drops
Stage N2	Mostly theta waves with some delta waves, sleep spindles and K complexes present	Slow eye movements like stage N1	Low muscle tones and activity like stage N1	Heart rate and blood pressure continue to decrease
Stage N3	Slow wave sleep dominated by theta waves	Very low or no eye movements	Muscle tones and activity further reduced from stage N2	Heart rate decreases and slows down
Stage REM	Low amplitude, mixed frequency theta with alpha waves mixed in, no K complexes or sleep spindles	Rapid eye movements	Very low muscle activity	Heart rate and blood pressure fluctuates and increases

Table 4: Differences of R and K manual with AASM scoring manual from 2007 [31]

Difference	R and K manual	AASM manual
EEG electrodes	Score sleep stages using central (C3, C4) leads	Score using frontal, central and occipital
Major Body movements	Movement time can be scored even if more than half of epoch is obscured	Only stage N3 recognized with delta wave measured with frontal leads
Slow wave sleep	Consists of both stage 3 and stage 4 with delta wave amplitude measured using central leads	No movement time staging
Terminology of stages	Stage 1, stage 2, stage 3, stage 4, and stage REM sleep	Stage N1, stage N2, stage N3, and stage R sleep
Reference electrode	Left and right ear or mastoid called *A1* or *A2*	Left and right ear or mastoid, termed *M1* or *M2*
stage 2 sleep scoring	3-minute rule that states if greater than 3 minutes pass between spindles or K complexes, then score stage 1 sleep	No 3-minute rule exists

Stage 1 sleep is a light sleep or a short transitional stage from wake to a deeper stage of sleep. The EEG patterns may be fast with low voltage amplitude making it difficult to interpret. Stage 1 is scored when more than half of the epoch contains theta waves (4-7Hz) with some low amplitude beta waves (≥ 14Hz) replacing the alpha waves (8-13Hz). Sharp vertex shaped waves may occur towards the end of stage 1 but sleep spindles and K-complexes are not present. In addition, EMG shows less activity and EOG may show signs of slow eye movements. If an arousal activity occurs between 3 to 15 seconds, the epoch is scored as wake instead. A person's breathing becomes shallow, heart rate becomes regular, blood pressure falls and minimum movement is observed. When sleeping in stage 1, the sleeper may be easily awakened and may feel like they haven't fallen asleep yet [30].

Stage 2 sleep is observed for most of the sleep cycle by PSG (up to 50%) that is dominated by theta waves (4-7 Hz) with some occasional quick bursts of EEG activity. EOG signals may mirror EEG signals and EMG activity is very low. Slow wave sleep occurs in this stage but only when 20% of an epoch is delta waves. Sleep spindles and k complexes are observed as well. K complexes are sharp, monophasic slow EEG wave with a sharp negative deflection followed by a slow positive deflection. There are no minimum amplitude criteria but must last for at least 0.5 seconds and are enough to score an epoch as stage 2 even without sleep spindles. They may be triggered with or without external stimuli such as a sudden sound. K complexes without external stimuli are referred to as spontaneous and be the result of endogenous brain activity. Sleep spindles are 12-14Hz sinusoidal EEG waves that appear like an unweaving spindle and are generated by the midline thalamic nuclei and represent inhibitory activity. They represent synchrony and symmetry between the two brain hemispheres and can attach to the tail end of a k complex. Some examples of k complexes and sleep spindles are shown in Figure 2. EOG and EMG have no specific criteria in stage 2 but an arousal may result in scoring of wake or stage 1. During stage 2 sleep blood pressure, brain metabolism, gastrointestinal secretion and cardiac activity decrease and descends deeper into sleep and difficult to wake up [30].

Stage 3 sleep also known as slow wave sleep (SWS) or deep sleep that is distinguished by high-amplitude slow wave EEG readings. No EOG or EMG rules are specified for stage 3 but generally each one is further reduced. Physiologically during a stage 3 sleep, a person has the highest threshold for arousals and parasomnias may

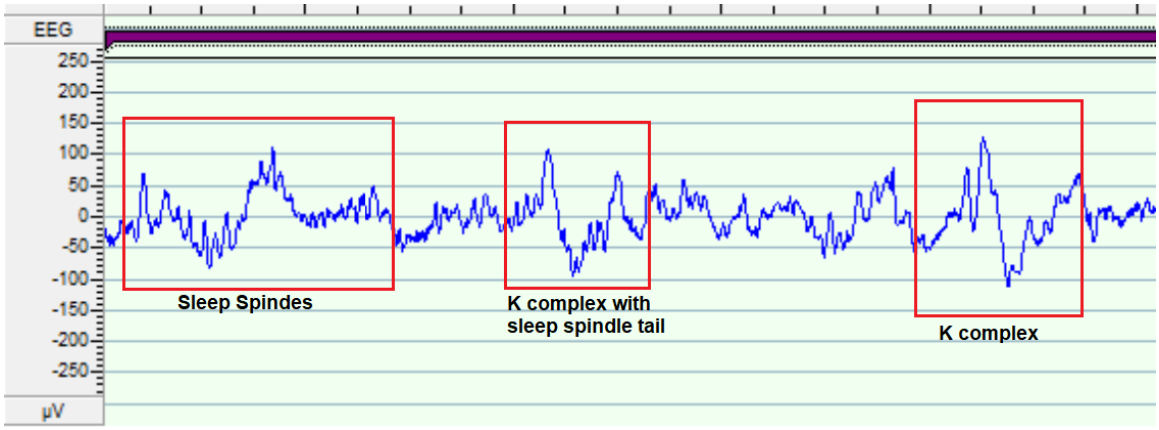


Figure 2: EEG waveform with examples of sleep spindles and k complexes

manifest such as sleep terrors and sleepwalking. K complexes and sleep spindles may appear in stage 3 and no EOG or EMG readings are specified but can be very low or stop entirely. Waking from stage 3, the person may appear confused or dazed that is known as ‘sleep inertia’ or ‘sleep drunkenness’ and may take several minutes to function normally [30].

Stage REM sleep is referred to rapid eye movement during sleep that are observed from the EOG sensors and usually occurs about 90-120 minutes into sleep onset. It is characterized by low amplitude and mixed frequency EEG waves with some alpha waves. Physiologically, blood pressure and heart rate may increase and breathing becomes irregular and body temperature fluctuates and usually dreaming occurs. EMG muscle tones are also very low as during REM sleep, the body suppresses muscle activity to not act out the dreams, however the eyes move around rapidly as if reacting to the image visualized in the dream. REM sleep is characterized with sawtooth EEG waves that are 2-6 HZ and evenly formed. REM stage will continue to be scored until another stage criteria is met for example, high EMG tones with no k complexes or sleep spindles present. If k complexes or sleep spindles appear in the first half of the next epoch without any rapid eye movements, then the epoch will be scored as stage 2. If the k complexes and sleep spindles occur in the second half, then the next epoch will continue to be scored REM and the following epoch will be scored stage 2. Arousal or major body movement also can end the REM stage however, if the EMG chin tone and rapid eye movements continue, then REM stage will continue to be scored [30].

2.2. Actigraphy

2.2.1. Introduction

Actigraphy is used for sleep and circadian rhythm research through a wearable device that measures motions of the body [34]. Actigraphy measures sleep through movement by assuming no movement to be sleep and movement to be wake. Many algorithms have been developed to distinguish wake from sleep by observing rest-activity patterns [34].Typically, actigraphy is a wrist worn device about the size of a smart watch but can be worn on any limb or the waist [35]. Many devices incorporate a 3-axis accelerometer for measurements, especially devices designed for athletes and fitness tracking throughout the day. A popular device used by the general public and clinical researchers is FitBit as it provides a low cost, field based and user-friendly experience that mostly monitors fitness statistics but also recently has been able to monitor quality of sleep [4], [36]. A more clinical device is known as the Actiwatch is a dedicated actigraphy wearable device that can be used up to 14 days on a full charge and can provide raw data on sleep, rest, activity and light exposure [35]. Actigraphy is a popular method for gathering sleep due to its non invasive nature. However, a drawback to using actigraphy is that it is not possible to diagnose many sleep disorders besides periodic limb movement disorder as it only measures sleep/wake states through movement. In addition, each sleep stage can not be measured with actigraphy alone and would require extra sensors to distinguish between stages.

2.2.2. Algorithm

Mullaney et al. [37] showed that possibility of data obtained from wrist-mounted movement could be scored manually to distinguish sleep from wake. However, the manual scoring process was laborious and reduced the practicality of the using actigraphy for regular use [39]. Webster et al. [38] developed a method for automatically scoring sleep and wake states with actigraphy. However, the method they developed was only optimized for their wrist activity device only and was uncertain if their method would work generally for any other device available commercially [39]. Therefore, Cole et al. in [39], and further expanded in [40] with Kripke et al., discussed and validated a more general algorithm that could be implemented in a wide variety of wrist worn actigraphy devices. The algorithm

for estimating sleep/wake states with actigraphy is a weighted sums equation that is based on a moving average window, i.e.:

$$D = P(W_{-4}A_{-4} + W_{-3}A_{-3} + W_{-2}A_{-2} + W_{-1}A_{-1} + W_0A_0 + W_1A_1 + W_2A_2) \quad (1)$$

where the A_0 value represents the activity scores from the current epoch being evaluated while the negative subscripts represent epochs in the past and positive epochs in the future. The *W* values represent the weighting factors for each epoch and is adjusted to acquire the best sleep/wake estimation. The *P* value is the scale factor to adjust the entire equation as needed for better estimations. The total equation is summed together to get a *D* sleep score value which is used to estimate sleep (D < 1) and wake (D ≥ 1) [39]. Each *A* value is obtained from the actigraphic device performing a zero-crossing method to generate the raw signals for motion [41]. In addition, each *A* value can vary in real time length for example, a 10 second epoch would have all actigraphy movements recorded over 10 seconds in a single *A* value epoch. Cole et al. [39] had tested many epoch lengths in seconds such as 2, 6, 10, 20, 30, 60 [39] and found that 10 seconds provided the best results. However, in [40] a 30 second epoch length was used to easily match the PSG epoch lengths and many actigraphy devices report activity in 30 second- or 1-minute lengths. Since actigraphy only estimates sleep or wake based on movement, including the future and past epochs is very important to improve the estimation as movements around the current epoch can be related and help estimate sleep or wake movements. For example, if a person is laying still but awake and move within a few minutes of each movement. Then it is likely that they are still awake during the epochs that they lie still as the Cole-Kripke actigraphy algorithm would misscore sleep 3.5 times more than wake. Five rescoring rules have been developed by Webster et al. [40] to mitigate the problem of misscoring[39]. The rescoring rules would process the sleep score again by checking how many sleep or wake epochs were around the current epoch. For example, a short wake epoch surrounded by long sleep epochs would be rescored to sleep and the opposite for short sleep epochs between long wake epochs. The combination of all these rules in [39] claimed to reduce the ratio of false sleep and false wakes from 3.5 to 2.5. Therefore, actigraphy is a useful method for estimating sleep and wake states throughout multiple nights and having very little impact on sleep quality which can allow for a more natural sleep and better data gathering as a result.

2.3. Ballistocardiography

2.3.1. Introduction

Ballistocardiography is a non-invasive method to measure ballistic forces produced by the body as a result of the circulation of blood from the cardiac cycle [41]. BCG was first observed by Gordon, J.W. in 1877 by measuring small motions in sync with heart rate pulses described in [24] but began to fade away from relevancy after the 1980s as a result of lack of understanding and standards and guidelines for interpreting the BCG results. However, due to recent advances in sensor technology with the development of more sophisticated and sensitive sensors, BCG has seen a resurgence in the medical field for long term non-invasive sleep assessment [42]. The BCG measures the reactions of the body from cardiac ejections of the blood [42]. The functions of the heart and movement of blood causes a counter force in the opposite direction and this recoiled force visualized by a BCG is shown in Figure 3 [33]. Starr et al. [43] set the ground work for standards to be used with BCG by focusing on longitudinal, head to toe analysis. Starr designated a pattern ranging from H to N with the H to L being the dominant waves and H-K being systolic which corresponds to contractions in the heart and L-N being diastolic that corresponds to relaxation from the heart [23]. However, the L-N waves are uncertain and believed to be the cause of blood flow directional changes [33]. The I-J complex has the greatest amplitudes during inspiration [23]. The baseline represents the body in a neutral state when it is motionless as presented by the red line in Figure 3 and any movement from the body would produce artefacts that can corrupt the signal during the movement [44].

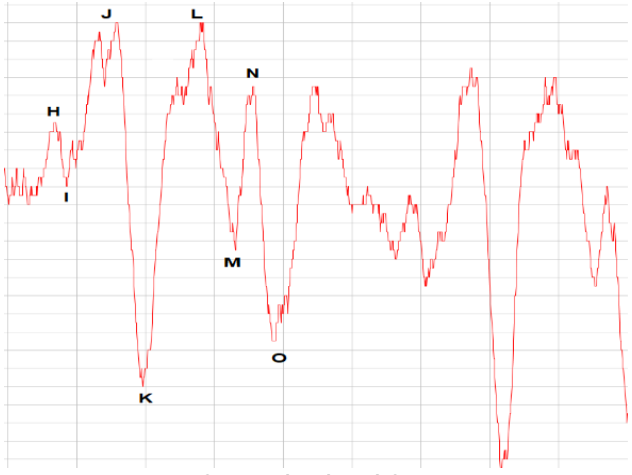


Figure 3: H-I waveform obtained from raw BCG reading

2.3.2. Cardiac Parameters

Through BCG, the cardiac parameters can be devised such as heart rate, heart rate variability and respiration rate that are required to estimate sleep stages like an ECG. In Figure 3, the H wave is a head-ward deflection is at the beginning at the near beginning of the R wave obtained from an ECG [44]. The J wave from BCG is the largest wave and occurs at the end of the systole, therefore it is used as the beat to beat values or R-R intervals for heart rate and heart rate variability as shown in Figure 1. In the BCG case, it is referred to J-J intervals [45]. Changes to the autonomic nervous system can be related to different stages of sleep and can be indirectly monitored by measuring heart rate and respiration [45]. Heart rate is a measure of how many pumps occur in 1 minute known as beats per minute (BPM). The respiration cycle consists of inhalation followed by exhalation and the respiration rate can be measure by the amount of breaths in a minute [33]. In addition, the respiration rate variability is the variation in respiratory time intervals and the respiration depth (Rdepth) is the amount of volume passing into the lungs during a single respiratory cycle [33]. Generally, body activity during sleep such as heart rate and respiration rate, decrease over the sleep cycle while does tend to become more irregular during REM sleep [23], [47].

In relation to heart rate, the heart rate variability is a very important parameter related to measuring sleep quality because of the relation to the autonomic nervous system and respiratory rhythms [48]. HRV is the fluctuations of time intervals between adjacent heart beat [49]. In addition, HRV constitutes as a marker for vagal modulation related to the parasympathetic (PNS) and sympathetic (SNS) nervous systems and a relationship exists between the two characterizing a Sympothavagal balance [48]. The SNS relates to the bodies fight or flight system and is active during stress or physical activity. In addition, SNS will compensate the active performance by increasing the circulation of blood and oxygen supply to organs, heart rate will increase in the heart and respiratory airways will expand to increase volume in the lungs [33]. The PNS is active during the resting and digesting times so the body can recover and works oppositely the SNS by decreasing the heart rate and respiratory rate to enhance recovery [33]. The sympathovagal balance describes the opposing SNS and PNS effects on the body but, the relationship between SNS and PNS is complex and can’t be described zero sum system [49], [50]. Increasing the PNS does not directly decrease the SNS and vice versa, instead the opposite system may increase, decrease or not change at all [49]. An example

of both systems engaged is when someone experiences high level of stress but breathes slowly [49]. Therefore, HRV has emerged as a prevalent method to measure the sympathovagal balance by observing the variation of heart rate R-R intervals during different activities and each of the sleep stages [50]. HRV is usually measured in time domain or frequency domain. Time domain measures the variation of time periods between each successive beat known as interbeat intervals (IBI) [49]. The standard deviation of normal sinus beats (SDNN) measures the standard deviation of successive R-R intervals and can be related to ultra-low-frequency (ULF), very-low-frequency (VLF) and low-frequency (LF) band powers and recommended to be recorded for 24 hours [49]. Percent of adjacent normal intervals (pNN50) is a measure of adjacent intervals that differ by more than 50 ms and can be correlated to PNS activity and HF band power [49]. The root mean square of successive differences (RMSSD) is calculated by obtaining successive time differences in heart beats and each value is squared and averaged before the total result is square rooted [49]. RMSSD measures the beat-to-beat variance in heart rate and vagally mediated changes in HRV and correlated to high-frequency (HF) power [49]. Frequency measures HRV the absolute or relative power in four frequency bands such as ULF (≤0.003 Hz), VLF (0.0033-0.04 Hz), LF (0.04-0.15 Hz) and HF (0.15-0.4 Hz) bands [49]. The frequency can be divided into low frequency (LF) bands that is related to sympathetic activity and stress and high frequency (HF) that is related to parasympathetic activity and relaxation [33], [49]. The ratio *LF/HF* can be used to estimate the activity between the SNS and PNS with a low ratio is seen when the body is conserving energy and a high ratio occurs when an active fight or flight behavior is happening [49]. Therefore, HRV is an important vital measuring the PNS and SNS to observe the transitions between each of the sleep stages [51].

Chapter 3.

Experimental Procedure and Setup

3.1. Experimental Study

The experimental protocol involving human subjects was approved by SFU Office of Research Ethics (study number 2017s0629). The experimental procedure consisted of recruiting willing and consenting participants through word of mouth and a follow up email for more information. All participant information was made anonymous and was only known by the author and senior supervisor, otherwise any personal information was not included in any of the analysis. The purpose of the human experiments was to gather natural sleep data from healthy adults ranging between the ages of 19-65 with actigraphy and BCG. Each of the participants considered themselves healthy without any known sleep disorders or illnesses. All participants were neither overweight or underweight and had a consistent BMI. None of the participants took any medication that could affect sleep and were also instructed not to drink any coffee at least 8 hours before the experiment or alcohol for 24 hours before the experiment. Each participant was instructed to try to sleep for at least 6 hours for each night but could sleep for any amount if they had to. All the participants slept for more than 6 hours. PSG and a video camera was also used but only for a gold standard validation for data analysis. However, the video camera was optional as some participants could feel uncomfortable with the recording. Once the participant had consented and filled out their agreement to participate in the study, they were briefed by the author on the setup and management of each piece of equipment. The briefing lasted for about 30 minutes and included how to setup each device in the participants sleeping environment. As the PSG was quite complicated with many electrodes that needed to be attached directly to the body, a detailed explanation of proper attachment procedure was performed, and an instruction manual was provided for the PSG in case the participant wanted to familiarize themselves with the PSG. The experiment would last 3 nights (didn't have to be consecutive) in the participants own home as this would provide a natural sleep environment and the BCG would calibrate and potentially improve the data by creating personal calibration values for each participant. The author provided each of the devices as well as a laptop to connect the actigraphy and BCG devices for data collection. Upon successful completion of the sleep study after each night, the participant

would return the PSG for data downloading and was given another PSG to use for the following night. The actigraphy and BCG data was stored locally on the laptop provided and returned to the author at the end of the study with the rest of the equipment. Ten participants were recruited for this study with nine being male and one female. An initial sample size and power test was performed to estimate how many participants should be included. The initial estimated accuracy of sleep state matches was observed to be about 75% from some pilot studies. The sample size was analyzed to get an improvement of 90% accuracy with a statistically significant power of 0.80, and it was determined that ten participants would be a sufficient participant size for this study and the inclusion of three nights of measurement per participant would further help in improving the accuracy. The Two participants had to be excluded from the study as one participants data was corrupted and could not be used and the other participant requested to not participate in the study after an initial run. The corrupted data resulted due to disconnection with some of the devices. As the laptop provided did not supply constant power to the USB ports, a subtle dip in power would result in one of the device disconnecting in the middle of the study. As the participant was asleep, they were unaware of the power loss and unable to fix the connection until they woke up the next morning. To rectify the problem, a USB hub with a separate power supply was provided to prevent the disconnection during the night. Due to scheduling conflicts the participants data was not able to be re-collected for a second time and had to be excluded from the results. Figure 4 show a closeup of the experimental setup with each device.

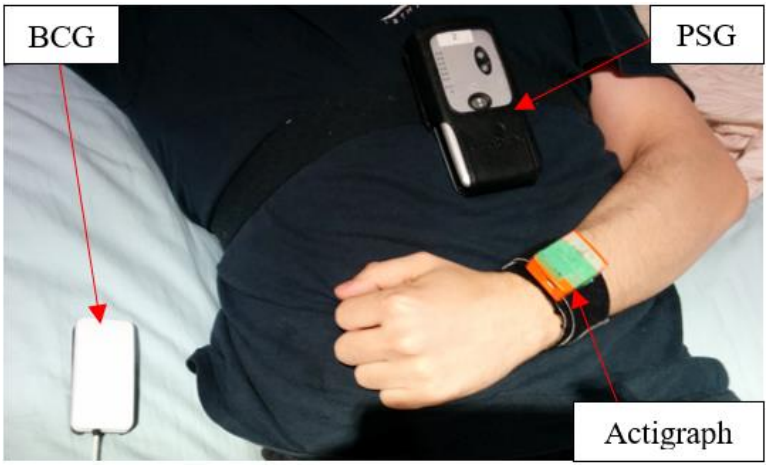


Figure 4: Close up of experimental setup with each device

3.2. Experimental Method

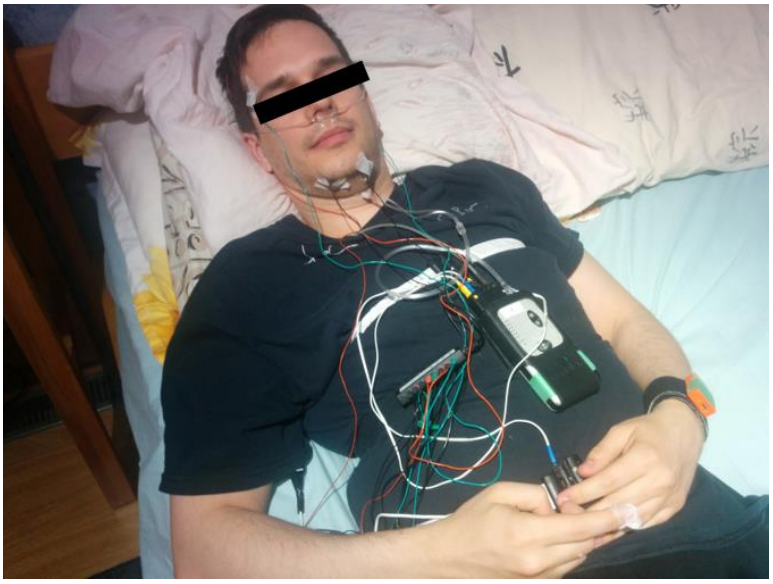


Figure 5: PSG setup worn by the author with all electrodes attached

The PSG device used for the experiment was the Embletta X100 by Natus Medical Incorporated. The Embletta PSG was used as a gold standard indicator for measuring sleep scores and the device is shown in Figure 5. The Embletta PSG was setup to measure sleep quality and ECG parameters according to the manual provided. The following parameters were measured during the study by the PSG: EEG, EOG, two chin EMG, two ECG, lower and upper torso respiratory effort belt, pulse oximetry, nasal canula and body position that is shown in Figure 5. Each of the electrodes were attached through sticky disposable electrode leads directly to the skin. This has been done for all electrodes except for the EEG that was located at the C_4/A_1 or slightly off center to the right location on the head and was attached with a conductive cup electrode with a conductive adhesive paste attached directly to the scalp. This electrode was unique because the hair on the head would prevent a proper connection with the disposable sticker; however, the reading would be the same regardless of the electrode used by the participant and it was up to the participants discretion which electrode type they wished to use. The Embletta PSG contained an event button that let the participant mark times throughout the night of excess activity and could be easily scored as wake because the participant was conscious. This event button was used to synchronize each of the sensors as it signified when the

participant laid in bed to finally sleep. Leaving the bed to go the bathroom for example would have the participant pressing the event when they left the bed initially and again upon returning to the bed. The data collected from the PSG was downloaded to a computer with the Remlogic software also by Natus Medical Incorporated that is included with the PSG device. A useful feature of the Remlogic software was automatic scoring to automatically determine sleep stages. According to [52], automated sleep scoring software can yield similar results to manual visual scoring by a trained sleep technician. But the automatic system may still need manual editing because any artifacts or patterns that may be scored intuitively by a human can be missed by a computer and scored incorrectly. As was the case for this study and the initial automated scores had to be manually edited and visually scored to have cleaner results as shown by the difference in hypnograms in Figures 6 and 7. This was also confirmed by a sleep expert (Professor Gerald Klosch) who after visually going through some of the sleep data mentioned that many instances would need to be edited from the automated scores. Each of the traces obtained were measured based on R and K rules described earlier in Chapter 2 with a focus on EEG, ECG and EOG. As an example, Figure 8 shows a section of stage 3 sleep because of the slow theta waves of EEG and lack of EMG and EOG activity and slower intervals between heart beats from the ECG. In addition to visually scoring each sleep stage from the software, a video camera with night vision was used to verify sleep states as well. As mentioned in [34], video recordings are a powerful and relatively cheap tool for assessing arousals and apneic events are real or the result of movement artifacts. The video analysis was also helpful as some of the scoring can be prone to error due to the participant attaching the sensor incorrectly or the sensor would detach during the night. This could corrupt portions of the data and make it difficult to score manually or automatically. Once a full sleep cycle was scored, it was exported as a text file detailing each 30 second epoch as a sleep stage. The sleep scores were then imported into Matlab to be used as a gold standard validation for the actigraphy and BCG algorithm.

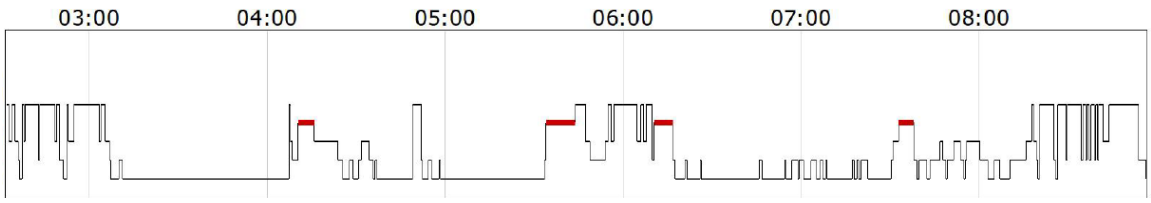


Figure 6: Automatically scored sleep stages by software

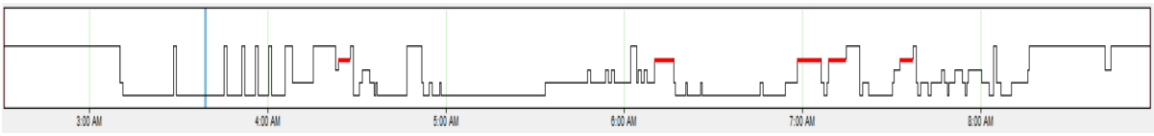


Figure 7: Manual visual score by human

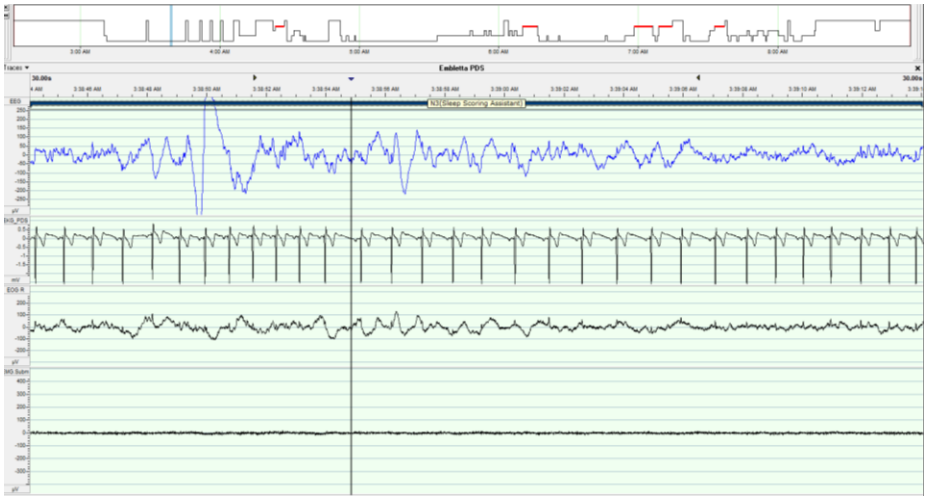


Figure 8: Stage 3 sleep score traces observed from Remlogic software

The next device used in the experiment was the Xsens Mtw Awinda wireless motion tracker developed by Xsens Technologies B.V. The Xsens Mtw Awinda is a wireless 9-DOF (IMU) with 3-axis accelerometer, 3-axis magnetometer and 3-axis gyroscope and can be easily attached to the body due to its small size [53]. The convenience of the small size and wireless motion tracking was an ideal solution for actigraphy because the 3-axis acceleration output could be processed to estimate sleep stages like a dedicated actigraph. The Xsens was attached directly to the participants non-dominant wrist by hook and loop straps but could be attached the dominant wrist if the participant wished too. The reason for this location was to have a benchmark with experiments done with Cole et al. [39] and Kripke et al. [40]. Figure 9 shows a close-up image of the Xsens MTw device and wireless transceiver while Figure 4 shows the Xsens

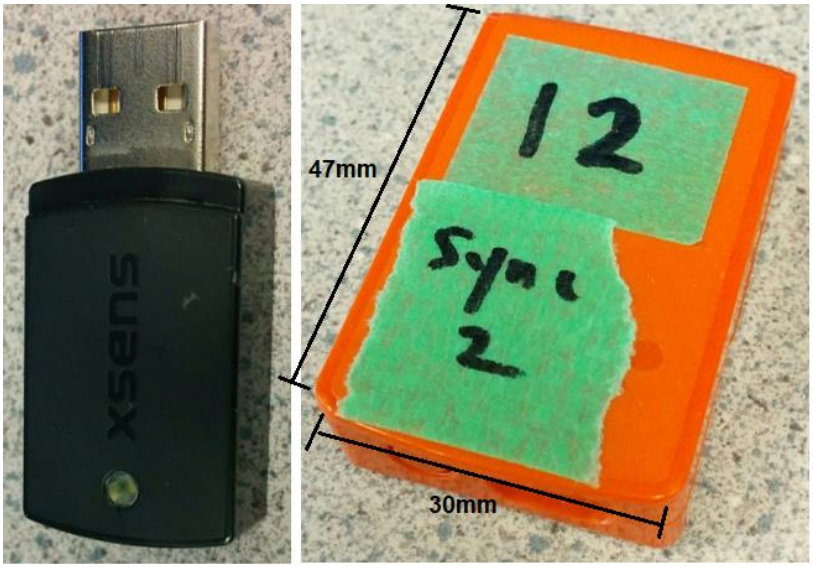


Figure 9: (Right) Xsens MTw Awinda, (Left) USB transceiver on left

MTw attached to the non-dominant wrist during an experiment. Software is readily available on the Xsens website that lets one record the motion activity in real time. However, an issue arose during the initial testing stages of the Xsens MTw was losing connection during the night and being unable to reconnect because the participant was sleeping and would be unaware the device had disconnected until they woke up. This was a major issue, as each test could only be done once per day during the natural sleep cycle and the issue caused many scheduling conflicts due to re-testing. With further investigation, it was determined that the issue was with the laptop as it did not provide a steady rate of power to the USB connection and would disconnect the device briefly. To remedy this, a USB hub was used with an external power supply to prevent any further disconnections. The parameters obtained and used from the Xsens MTw was the 3-axis acceleration values *(x, y and z)*. Each of the acceleration axis signals needed to be normalized to obtain the vector magnitude using the following equation [41]:

$$V = \sqrt{x^2 + y^2 + z^2} \tag{2}$$

Figure 10 shows the raw acceleration signals obtained and the normalized signals. Furthermore, the signals had to be converted into 30 second epochs to be comparable to the PSG epochs. The zero-crossing method was used to determine how many times the

normalized signal would cross zero for each 30 second epoch and tallied up shown in Figure 11. Each of these summed acceleration epochs were used as the *A* values for weighted sums equation shown in Equation 1 with the populated values shown in Equation 3 and is referred to as the Cole-Kripke equation. The Cole-Kripke equation is based on a moving average window that uses acceleration epochs in the past and future to score each epoch as sleep or wake.

$$D = 0.0001(11A_{-5} + 28A_{-4} + 16A_{-3} + 28A_{-2} + 28A_{-1} + 33A_0 + 29A_1 + 23A_2) \quad (3)$$

Figure 11 shows the corresponding Cole-Kripke algorithm output and the sleep scores are determined by applying a threshold. Wake is considered when the value is above 1 and less than 1 is scored as sleep. The idea is that not all movements are considered as wake during the night. Sometimes a person can move slightly while they sleep and not wake up and the algorithm would reflect that by differentiating between the movement states. Each of the weights and number of epochs used in past or present can be determined by trial and error or optimization techniques. Figure 12 shows the final output of scored epochs as sleep or wake compared to PSG. Genetic algorithms were employed to optimize the algorithm and validated by reducing the error from matching the

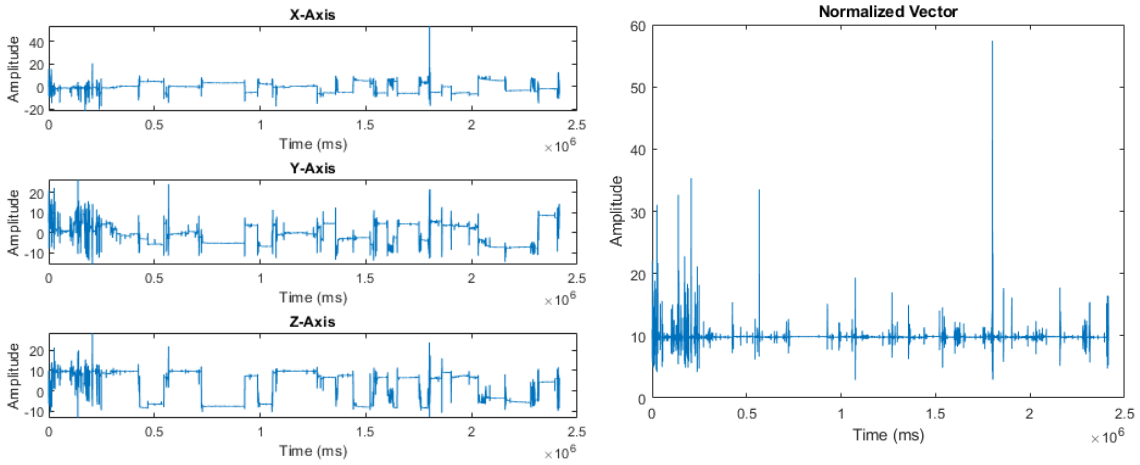


Figure 10: (Left) raw acceleration signals; (Right) normalized vector signal

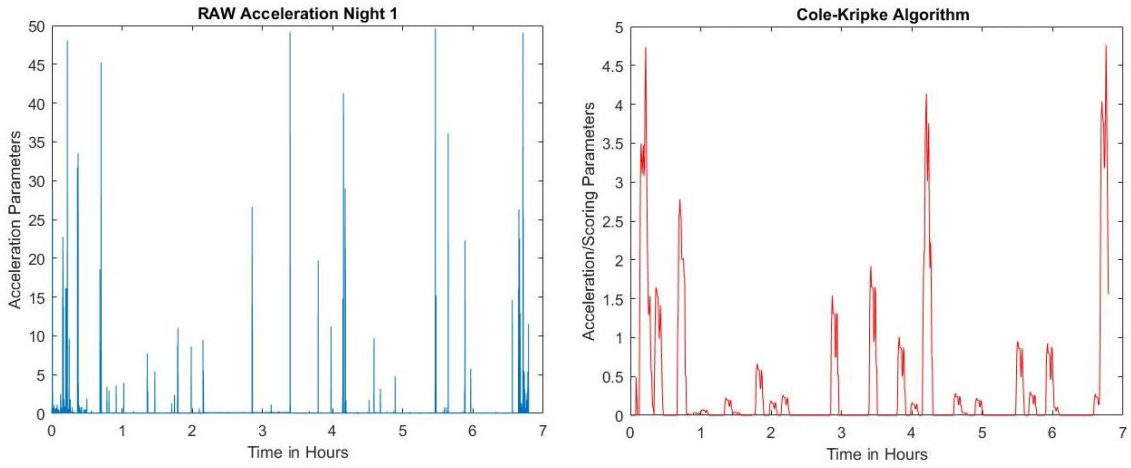


Figure 11: (Left) Zero crossing method summed acceleration signals; (Right) Corresponding Cole-Kripke algorithm results

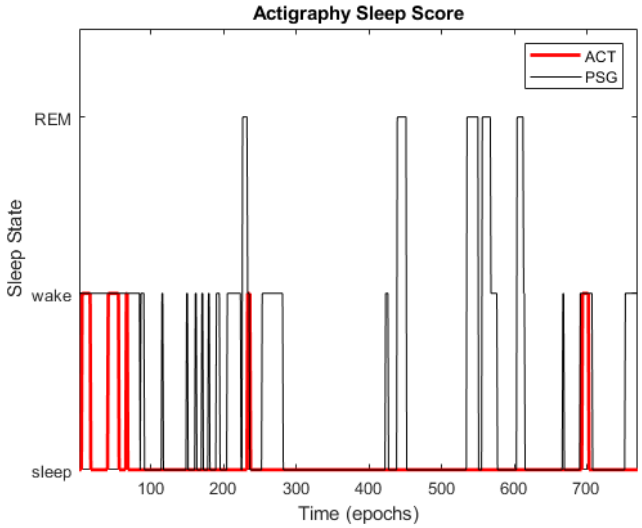


Figure 12: Actigraphy sleep states compared with PSG sleep states

PSG and the actigraphy sleep states; thus, increasing the accuracy of correctly matched epochs. Genetic algorithms were chosen to find a good solution for this population as it was relatively small and all participants were young adults with no sleep disorders and no abnormal sleeping patterns. However, when more diverse groups of people are introduced into the system, machine learning algorithms can be used to begin detecting patterns in different sleep disorders as well as more active sleepers and classify a more sensitive “Cole-Kripke” equation for people with more movement during their sleep.

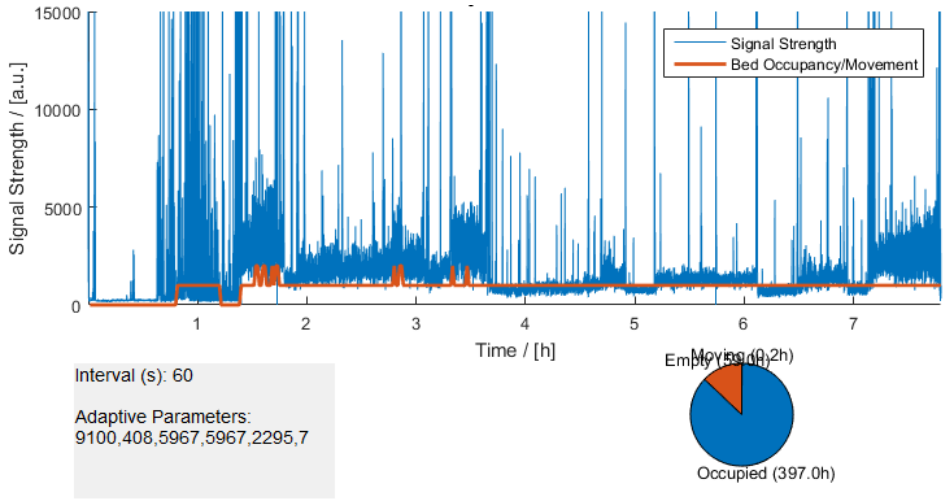


Figure 13: BCG bed occupancy calibration

Another device that used was the Murata Contactless Bed Sensor SCA11H as the BCG device developed by Murata Manufacturing Co., LTD. The Murata bed sensor was designed uses ultralow noise MEMS accelerometers with a noise density below 150 $\mu m/s^2/Hz^{1/2}$ that claims to be 5 times better than other industrial MEMS accelerometers and 20 times better than consumer grade BCG sensors [54]. In addition, the small size of the sensor, made it non-intrusive to the participant while they slept. The Murata bed sensor was placed on top of the mattress and clamped between the bed sheet with a magnet to prevent it from moving around during the night. Murata provides a GUI that can be used on a personal computer or Android device that connected to the bed sensor through Wi-Fi and collected data in real time. The laptop provided to the participant had the software installed and the participant had to sync the bed sensor with their home modem over Wi-Fi to start the data collection process. The Murata bed sensor also had an intelligent calibration feature that would calibrate the sensor for each night the participant slept in their bed. Initially, the participant would lay in the bed for 1 minute and then left the bed empty for 1 minute so the bed sensor could calibrate the difference between empty and occupied bed status for the participants mattress. But each night the participant slept, the occupancy data could be uploaded to the calibration GUI to improve the detection of bed occupancy [55]. Three nights were chosen for the study because according to Murata, the bed sensor calibrations would be at its best after three sleeps of calibration [56]. The bed occupancy of one night from the Murata GUI can be seen in Figure 13 with the calibration

parameters with at least one hour of empty bed required in the beginning to measure between occupied and empty. The Murata bed sensor outputs the following data at a frequency of 1 Hz in a text file that was used for analysis with Matlab: *timestamp, Heart Rate, Respiration Rate, Stroke Volume (SV), Heart Rate Variability, Status, beat to beat, beat to beat prime, beat to beat double prime)* [54].The values that were used for this experiment were the heart rate, heart rate variability and the respiration rate. Previously extensive clinical trials and validation for each vital signal and sleep stage state estimation were performed at the Turku University as referenced in [33]. Correlation between the Murata bed sensor and PSG values obtained by [33] were as followed: HR (r=0.97), low frequency heart rate variability (LFHRV) (r=0.71), high frequency heart rate variability (HFHRV) (r=0.71), respiration rate (RR) (r=0.54) and respiration rate variability (RRV) (r=0.49). An r value of 1 would indicate perfect correlation and a 0 value would indicate no correlation. Even though the RR and RRV correlation was lower and not as good as the cardiological parameters, the typical difference was not significant from the BCG with PSG. Examples were provided in breathes per minute for RR and ms for RRV comparing the BCG to the PSG. The BCG estimation of respiration events still followed a similar trend but offset from the PSG and could still be viable for estimating significant changes in the respiratory cycle. Therefore, the BCG sensor developed by Murata is a viable option to get good correlation from a gold standard PSG device. Conveniently the clinical studies done at the Turku University used the same Embletta X100 PSG device to validate all the vital signs as the PSG device in this study; thus, making the Murata bed sensor a confident choice to use as a BCG sensor.

The algorithm developed to measure sleep stages used many recommendations from [33] to setup the BCG sensor and analyze each of the vital signals. The raw output from the Murata bed sensor produced vital signals with the following units in Table 5. The raw outputs of each of each vital sign were very noisy and had to be filtered by an infinite impulse response (IIR) low pass (lp) filter as shown in Figure 14. Specifically, the lp filter was an exponential moving average filter presented by the following equation:

$$y(t) = (1 - k) \cdot y(t - 1) + k \cdot x(t) \tag{4}$$

where *k* is the filtered constant, *x(t)* is the original unfiltered value input, *t* is the time or epoch count, *y(t)* is the filtered value and *y(t-1)* is the previous filtered value.

Table 5: BCG outputs and relative units of measurement

BCG Signal	Unit
Heart Rate	Beats per minute
Heart Rate Variability	ms
Respiration Rate	Beats per minute
Respiration Rate Variability	ms

The low pass filter was done again in reverse for each parameter in order to avoid the initial delay created by the first low pass filter. Since the filter requires a previous value, the first value (*y(1) = x(t)*) was taken as the raw value and filtered from there. Performing the filter in reverse as in starting from the last value and filtering back to the first value would help remove the weight from the initial unfiltered value. Each of the reverse low pass filters used *k=1/512* for each of the filtering constants. The following equations were derived from [33] to measure each of the specific vital signs:

$$HFHRV = lp(|b2b - b2bavg|, k) \tag{5}$$

Where the absolute difference of the original beat to beat (b2b) and the filtered beat to beat (b2bavg) with *k=1/*2 to obtain the HFHRV [33].

$$LFHRV = |\frac{60000}{HR} - \frac{60000}{lp(HR,k)}| \tag{6}$$

where the HR is converted into ms for HRV by dividing the HR by 60000 and then obtaining the absolute difference between the raw HR and filtered HR and *k=1/512* for the LFHRV [33].

$$Rdepth = \frac{|SV - lp(SV,k)|}{SV} \tag{7}$$

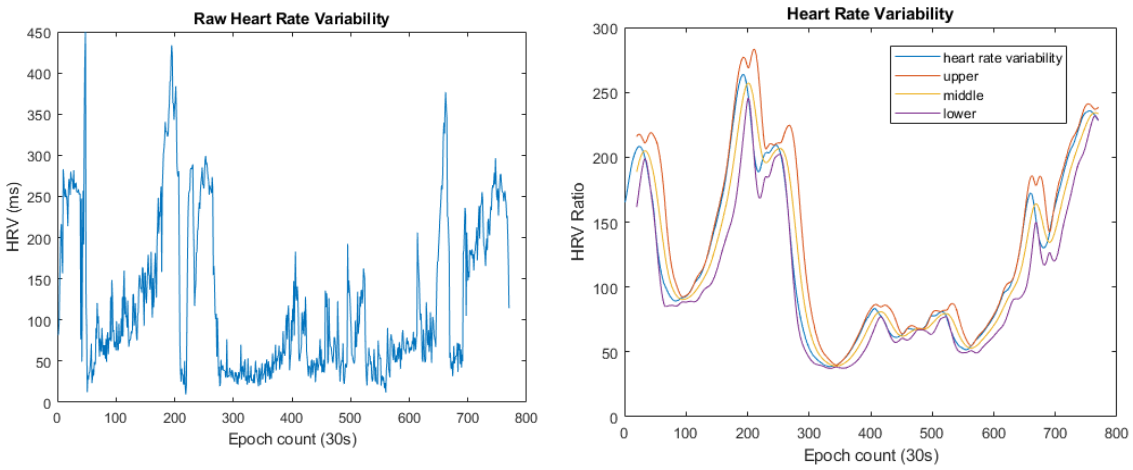


Figure 14: (Left) Raw HRV signal; (Right) Low pass filtered HRV signal

where the respiration depth (Rdepth) is the relative volume of air that passes through the lungs in one respiratory cycle (inhalation and exhalation) [33]. The Rdepth is calculated by the absolute difference of the SV and filtered SV and divided over SV with *k=1/16* [33].

$$HRV = \frac{HFHRV}{LFHRV \times Rdepth} \tag{8}$$

where the HRV is obtained by combining the HF and LF HRV components and scaled with the Rdepth. Discussed earlier in this chapter with cardiac parameters, it was mentioned that the frequency ratio of *LF/HF* HRV was important for observing the activity between PNS and SNS. However, the bed sensor by Murata does the opposite by calculating the *HF/LF* ratio. The reason for this is to have a more positive number represent a more relaxation and recovery. In addition, Rdepth is included in Equation 7 because the HF component is related to respiration and in the event of a hypoxia event, the breathing will get deeper and indicate higher relaxation. But the opposite would be in effect as the participant would be waking briefly from the event [57]. The Murata bed sensor outputs the HRV component as the value from Equation 8 [33].

$$RRV = \left| \frac{60000}{RR} - \frac{60000}{lp(RR,k)} \right| \tag{9}$$

where the RRV is calculated in a similar way as the LFHRV in Equation 5 and *k=1/512* [33].

Murata has outlined sleep states for each of the vital parameters measured by the BCG bed sensor in [54]. According to Murata, REM sleep and wakefulness is difficult to distinguish as both have a similar profile except for a slight difference between RRV readings. In [33], movement and bed occupancy in the bed is used to distinguish the difference between REM and wake. In this study, movement from an actigraphy is used to distinguish between REM and wake. Also, bed occupancy is included for extra verification that the participant is awake as usually if a participant leaves the bed, it can be assumed that they are awake. To measure each of the vital signals whether they are increasing, decreasing or relatively stable, Bollinger bands were used. Bollinger bands were invented by John Bollinger in 1983 for detecting trends in the stock market [58]. They measure volatility of a time series data set by generating a moving average and lower and upper moving average offset by the standard deviation. Table 6 shows how the sleep states are determined with changes from the Bollinger bands and recommendations from [54]. The standard lag time for moving averages with Bollinger bands is 20 days when used for technical trading in the stock market. 20 epochs were also used as the lag time with the BCG data as the first 50 epochs (25 minutes) were assumed to be awake and usually had a lot of fluctuations as the participants would climb into bed and move around before falling asleep or would lie still but awake initially. Figure 14 shows an example of the HRV signal with Bollinger bands. Volatility is measured by calculating the band width between of the upper and lower bands.

Table 6: BCG Bed Sensor sleep stages

	Sleep	REM Sleep	Wake
HR	Decreasing or significant HR decrease	Increasing or significant HR increase	Increasing or significant HR increase
HRV	Increasing	Decreasing	Decreasing
RRV	Decreased and stable	Increasing	Increased and stable
Rdepth	Decreasing	Increasing	Increasing

If the upper and lower bands are close together, then the graph is considered stable and when the bands are far apart, they graph is volatile and unstable [59].

Equation 10 shows the calculation for measuring bandwidth:

$$Bandwidth = \frac{Upperband - Lowerband}{Middleband} \cdot 100 \quad (10)$$

To measure the increase or decrease, the *%B* is calculated in Equation 11 with *x(t)* being the signal and *t* being the time and showed where the signal is between the lower or upper band as a percentage. The signal would be increasing when it is between the middle and upper band and decrease between the lower and middle band [60]. The signal may have small hills and valleys but generally still trending up or down and using Bollinger bands would show this hard increase or decrease.

$$\%B = \frac{x(t) - Lowerband}{Upperband - Lowerband} \quad (11)$$

Knowing when the vital signals are increasing, or decreasing is important to determining sleep stages as a heart rate decrease would signify sleep or resting. In addition, an increase or decrease of the heart rate by 5-10 bpm could be considered falling asleep or waking up respectively [54]. Based on the analysis in [33], it was observed that HRV was at its lowest during wake and highest during sleep and RRV was lowest during sleep and highest at wake. If any of these parameters were stable at an excessive value, sleep or wake would be assumed until a significant *%B* value would increase or decrease the signal. Figure 15 shows a flowchart of the combined sleep scoring algorithm with both devices. The actigraphy sleep and wake states are compared with the BCG states by seeing if there is excessive movement during a REM or wake BCG epoch. The actigraphy is used to distinguish between wake and REM primarily with movements during a REM stage being scored as wake. Excessive movements with the actigraphy are considered wake and leaving the bed is also considered wake. However, during idle sleep in the bed, the sleep stages are primarily scored from the BCG because of the cardiac properties measured. Without any movement from the actigraphy, any changes to heart rate, HRV and RRV would be used primarily to determine sleep stages. Significant changes in heart rate would be a clear indicator of a sleep or wake state and a consistent rate would help identify how long the stage would last.

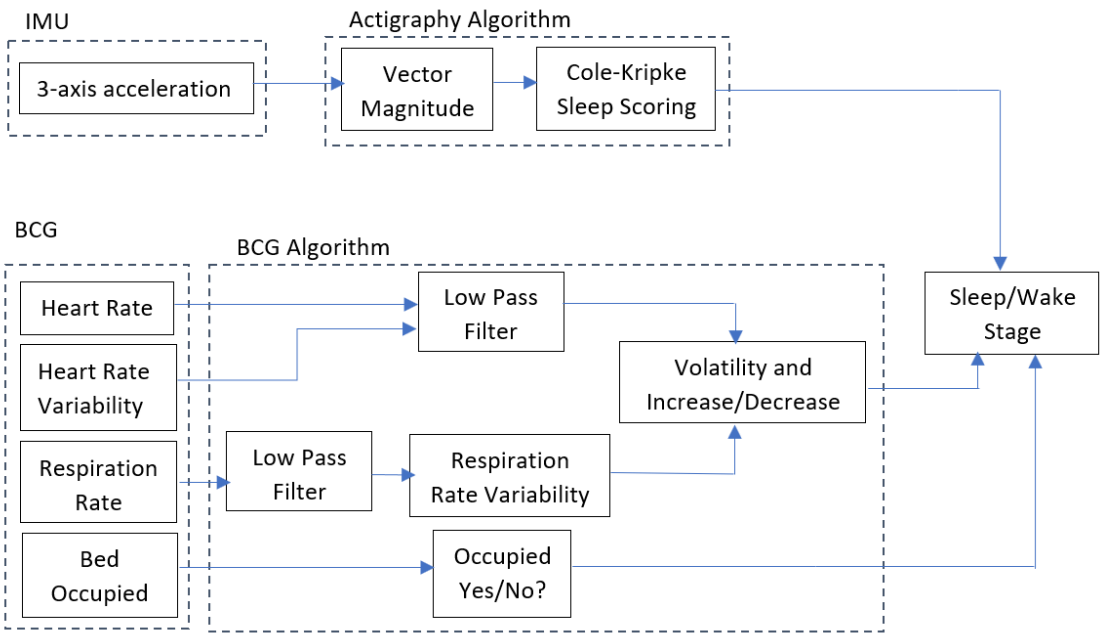


Figure 15: Proposed algorithm flowchart combining BCG and IMU (actigraphy)

Chapter 4.

Results and Discussion

4.1. Results

The actigraphy and the BCG were both compared to the PSG to measure accuracy by matching the correct epochs over a sleep cycle. A true positive match was considered when the PSG and algorithm scored wake and true negative when both scored sleep, presented in Table 7.

Table 7: True/False classification table

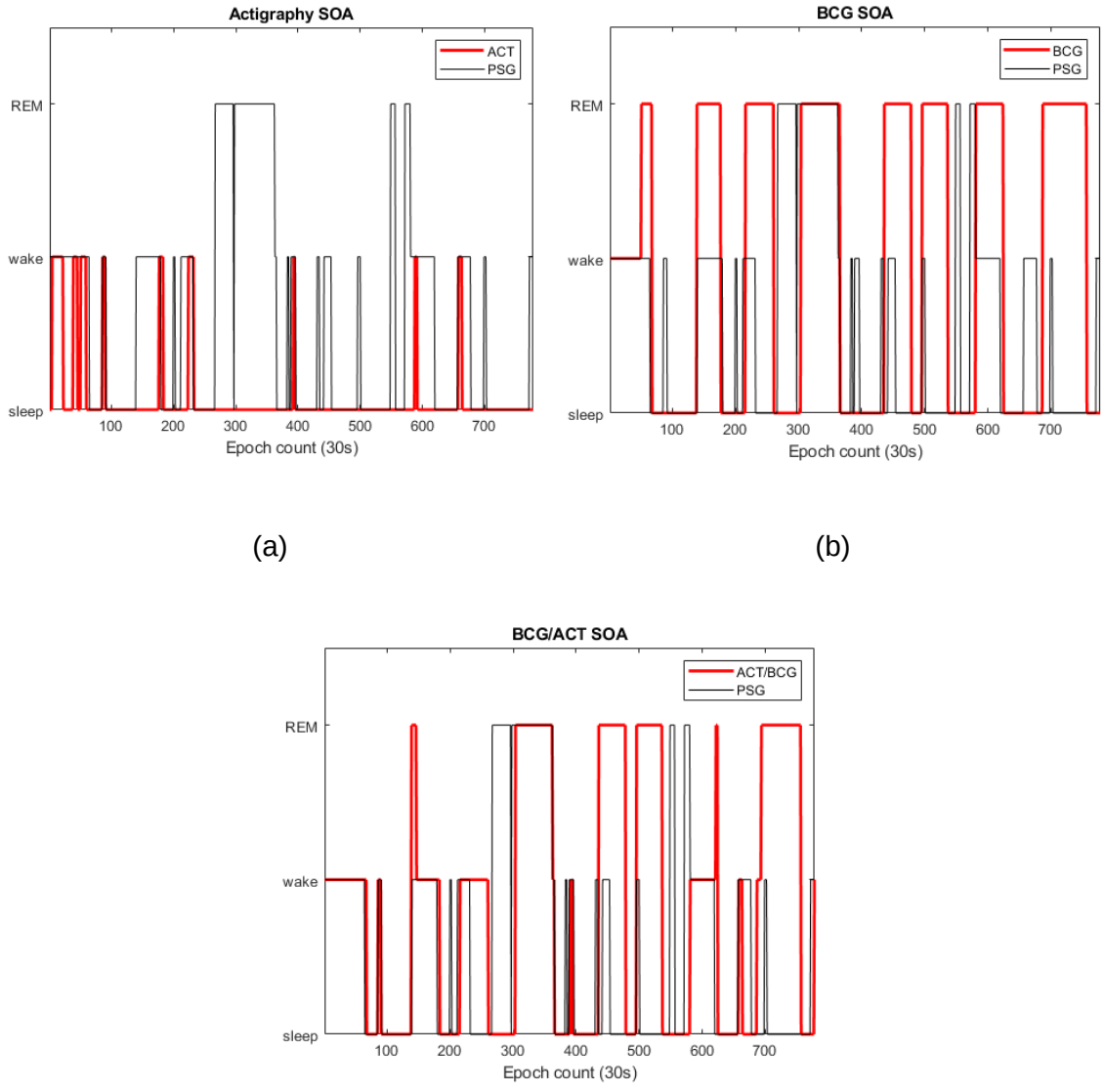
True Positive PSG: Wake Algorithm: Wake	False Positive: PSG: Sleep Algorithm: Wake
False Negative PSG: Wake Algorithm: Sleep	True Negative: PSG: Sleep Algorithm: Sleep

The sensitivity and specificity were determined to measure how many correct matches there were between the algorithm and the PSG. Sensitivity relates to correct wake classification and specificity relates to correct sleep classifications presented in the following equations.

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (12)$$

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive} \quad (13)$$

In Figure 16, the black line indicated the sleep state obtained from the PSG and the red lines are the sleep states scored from the respective device. REM sleeps were also scored as sleep for accuracy measurement as the participant should be sleeping and have extremely minimal movements. The standard deviation measures the spread of all the participants sleep cycles together to see which method was more consistent.



(a) (b)

(c)

Figure 16:Sleep scored epochs throughout the night, (a) is just the actigraphy IMU, (b) is the BCG bed sensor and (c) is the combination algorithm with actigraphy and BCG

Table 8: Accuracy, sensitivity, specificity, standard deviation, kappa and chi squared P-value of each device compared to PSG

Method	*Accuracy %*	*Sensitivity*	*Specificity*	*Std*	*Kappa*	*P-Value*
Actigraphy	80.4	18.4	98.8	8.80	0.22	0.51
BCG	81.6	27.2	98.9	9.44	0.33	0.34
Actigraphy/BCG	86.2	66.4	90.5	6.60	0.58	0.97

The sensitivity and specificity variation are visually presented in Figure 17. Each method would estimate sleep states differently and would lean to wake or sleep exclusively and will be discussed further in the next section. Table 9 shows the total amount of epochs collected and the average total sleep and wake times (TST and TWT, respectively) as well as the sleep efficiency (SE) for each method compared to PSG.

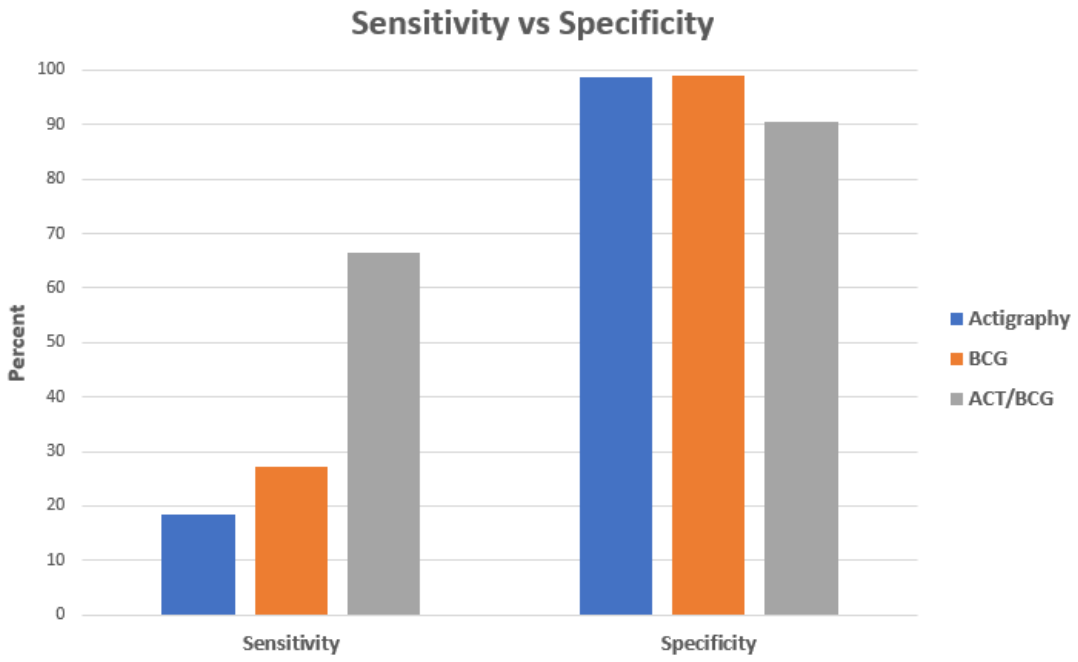


Figure 17: Visual representation of the sensitivity and specificity

Table 9: Total sleep and wake time in 30s epochs for each method

	PSG	**Actigraphy**	**BCG**	**Actigraphy/BCG**
Total Epochs	17828			
Total TST (epochs)	13618	16804	16678	13592
Average TST (epochs)	592.09	730.61	725.13	590.96
Total TWT (epochs)	4210	1024	1150	4236
Average TWT (epochs)	183.04	44.52	50	184.17
Average SE (percent)	76.55	94.55	93.43	76.66

Each of the units on Table 9 are in 30 second epochs. The total epochs are the total amount of epochs collected for every night and participant. TST and TWT are the total amount of sleep and wake epochs counted for every night and the average amount of epochs for each criterion. SE is calculated by dividing the TST by the total time of the sleep cycle and represents how much sleep a person gets over their total time in bed. The higher the SE, the more time a person spends sleeping in bed rather than staying awake in bed. A higher SE will improve daily life and performance by providing more rest from sleeping more efficiently [61]. The appendix shows the individual participant results and most participants were consistent with the population. Only the actigraphy results showed some outliers as some participants had very subtle or minimal movements during the night. Examples of these outliers are discussed in the next section. Table 10 and Figure 22 show each of the nights for the BCG sensor and the calibration performed for each successive night generally improved the accuracy. Some of the nights were slightly calibrated by maintaining a steady trend. Each participant used the BCG sensor in their own bed and each mattress was different and likely influence the calibrations depending

Table 10: BCG accuracy improvements from sensor calibrations each night

	P1	*P2*	*P3*	*P4*	*P5*	*P6*	*P7*	*P8*
Night 1	64.0%	76.4%	89.7%	71.1%	64.0%	74.3%	84.7%	85.4%
Night 2	62.3%	83.7%	93.9%	68.7%	75.7%	89.7%	78.2%	89.5%
Night 3	79.6%	89.7%	92.0%	81.7%	91.0%	85.1%	N/A	84.9%
R^2	0.67	0.99	0.29	0.59	0.99	0.47	0.81	0.01

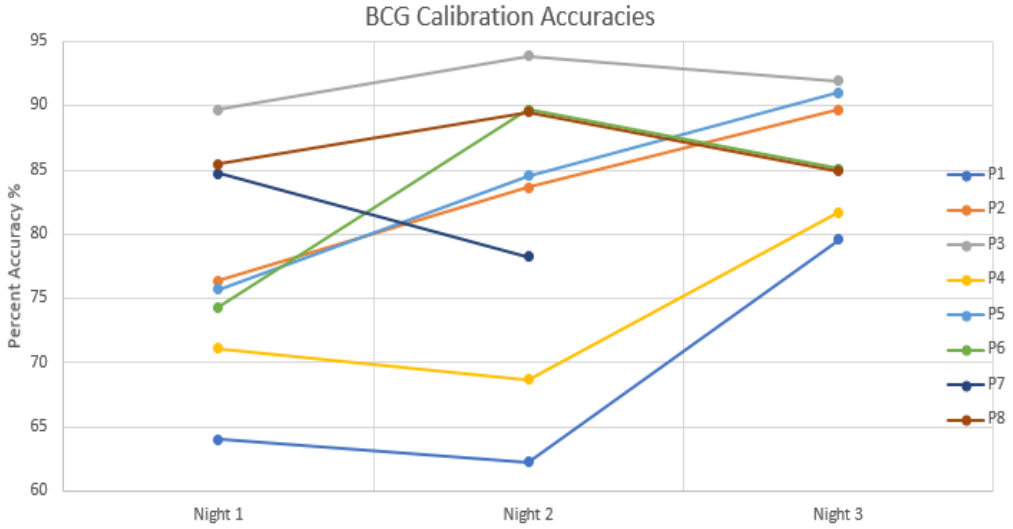


Figure 18:Visual presentation of calibration accuracy over each night

on how well the BCG would measure signals from the mattress. With the techniques recommended by [33], the BCG was set up to detect sleep with heart and respiratory variables. Bland-Altman plots were generated to observe the agreement between each of the methods compared to PSG. The agreement between sleep efficiency was compared

for each device by measuring the mean difference to evaluate a bias [62]. However, only the intervals of agreement are defined but does not necessarily mean that the limits are acceptable and a priori must be defined to evaluate the significance of the plots [62]. The y-axis is the difference between methods and the x-axis is the mean of both methods. The yellow line in Figures 18-20 represents the bias and shows how closely both methods measure results with a large offset from zero could swing the bias more towards one methods agreement. In this case, an agreement between PSG and the devices should be close as each method is trying to replicate the sleep/wake instances of the gold standard PSG. The orange lines represent the limits of agreement as a range where 95% of the data points should fall into [62]. The limits are calculated based on the means *d* and standard deviation *s,* with the associated 95% confidence interval of 1.96:

$$Upper\ LOA = d + 1.96s \tag{14}$$

$$Lower\ LOA = d - 1.96s \tag{15}$$

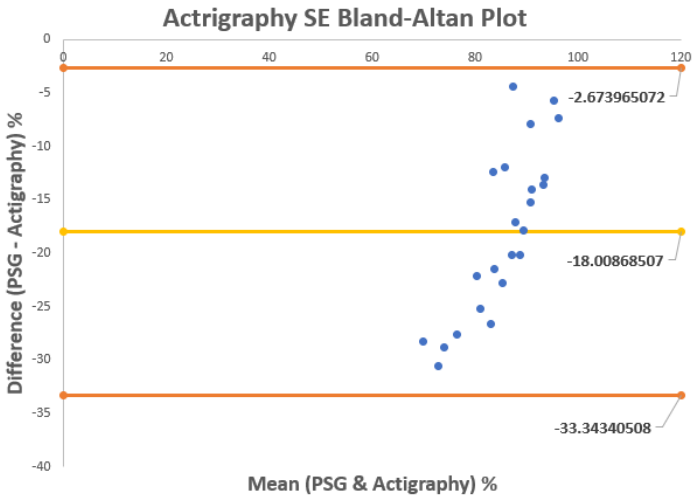


Figure 19: Bland-Altman plot for actigraphy and PSG

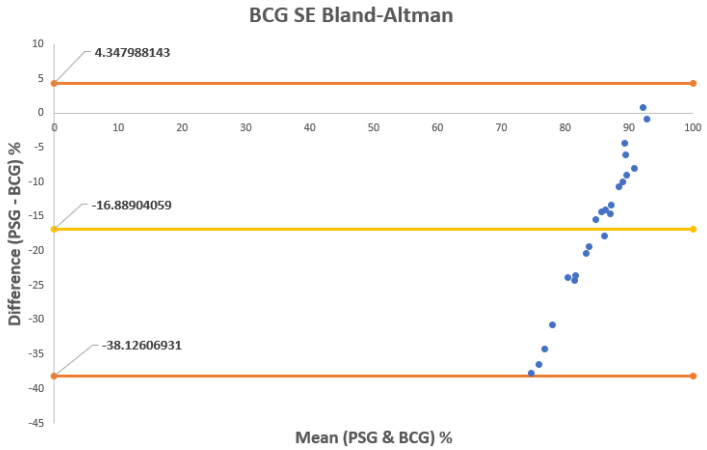


Figure 20: Bland-Altman plot for BCG and PSG

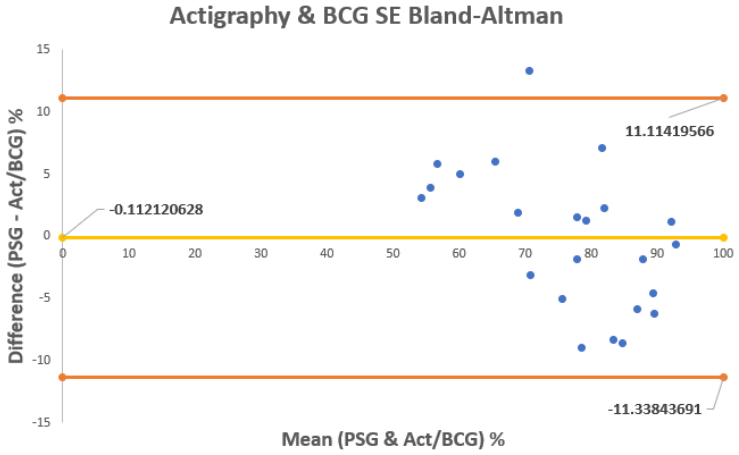


Figure 21: Bland-Altman plot for actigraphy/BCG algorithm and PSG

4.2. Discussion

Each participant used all three devices over the three nights of sleeping to gather a data set that could be used to estimate sleep states. Roughly 23 individual participant sleeps cycles with at least five hours for each individual sleep was collected. Each of the devices were compared to the gold standard PSG sleep states scored manually. One participant had the actigraphy IMU and the BCG bed sensor disconnect prematurely before they woke up and had to have their measurements disqualified and another

participant lost a single night to similar reasons, but the two previous data sets were used for analysis. Synchronizing each of the devices was deemed vital to get an accurate measurement of all the epochs lining up. The PSG was synced by having the participant press the event button to signal when they were getting into bed. The BCG bed sensor was synced by detecting bed occupancy when the participant first enters the bed. As part of the calibration procedure, the Murata bed sensor required at least one hour of empty bed before the participant went to sleep and the first occupied bed time was used to sync the BCG sensor. The actigraphy IMU synced by having the participant stand still initially facing the bed and the motion of entering the bed was many movements in quick succession. In addition, the video camera and PSG tracked the real time, and this was used to verify synchronization as close as possible. However, some error may still arise between each of the devices, as they could not be electronically synced due to each device being from a different manufacture and not directly compatible.

Measuring sleep states with an actigraphy device is very convenient as it has very little impact on the participants natural sleep cycle due to the small size of it. Therefore, a natural quality sleep should be measured but the only parameters that are measured are motion of one or more limbs. As shown in Figure 16 (a), only sleep or wake states can be measured from the motion data. As a result, many papers such as [10] and [19] have mentioned that actigraphy usually over-estimates sleep than wake. The results obtained from this study show similar findings. Upon first inspection, the matched accuracy is about 80% correctly matched epochs. However, people usually do not move very much during the night as they are sleeping or trying to get to sleep by laying still until they fall asleep. Only when people are restless or uncomfortable would they move extensively, and this activity would be captured by actigraphy. In this study, the actigraphy IMU was only placed on the non-dominant wrist which means that if, for example, they would scratch their nose with their dominant hand the actigraphy IMU would not capture this as wake and continue to score it as sleep. In Figure 21, the participant had carefully entered their bed without any motion and laid very still throughout the night. The accuracy between the actigraphy and PSG was around 92% correctly matched epochs because of all the scored sleep epochs. Watching their sleep cycle from the camera playback showed that they had opened their eyes a few times during the night and mostly moved their head and torso slightly; while the non-dominant wrist did not see enough motion to score wake instances.

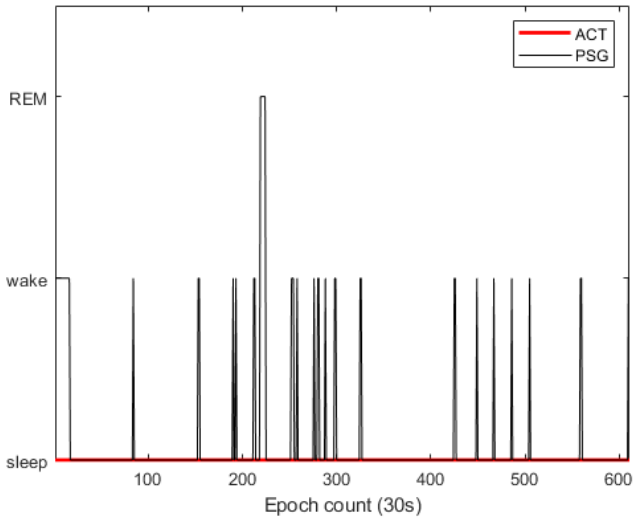


Figure 22: Sleep cycle with very low activity, every epoch scored as sleep

During this study, by the third night many of the participants would become familiar with the whole sleep setup and would get comfortable quicker and having a more natural sleep without invasiveness of the PSG affecting them much. Figure 17 compares each of the sensitivities and specificities among the methods with actigraphy having the widest spread with a very low sensitivity (wakes) and very high specificity (sleeps). In addition, Figure 18 shows an agreement between the PSG and the actigraphy with a negative bias meaning that the results are skewed towards one method. This shows how actigraphy measurements overestimate sleep and would score a much higher SE and does not reflect the participant's actual SE throughout the night. The data points create a linearly increasing trend that can confirm the overestimation of sleep by the inflated SE values. The signals from actigraphy would still be helpful for combining with BCG as the activity detection would help separate wake from REM situations.

The Murata bed sensor was used to measure the cardiac effects while the participant sleeps without being intrusive. By measuring the vibrations recoiled from the body to evaluate HR, HRV and RRV, it was very sensitive to any movement the participant made during the night and would cause motion artifacts that are convenient for estimating wake times during the night. The BCG had a higher sensitivity to detect wake epochs because more variables could be measured to score each sleep stage. The change in heart rate was vital to see when a person is resting or active as a lower heart rate would

likely signify sleep. But a higher heart rate while laying still would signify wake as the participant was still awake. In addition, HRV has become an important measure for estimating sleep by measuring the ratio between the SNS and PNS and incorporated with the respiratory system. Each participant claimed to be a healthy individual with no known sleep problems and should have a normal respiratory cycle when sleeping with no apneic events. Figure 19 shows a very similar pattern to Figure 18 with just actigraphy compared to PSG agreement. With a large bias towards the BCG device as sleep was also overestimated due to the similarities to wake and REM. The accuracy results and agreement were like the actigraphy value with a very similar standard deviation but with the influence of detecting more wake instances rather than overestimating sleep like actigraphy.

Combining both devices to detect sleep showed an improvement in accuracy and a more consistent deviation detecting sleep and wake states compared to the PSG. Figure 17 showed a much better spread between specificity and sensitivity by using both sensors. In addition, Figure 20 showed a much better agreement between the PSG and the combined devices. The bias was very close to zero (-0.11) showing the agreement between SE measurements. One of the values fell outside of the limits of agreement that could be the result of the actigraphy overestimating sleep like in Figure 21 and affecting the overall agreement. However, 95% of the data points fall within the range of the limits of agreement and 5% of the data is expected to be outside due to a chance situation. The kappa values obtained from each of the device methods was significantly increased by the combination by about double, verifying the interrater reliability with the PSG. The Chi-square test p-values are all above the null hypothesis of 5% alpha and makes each of the methods statistically significant for analysis. The combined method shows the highest p-values and less differences occurs between the PSG and combination. In comparison, however, as the p-values are lower for the separate devices, there is a greater difference between each separate device and the PSG as actigraphy and BCG separately would generally overestimate sleeps. The results obtained in these experiments with the combined devices are comparable to other studies done with actigraphy or BCG separately. For example, actigraphy was used in [10] to obtain an overall accuracy of about 86% with two dedicated wrist-worn actigraphic devices and compared with PSG. While the accuracy results were good, the actigraphy devices in their study still overestimated sleep as is expected from estimating sleep states with only actigraphy. The

study in [26] used BCG to estimate sleep stages by placing load cells on each of the bed legs and a polyvinylidenefluoride strip on the mattress to measure the BCG cardiac parameters. The overall accuracy they reported was about 77% correct sleep stage detections but also good estimation of wake and REM sleeps from the use of heart rate and HRV. The overall accuracy of the combined devices was about 86% and very similar to the actigraphy by itself. However, the detection of wakes compared to sleep was much better with both devices as inclusion of cardiorespiratory signals can help distinguish between each stage. As both devices are non-intrusive and this specific setup, the sleeping person would sleep as if they only had the wrist worn actigraphy device attached because the BCG sensor would lay in their bed. Therefore, it would be just as comfortable for the participant to sleep with just actigraphy but include BCG signals to better analyze sleeping data for a more accurate assessment. In this data set, the participants had the PSG device attached with multiple electrodes and wires throughout their body. Therefore, each participant would experience more discomfort than usual and have a harder time falling asleep. This was confirmed by questioning each participant after the experiment on how their sleep was. Most of them described it as uncomfortable initially and required getting used to. Also, with the added sensors and devices on their body, they moved slowly while in bed to prevent anything from detaching and could be why some of the actigraphy readings had detected very few wake instances. As the actigraphy device was on the non-dominant hand, most people would use their dominant hand when adjusting anything in the bed and would result in the non-dominant hand not moving while they were awake. But with the inclusion of BCG to detect cardiac signals, the slower movements could still be compared to the changes in HR, HRV and RRV to better estimate if the movement is related to wake or still sleep. One participant likes to sleep on their stomach and found with the PSG it was difficult to find a comfortable position to sleep like that. As a result, they had to adjust the PSG device more to their side as opposed how it is shown in Figure 5 on the torso and took more time to fall asleep in the new position for them. The participants were generally more awake than usual due to the discomfort and this was detected by the combined actigraphy and BCG sensors. Once they were familiar with each device, specifically the PSG, it did not affect their sleep as much. By the final night, they could put on all the devices relatively quickly and knew what to expect which would likely result from a more natural sleep cycle with the gold standard validation. The participants would likely have a more comfortable sleep without a PSG as both the sensors are non-invasive and could perform a much better sleep analysis with the sensors.

Chapter 5.

Conclusion

5.1. Conclusion

Sleep is a very vital component of the human life for resting our bodies to be alert and active for the following days. Many people have trouble sleeping due to sleep disorders or other health problems and as a result, these health problems can be detected based on one's circadian rhythm and sleep cycle. Therefore, effectively detecting sleep has emerged as an important topic to study in both the medical and engineering fields. The gold standard for detecting sleep is PSG that is used in clinical settings to measure individual sleep stages and diagnose sleep disorders. However, PSG is not very convenient and usually only done for a single night. Research has been done to find alternatives for sleep analysis that are convenient for both the clinician and the patient over multiple nights. Actigraphy has been considered a non-intrusive method for sleep analysis by using an accelerometer IMU to detect and analyse limb movements during the sleep cycle. Another non-intrusive method to for sleep analysis is BCG that includes an accelerometer sensor placed in the bed with the sleeping participant, to detect recoiling effects from their cardiorespiratory system to estimate cardiac related vitals and used to estimate sleep states. The BCG used in this project was developed by Murata Manufacturing Co. and had undergone clinical tests to verify each of the detectable parameters with acceptable results. This provided good confidence to use this BCG sensor for the study presented in this thesis. In addition, a light and sound sensor could be incorporated into the system to detect lights ON/OFF times and snoring. The light sensor would begin scoring the sleep stages without the participant requiring to manually set the system for sleep scoring even if the participant would forget to start the scoring. Also, a sound sensor would allow the system to listen to any snoring or respiratory events to help asses when the participant is sleeping. Any talking or loud noises that could wake someone could be compared with changing movement or cardiorespiratory events to add an extra layer to the analysis. The BCG works through Wi-Fi and is compatible with Android devices. Therefore, an Android smart watch can be used for actigraphy to directly integrate with the BCG over a network to directly sync the measurements for accurate epoch by epoch analysis. As only healthy participants were used during this study, another

group of participants who have different sleeping patterns would need to be evaluated; for example, older adults who are more likely to have illnesses and sleeping disorders that would affect their sleep. Also, older adults are not as active as young adults and would likely not move in their sleep as much as a younger adult. Therefore, the algorithm would need to be more sensitive to detect subtle movements as well as have specific cardiorespiratory events accounted for illnesses or sleep disorders that can affect the heart. A person with a heart condition would likely need to be monitored much closer than a healthy person to make sure there is no emergency response required. The objective of this thesis was to combine both sensors to develop a method for analyzing sleep more effectively while maintaining a non-intrusive sleeping environment to measure a natural sleep cycle.

An experimental study was performed for 10 healthy participants while they slept in their own home. Eight participants were used in the end for natural sleep cycle analysis with both the combined use of the actigraphy and BCG. PSG was used as a gold standard verification for each of the devices. An initial general algorithm was developed for the accelerometer IMU to be used for actigraphic sleep analysis by measuring non-dominant arm movements and relating them to sleep or wake states. The algorithm also interpreted the BCG measurements to further improve the sleep analysis by including the cardiac parameters offered such as HR, HRV and RRV. The algorithm combined both sensors to improve sleep analysis results as shown in the results section of this thesis. The actigraphy and BCG sensors separately detected about 80% of correct sleep states while the combined method accuracy improved to 86% with more consistent standard deviation between participants. In addition, using both sensors scored more wake states appropriately than each of the separate sensors by themselves. As actigraphy specifically has been known to overestimate sleep states, the combined system shows great improvement by having an improved 70% wake detection compared to the actigraphy's 20%. Using both an actigraphy and BCG device combined would provide valuable sleep analysis as together they do not interfere with a patient while they sleep and would measure natural sleep over multiple days.

5.2. Future Work

For future research, it would be recommended to have a larger sample size to further validate the combined use of both devices. Also, a more diverse group would be

beneficial such as seniors and younger children and people with sleep disorders. Having a diverse group would expand the results by observing trends among different sleep disorders and sleeping patterns such as people who move around during their sleep or time in bed frequently. The activity throughout the night would help distinguish between wake and sleeping movements to help separate each sleep state. This study is designed to be convenient in any sleeping environment; therefore, it is recommended to obtain sleep analysis from a wide variety of sleeping environments by measuring BCG data on different mattresses. Obtaining accurate results with varying bed and environment conditions would make this method more acceptable to the general public and clinicians by making the test more portable. Also, to test the algorithm with various devices such as smart watches for actigraphic measurements. Having access to any compatible accelerometer device would meet specific participant or researcher requirements to analyze natural sleep and flexibility for system integration. In addition, commercially available smart watches are relatively inexpensive and can easily be integrated with many systems. Having actigraphy measurements obtained from a smart watch would be very convenient for future expansions as well to improve any quality of life features. Adding any device or sensor should not impact the participants sleep environment and therefore, any additional sensors being included would likely not touch the participant. For example, a light or noise sensor being built into the smart watch would be a convenient way to potentially improve the analysis without any impact on the participants natural sleep. Each of the devices should be synchronized to capture accurate analysis as an out of sync analysis could incorrectly score the entire sleep cycle. Using an actigraphy and BCG that could be processed together through a hub or receiver that would match the frequencies precisely and would be a very beneficial future step. Most of the future considerations are related to improving the comfort for the participant as this would improve the sleep quality for them and provide good quality sleep data for analysis.

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Appendix A: Ethics Approval

SFU
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Associate Director 778.782.9631
Manager 778.782.3447

Amendment Approval - Delegated

Study Number: 2017s0629
Study Title: Development of an accurate sleep detection algorithm using advanced wrist actigraphy

Amendment Approval Date: February 11, 2019
Principal Investigator: Jaworski, Dominic
SFU Position: Graduate Student
Expiry Date: November 8, 2019
Supervisor: Park, Edward
Faculty/Department: Mechatronics Systems Engineering

SFU Collaborator: N/A
External Collaborator: N/A
Research Personnel: Aziz, Omar; Musgni, Magnus; Yoon, Paul; Arafa, Ahmed
Project Leader: N/A

Funding Source: Natural Sciences and Engineering Research Council of Canada
Funding Title: Sensor Fusion for Health-tracking Wearable Devices and Internet of Things

Document(s) Approved in this Amendment:

- Amendment Request Form – Uploaded February 11, 2019
- Consent Form – Dated January 23, 2019
- Study Description – Dated January 23, 2019

The amendment(s) for ethical review and the document(s) listed above have been reviewed and the procedures were found to be acceptable on ethical grounds for research involving human participants.

Please note that approval of the amendment(s) does not change the expiry date on the current SFU REB approval of this study. The approval for this study expires on the **Expiry Date. An annual renewal form must be completed every year prior to the Expiry Date. Failure to submit an annual renewal form will lead to your study being suspended and potentially terminated.**

This letter is your official Amendment Approval documentation for this project. Please keep this document for reference purposes.

The amendment to this study has been approved by an authorized delegated reviewer.

SFU
RESEARCH ETHICS
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Appendix B: Consent Form

Consent Form

Development of an accurate sleep detection algorithm using advanced wrist actigraphy

Study Team

Principal Investigator: Dominic Jaworski, Graduate Student, Mechatronics Systems Engineering, Simon Fraser University, cell: [redacted]

This study is part of Dominic Jaworski's masters graduate degree and will be published as part of his master's thesis.

Sponsor

This study is funded by NSERC Discovery "Sensor Fusion for Health-tracking Wearable Devices and Internet of Things".

Study Purpose

We are doing this study to learn more about sleep quality for healthy adults over the age of 19. We want to learn more about sleep quality and how to properly measure and represent it without interrupting your natural sleep.

Voluntary Participation

Your participation is voluntary and will occur during your natural sleep time in your own bed. You may choose to withdraw at anytime during the study even at night if you consider the study to uncomfortable for you to sleep. You may also choose to withdraw from the study even after you have finished your experiment without giving reason.

Study Procedures

If you choose to participate in this study, the study will proceed like this:

- You will be briefed on the sensors and devices before the study begins.
- All equipment will be given to you and will be taken home.
- You will begin the study by yourself before you naturally go to sleep.
- Follow the instructions provided on how to attach the device and sensors. It is recommended to start attaching the sensors 30 minutes before you plan to sleep.
- Sleep naturally and comfortably while the sensors collect data. If you happen to wake during the night, do not remove any of the sensors and try to go back to sleep. If any sensors come loose during the night, try to reattach the sensors.
- Set up the video camera to record yourself while you sleep so your motions are visible. Set up the camera in such a way that you feel comfortable. Videos will be used to verify any sleep disturbances throughout the night as they may arise.

- When you wake up the next day, remove all the sensors and put everything back in to the device packaging.
- Perform the experiment for two more days at your convenience (days do not have to be consecutive)
- Return the device and sensors to the study team for analysis.

Potential Risks of the Study

- There should not be any more risk than sleeping with a wrist watch or a smart watch type device.
- A device a little larger than a smart phone will be attached via Velcro to your torso that may cause some discomfort if you sleep on your stomach, otherwise should be unnoticeable
- Adhesive sensors will be attached directly on your skin around your head, thighs and torso. The only risk is some irritation to the skin when attempting to remove the sensors at the end of the study.
- Wires will be run from the sensors to the device and you may position each of the wires in the most comfortable way you desire. The wires should be short, and length can be adjusted so that you do not get tangled in them while you sleep. Having the wires under your sleep clothes should greatly reduce any risk of getting tangled while you sleep.

Benefits of the Study

- Gathering data on how people sleep will be beneficial for developing algorithms and devices that detect sleeping patterns of people.
- One of the benefits is to be able to detect when someone is asleep or awake without any direct contact with another person. Letting that person live an independent life especially people who live in a care home and need constant medical supervision.

Confidentiality

This study is part of a graduate study and therefore the results from the experiments will be used in a graduate thesis. Each participant will be presented anonymously in the thesis by generally referring to them without using any personal names. Your physiological data such as height, weight etc. will be likely be presented in the thesis. A picture of your face or body at the sensor locations may be also presented in the thesis. Otherwise, no personal information will be shown and any images of you will not be shown upon your request to do so.

Organizational Permission

Permission to conduct this research study from the Simon Fraser University Ethics Board.

Study Results

The study results will be published in a graduate thesis and may also be published in academic journals and articles.

Contact Information for Questions about the Study

If you have any concerns or questions about your participation in the study or about the study itself, feel free to contact the principal investigator, Dominic Jaworski, MASc graduate student, Simon Fraser University with the following contact details:

Principal Investigator: Dominic Jaworski
Email: [redacted]
Phone: [redacted]

Future Use of Participant's Data

The data collected in this study will be used in academic journals and articles. The data and academic papers directly referencing this data may be referenced in other articles written in the future.

Participant Consent and Signature

Taking part in this study is entirely up to you. You have the right to refuse to participate in this study. If you decide to take part, you may choose to pull out of the study at any time without giving a reason and without any negative impact.

- Your signature below indicates that you have received a copy of this consent form for your own records.
- Your signature indicates that you consent to participate in this study.
- You do not waive any of your legal rights by participating in this study.

Participant Signature Date (yyyy/mm/dd)

Appendix C: Participant Data

The following tables show the averaged results collected for each participant over the three nights. Each table shows the matched averages, sensitivity and specificity, total sleep and wake times, sleep efficiency and the Cohen Kappa relation. Each method was compared with the same PSG outputs.

Table A 1: Actigraphy averaged results for each participant

	Acc.	*Sens.*	*Spec.*	*TST*	*TWT*	*SE*	*Kappa*
P1	71.26	25.22	97.76	702.66	87	89.01	0.26
P2	84.17	3.65	99.87	642	9	98.81	0.05
P3	87.75	16.36	100	798.67	21.33	97.73	0.23
P4	71.5	26.34	95.89	781.33	93.33	89.34	0.27
P5	81.29	26.98	98.09	706.67	58.33	92.71	0.31
P6	82.72	15.23	99.85	676	21.33	96.83	0.21
P7	78.98	8.96	99.55	763	18.5	97.61	0.12
P8	84.78	21.33	99.48	785.33	38.67	95.41	0.28

Table A 2: BCG averaged results for each participant

	Acc.	*Sens.*	*Spec.*	*TST*	*TWT*	*SE*	*Kappa*
P1	68.63	17.22	99.52	739.67	50	93.66	0.20
P2	83.255	25.74	95.72	601	50	92.23	0.23
P3	91.72	43.49	100	770	50	93.75	0.56
P4	71.34	17.19	99.77	824.67	50	94.19	0.21
P5	83.76	31.06	100	715	50	93.39	0.41
P6	83.05	26.71	97.72	647.33	50	92.81	0.30
P7	81.78	23.78	98.58	731.5	50	93.60	0.30
P8	86.61	31.14	99.68	774	50	93.90	0.42

Table A 3: BCG/actigraphy averaged results for each participant

	Acc.	*Sens.*	*Spec.*	*TST*	*TWT*	*SE*	*Kappa*
P1	84.51	78.88	86.07	484.67	305	61.57	0.66
P2	88.10	49.01	93.01	536.67	114.33	83.69	0.42
P3	93.36	69.74	97.2	715.33	104.67	87.43	0.72
P4	72.68	71.96	73.32	514.67	360	58.42	0.42
P5	86.54	72.50	90.95	584	181	76.41	0.61
P6	88.56	65.69	90.91	545.333	152	77.52	0.55
P7	87.60	53.14	97.60	673	108.5	86.02	0.59
P8	91.41	65.73	97.32	701.33	122.67	85.33	0.69

Appendix D: Preliminary Actigraphy Analysis

Initially, a few methods were implemented to improve the actigraphy beyond just adjusting the Cole-Kripke algorithm weights. First a rescoring method was devised to try to filter out any unnecessary movement events and collect excessive movement activity into one long wake instance. Next, orientation was considered to potentially improve the sleep scoring by trying to relate sleep/wake instances to common positions that the participants would sleep with.

First, the rescoring was implemented into the algorithm by attempting to observe continuous patterns of sleep and wake. For example, if there was a short wake instance surrounded by long sleep, the short wake would be rescored into sleep. If there were many wake instances within proximity, then the short sleep instances would be rescored to wake instances. The details for the rescoring are outlined in the following rules.

1. 90 seconds of continuous wake would always be considered wake
2. 330 seconds or more of continuous sleep before and after a wake instance would rescore the wake into sleep
3. Less than 330 seconds of sleep between wake instances would rescore the sleep instance into wake

The idea was to observe consecutive sleep or wake instances and rescore them accordingly by combining many wake instances together into a single wake as a participant would move around frequently over a short period of time would likely be awake. However, if the participant was idle for a consecutively long time, they would likely be considered asleep and any short movements would likely be the result of slightly adjusting their body but not actually waking up. Therefore, only significant movement would be considered as wake instead of each individual small movement activity. The issue that arose was that each participant had a different sleeping pattern and a universal ruleset was difficult to create for everyone. Table A4 shows the results for a single participant over multiple nights and Table A5 shows different participants being evaluated. The participant in Table A4 was the author and multiple nights were performed to asses the algorithm and logistics of deploying the device to each participant in the future.

Table A 4: Actigraphy percent correct matches of normal scoring, normal scoring with rescoring and orientation rotation rescoring included

	N1	N2	N3	N4	N5	N6	N7	N8	N9	Avg	STD
Calculated	88.8	81.1	71.5	80.3	71.7	83.8	77.0	61.9	71.6	76.4	7.6
Rescoring	88.6	84.0	76.1	88.6	73.6	86.1	79.8	63.2	75.1	79.5	7.9
Rotation Rescore	97.1	85.5	N/A	83.2	45.4	83.2	50.8	47.4	45.4	67.2	20.4

Table A 5: Actigraphy percent correct matches for normal scoring and rescoring

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	Avg	STD
Calculated	96.1	96.9	94.5	90.9	92.0	90.2	79.7	87.1	96.1	70.2	89.4	8.5
Rescoring	97.3	95.0	5.7	94.1	92.6	89.0	81.2	73.4	97.32	95.6	82.2	28.0

Table A4 shows that the accuracy had increased for all the nights for the single participant. However, the increase was only about a 3% increase and this is a similar comparison to other literature with a rescoring method. However, the overall accuracy decreased when the rescoring rules were used for each of the other participants. This is likely due to each participant having a different sleeping pattern and locking down rescoring rules for each of them would be difficult. In Figures A1 and A2, the rescoring would remove a lot of the wake instances if there was not much movement and would likely be the reason for the lower accuracy. Therefore, it rescoring was not used in the experiments.

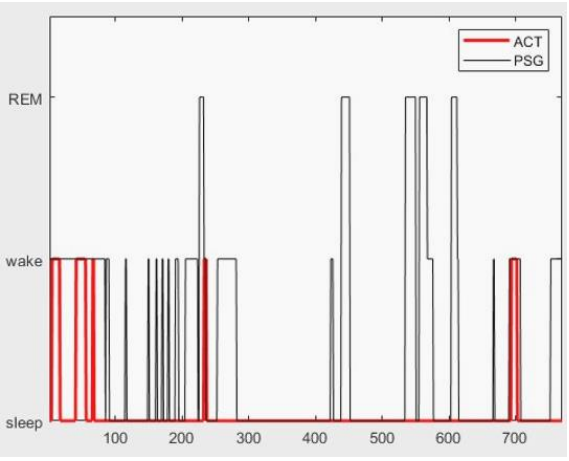

Figure A 1: Normal Scoring

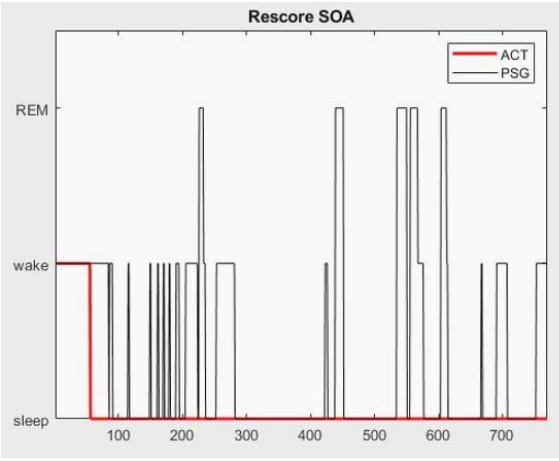

Figure A 2: Rescoring

Next, orientation scoring was attempted to improve the accuracy by observing the position they would sleep in and for how long. The idea was to see if they would sleep on their back, front or sides and for how long at a time. The participants would report what they believed was their most common sleeping position and the algorithm would try to improve the accuracy by assuming more sleep would occur during their favored position. The Xsens mTW sensor included a gyroscope and could be used to calculate the roll, pitch and yaw throughout the night. In addition, the amount of aggressive rotation was considered into the sleep or wake states. For example, if someone is tossing or turning throughout the night, they would likely be turning from side to side and this would signify a wake instance more likely than moving the arm a little. Shown in Figures A3 and A4, the orientation would significantly over estimate wake instances as the person would lay in positions they normally would not sleep in and be considered awake. Also, the inclusion of orientation would increase the wake detection as the inclusion of rotation would add an extra layer in motion activity. However, the issues related to using a single sensor on the wrist and would be difficult to distinguish between all the sleep positions. Since the wrist could be orientated in multiple directions while the torso faces another direction. For example, if the torso is facing towards the ceiling, the wrist could be orientated to either face the ceiling or to the side away from the torso and could be viewed as a different orientation. As well as laying on the side, the wrist could be facing the ceiling and resulting in a sleeping on back position instead of a side sleeping position. If more sensors were

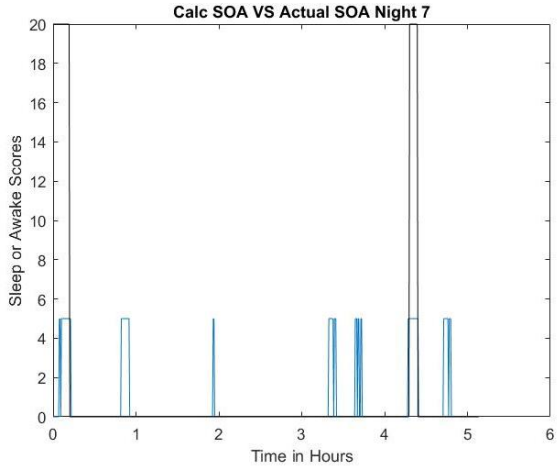

Figure A 3: Normally scored sleep

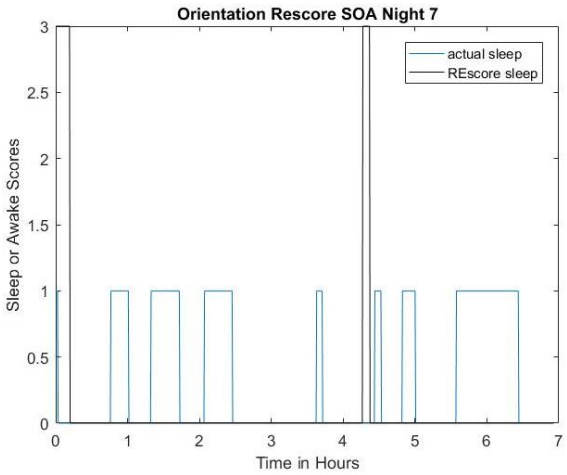

Figure A 4: Orientation scored sleep

used to map the full arm, then it would likely increase the orientation likelihood of estimating the correct position. For example, if a sensor was placed on the wrist, elbow and shoulder, then it would be easier to determine the sleep position because the whole arm can only move so much while laying in each position. However, more sensors were not used as this would create a more invasive sleep monitor by attaching more sensors to the body during the night. The single Xsens sensor on the wrist was chosen as it was supposed to simulate a smart watch that could be used to measure actigraphic movements. Therefore, orientation was removed from the algorithm as it did not provide any benefit to assessing sleep accuracy with this specific setup.

The final algorithm used only the normal scoring for actigraphy without rescoring or orientations. Rescoring could likely be effective with this system but would need to be tuned significantly before it could be used to rescore the states correctly. An alterative solution is to have different rescoring rules for different groups of people. Such as people who move very little during the night such as older people, the rules would be different from more active or younger sleepers. Then each person could use their own specific type of algorithm to help detect each of the sleep states much better. As for orientation, it does not seem viable to score sleeping positions in the current setup with only one actigraphy sensor attached to the wrist. More sensors or a different location for the sensor would be recommended to improve the orientations but this would likely reduce the convenience of the system and would not be used. Therefore, the current setup with one wrist sensor and one BCG is used and continually improved in the software to obtain the best sleep assessment.