Unobtrusive sleep monitoring using bed-sheet pressure sensors

by

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Surveillance non-intrusive du sommeil à l'aide d'un matelas à capteurs de pression textiles

Georges MATAR

RÉSUMÉ

Au moins 50% de la population mondiale des personnes âgées, dont le pourcentage est en croissance rapide, souffre d'un sommeil perturbé. Les études du sommeil sont une approche servant d'outil de diagnostic aux professionnels de la santé. Actuellement, la méthode conventionnelle d'étude du sommeil est la polysomnographie (PSG) enregistrée dans un laboratoire du sommeil. Cependant, la PSG est intrusive, nécessite des techniciens qualifiés, et nécessite une grande allocation des ressources matérielles et professionnelles. Avec l'introduction de technologies commerciales dans le domaine médical, des méthodes alternatives ont été conçues pour essayer de donner une estimation fiable des stades et de la qualité du sommeil. Cependant le manque de validation ou d'un consensus scientifique concernant la fiabilité de ces appareils demeure un défi pour les chercheurs et l'industrie. Ces outils peuvent désormais être utilisés à domicile plusieurs nuits. Les activités cardio-respiratoires et physiques sont les mesures physiologiques les plus prometteuses pour détecter les stades du sommeil sans PSG complète. Les impacts et les budgets liés aux troubles du sommeil sont phénoménaux, ce qui met l'accent sur le fait que le domaine nécessite davantage de recherche. Cette thèse vise à fournir au lecteur une perspective de recherche multidimensionnelle sur les études du sommeil et la surveillance des paramètres physiologiques pendant le sommeil à l'aide de techniques et d'appareils d'acquisition des données non-intrusifs d'acquisition de données. Dans cette optique, nous présentons une revue exhaustive de la littérature de recherche sur les développements en matière d'évaluation non-intrusive du sommeil. En outre, une catégorisation des approches actuelles est présentée en fonction de considérations méthodologiques, allant des protocoles d'acquisition de données et des mesures physiologiques au traitement de l'information. Nous examinons trois fonctions physiologiques principales qui pourraient potentiellement être explorées pour faire avancer les études du sommeil non intrusives basées sur des fonctions du système nerveux autonomes, principalement l'activité cardiaque, la respiratoire et le mouvement. Cette dernière revue nous a aidé à réaliser nos trois contributions. Premièrement, nous proposons une méthode autonome pour classifier les quatre postures du sommeil chez des adultes en bonne santé: dorsal, abdominal, latéral gauche et droit, sans capteurs ou câbles attachés sur le corps ni aucune contrainte imposée au sujet, en utilisant un matelas à capteur de pression. Contrairement à la majorité des travaux similaires antérieurs, les postures dorsale et ventrale ont été séparées avec succès dans la classification. Nous avons constaté que l'utilisation de l'information sur la répartition du poids corporel ainsi que sur la forme et les contours du corps contribue à une meilleure classification et, par conséquent, aide à séparer les postures dorsale et ventrale. Les résultats sont prometteurs pour une surveillance discrète de la posture de manière satisfaisante. La méthode peut être utilisée dans les études du sommeil, les procédures post-chirurgicales ou les applications nécessitant une identification de la posture sur le lit. Deuxièmement, nous tirons parti des résultats de la classification de la posture fiables pour mettre au point une surveillance non-intrusive de la fréquence respiratoire au lit adaptive à la posture à l'aide de

capteurs de pression. Tout au long de cette contribution, nous avons démontré qu'avec un traitement de signal approprié, le matelas à capteurs de pression pourrait être utilisé de manière interchangeable avec les ceintures respiratoires agréées pour l'usage médical par l'association Américaine de la médecine du sommeil (AASM), offrant ainsi une solution plus pratique et nécessitant moins de ressources pour les sujets et les professionnels de la santé. Et troisièmement, nous proposons et validons cliniquement une méthode de classification basée sur l'apprentissage machine profond pour identifier non-intrusivement les stades du sommeil pendant la nuit en utilisant un matelas à capteurs de pression. Bien que les résultats présentés ne donnent pas encore satisfaction pour prétendre l'adoption éventuelle de capteurs de pression de drap de lit en clinique du sommeil, nous estimons que le potentiel d'une telle application mérite d'être largement reconnu et approfondi. Nous soutenons que la méthode proposée pourrait constituer une étape vers des études du sommeil non-intrusives nécessitant moins de ressources. Par la suite, nous formulons des recommandations et des mesures pratiques pour les projets futurs cherchant à contribuer à des études non-intrusives de sommeil en utilisant des matelas à capteur de pression. Nous discutons des limites et des défis auxquels sont confrontées les solutions actuelles, et nous mettons en évidence des domaines de recherche ouverts, qui, nous l'espérons, ouvriraient la voie à de futurs efforts de recherche sur la question: comment évaluer les stades et la qualité du sommeil de manière moins intrusive et fiable?

Mots-clés: Surveillance non-intrusive du sommeil, matelas à capteurs de pression, respiration, mouvements respiratoires, prévention des uclères/plaies, posture du corps humain, cartographie de la distribution du poids du corps, actigraphie, mouvements du corps, surveillance du patient, polysomnographie, activité cardiaque.

Unobtrusive sleep monitoring using bed-sheet pressure sensors

Georges MATAR

ABSTRACT

At least 50% of the world's elderly population, whose range is fast growing, experience disturbed sleep. Sleep studies have become an extensive approach serving as a diagnostic tool for health-care professionals. Currently, the gold-standard is Polysomnography (PSG) recorded in a sleep laboratory. However, it is obtrusive, requires qualified technicians, is time consuming, and expensive. With the introduction of commercial off-the-shelf technologies in the medical field, alternatives to the conventional methods which may be now used at home on several nights have been conceived to ensure sleep stages and sleep quality detection. However, the lack of validation or scientific consensus regarding the reliability of these devices remains a challenge for researchers and the industry. Cardio-respiratory and physical activities remain the most promising physiological measurements to detect sleep stages without complete PSG. The statistically proven impacts and budgets related to sleep disorders are phenomenal, showing that the field needs more research. This thesis aims at providing the reader with a multidimensional research perspective on sleep studies and physiological parameters monitoring during sleep using unobtrusive data acquisition techniques and apparatus. In this vein, we present an exhaustive review of developments made in unobtrusive sleep assessment. Additionally, a categorization of current approaches is presented based on methodological considerations, from data acquisition frameworks and physiological measurements, to information processing. We discuss the three main physiological functions that could potentially be explored to advance unobtrusive sleep studies based on autonomous physiological functions, mainly cardiac, breathing, and movements activities. The latter review helped us achieve our three contributions. First we propose an autonomous method for classifying the four state-of-art human body lying postures (HBLP) in healthy adults subjects: supine, prone, left and right lateral, with no sensors or cables attached on the body and no constraints imposed on the subject, using a pressure sensor mattress. In contrast to the majority of previous similar works, prone and supine postures were successfully separated in the classification. We found that using the body weight distribution along with the shape and edges contributes to a better classification performance, and hence, helps separate supine and prone postures. The results are satisfactorily promising towards unobtrusively monitoring the posture for ulcer prevention. The method can be used in sleep studies, post-surgical procedures or applications requiring HBLP identification. Second, we leverage the reliable results of posture classification in order to develop an unobtrusive posture-adaptive in-bed breathing rate (BR) monitoring system using bed-sheet pressure sensors. Throughout this contribution, we demonstrated, that with proper signal processing, pressure sensor mattresses could be used interchangeably with respiratory belts, which have been approved for medical use by the American Association of Sleep Medicine (AASM), providing a more convenient solution for both subjects and health professionals. Third, we propose and clinically validate a deep learning based classification method for unobtrusive identification of sleep stages using bed-sheet pressure sensors. Although the results presented in this paper are primary and not yet satisfactory to claim an eventual adoption of bed-sheet pressure sensors in sleep clinics, we believe that the

potential of such applications is worth being recognized and further explored. We argue that the proposed method could be a step towards unobtrusive sleep studies that require less resources. Subsequently, we give recommendations and practical steps for future endeavors seeking to bring contributions to unobtrusive sleep studies using pressure sensor mattresses. We discuss limitations and challenges facing current solutions, and we highlight open research areas, which we hope would pave the way for future research endeavors addressing the question: how to assess sleep stages and sleep quality less intrusively, and reliably?

Keywords: Unobtrusive sleep monitoring, pressure sensor mattress, respiration, breathing movements, bed pressure ulcer prevention, human body lying posture, body pressure mapping, actigraphy, body movements, patient monitoring, polysomnography, cardiac activity.

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ADC	analog-to-digital conversion
ANN	artificial neural network
AR	auto-regressive
AUC	area under curve
BA	bland altman
BPM	breaths per minute
BR	breathing rate
CE	cross-entropy
CÉAMS	center for advanced research on sleep medicine
CGM	conjugate gradient methods
CPAP	continuous positive airway pressure
CPM	counts per minute
DI	digital integration
ECG	electrocardiogram
EEG	electroencephalogram
EMG	electromyogram
EOG	electroocculogram
FFANN	feed-forward artificial neural netowrk
FN	false negative

FP	false positive
FSR	force sensitive resistor
HF	high frequency
HoGs	histogram of oriented gradients
HRV	heart rate variability
HSCM	hôpital du sacré-coeur de Montréal
IR	infrared
ICSD-3	international classification of sleep disorders-third edition LOA
LOE	limit of agreement
LOE	line of equality
LBPs	local binary patterns
LF	low frequency
MA	moving-average
NIR	near infrared
NREM	non rapid eye movement
OSA	nbstructive sleep apnea
OSAS	obstructive sleep apnea syndrome
PCA	principal component analysis
PCC	pearson correlation coefficient
PIM	proportional integrating mode

PSG	polysomnography
PLM	periodic limb movement
PLMD	periodic limb movement disorder
PLMS	periodic limb movement during sleep
PSD	power spectral density
REM	rapid eye movement
RGB	red-green-blue
RBD	rapid eye movement behavior disorder
R/K	Rechtschaffen and Kales
RIP	respiratory inductance plethysmography
RLS	restless legs syndrome
RRV	respiratory rate variability
SA	sino-atrial node
SBD	sleep breathing disorders
SBSM	society of Behavioral Sleep Medicine
SCG	scaled conjugate gradient
SD	standard deviation
SDB	sleep disordered breathing
SDNN	standard deviation of N-N intervals
TAT	time above threshold

TN	true negative
ToF	time of flight
TP	true positive
TST	total sleep time
USB	Universal Serial Bus
ZC	zero crossing

INTRODUCTION

According to sleep research, the numbers related to sleep disorders propagation worldwide are becoming phenomenal where at least half of the people over the age of 65 experience disturbed sleep (Monane, 1992). With the perpetual increase of the elderly population percentage, as shown in figure 0.1, this number is expected to fast grow with a tendency to continue, leading to an increase in sleep disorders around the world with increases in the demanding budgets and care (United Nations, Department of Economic and Social Affairs, Population Division, 2015). Researchers have shown the direct socioeconomic impact on the population and the public health, including work accidents, lack of productivity, isolation, depression and numerous more impacts were documented (Leger, 2000; Metlaine, Leger & Choudat, 2005; Sigurdson & Ayas, 2007).

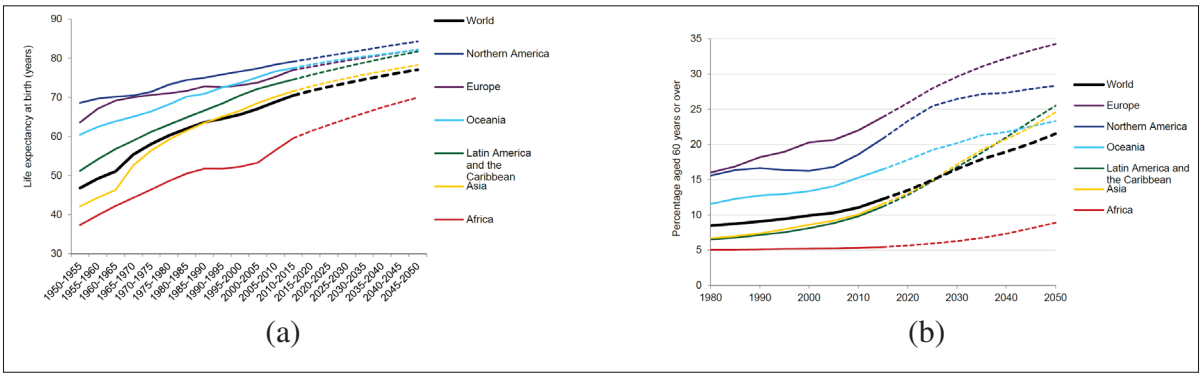

Figure 0.1 Population aging: (a) life expectancy at birth, and (b) percentage of people aged 60 years or older
Adapted from United Nations, Department of Economic and Social Affairs, Population Division (2015)

Moreover, sleep disorders are the result of physiological disturbances and an inducing factor to others, making sleep a very important consciousness state to maintain a healthy well-being and long-term physiological functions (Altevogt, Colten et al., 2006) and (Barnes & Drake, 2015).

Increased risk of depression, stroke, hypertension, heart attach, obesity, and diabetes, are some of the deleterious cumulative long-term effects induced by sleep disorders (Medic, Wille & Hemels,

2017). Over the last decades sleep research has revealed the widespread impacts of sleep alterations on human health. Altevogt *et al.* (2006) have reviewed the prevalence, manifestations, comorbodities, risk factors, and etiology of the most common sleep disorders, including restless legs syndrome, parasomnias, sleep-related psychiatric disorders, sleep-related neurological disorders, sleep loss, sleep-disordered breathing, insomnia, circadian rhythm sleep disorders, and narcolepsy.

Despite the fast spreading and impact of sleep disorders, the majority of people remain not willing to resorting to the current medical sleep evaluation (LeBlanc, Morin, Bélanger, Ivers & Coté, 2011). The reasons for that reduction include the burdensome physiological signal acquisition protocols and clinical conditions that alter both comfort and sleep quality of the subjects, the very high costs of sleep evaluations, and the long waiting lists before exam (Kingshott & Douglas, 2000).

Therefore the need for less constrained sleep evaluations in more ergonomic conditions has given rise to a prominent research line through which researchers have been trying to propose unobtrusive alternative solutions to the conventional methods. These alternatives mainly consist of significantly reducing the large number of sensors attached on the body and making the signal acquisition process more comfortable. The importance of such methods is that they allow to measure the 'real sleep' of the individuals in their home, not the sleep in an hostile or unusual situation such as in sleep clinics. This is done by targeting unobtrusive physiological signals such as breathing, cardiac, and movement activities instead of obtrusive conventional measures such as Electroencephalogram (EEG), Electroocculogram (EOG), and Electromyogram (EMG) that are all subjected to direct contacts with the subject's body. With the application of unobtrusive sleep studies, not only comfort, costs and waiting lists are bound to improve, but also 1) this gives the option to measure sleep in ecological conditions i.e., at home, through several nights and 2) it enables the reach of more people with sleep tests where the collected big data can

constitute an impactful step forward in sleep research. We spend the third of our lifetime sleeping at home. Subjects' domicile could become a "laboratory" by assessing peoples general health through unobtrusive sleep evaluations. In this vein, several algorithms and hardware have been proposed, implemented, and some of them have succeeded to reach industrial gates, thus they can be classified in two groups: industrial and academic.

The concept behind these systems is to monitor certain physiological behaviours such as physical activity, HRV, and BR, and correlate their evolution with the occurrence of sleep stages as defined by the Polysomnography (PSG), or with general sleep parameters such as total sleep time (TST) or wake after sleep onset, which is the amount of wake time in minutes during the attempted sleeping period, after sleep onset has been achieved. However, due to the acquisition process induced challenges facing signal quality, none of the proposed unobtrusive methods has succeeded in joining the medico-industrial production who's typical outcome is a validated, widely used, and class-defined medical device (Baig, Gholamhosseini & Connolly, 2013) and (Hao, Xing & Zhou, 2013).

Advancements in the last decade related to the design of alternative solutions for unobtrusive sleep assessments have shown that an interdisciplinary collaborative work is essential. Thus a substantial collaboration combining medicine with engineering to assess medical and technical constraints arising in the hardware integration and signal acquisition as well as in various levels of signal processing and data communication, is crucial. Previous works have been focusing on developing unobtrusive sensing devices and hardware (Zheng, Ding, Poon, Lo, Zhang, Zhou, Yang, Zhao & Zhang, 2014). Thus, several sensing approaches and sensor types have been conceived and regarded as potential hardware solutions to specific types of parameters or sleep monitoring like posture identification applications (Ni, Abdulrazak, Zhang & Wu, 2010) and sleep/wake measurement (Guerrero-Mora, Elvia, Bianchi, Kortelainen, Tenhunen, Himanen, Méndez, Arce-Santana & Gutiérrez-Navarro, 2012). Although the existing unobtrusive means

for sleep evaluation do not provide the necessary information for rigorous classification of sleep cycling and sleep stage scoring, yet, it can provide general and limited indications on certain important aspects of sleep such as the physical and cardiac activities during sleep.

Accordingly, the need for more advancement in this fields requires defining the challenges and opportunities paving this line of research.

In this thesis, we explore unobtrusive sleep monitoring techniques by presenting an exhaustive literature review. Moreover, we significantly contribute to the field by using a pressure sensor mattress placed under the subject's bed-sheet in order to measure physiological data and validate the measurements with respect to clinical reference. More precisely, the following research questions are explored in this thesis:

1. From both physiological and technical points of view, how can we measure physiological signals to monitor sleep from autonomous nervous functions, consequently reducing the constraints imposed by conventional sleep measurements?

2. To what extent the techniques that have been proposed in the literature to unobtrusively monitor sleep can be trusted or generalized in order to gradually provide a reliable sleep stage estimation?

3. How can we provide a reliable unobtrusive sleep posture classification using a pressure sensor mattress placed under the subject's bed-sheet, while separating supine and prone position?

4. How to unobtrusively monitor BR in all sleep postures using a pressure sensor mattress placed under the subject's bed-sheet?

5. Is it possible to estimate sleep stages using the body pressure distribution on the mattress overnight?

6. What are the future research lines in unobtrusive sleep monitoring and what challenges are they facing?

In the light of the comprehensive review that we presented, we were able to identify and complete three contributions to the field.

We propose a set of features and algorithms to classify sleeping postures adaptively, with a state-of-the-art results while classifying prone and supine postures separately. In fact, sleep posture is an important factor to consider when studying the dynamic body pressure distribution on mattress. For illustration purposes, the breathing induced variation of the body pressure distribution on the mattress is different with posture changes as shown throughout the Chapter 3. Four main postures are considered: prone, dorsal, left, and right lateral. For instance, the breathing induced pressure variation tends to be ampler in prone position than dorsal one, and located in different areas on the pressure sensor mattress. Hence estimating the posture before monitoring the dynamic aspects such as breathing activity is crucial.

We propose an algorithm that, uses the estimated posture to reconstruct a noise-free and posture-adaptive breathing signal. We then compute the breathing-rate accordingly, achieving novel results with an exhaustive comparison to the literature.

We conducted experiments at the center for advanced research on sleep medicine (CÉAMS) of the *hôpital du sacré-coeur de Montréal (HSCM)*. A certificate of ethics compliance was issued by the ethics committee of the HSCM. The experiments consisted of a simultaneous recording of the body pressure distribution on the mattress, and the conventional PSG test. A bed-sheet pressure sensor was placed under the subject's bed-sheet during sleep overnight, while the PSG electrodes were attached on the body. A sleep professional labelled the collected data by giving a sleep stage label for each epoch (time segment) of 30 seconds. We removed the artefacts, anonymized, and stored the data for unobtrusive sleep monitoring.

Based on the collected data, we present a bed-sheet pressure based sleep stages classification method. We validate the method using the conventional PSG criteria and compare the obtained results with available methods.

The goal of this thesis is to develop an unobtrusive monitoring approach of physiological data during sleep. This approach could be leveraged to help reduce burdensome signal acquisition protocols during sleep and tends to optimize resources. The challenge is that using alternative unobtrusive techniques to measure physiological data is prone to noise and unwanted variations in the data. For instance, a breathing signal acquired using the body weight distribution on a pressure sensor mattress could highly vary depending on the sleeping posture, the body shape, and weight. The specific objectives are listed below:

- Investigate autonomous physiological parameters and monitoring techniques that could be used to provide reliable unobtrusive sleep monitoring. This also includes also exploring the physiological changes during sleep and their signification.

- Propose a method to identify the 4 aforementioned HBLP in healthy adults using bed-sheet pressure sensors. The challenge is to distinguish prone and abdominal postures as two separate classes while preserving a high accuracy and generalization performance, considering the importance of classifying the posture to adaptively detect the amplitude and position of breathing patterns on the mattress.

- Propose a method to unobtrusively monitor the BR using a bed-sheet containing elastic textile pressure sensors placed under the subject's bed-sheets, while accounting for posture change during sleep. The realization of this objective proves that a pressure sensor mattress could be used interchangeably with a respiratory belt, which makes breathing monitoring less obtrusive.

- Create an original database of body pressure distribution on mattress acquired simultaneously with the conventional PSG signals with sleep stages labelled. The potential of such database lies in the design and training of a supervised deep learining classifier to build a sleep stages classification that is automatic and unobtrusive.

- Propose a method of unobtrusive sleep monitoring using bed-sheet pressure sensors by automatically estimating sleep stages using on-mattress body pressure distribution data.

This thesis is organized into four chapters. Chapter 1 is an exhaustive literature review in which we give an introduction on sleep physiology, disorders, and monitoring techniques. It presents a survey of the state-of-the-art techniques of sleep monitoring that constitute the central topic of this thesis. The following three chapters address each of the aforementioned objectives. The literature related to each specific topic is reviewed in the corresponding chapter.

In the following, we present the four main contributions we accomplished through this thesis, presented by chapters and peer-reviewed publications:

Contribution 1: exhaustive review of physiological patterns and measurement techniques explored in unobtrusive sleep monitoring.

The main objective of this contribution is to present a comprehensive review on the advancements in unobtrusively measuring autonomous physiological functions, i.e., cardiac activity, breathing and body movements activity. Technical considerations and challenges encountered in the acquisition and signal processing steps are discussed while comparing the proposed methods and algorithms.

The value of this work lies in what it adds to the existing literature in this field. For instance, previous works have reviewed only devices existing in the market. This work however, covers the behind-the-scenes researches that have not reached market yet and may have potential applications. In chapter 1, we present an overview of unobtrusively measurable physiological

patterns during sleep, and we present and discuss activity based unobtrusive sleep monitoring technologies in a technical way.

This work has been published in the following peer reviewed journal paper, which has been already cited 13 times as till 17 february 2020:

Matar, Georges, Jean-Marc Lina, Julie Carrier, and Georges Kaddoum. "Unobtrusive sleep monitoring using cardiac, breathing and movements activities: an exhaustive review." IEEE Access 6 (2018): 45129-45152.

Contribution 2: a feature extraction technique and algorithm for in-bed posture classification using bed-sheet pressure sensors

Video-surveillance, the conventional method of human body lying posture (HBLP) monitoring, suffers from various limitations, such as subject's privacy and field-of-view obstruction. We propose an autonomous method for classifying four state-of-art HBLPs in healthy adults subjects, namely supine, prone, left and right lateral, with no sensors or cables attached on the body and no constraints imposed on the subject. In contrast to the majority of previous similar works, prone and supine postures were successfully separated in the classification. We found that a combination of body weight distribution, along with shape and edges features extracted from the pressure images, contributes to a better classification performance and enables the separation of supine and prone postures. The results are satisfactorily promising towards unobtrusively monitoring posture for ulcer prevention. The method can be used in sleep studies, post-surgical procedures, and applications requiring HBLP identification. We explain this contribution in chapter 2.

This work has been published in the following peer reviewed publications:

Georges Matar, Jean-Marc Lina, Julie Carrier, Anna Riley, and Georges Kaddoum. "Internet of Things in sleep monitoring: An application for posture recognition using supervised learning." In 2016 IEEE 18th International Conference on e-Health Networking, Applications and Services (Healthcom), pp. 1-6. IEEE, 2016.

Georges Matar, Jean-Marc Lina, and Georges Kaddoum. "Artificial neural network for in-bed posture classification using bed-sheet pressure sensors." IEEE journal of biomedical and health informatics (2019).

Contribution 3: a method and algorithm for unobtrusively monitor BR using bed-sheet pressure sensors

We propose in this contribution an indirect and contactless method to adaptively monitor breathing movement using a pressure sensor mattress placed under the subject's bed-sheet. In addition, we reconstruct the breathing movements signal, and compute the BR over 30 seconds time windows. A ten-sinusoidal model-based extended Kalman Filter was used to adaptively estimate the breathing movements signal from the body pressure distribution data. The model is posture-specific, i.e., the model's parameters are optimized based on the detected posture. The artificial neural network (ANN) model developed and detailed in chapter 3, was used to detect four sleeping postures to perform the optimization step accordingly. Based on the classified posture, a kalman filter model is selected and the breathing signal is reconstructed to compute BR. We show and discuss the consistency of the proposed method and the potential usage in several medical applications requiring respiration monitoring during sleeping or in-bed patients. Finally, we show that pressure sensor mattresses could be used interchangeably with respiratory belts which have been approved for medical use by the AASM, providing a more convenient solution for both subjects and health professionals. We explain this contribution in chapter 4.

This work was submitted in the following peer reviewed journal paper (Under review):

Georges Matar, Jean-Marc Lina, Julie Carrier and Georges Kaddoum. "Kalman filtering for posture-adaptive in-bed BR monitoring using bed-sheet pressure sensors." Submitted to *IEEE journal of biomedical and health informatics* journal in October 2019.

Contribution 4: a method and algorithm for an automatic and unobtrusive classification of sleep stages using bed-sheet pressure sensors

We propose a method to automatically classify sleep stages using data collected from bed-sheet pressure sensors. We propose an automatic feature extraction from pressure data divided into 30 seconds epochs using convolutional neural networks and feed the feature to an artificial deep neural network to classify sleep stages. We collected and labeled pressure and PSG data

and clinically train and validate the proposed classification model. We conclude that using the dynamic body pressure distribution on mattress it is possible to identify sleep stages. The advantage of the presented results lies in the potential application of pressure sensor mattresses, as an unobtrusive data acquisition method in the field of sleep stages classification.

This work was submitted in the following peer reviewed journal paper (under review):

Georges Matar, Jean-Marc Lina, Julie Carrier and Georges Kaddoum. "Deep learning based unobtrusive sleep stages classification using bed-sheet pressure sensors." Submitted to *biomedical signal processing and control* journal in November 2019.

CHAPTER 1

LITERATURE REVIEW

1.1 An overview of sleep stages, disorders, and monitoring techniques

1.1.1 Sleep stages

Sleep is a physiological state defined by specific characteristics (Roehrs, 2000). Being periodic, naturally-occurring, reversible, recurring and involving suspension or reduction of alertness and muscular activity, it has always been a subject of interest for researchers, even regarding the question 'why humans need to sleep?' a scientific consensus has not been reached yet (Cirelli & Tononi, 2008).

The sleep architecture is a sequence of sleep cycles, where each one is formed by different sleep stages. Each stage is characterized by specific physiological changes. There are 4 sleep stages: Rapid eye movement (REM) sleep, and three non-REM (NREM) stages: NREM1, NREM2, and NREM3 reflecting the progression from lighter (NREM1) to deep (NREM3) sleep. In 1968, Rechtschaffen and Kales (R/K) proposed the "Manual of Standardized Terminology, Techniques, and Scoring System for Sleep Stages of Human Subjects" to score sleep stages based on pre-defined criteria of the physiological parameters measured during sleep (EA, 1969). The AASM issued the latest version to date (v.2.5.0) of the manual of sleep scoring and associated events in 2018 that is based on the R/K and researchers' recent findings (Berry, Brooks, Gamaldo, Harding, Marcus & Vaughn, 2018). The manual is continuously upgraded. Moser, Anderer, Gruber, Parapatics, Loretz, Boeck, Kloesch, Heller, Schmidt & Danker-Hopfe (2009) compared the effects of both scoring systems on the derived scoring parameters and the overall scoring outcome. Fig. 1.1 shows a brief description of the physiological parameters changes with respect to each sleep stage, as well as the transition-specific physiological changes that are noted during transitions between sleep stages.

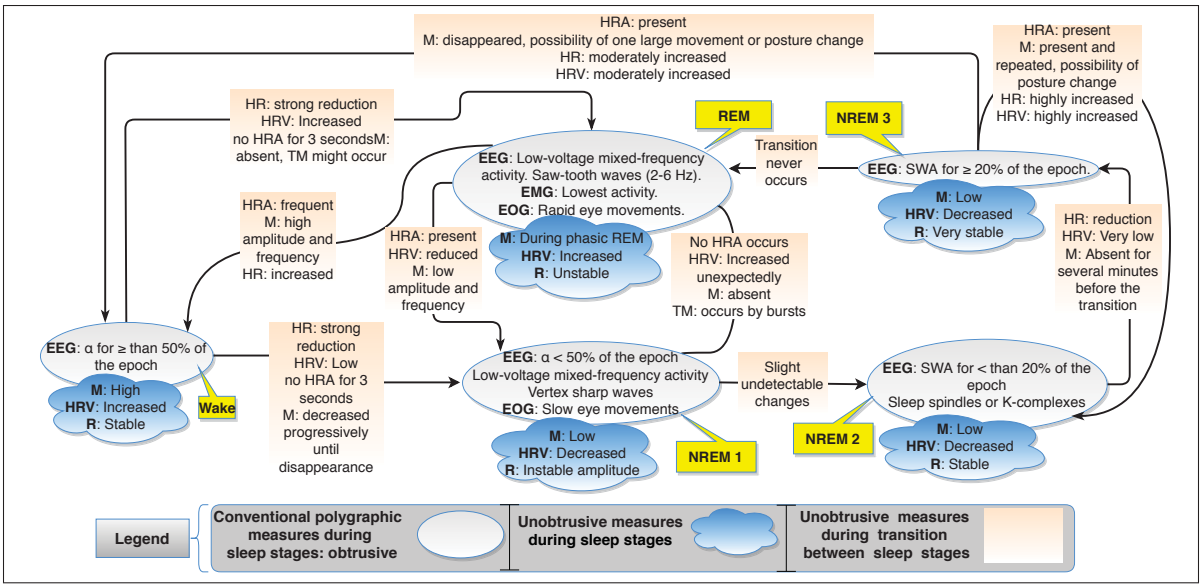

Figure 1.1 Physiological changes during sleep stages in accordance with the AASM

For instance, cardiac, breathing, and body movement activities that could be measured unobtrusively are shown separately from the conventional polygraphic EEG, EOG, and EMG signals that are the gold standard used to score sleep stages, and derive the evolution of sleep stages over time, i.e., sleep hypnogram.

1.1.2 The burdensome impact of sleep disorders

There exist seven major categories of sleep disorders, according to the latest international classification of sleep disorders (ICSD-3) (Sateia, 2014). They can be classified as follows: 1) sleep-related breathing disorders, 2) insomnia disorders, 3) circadian rhythm sleep/wake disorders, 4) central disorders of hyper-somnolence, 5) parasomnias, 6) sleep-related movement disorders and 7) other sleep disorders. Numerous physiological dysfunctions underlaying sleep disorders have been described in the literature. Among these are neurological factors such as narcolepsy and periodic limb movement disorder (PLMD), or sleep breathing disorder (SBD) such as obstructive sleep apnea (OSA).

The negative physiological impacts of sleep disorders are serious. Accordingly, studies have shown that one night of sleep deprivation can cause impairments to insulin sensitivity equivalent

to a six months of a high-fat diet (Broussard & Brady, 2010). Moreover sleep disorders can alter pain tolerance in humans (Onen, Alloui, Gross, Eschallier & Dubray, 2001), can cause heart dysfunctions such us ischemic heart disease (Knutsson, Jonsson, Akerstedt & Orth-Gomer, 1986), and cause a wide range of health issues such as metabolism impairment and hormonal disturbances leading to severe physiological alterations and bad consequences (Naitoh, Kelly & Englund, 1990).

Sleep disorders are not only known to induce short and long-term health issues and have bad physiological consequences (Harvey Moldofsky, 2001; Manocchia, Keller & Ware, 2001), but they are also a consequence of physiological disturbances (Misra & Malow, 2008). In fact, occurrences of sleep disorders could also be a manifestation or a symptom displaying autonomous physiological function abnormalities that, if left untreated, could cause severe health conditions (Ribeiro, Hampton, Morgan, Deacon & Arendt, 1998). Beside health related problems, sleep disorders were shown to have a potential sociological, professional (Léger, Guilleminault, Bader, Lévy & Paillard, 2002), and economical (Hillman, Murphy, Antic & Pezzullo, 2006) impact on the world population. For instance, around 150 Million people are estimated to have sleep disorders. In the United States, 50-70 million adults have a sleep disorder, 48.0% report snoring, and 37.9% reported unintentionally falling asleep during the day at least once in the preceding month (Leger, 2000; Metlaine *et al.*, 2005; Sigurdson & Ayas, 2007). Motivated by this major prob, numerous studies were designed to make the acquisition protocol during sleep studies less obtrusive, including home-based solutions, wearable textiles, and electronic gadgets. In the next sub section, we give a brief classification of the devices types based on their relative clinical significance, and based on the world-wide established medical devices classification (Cheng, 2003).

1.1.3 State-of-the-art sleep monitoring techniques

In this subsection, we classify the devices currently used in sleep studies in both research and clinical environments into four categories. Sleep studies are medical examinations performed to evaluate the sleep quality of people based on scoring schemes. The aim of sleep monitoring is

to explore a person's abnormal sleeping state that is a result of some health issues, and a cause of others. Hence sleep monitoring techniques serve as a diagnostic tool and an identifier for several health problems. Depending on the application, sleep monitoring devices can be divided into four main types ranging from 1 to 4. In general terms they can be described as follows:

- **Type 1:** trust-worthiest among others for sleep diagnosis. Operate in attended sleep tests that take place in clinical places, the most known among them is PSG (Fig. 1.2) (Douglas, Thomas & Jan, 1992b).

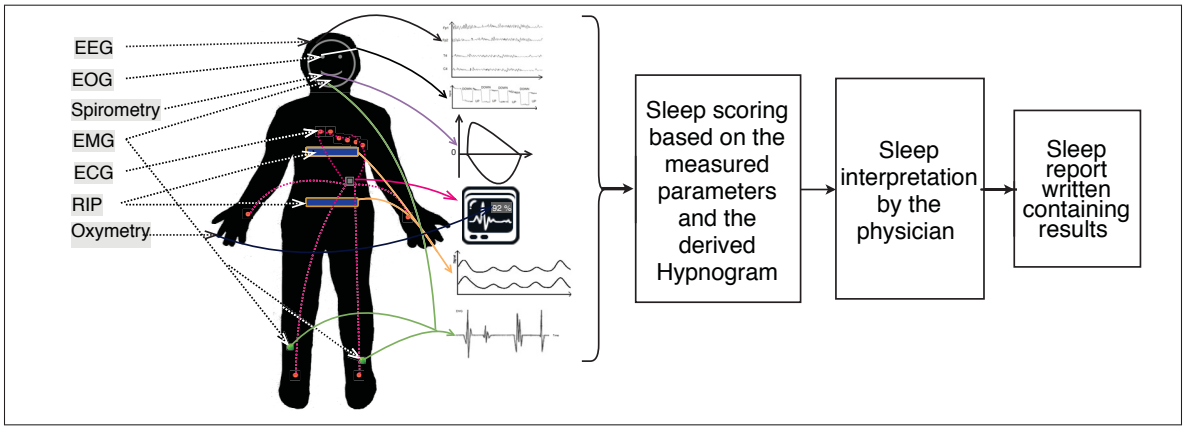

Figure 1.2 Typical acquisition protocol and general workflow in a PSG procedure. 22 sensors and wires, attached on the body

- **Type 2**: being able to carry out the full spectrum of PSG signals in an unattended signal acquisition protocol, type 2 devices provide the advantage of longer term PSG recording, which makes them suitable to diagnose an important range of sleep disorders, with lower yet acceptable precision in the results (Fry, DiPhillipo, Curran, Goldberg & Baran, 1998; Iber, Redline, Gilpin, Quan, Zhang, Gottlieb, Rapoport, Resnick, Sanders & Smith, 2004).

- **Type 3**: unattended, physiological parameters specific, e.g, respiratory monitoring devices, such as continuous positive airway pressure (CPAP) machines.

- **Type 4**: unattended, portable non-medical devices delivering highly unobtrusive measurements at the expense of accuracy and reliability, also referred to as electronic gadgets.

Several types of conventional sleep quality assessment methods exist. Each of them is prescribed depending on the person's health status and the aim behind the study. Some are very specific and designed to measure somnolence and specific sleep characteritics. These include the multiple sleep latency test (Carskadon, 1986) and the maintenance of wakefulness test (Littner, Kushida, Wise, G. Davila, Morgenthaler, Lee-Chiong, Hirshkowitz, Loube, Bailey, Berry, Kapen & Kramer, 2005). Meanwhile, others are designed to measure sleep quality in general such as home-based portable monitor (Ajilore, Stickgold, Rittenhouse & Hobson, 1995) and the most widespread PSG test (Douglas *et al.*, 1992b). In addition, more specialized sleep studies exist with a relatively narrow and focused application. Instead of aiming to classify sleep stages, such tests are only used to diagnose specific parameters such as breathing activity. The most common among them are the ones dedicated to analyze obstructive sleep apnea syndrome (OSAS) such as CPAP or CPAP Titration (Berkani, Lofaso, Chouaid, d'Ortho, Theret, Grillier-Lanoir, Harf & Housset, 1998), Bi-Level Titration (Kasai, Narui, Dohi, Ishiwata, Yoshimura, Nishiyama, Yamaguchi & Momomura, 2005), and Split Study for severe OSAS cases (Dernaika, Tawk, Nazir, Younis & Kinasewitz, 2007). Moreover, there are some modifications to the nocturnal PSG test (Robinson, Walsleben, Pollack & Lerner, 1998) such as the expanded EEG sleep recording test (Bonnet & Arand, 2000), where a recording of a full montage of EEG is required to analyze not only sleep disorders but also the existence of nocturnal seizures, and the nocturnal PSG Test with End Tidal CO2 (Vos, Folgering & Van Herwaarden, 1993).

Being the most accurate and trust-worthy among all other means to conduct sleep studies for general sleep disorders, the PSG abides, the decisive and far-reaching approach in many cases (McGregor, Weitzman & Pollak, 1978). Fig. 1.2 illustrates the sensors attached to the body and the general procedure followed in a PSG test. During a PSG procedure, the movement of the chest and abdominal wall, the blood O2 saturation, the brain and heart electrical activities, the eye movements, the respiration, the limb and the chin muscles' activities are measured. Data is partitioned into 30 seconds epochs based on the criteria defined by the manual to score sleep stages (Berry *et al.*, 2018). Afterwards, the scoring results are sent to the physician

for interpretation. However it remains a complex, high demanding and obtrusive procedure especially for some people having a low requirement for a sleep assessment. For example, for a suspicious diagnosis that need to be ensured, and mostly for adult and elderly people that for some reason need to be health-monitored during sleep, such as people having unjustified and frequent laziness, increased sleep propensity along day, or abnormal sleeping behaviour.

1.2 Unobtrusively measurable physiological patterns during sleep

During sleep monitoring, in order to detect abnormalities and irregularities, it is important to take into consideration the normal sleep patterns, or physiological changes that are supposed to occur during each stage. Monitoring the brain activities provides the most useful information about sleep regulation. In a PSG procedure, this is directly measured through EEG recording.

The brain's electrical activity measurements is in the range of a few hundreds of micro-volts, making it hard to measure using unobtrusive apparatus, i.e., sensors requiring a minimal contact with the subject and maintaining comfort during acquisitions. On the other hand,

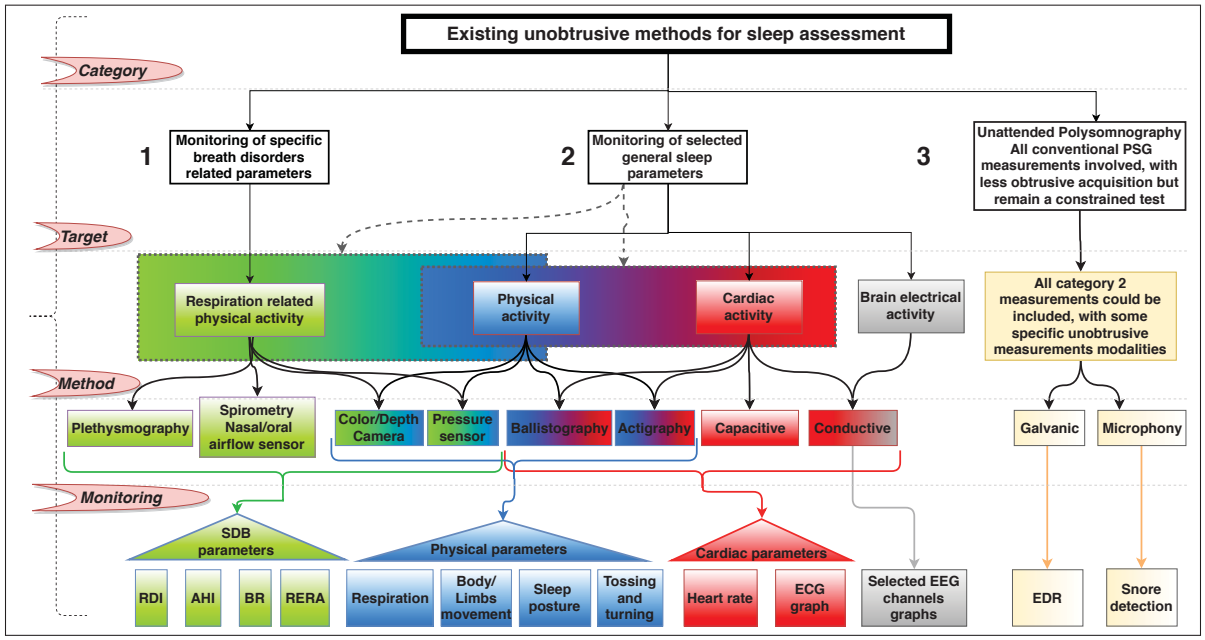

Figure 1.3 Unobtrusive sleep monitoring methods

since the autonomic nervous system is highly influenced by the activity of the central nervous one (Shannahoff-khalsa & Yates, 2000), autonomic physiological functions such as blood pressure, muscular activity, movements, and the cardiac activity are affected and altered by the central nervous system. In addition, these autonomic functions are displayed in ample variations (millivolts for ECG, movements, or breathing) compared to the EEG's small amplitude variations, which makes them less sensitive to noise and more suitable for unobtrusive measurement apparatus that require less stable contact with the body. Hence, unobtrusive sleep monitoring consists of capturing physiological changes such as breathing and body activity, that are alternative to conventional PSG measures such as brain and muscles activities, but without interfering with the subject's comfort during sleep. For instance, vagal activity related features have been showing promising results that could lead to a reliable estimation of sleep hypnogram using unobtrusively acquired physiological signals. The diagram depicted in Fig. 1.3 shows three categories of sleep monitoring methods that will be addressed in this chapter: monitoring of breath disorders related parameters, monitoring of selected general sleep parameters, and unattended PSG. For each monitoring method, the physiological behavior, the acquisition method and hardware, and the obtained physiological parameters are given. In this section, each of the three activity patterns and its relationship with sleep cycles and staging is described and discussed in details.

1.2.1 Breathing activity patterns

The respiratory effort has been used to analyze sleep in humans using several characteristics such as the spectral power features variations in respiratory rate and the respiratory effort's signal regularity (Douglas, White, Pickett, Weil & Zwillich, 1982). Patterns of body movement are induced by breathing over time, and they depend on the posture of the body on the mattress (Oksenberg & Silverberg, 1998). Therefore, it is possible to continuously monitor the respiratory movement in order to calculate the respiration rate (BPM) and other characteristics such as regularity and depth of the signal. Several aspects make breathing activity a physiological activity to study during sleep:

1. sleep stages estimation: respiratory patterns have been shown to vary during different sleep stages which makes it possible to combine respiration with other parameters to improve the estimation of sleep stages and related hypnograms. Benarroch (2019)

2. SDB are one of the most widespread sleep disorders and they could be detected and identified by monitoring breathing.

3. BR is one of the five vital signs that provide measurements of the body's most basic functions, thus an irregular BR may be a symptom of other medical conditions, which makes it a very interesting behavior to monitor during sleep to unveil abnormal conditions.

Researchers have shown that respiratory rate variability (RRV) analysis during sleep could give potential insights on sleep stages. This latter is modelled in (Gutierrez, Williams, Alrehaili, McLean, Pirouz, Amdur, Jain, Ahari, Bawa & Kimbro, 2016) as follows:

$$RRV = (100 - \frac{H_1}{DC})\%, \tag{1.1}$$

where H_1 and DC are the spectral amplitude of the first harmonic peak and the zero frequency peak, respectively. For instance, as defined by (1.1), RRV is proven to have different values at each sleep stage, with the lowest occurring in NREM3, followed by NREM2, NREM1, REM, and wake that has a higher value than all the other sleep stages, including REM (Gutierrez *et al.*, 2016).

During wake, breathing becomes irregular if the eyes are open and tends to be more regular with closed eyes. During NREM1. In NREM 2 and 3, breathing becomes regular with few disturbances or some variations in rate. In the REM phase, breathing becomes irregular with short breathing breaks.

It is worth noting that, as for the respiratory amplitude, the volume of inhaled air is more irregular with a smaller tidal volume during REM than NREM stages (Tabachnik, Muller, Bryan & Levison, 1981).

1.2.2 Body movement patterns

Body movements occur in specific stages of sleep with patterns, durations, and frequencies, that indicate the state of the person and can provide insights on further physiological changes. The movements can be analyzed and a variety of parameters can be used to monitor sleep or diagnose sleep disorders.

In this chapter, the term *body's physical condition* during sleep is used to designate the absence or presence of physical activity of the body and limbs. Specific behaviors characterize a normal and abnormal body's physical condition during sleep:

Normal physical conditions during sleep: random, periodic, and absence of movements that occur naturally and are not associated with any disorder, including:

- **Major body movements**: can be defined as body movements and muscular activity that are characterize of arousals and are used to discern wake periods from sleep. For instance, if they occur for more than 15 seconds during a 30 seconds epoch of sleep, the epoch is classified as wake state.
- **Minor body movements**: lighter body or limb movements that occur during sleep and do not induce the identification of the corresponding epoch as a wake state. After deep sleep at NREM3, a transition to lighter sleep stages, NREM2 then NREM1, is accompanied by the occurrence of possible minor body movements.
- **Periodic movements**: periodic patterns of minor chest movements are induced by breathing due to the change of the diaphragm's volume during the recurring periodic inspiratory and expiratory phases. An increase, then a pause followed by a decrease of volume are induced by inspiration, inspiratory hold and expiration, respectively.
- **Body paralysis**: during REM sleep, the body and members undergo a muscular atonia with occurring muscular twitches, also referred to as paralysis, which can be used as one of the biomarkers of the REM sleep state in both conventional and unobtrusive sleep monitoring techniques.

Abnormal physical conditions during sleep: includes all types of random and periodic movements or movements that are not supposed to occur naturally. These movements are associated with well known disorders and physiological disturbances. For instance, the REM behavior disorder (RBD), where people physically act their dreams, could be potentially dangerous (Schenck & Mahowald, 2002). Another disorder is the periodic limb movement disorder (PLMS) and occurs commonly with ageing. It is one of the most widespread among sleep movement disorders and consists of repetitive movements of the limbs that occur sporadically, more often in the legs i.e., PLMS, than arms i.e., periodic arms movement disorder. These movements often involve an extension of the big toe accompanied by an occasional slight bend of the hip and knee, and a dorsiflexion of the ankle. They do not prevent the person from sleeping; however, they affect sleep quality. They can last between 0.5 to 5 seconds with a period of 20 to 40 seconds, where the process could be repeated for few minutes to an hour. Although they are not supposed to occur naturally, they are not considered as a disorder unless they severely affect sleep and daily life. In this case, then they are known as PLMD. REM SBD was shown to impact body movement patterns and muscle tone (Cygan, Oudiette, Leclair-Visonneau, Leu-Semenescu & Arnulf, 2010), such as punching, kicking, arm falling, or jumping from bed, in response to action-filled dreams. Several other sleep movement disorders exist such as hypnic jerks, bruxism, rhythmic movement disorder and nocturnal leg cramps (Merlino & Gigli, 2012).

1.2.3 Cardiac activity patterns

There exists a considerable number of works aiming to discuss and assess the relationship between HRV, or the physiological cardiac changes, and the evolution of sleep stages (Bonnet & Arand, 1997; Brandenberger, Buchheit, Ehrhart, Simon & Piquard, 2005; Hall, Vasko, Buysse, Ombao, Chen, Cashmere, Kupfer & Thayer, 2004; Lee, Chou, Lai, Liu & Chiu, 2005). Authors in (Jurysta, Van De Borne, Migeotte, Dumont, Lanquart, Degaute & Linkowski, 2003) and (Ako, Kawara, Uchida, Miyazaki, Nishihara, Mukai, Hirao, Ako & Okubo, 2003) have studied the correlation between EEG power spectrum and HRV. Jurysta *et al.* (2003) have shown that the HRV's high frequency power normalized with respect to the total frequency power (low

frequency+high frequency) is linked to all EEG power bands, and that delta band changes in the EEG signal is preceded by a significant change in the cardiac vagal activity. In fact, the aforementioned electro-cardiac changes are correlated with cycling of sleep stages and could be measured and evaluated through a HRV analysis, which can help to a sleep quality assessment as it will be described in this section.

ECG, which has been used for decades as a partial measure and a part of the combination of signals needed to be acquired and analyzed. However, for non-diagnosis uses of sleep assessments, i.e., where a general insight on sleep and not detailed diagnosis of cardiac activity is required, ECG can be used as a standalone approach along with HRV analysis.

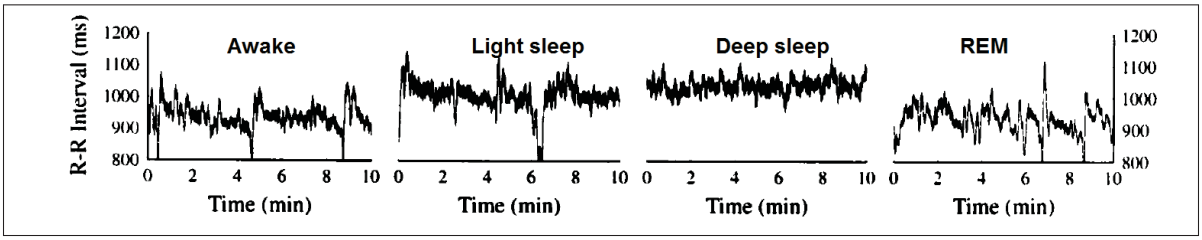

Figure 1.4 HRV changes with sleep stages. R-R intervals plotted over time during: Wake, Light (Including stages 2 or 3), deep (stages 3), and REM sleep Adapted from Togo & Yamamoto (2001)

Currently used conductive ECG electrodes requires a direct contact with the skin that should remain stable all night, which is a severe limitation for unobtrusive applications. Moreover, tosses involving posture changes are not allowed during conventional ECG acquisitions. Using unobtrusive means of acquiring ECG signals can overcome such limitations and should take into account unavoidable tosses that are a part of sleep. Precisely, unobtrusive acquisitions could take advantage and exploit, position changes, and tosses as an indicators that help the sleep assessment instead of altering it.

Sleep staging using HRV analysis

HRV analysis consists of assessing how much variability the time-duration between consecutive heart-beats can undergo over time (Saykrs, 1973). The time interval between two beats is referred to as R-R interval, where R is the peak of the QRS complex. Several methods have been used in the literature to show the strength of correlation between HRV and autonomic physiological functions (Laude *et al*, 2004) and (Carney *et al*, 2001). The first to observe beat-to-beat variability was Hon (1965). He noticed that R-R intervals were the only parametric variation to occur before a fetal distress. Since then, researchers have been trying to explore HRV by proposing hypothesizes to be tested, methods, and algorithms (Rajendra Acharya, Paul Joseph, Kannathal, Lim & Suri, 2006). Different types of HRV analysis methods exist. Time-frequency methods of HRV analysis consist of extracting time and/or spectral parameters from the ECG signal, such as time lapses between two consecutive R peaks. Time-frequency methods are the most widespread, whereas spectral methods yield the best results in sleep staging procedures. Several types of noise that should be taken into account can be found in unobtrusively acquired ECG signals. For instance, in applications where there is no direct contact between the electrodes and the person's skin, e.g., capacitive coupling in which we have to acquire ECG signals from a subject that is not in a clinical room, a high input impedance for the system is induced due to the body-electrode poor contact interface (Stein & Pu, 2012).

1.3 Physical activity based unobtrusive sleep monitoring technologies

Acitivity based sleep monitoring methods have been existing since 1922 (Orthner, 1969), including systems that use slow motion cinematography (Cooper, 1965), motion induced ultrasonic interruption (Peacock & Williams, 1962), and many others.

Previous works have tried to compare between several acquisition methods such as video monitoring and actigraphy (Borazio & Van Laerhoven, 2012) and (Sitnick, Goodlin-Jones & Anders, 2008). Here, only the widespread systems that are still used in modern research and sleep studies are covered and discussed, i.e., actigraphs, cameras and IR.

1.3.1 Sleep actigraphy

Sleep actigraphy consists of recording the body's movements during sleep. Depending on the application, the recorded data can be used to predict some insights on the neurobehavioral state, infer sleep or discern wake periods. By counting the number of body movements and assessing their amplitudes, sleep parameters, such as quality, latency, duration, efficiency, and fragmentation, circadian rhythms, sleep and wake periods, and activity levels (Gorny & Spiro, 2001). Actigraphy is convenient in sleep studies because it is a low-cost unobtrusive method that could be used in both clinics and subjects' homes. Hence, actigraphy can be used for acquiring sleep related data in situations where PSG is logistically impractical, or for long acquisition periods in the patients home.

The AASM indicates in it's practice guidelines that actigraphy is reliable in measuring sleep for healthy adults (Morgenthaler, Alessi, Friedman, Owens, Kapur, Boehlecke, Brown, Chesson Jr, Coleman, Lee-Chiong et al., 2007). Moreover, actigraphy was shown to be sufficiently sensitive to be used in more specific applications of sleep studies. For instance, monitoring sleep changes following treatment for insomniac patients has been explored in (Brooks III, Friedman, Bliwise & Yesavage, 1993) and (Hauri & Wisbey, 1992). In 2015, the SBSM has published a guide to actigraphy monitoring, to assist clinicians and researchers using actigraphy, citing more than 150 actigraphy based works, including many on sleep applications (Ancoli-Israel, Martin, Blackwell, Buenaver, Liu, Meltzer, Sadeh, Spira & Taylor, 2015). Despite their usefulness in specific applications, sleep actigraphy systems have limitations such as inaccuracies in the number of activity accounts, and lack of clinical validation (Matar, Lina, Carrier & Kaddoum, 2018).

1.3.2 Sleep video monitoring

Several types of sensors have been used for video monitoring during sleep studies to monitor different physiological aspects such as posture, body and limb movements, breathing activity, and sleep/wake states (Yang, Cheung, Chan & Stankovic, 2014). Depending on the application,

the targeted measures and the clinical and environmental constraints, RGB, IR, or thermal cameras, are used as a standalone or in combination in the data acquisition steps (Falie, Ichim & David, 2008; Gade & Moeslund, 2014; Lee & Nevatia, 2007; Li, Yadollahi & Taati, 2017; Procházka, Schätz, Vyšata & Vališ, 2016; Shotton, Sharp, Kipman, Fitzgibbon, Finocchio, Blake, Cook & Moore, 2013; Yang *et al.*, 2014; Yang, Cheung, Stankovic, Chan & Ono, 2017).

Despite its limited clinical applications, sleep video monitoring offers several advantages over other conventional or unobtrusive methods, especially when used for specific applications such as periodic limb detection. Some of the main advantages of sleep video monitoring over conventional methods can be resumed as follows:

- Unobtrusive; requires no direct contact with the subject; does not induce skin discomfort caused by electrodes; does not limit or constraint movements; and can be adopted outside supervised clinical conditions.

- Apart from tibials, where EMG electrodes are applied (Berry, Brooks, Gamaldo, Harding, Marcus, Vaughn et al., 2012), some legs muscles activity are often missed by EMG. This information is preserved in 3D methods of video monitoring (Garn, Kohn, Dittrich, Wiesmeyr, Kloesch, Stepansky, Wimmer, Ipsiroglu, Grossegger, Kemethofer & Seidel, 2016).

- EMG signals are sensitive to tonic muscle contractions leading to an over detection of limb movements in most PSG procedures caused by signal deflections over time. Moreover, an alteration of skin-electrodes contact causes signal deflections and false movements annotations, which can affect sleep/wake detection and an overestimation of the PLM index (number of PLM per hour of sleep time). These problems can be avoided in video monitoring. Next, we will present the two widely used video-based monitoring methods.

1.3.2.1 Posture and movement monitoring

Researchers have been trying to develop and validate materials and methods to make video-surveillance a potential solution for posture and movement analysis and quantification during sleep. Image processing based approaches are essential to extract the human body from

the captured images during video-surveillance. Several approaches have been proposed and implemented such as skin and edge segmentation and skin color detection in order to provide a reliable estimate of sleep/wake states and further sleep parameters and behaviours such as sleep latency, TST, sleep efficiency, PLM index, and awakenings by detecting and tracking human body movement (Al-Tairi, Rahmat, Saripan & Sulaiman, 2014; Garn *et al.*, 2016; Ghimire & Lee, 2013; Heinrich, Geng, Znamenskiy, Vink & de Haan, 2014). Moreover, some works have succeeded to reach further levels of sleep analysis by providing a relatively acceptable classification of the five sleep stages in question (N1, N2, N3, W and REM) (Scatena, Dittoni, Maviglia, Frusciante, Testani, Vollono, Losurdo, Colicchio, Gnoni, Labriola et al., 2012). Despite the advantages this method can provide, it suffers from weaknesses when used in posture and/or movement detection. For instance, lower limbs are harder to detect in some cases such as sleep-monitoring a female wearing a one-piece sleep dress, or a person covered by a blanket, leading to a posture misclassification and in some cases, movement underestimation due to undetected limbs, especially for skeleton-based video tracking. Moreover, the required vision to detect some joints can be occluded and confusion may occur for some postures classification as well (Booranrom, Watanapa & Mongkolnam, 2014). Researchers have also been trying to identify posture and estimate sleep stages using bed sheets containing textile based pressure sensors (Walsh, McLoone, Ronda, Duffy & Czeisler, 2017; Waltisberg, Amft, Brunner & Tröster, 2017). In our previous work, a support vector machine algorithm has been developed and tested to automatically identify postures (Matar, Lina, Carrier, Riley & Kaddoum, 2016). Unlike other methods including camera surveillance, the advantage of the proposed method lies in its ability to recognize postures without interfering with the subject's comfort. Precisely, some types of clothes or blankets may obstruct the view of cameras and impact the performance, which is not the case with pressure sensor mattresses.

1.3.2.2 Breathing activity monitoring

sleep video monitoring has been used to monitor breathing activity and detect specific breathing disorders (AL-Khalidi, Saatchi, Burke, Elphick & Tan, 2011a). For instance, the physiological

changes induced by breathing, discussed in section 1.2.1, could be detected via several methods and algorithms. There are two main approaches in the literature to monitor breathing using video surveillance:

Depth information based monitoring: consists of dynamically using the skin-IR sensor distance via points or patches of interest, in order to have a surrogate measure of the volume change induced by breathing.

Skeleton tracking: consists of detecting joints in the human body and monitoring their periodic displacement in the frequency range of respiration in order to correlate this change with breathing.

Applications of such approaches vary from simple BR monitoring to more complex identification such as apnea and hypopnea events.

Authors in (Tataraidze, Anishchenko, Korostovtseva, Kooij, Bochkarev & Sviryaev, 2015) have classified wake, REM, and NREM using respiratory features extracted from plethysmographic data and achieved an accuracy of 80.30% with a cohen's kappa coefficient of approximately $\kappa = 0.65$. Another approach that could be used for unobtrusive moniroting of breathing activity and that has been merely explored by researchers is based on dynamically acquiring the body pressure distribution on the mattress during sleep. We acquired pressure images of the body during sleeping positions at a frame rate of 10 Hz in order to extract breathing activity information from the data. The algorithm developed in (Matar *et al.*, 2016) has been used to identify sleep postures, and accordingly select a collection of pressure sensors that are believed to be involved in acquiring the volume changes induced by breathing i.e., the chest area. Fig. 1.5 shows a sample of the obtained signal for dorsal posture.

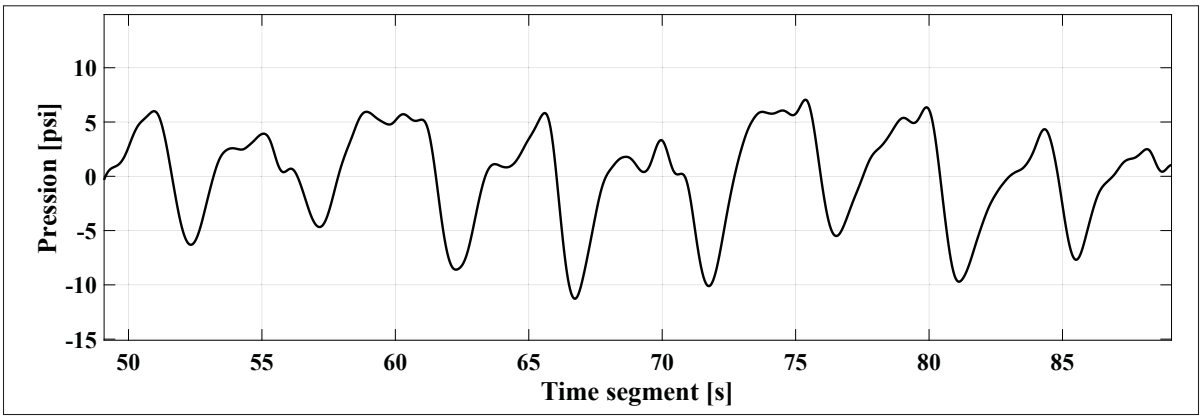

Figure 1.5 Respiratory effort signal derived using a pressure sensor mattress from a subject sleeping in a dorsal position

1.4 Cardiac based unobtrusive sleep monitoring methods

1.4.1 HRV Analysis in sleep studies

Researchers have tried to classify sleep stages using several types of HRV features such as time and frequency domain, geometric, and non linear methods (Ebrahimi, Setarehdan, Ayala-Moyeda & Nazeran, 2013; Rajendra Acharya *et al.*, 2006). For instance, wake and REM stages have been proven distinguishable using a combination of non-linear features and a global increase of linear HRV features (Jovic & Bogunovic, 2011). Xiao, Yan, Song, Yang & Yang (2013) have interestingly obtained an accuracy of 88.67% with a cohen's kappa coeffitient of $\kappa = 0.7393$ while trying to classify three states, i.e., wake, REM, and NREM, using a combination of 41 features including time and frequency domain, and geometric features. Time and frequency domain feature extraction methods for sleep studies are briefly discussed in this chapter.

Frequency domain methods: consist of counting and assigning the number of N-N intervals that belong to the specific pre-defined frequency ranges.

There exist several methods in the literature that serve in extracting these parameters, such as the classical PSD estimation (also called power spectral estimation), Lomb-Scargle periodigram

and wavelet entropy measures (İşler & Kuntalp, 2007). Among them, fast fourrier transform based methods which include parametric and non-parametric methods are the most widespread.

- **Non-parametric methods** consist of finding a reliable estimate of the PSD by performing some operations such as smoothing and averaging, applied directly on the autocorrelation function of the signal or its periodigram. No prior information or assumption is made on how the data is produced. Classic methods include The Barlett (Bartlett, 1948), The Welch (Welch, 1967) and The Blackman and Turkey method (Blackman & Tukey, 1958). Being data-driven techniques, non parametric methods offer advantages such as algorithm simplicity and computation speed but require a high amount of data to obtain a consistent HRV analysis.

- **Parametric methods** frequency domain parametric methods consist in modeling the data as an output of a linear system that is driven by white noise. Hence, the estimation problem becomes estimating the model parameters. The most widespread method consists of modeling the data using an autoregressive (AR) model. Several approaches have been proposed to estimate the AR model parameters such as Yule-Walker, Burg, foward-backward least squares, and maximum likelihood estimators (Percival & Walden, 1993). Alternatives to the AR model include maximum entropy spectral estimation, moving average (MA) and AR MA estimators (Akaike, 1969; Bingham, Godfrey & Tukey, 1967). In special cases, e.g., the signal is relatively short, parametric methods could yield higher resolutions, leading to smoother spectral components. One limitation of these methods is validating the suitability of the chosen model and model complexity (e.g., order).

Time domain methods it is noteworthy that a time-varying form of AR models has also been used in time-domain methods (Bianchi, Mainardi, Meloni, Chierchiu & Cerutti, 1997). Unlike frequency domain methods, time domain methods for analyzing cardiac variability consist of calculating statisfical parameters from the ECG signal over time, hence no signal transformation to frequency domain is required. Although less used than frequency domain methods in general sleep stage identification purposes, time domain methods have been used for specific applications where the amplitude of physiological changes are more ample than those occurring between sleep stages, such as sleep-related breathing disorders. For instance, the authors in (Roche,

Gaspoz, Minini, Pichot, Duverney, Costes, Lacour, Barthélémy et al., 1999) used time domain methods to feed a classifier in order to identify OSAS patients. Computed parameters in time domain methods include SDNN, mean of the standard deviations of all N-N intervals for the consecutive 5-minutes segments (SDNN index), square root of the mean of the sum of the squares of differences between consecutive RR intervals, SD of the averages of N-N intervals in all 5-minute segments, and standard error of N-N intervals.

CHAPTER 2

ARTIFICIAL NEURAL NETWORK FOR IN-BED POSTURE CLASSIFICATION USING BED-SHEET PRESSURE SENSORS

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2.1 Abstract

Pressure ulcer prevention is a vital procedure for patients undergoing long-term hospitalization. A human body lying posture (HBLP) monitoring system is essential to reschedule posture change for patients. Video-surveillance, the conventional method of HBLP monitoring, suffers from various limitations, such as subject's privacy, and field-of-view obstruction. We propose an autonomous method for classifying the four state-of-art HBLPs in healthy adults subjects: supine, prone, left and right lateral, with no sensors or cables attached on the body and no constraints imposed on the subject. Experiments have been conducted on 12 healthy adults (age 27.35 ± 5.39 years) using a collection of textile pressure sensors embedded in a cover placed under the bed-sheet. Histogram of oriented gradients (HoGs) and local binary patterns (LBPs) were extracted and fed to a supervised ANN classification model. The model was trained based on the scaled conjugate gradient back-propagation. A nested cross-validation with an exhaustive outer validation-loop was performed to validate the classification's generalization performance. A high testing prediction accuracy of 97.9% with a Cohen's Kappa coefficient of 97.2% have been interestingly obtained. Prone and supine postures were successfully separated in the classification, in contrast to the majority of previous similar works. We found that using the information of body weight distribution along with the shape and edges contributes to a better classification performance, and the ability to separate supine and prone postures. The results are

satisfactorily promising towards unobtrusively monitoring posture for ulcer prevention. The method can be used in sleep studies, post-surgical procedures or applications requiring HBLP identification.

2.2 Introduction

Bed pressure ulcers, also known as bedsores or decubitus ulcers are a serious health disease caused by remaining long period of time in the same posture. This results in a partial or complete soft tissue's blood flow obstruction, leading to damage in the skin and/or underlying tissue. Every year, more than 2.5 million people develop bed pressure ulcers in the United States, and more than 10% of nursing home residents suffer from bed ulcers (Soban, Hempel, Munjas, Miles & Rubenstein, 2011). In European and Canadian hospitals, the percentage of hospitalized patients developing bed ulcers range from 8% to 23% and 26%, respectively. Bed pressure ulcers are a risk factor for death. For instance, there were 30000 documented deaths globally in 2013 because of pressure ulcers (McInnes, Jammali-Blasi, Bell-Syer, Dumville & Cullum, 2011; Ostadabbas, Yousefi, Nourani, Faezipour, Tamil & Pompeo, 2012). A general prevention procedure consists of three main steps: 1) monitoring the patient and acquiring body posture data (using hardware like cameras or infrared) and/or on-mattress body pressure map, 2) analyzing the acquired data and taking a decision to act, and 3) changing the body's posture or redistributing the pressure over different body regions. Figure 2.1 shows a diagram of the prevention procedure using a pressure sensor mattress. Thus one of the essential measures in pressure ulcer prevention is a frequent redistribution of the body pressure on the mattress.

This procedure is usually done by means of manual intervention of caregivers that keen to change subjects HBLP continuously. For instance, continuously keeping track of the body posture for a group of patients in an intensive care unit becomes a laborious task. For optimally using hospital human resources, automatic systems are employed in units where pressure bed ulcers are likely to occur. These systems use a HBLP identification hardware and software, along with data log to save a record of the subjects HBLP history.

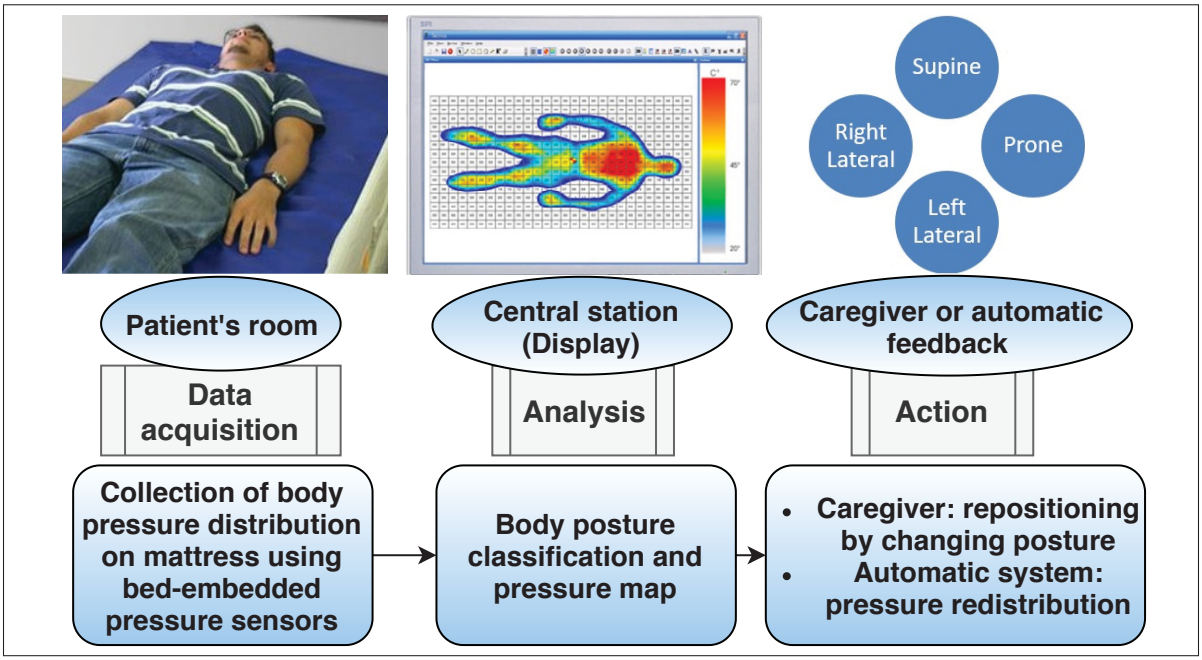

Figure 2.1 A three steps general work-flow diagram showing bed pressure ulcer prevention using a pressure sensor mattress: from data acquisition to analysis and action

HBLP has been one of the essential physiological behaviors to monitor during and after medical procedures both in clinic and domicile. Researchers have been trying to identify HBLPs by proposing several data acquisition hardware and processing algorithms. We presented in a previous work an exhaustive review of these methods in the context of unobtrusive sleep monitoring (Matar *et al.*, 2018). Among them, the most widespread systems are based on camera and near-infrared sensors or inertial sensors such as accelerometers, magnetometers, wireless devices and gyroscopes (Chang, Yu, Luo, Duan, Tu, Zhao, Nagraj, Rajiv, Priebe, Wood & Stachura, 2018; Liao & Yang, 2008; Nakajima, Matsumoto & Tamura, 2000). For instance, Nuksawn, Nantajeewarawat & Thiemjarus (2015) have proposed a posture detection method using a tri-axial accelerometer worn by the subject in the chest region. 4 HBLPs along with 3 more postures, i.e., standing, sitting and walking, have been identified with an overall detection accuracy of 85.68%.

Various methods based on pressure distribution data have been proposed. Yousefi, Ostadabbas, Faezipour, Farshbaf, Nourani, Tamil & Pompeo (2011) have proposed a HBLP identification method using a PCA based algorithm. They obtained an overall classification accuracy of 80%. Huang, Wai, Foo, Biswas, Hsia & Liou (2010) have used both camera and Force Sensitive Resistor (FSR) based pressure sensing in order to prove the high performance improvement in accuracy detection when compared with standalone systems such as an FSR pressure mattress or camera.

Several methods proposed have ignored classifiying separately supine and prone postures. Hsia et. al have proposed a method for HBLP detection using FSR made pressure sensor arrays (Hsia, Hung, Chiu & Kang, 2008). Having only the dorsal region covered by sensors, they were able to separate between three classes, i.e., supine, left and right. In addition to posture identification, two or three positions of the hands with respect to the body were identified. An average accuracy of 81.3% was obtained for the three postures classification. The feature vector chosen, i.e., images kurtosis and skeweness, is sensitive to rotation and body angle, which explains the relatively low classification accuracy obtained. Ostadabbas, Pouyan, Nourani & Kehtarnavaz (2014); Pouyan, Birjandtalab, Heydarzadeh, Nourani & Ostadabbas (2017) have similarly proposed a method for identifying 3 HBLPs while ignoring the prone posture. Matar *et al.* (2016) have proposed a posture detection methodology using the body pressure distribution on mattress based on binary images. Only three postures have been identified: left, right, and one class for supine and prone postures together. Although the good performance of the algorithm with a Cohen's Kappa coefficient of 86.6%, supine and prone postures have not been identified separately due to two main factors: the strong shape similarity between both postures and the missing weight distribution information as the images were binary and do not contain the pressure values.

For instance, a challenge has been facing researchers in automatic classification of HBLP: the compromise between accuracy and the number of classes to be identified. A relatively lower accuracy has accompanied 4 classes classification, i.e., where prone posture is classified separately than supine, while a better one has been obtained in 3 classes ones, i.e., posture and prone postures are considered as one class.

To tackle this challenge, we conduct a preliminary experiment in healthy adult subjects to propose a novel approach for identifying the 4 most common HBLPs used for ulcer prevention procedures: supine, prone, left and right lateral, using unobtrusive data acquisition protocol, i.e., body pressure distribution. It consists of a combination of features that we extract, i.e., HoGs and LBPs from data in order to perform the classification learning. We demonstrate throughout the paper the impact of this extraction on the classification performance. We show that our method is able to preserve a high accuracy and generalization performance in the 4 classes classification, prone posture included, which gives a consistent resolution to the compromise that has been faced in this task in the literature. An exhaustive comparative table is presented at the end of the paper, stating the state-of-the-art works in the literature in order to compare results and show our contribution.

At the hardware level, a bed-sheet containing textile-made pressure sensors is placed under the subject's bed-sheet. The sensor type is chosen to prevent any discomfort with the subject, with highly elastic sensors that have no direct contact with the body. At the software level, a data pre-processing scheme has been carried out in order to feed a neural network based machine learning algorithm. An extensive validation procedure is presented in order to validate the choice of hyper-parameters and model's data independence with regards to prediction accuracy.

Other key sub-contributions can be summarized as follows:

- **Discriminative features**: we propose a novel combination of extracted features (HoG+LBP) associated with pressure images posture shapes and body weight distribution that could help identifying 4 HBLPs in healthy adults without any direct contact with the body, while preserving high classification accuracy and generalization performance.
- **Model consistency**: we perform a nested cross-validation with an exhaustive outer loop to validate model's performance on a high number of data sets in order to demonstrate the model's consistent generalization performance.

- **Number of classes**: we extract the 4 most common classes of HBLPs, while being able to separate prone and supine postures, which could be a crucial step in clinical ulcer prevention frameworks.

The subsequent sections are structured as follows: section 2.3 describes the methodology including data acquisition, pre-processing and feature extraction, the learning model and validation procedure. Section 2.4 presents the conducted experimentation and the obtained results. A discussion of the results and an exhaustive comparison to the state-of-the-art works that are based on pressure distribution data to identify postures are presented in section 2.5. In section 2.6, concluding remarks, future perspectives and open related research areas are highlighted.

2.3 Materials and methods

This section presents all the methodology stages from hardware used and data acquisition to software and classification's output.

2.3.1 System

The hardware used for data acquisition is a pressure sensor mattress manufactured by Sensor Products® (Sensor Products). It consists of a 2.5 mm thick bed-sheet containing a matrix of 64×27 textile made piezo-resistive pressure sensors placed under the bed-sheet of the subject, i.e., no direct contact with the body. The measurable pressure ranges between 0 and 2 PSI. Each sensor has a size of 25.4×25.4 mm covering a total sensing area of 1854×762mm out of 1950×863 mm of the total area of the bed-sheet. The sampling frequency could reach up to 35 Hz. The data processing was performed using Matlab software on a data processing machine with a CPU of 3.4 GHz. The connection between the bed-sheet and the computer station is done through a Wi-Fi unit for wireless connection.

Table 2.1 Database structure table: number of frames for each posture, and the average number of frames per subject per posture

Supine	**Prone**	**Right**	**Left**
Number of frames per posture			
296	279	255	286
Average number of frames per subject for each posture: Mean (± Standard deviation)			
≈ 24.67 (±7.19)	≈ 23.25 (±1.42)	≈ 21.25 (±6.09)	≈ 23.83 (±3.80)

2.3.2 Data acquisition

A set of experiments has been conducted in order to collect the data required for learning, validating, and testing the model. The experimentation is ethic-compliant and has been accredited a certificate of ethics (Number: H20170503) by the research ethics committee at the *École de technologie supérieure* university. The experiment consisted of collecting pressure images of the body of each subject lying in each of the 4 postures: supine, prone, right and left lateral.

A total of 12 adult healthy subjects (10 males and 2 females, mean age 27.35 ± 5.39 years) have participated in the experiments. To make sure that the model performance generalizes to different body types, the selected participants had a large variance of weights and heights i.e., inter-subject variations for weight and height were between 110 and 286 lbs, and 5 feet 1 inch and 6 feet 1 inch respectively. It is noteworthy that the gender unbalance present in the data has no effect on the experiment or the model to be built, knowing that men and women have the same body shape and body pressure distribution on mattress except differences that are slightly detectable in the prone posture exclusively. Since the subjects are healthy adults, the scope of this paper can be limited to healthy young subjects. A set of specific instructions has been given to participants during the experiments in order to make sure that 1) inter-frame variance is preserved in the collected data, and 2) a maximum possible number of posture variants are collected. No single posture variant was collected twice for a specific subject. For

instance, several combinations of different angles with respect to the body, of the four limbs have been used at slightly different angles between users e.g., one of the prone posture variants was: left arm up (above shoulder), right arm down (close to hip), left leg folded, and right leg unfolded, or one of the left posture variants was curled up body, arms folded, and legs folded. In addition to limbs position combinations, different on-mattress body locations and orientations have been tried e.g., body on the extreme left of the mattress, and body's angle is 70 degrees instead of 90 with respect to the horizontal axis of the mattress. On average, for each of the four postures for each subject, around 23 different frame variants have been collected to enhance the generalization performance of the classifier by recognizing the more possible variants of each of the 4 postures. Labels for classes were assigned as follows: 1,2,3 and 4 for supine, prone, right and left lateral, respectively. After acquisition, a frames selection procedure has been then adopted to avoid taking a duplicate pressure frame of the same posture of a specific subject.

Hence the database consisted of a total number of $N = 1116$ collected frames divided per posture and per subject as shown in Table 2.1. As shown in equation (2.1), for each subject $Z = 1, 2, ..., 12$, for each image $\mathbf{\Phi_Z^{(i)}}$, $i = 1, 2, ..., N$, the $\mathbf{m} \times \mathbf{n}$ matrix of pressure values was converted to a feature vector $\Phi_{Z_{11}}^{(i)} ... \Phi_{Z_{mn}}^{(i)}$ having a size of 1728, where m=64 and n=27, and where $\Phi_{Z_{jk}}^{(i)}$ represents the pixel value of the j^{th} row, k^{th} column of the i^{th} sample belonging to the subject Z in the database matrix.

$$\mathbf{\Phi} = \begin{bmatrix} \Phi_{Z_{11}}^{(1)} & \Phi_{Z_{12}}^{(1)} & \Phi_{Z_{13}}^{(1)} & \dots & \Phi_{Z_{mn}}^{(1)} \\ \Phi_{Z_{11}}^{(2)} & \Phi_{Z_{12}}^{(2)} & \Phi_{Z_{13}}^{(2)} & \dots & \Phi_{Z_{mn}}^{(2)} \\ & & \dots\dots\dots\dots & & \\ \Phi_{Z_{11}}^{(N)} & \Phi_{Z_{12}}^{(N)} & \Phi_{Z_{13}}^{(N)} & \dots & \Phi_{Z_{mn}}^{(N)} \end{bmatrix} \tag{2.1}$$

In order to be able to validate on new subejcts, the subscript Z is preserved to identify the group of samples belonging to one subject.

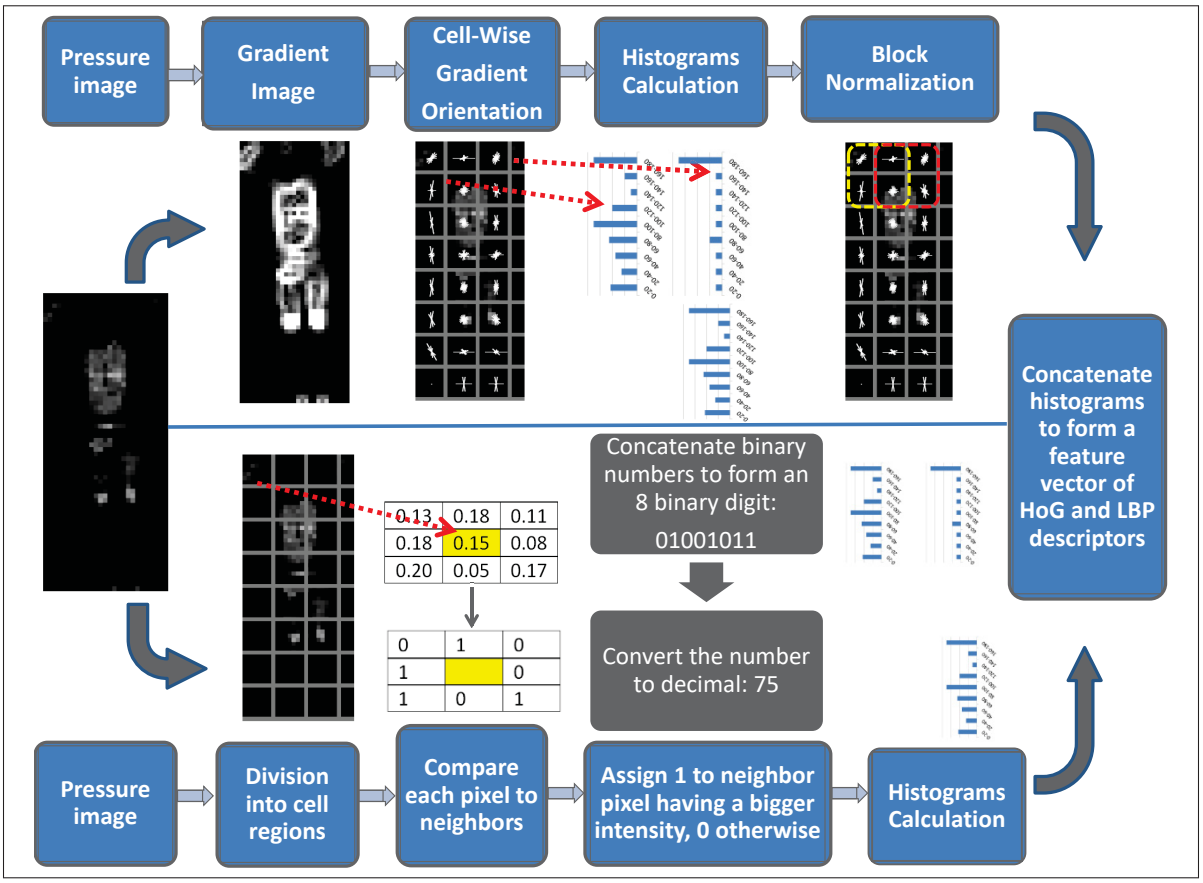

Figure 2.2 Feature extraction work-flow diagram showing HoG and LBP feature vectors extraction to decode shape and patterns information in the sample pressure images

2.3.3 Feature extraction

To extract a complementary information from the sample images in order to perform posture recognition, a set of features able to exhibit shape or edges, contrast and texture information has been computed following the diagram shown in Figure 2.2. Thus the feature extraction consisted of three main steps: computation of HoG and LBP descriptors followed by a principal component analysis (PCA) to project the data to a lower dimensional but more informative space by considering only the features having significant inter-sample variances in the analysis.

2.3.3.1 Histogram of oriented gradients

HoG features extraction aims at characterizing objects by quantifying the orientations of gradients in an image, which represent the edges directions. The approach behind HoG features has been first proposed by McConnell (1986) and became widespread in computer vision applications in 2005 when Dalal & Triggs (2005) published their work on pedestrian detection using HoG features. The results obtained have shown that this descriptor is very well adapted for this task. Given the data similarity and the objective behind both HBLP and original human shape detection, we decided to extract HoG feature descriptors from pressure images in order to identify HBLP. The HoG feature descriptor is calculated as follows:

For each image i, for each pixel (x,y), the intensity value $\Phi_Z^{(i)}(x, y)$ is used to:

- Calculate gradient:

$$\begin{aligned} G_{Z,x}^{(i)}(x, y) &= \Phi_{Z_{x+1,y}}^{(i)} - \Phi_{Z_{x-1,y}}^{(i)} \\ G_{Z,y}^{(i)}(x, y) &= \Phi_{Z_{x,y+1}}^{(i)} - \Phi_{Z_{x,y-1}}^{(i)} \end{aligned} \tag{2.2}$$

- Compute gradient's magnitude Mag and direction θ:

$$\begin{aligned} Mag_{Z_{x,y}}^{(i)} &= \sqrt{G_{Z,x}^{(i)}(x, y)^2 + G_{Z,y}^{(i)}(x, y)^2} \\ \theta_{Z_{x,y}}^{(i)} &= \arctan \frac{G_{Z,x}^{(i)}(x,y)}{G_{Z,y}^{(i)}(x,y)} \end{aligned} \tag{2.3}$$

A multi-scale approach is applied on the image in order to analyze shapes and patterns as follows:

1) Cells: the image is first divided into rectangular regions of pixels groups called cells. Each cell has a $\Lambda_{C_x} \times \Lambda_{C_y}$ pixels size.

Having $\theta \in [0, 180]$, the range θ is divided into υ gradient orientation bins as follows:

$\left[\frac{\upsilon \times 180}{\upsilon_{Total}}, \frac{(\upsilon+1)\times 180}{\upsilon_{Total}}\right]$, where $\upsilon = 0, ..., \upsilon_{Total} - 1$. A υ_{Total}-bins HoGs is then calculated by applying a cell-wise weighted voting, as follows:

$$h[\upsilon] \overset{h}{\leftarrow} [\upsilon] + Mag^{(i)}_{Z_{x,y}} . \left[1 - |\theta^{(i)}_{Z_{x,y}} - C_\upsilon| . \frac{\upsilon_{Total}}{180}\right]. \tag{2.4}$$

Where $h[\upsilon]$ denotes the histogram value for the bin range υ, and C_υ denotes the center of the bin υ. Hence for each pixel, the magnitude $Mag^{(i)}_{Z_{x,y}}$ of the gradient orientation $\theta^{(i)}_{Z_{x,y}}$ is divided into two values based on its contribution ratio to the two closest bins, which is defined by the distance between $\theta^{(i)}_{Z_{x,y}}$ and the centers of the bins.

This is done by adding the Mag value for each bin that contains the corresponding θ of the pixel intensity. This process of histogram calculation is then repeated for each cell of the image.

2) Blocks: then the image is divided into wider regions called blocks, where each block is a group of $[\Lambda_{B_x}, \Lambda_{B_y}]$ cells. Blocks are overlapped then normalized in order to ensure adequate contrast normalization and robustness to illumination changes:

$$h_{norm}(\upsilon) = \frac{h(\upsilon)}{\sqrt{||h(\upsilon)||_2^2 + \epsilon}} \tag{2.5}$$

where $||.||_2$ denotes the Euclidean norm operator and ϵ denotes a small constant added to avoid division by zero, i.e., $\epsilon = 10^{-5}$. The size of blocks overlapping, e.g., 2 cells horizontally and 1 cell vertically, determines both how much information would be captured from the image and the size of the feature vector. A larger overlapping leads to a greater geometrical resolution to detect edges and a larger feature vector.

The size of the HoG feature vector can be calculated as follows: $\eta_{HoG} = \zeta \times \upsilon \times \gamma$, where ζ, υ and γ are the block size, i.e., the number of cells per block, the number of calculated orientation gradients and the number of blocks per image, respectively. γ can be calculated as follows:

$$\gamma = \left\lfloor ((\Lambda_{I_{x,y}} \oslash \Lambda_{C_{x,y}}) \ominus \Lambda_{B_{x,y}}) \oslash (\Lambda_{B_{x,y}} \ominus \Lambda_{O_{x,y}}) + 1 \right\rfloor \tag{2.6}$$

where $\oslash$ and $\ominus$ denote element wise division and subtraction, respectively. $\Lambda_{X_{x,y}} = [\Lambda_{X_x}, \Lambda_{X_y}]$ denotes image ($X = I$), Cell ($X = C$), block ($X = B$) and overlapping ($X = O$) sizes in the x and y dimensions, respectively.

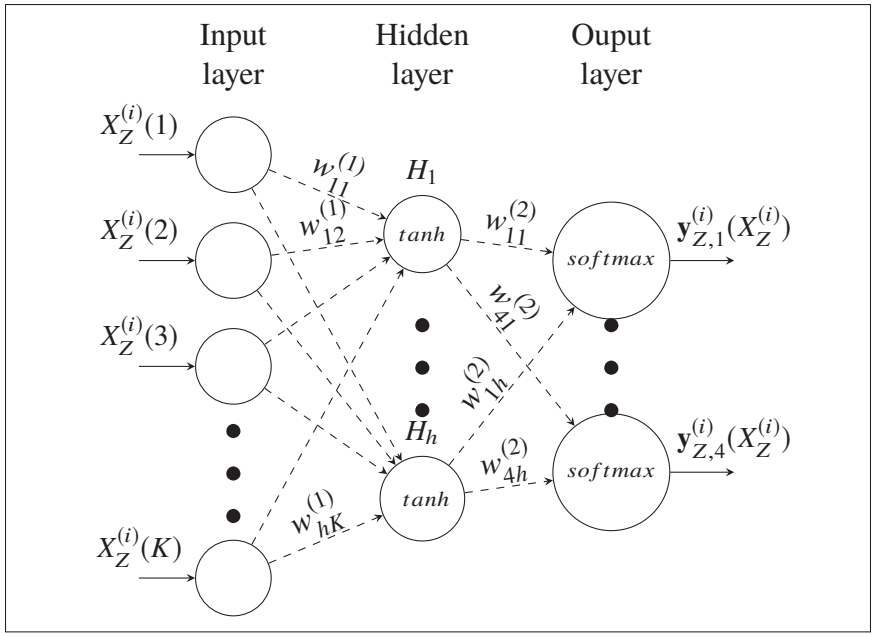

Figure 2.3 A diagram showing the FFANN architecture with weights, activation functions, and the input-output parameters and layers

2.3.3.2 Local Binary Patterns

LBP is a feature extraction method that aims at encoding local texture information in the image. The modern generic LBP has been first proposed in (Ojala, Pietikainen & Harwood, 1994). LBP feature descriptors have shown a robustness in image classification tasks. Moreover, combining LBP with HoG features has shown a particular improvement in the human shape detection efficiency (Wang, Han & Yan, 2009). LBP feature descriptors have been extracted from the pressure images as follows:

For each pressure image:

- Divide the image into Nc_{lbp} cells, where each cell contains $\Lambda'_{c_x} \times \Lambda'_{c_y}$ pixels

- For each cell:

  for each pixel, consider a neighborhood of a Λ'_N pixels inside a disc centered at the pixel v_p. Hence, compare the intensity value v_p to each one of its neighbor pixels $v_{(p+i)}$, where $i = 1$,..., Λ'_N. If $v_{(p+i)} \geq v_p$, then $v_{(p+i)} \leftarrow 1$, or $v_{(p+i)} \leftarrow 0$, otherwise.
- The resulting neighboring pixel values (0s and 1s) are concatenated in a binary number. This number is then converted to decimal.
- Each pixel in the neighborhood of v_p has an assigned decimal value, the process is repeated for all pixel neighborhoods in a cell.
- An histogram is then calculated for each cell. Histogram values are then concatenated to form the LBP feature vector of size η_{LBP}.

The size of each extracted HoG + LBP feature vector is equal to $M = \eta_{HoG} + \eta_{LBP}$. Let $\boldsymbol{\phi}$ be the $N \times M$ database matrix containing the concatenated HoG + LBP extracted features for each sample $\phi_Z^{(i)}$, $i = 1, ..., N = 1116$‘ respectively.

2.3.3.3 Principal Component Analysis

PCA is a feature selection technique that allows to keep the features having the most variance (Hotelling, 1933). PCA usage aims at reducing the dimensionality of data by making a set of possibly correlated variables, linearly uncorrelated. A high variance is preserved in the transformed data by applying a selection of features based on the associated variance.

The mean of each column of the matrix $\boldsymbol{\phi}$ is calculated, then subtracted from each one of the feature values, in order to center the data, let the centered database matrix be $\overline{\boldsymbol{\phi}}$. The reduced dimensions data matrix $\mathbf{X}$ is obtained by projection of the original data matrix $\overline{\boldsymbol{\phi}}$ as follows: $\mathbf{X} = \frac{1}{\sqrt{\mathbf{N-1}}}\overline{\boldsymbol{\phi}}^{\mathbf{T}} V = \mathbf{U}\Sigma$, where $\frac{1}{\sqrt{\mathbf{N-1}}}\overline{\boldsymbol{\phi}}^{\mathbf{T}} = U\Sigma V^T$, and X is a $N \times M$ matrix having the same dimensions of the original data matrix $\overline{\boldsymbol{\phi}}$. Hence, the columns of V are the principal components of $\overline{\boldsymbol{\phi}}$, and are arranged by descending order based on the corresponding elements of Σ, called eigen values. Let $X_Z^{(i)}(a)$ be the a^{th} element ($a = 1, ..., K$) of the i^{th} sample (row) that belongs

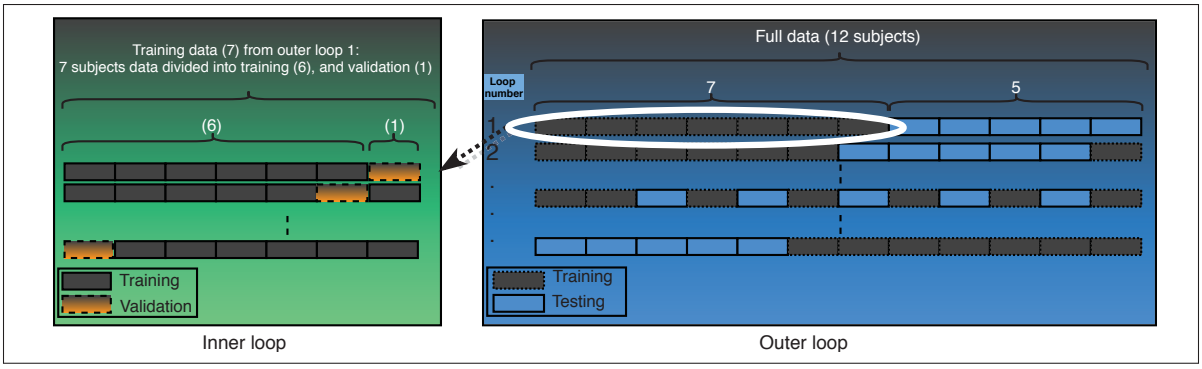

Figure 2.4 Nested validation scheme

to subject Z. Hence, $L = N \times K$ will be the dimension of the new space in which the data is projected, where K represents the number of selected eigenvalues and vectors to be taken into consideration. The PCA was applied on each training-testing data split according to the proposed nested cross-validation scheme.

2.3.4 Feed-Forward ANN (FFANN)

FFANN has been widely used in classification problems as it has several advantages: the ability to process a large number of inputs and infer complex and hidden non-linear relationships, and the ability to generalize its prediction performance on new unseen data. Moreover, FFANNs usage do not impose constraints on the data and does not require knowing beforehand the data probabilistic distribution. Instead, a parametric form of basis functions is used by fixing only the number of basis functions while allowing their parameter values to be adaptive in order to learn non-linear relationships from the data. Although FFANNs have a minor drawback, i.e., the likelihood function used in training is not a convex function of the model parameters making the training more time-consuming and complex, however, they result in compact models that are easy to evaluate during the prediction on new data, or the testing phase. Hence computational resources and time used in training (once) are often worth creating an easy-to-evaluate model during new predictions performance (Bishop, 2006).

2.3.4.1 Network Architecture

A set of several parameters define the network architecture. Figure 2.3 shows the network used in this paper. The input layer takes the K inputs $X_Z^{(i)}(1), ..., X_Z^{(i)}(K)$ of each sample, that are the features kept in the PCA procedure, the hidden layer has h hidden nodes $H_1, ..., H_h$, and the output layer has the four output classes $\mathbf{y}_{Z,1}^{(i)}(X_Z^{(i)})$, ..., $\mathbf{y}_{Z,4}^{(i)}(X_Z^{(i)})$ that represents the supine, prone, right and left HBLP, respectively. Network architecture plays a crucial role in defining the performance of the model and its approximation properties. Researchers have explored methods in order to define rules for optimal parameters selection (Bishop, 2006). The *universal approximation* is a well-known theorem in ANN's mathematical theory that states that an ANN with a single hidden layer having a finite sufficient number of nodes is a universal approximator among continuous functions of $\mathbb{R}^n$ (Csaji, 2001). As shown in Figure 2.3, a one hidden layer was used in this paper.

One of the common rules when determining the optimal number of hidden nodes states that this number usually lies between the number of input and output layers (Heaton, 2008). Accordingly, the optimal number of nodes in a hidden layer that gives the best performance in terms of minimal error classification is usually between the number of output classes, i.e., 4 in HBLP detection, and the number of inputs, i.e., K. A batch optimization technique has been adopted to determine the optimal h, setting the boundaries as follows: $4 \leq h \leq K$ for each data split through the nested cross-validation scheme.

The hyperbolic tangent transfer function, i.e., $H(a) = \frac{e^{(a)} - e^{(-a)}}{e^{(a)} + e^{(-a)}}$ and the normalized exponential transfer function, also called *softmax*, $\sigma_k = \frac{e^{a_k}}{\sum_j e^{a_j}}$, where a is a given input, and $k = 1, ...4$, is the output class, were used as activation functions for each of hidden and output layers nodes, respectively. Hence, the overall network function can be written as follows:

$$y_k = \sigma_k \left(\sum_{j=1}^{h} w_{kj}^{(2)} H \left(\sum_{l=1}^{K} w_{jl}^{(1)} X_Z^{(i)}(K) + w_{j0}^{(1)} \right) + w_{k0}^{(2)} \right) \tag{2.7}$$

2.3.4.2 Training and error back-propagation scheme

Basic FFANN training consists of adjusting the network weights in order to minimize the error function. The Cross-Entropy (CE) error function (eq. 2.8) was used in evaluating the model's performance, as faster training and improved generalization performance could be reached by minimizing the CE error function instead of the sum of error squares.

$$E(w) = -\sum_{i=1}^{K} (t_i \ln y_i + (1 - t_i) \ln (1 - y_i)) \tag{2.8}$$

where t_i, and y_i are the target value, and the predicted (Eq. 2.7) value for the sample $X_Z^{(i)}$, respectively. Moreover, the supervised learning algorithm based on the scaled conjugate gradient (SCG) was used in back-propagating the CE errors. SCG's performance has been benchmarked against state-of-art algorithms such as conjugate gradient backpropagation, and has yielded better results in terms of convergence, computation time and complexity (Møller, 1993). While considered as one of the conjugate gradient methods (CGMs), SCG differs from CGMs in two keypoints making it a faster and more accurate method: 1) to determine the stepsize during optimization procedure, instead of approximating the Hessian matrix at each iteration with a time-consuming line search procedure like in CGMs, SCG estimates the second derivative matrix $E''(w)$. 2) CGMs require the positive definiteness of the hessian matrix, which could prevent the algorithm reaching a good performance, while in SCG, a coefficient λ is added to the solution, and raised by a constant factor whenever the hessian matrix is not positive-definite following the Levenberg-Marquardt algorithm, a $\lambda = 1.e^{-5}$ was chosen in our algorithm (Fletcher, 2013).

2.3.5 Nested Cross-Validation

Model selection and evaluation is one of the most essential steps that make model predictions reliable and trustworthy. The nested validation consists of using two distinct sets, called validation set and test set, when selecting the model's optimal hyper-parameters and when evaluating the model performance respectively, avoiding optimistically biasing the model evaluation.

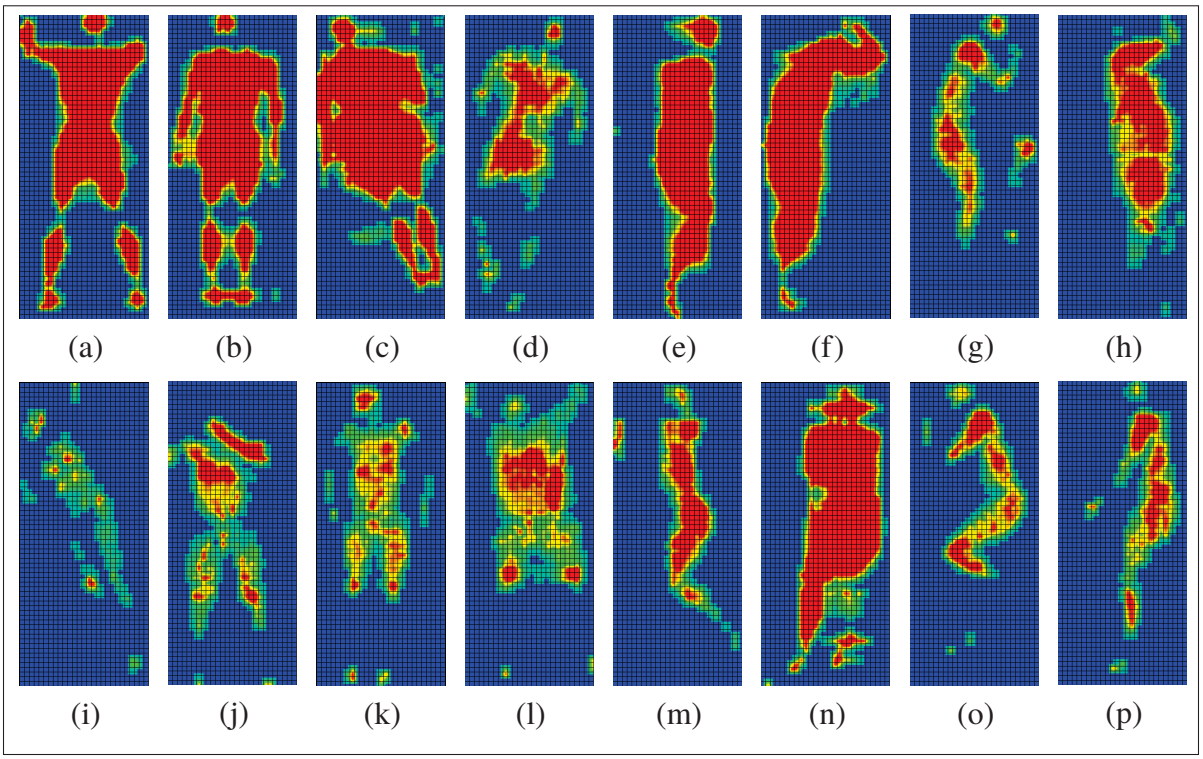

Figure 2.5 Body pressure distribution images of 4 postures:
supine (a) to (d), left (e) to (h), prone (i) to (l), and right (m) to (p)

By fitting a model to each training set in the inner loop, the prediction performance is approximately maximized, and directly maximized by selecting the optimal model hyper-parameters in the validation set. In the outer loop, several test splits are performed in order to test the generalization performance of the selected model and make sure that data-dependency is avoided. Figure 2.4 illustrates the nested validation scheme we adopted in this paper. In the outer loop, data frames belonging to the 4 postures of 7 subjects have been used for training, and the remaining part of the data for testing. In the inner loop, a Leave-Subject-Out cross-validation has been applied, in order to train the FFANN on 6 subjects data, and validate on 1, where all the 7 possible combinations of training-validation sets were tested by leaving at each time one subject data for validation.

Hence on average, i.e., while taking into account the slight imbalanced number of instances between classes, outer loop's data is divided as follows: $\frac{7}{12} \approx 58\%$ for training, and $\frac{5}{12} \approx 42\%$

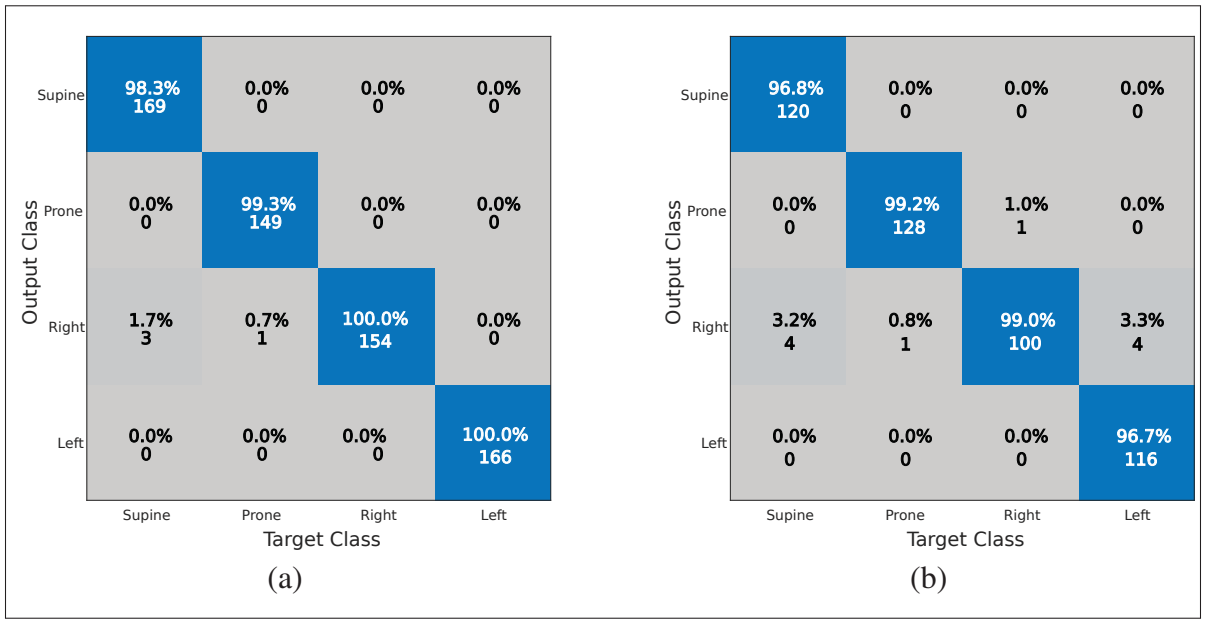

Figure 2.6 Training (a) and testing (b) confusion matrices of the selected classifier model, showing the classification accuracy and confusion for each of the 4 classes in terms of percentage (%) and number of samples

for testing, while the inner loop's data is divided as follows: $\frac{6}{7} \approx 86\%$ for training, and $\frac{1}{7} \approx 14\%$ for validation.

2.4 Experimental Results

Figure 3.2 shows 4 samples of pressure images acquired from different subjects laying in one of the four postures. Two important aspects regarding the data distribution can be noticed when comparing samples belonging to different classes. First, considering only the shape information, samples like (i) - (k) and (n) - (o) give a concrete example of the large intra-class variance, while (b) - (k) and (a) - (l) give an example of large inter-class similarity. Second, by considering only the weight information which is explicitly displayed by the pixels intensities and patterns, the intra-class variance can be appreciated by comparing (e) - (g) and (m) - (n), and an inter-class similarity by considering (c) - (n), and (p) - (g). Such variability in the data distribution makes

the classification a challenging task using only the shape information, specially when considering inter-class similarity and intra-class variance.

In section 2.3, the parameters that play an important role in the network performance have been specified and described e.g., the number of the network hidden layers and nodes, along with the adopted validation scheme. A batch optimization procedure has been performed in order to select the parameters involved in the feature selection step and in building the neural network model. Thus regarding the HoG feature extraction, the parameters selected were as follows: number of histogram bins $\upsilon_{Total} = 9$, number of pixels per cell $\Lambda_{C_{x,y}} = [8, 8]$, number of cells per block $\Lambda_{B_{x,y}} = [2, 2]$, number of cells overlapping between two consecutive blocks $\Lambda_{O_{x,y}} = [1, 1]$, giving a HoG feature vector size $\eta_{HoG} = 504$. It is noteworthy that the results of the optimization procedure were in accordance with the recommendations given by Dalal and Triggs regarding HoG parameters selection for human shape detection (Dalal & Triggs, 2005). As for the LBP feature extraction, the size of the neighboring circular window considered for each pixel, and the number of cells, lead to insignificant impact on the performance, but imposed an important change to the feature vector length. Accordingly, the smaller circular window size and cells number per image were selected i.e., the neighboring 8 pixel to the current one $\Lambda'_N = 8$, and 1 cell per image were selected $Nc_{lbp} = 1$ in order to capture information over larger regions. Hence the obtained LBP feature vector size is $\eta_{LBP} = 75$, and the overall feature vector size is $M = \eta_{HoG} + \eta_{LBP} = 579$. With a kept explained variance of he dimensionality reduction procedure with PCA has led to a notably smaller feature vector size $K = 46$.

Figure 2.6 shows the training (a) and testing (b) confusion matrices. As shown, a relatively high true positive scores were obtained in both training and testing steps, with a slight but acceptable decrease in performance between training and testing due to testing the model on data that has never been seen before, i.e., belonging to new subjects. An overall classification accuracy of 99.4 and 97.9% were obtained for training and testing, respectively. In order to assess the reliability of the results, the agreement by chance has been calculated and ignored through a

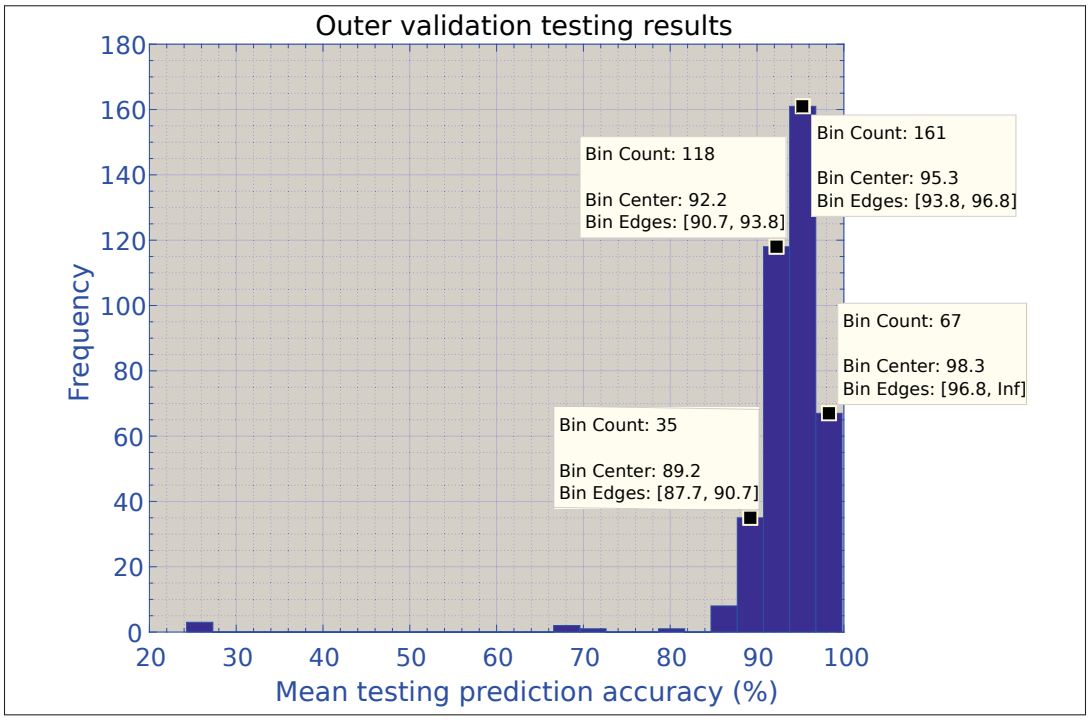

Figure 2.7 Histogram of mean testing prediction accuracy performed in the outer loop of the nested validation, showing the number of models that yield to corresponding classification accuracy

Cohen's kappa calculation. The obtained testing Cohen's Kappa coefficient was 97.2% which reflects the high intended agreement.

Figure 2.7 shows the histogram of average testing prediction accuracy (0-100%) over a total of 396 randomly selected models that were built in the outer validation loop of the carried out nested validation. As shown by the plot more than 86% of the models have given a prediction accuracy of more than 91% which shows 1) the effectiveness of the adopted feature selection procedure and the used learning criteria to build the classifier, and 2) the model's independence with respect to the data and the prevention of over-fitting the weights to a specific data-set.

2.5 Discussion

In this section, we compare the obtained results to previous works, and we discuss the proposed method.

Table 2.2 An exhaustive comparison of the proposed method to the state-of-the-art methods that use pressure sensor mattresses to classify body posture unobtrusively

Author name, year	Database	Pressure sensor type	Feature extraction	Classification method	Number of identified postures	Accuracy
Prone and supine postures not separated, but merged or prone posture excluded.						
Enokibori & Mase (2018).	n_T = 19, $\hat{m}$ = 42.89, n_F = 448	3200 uniformly distributed pressure sensor.	No feature extraction.	Deep neural networks.	3, prone excluded.	99.7%.
Heydarzadeh *et al.* (2016).	n_T = 10, $\hat{m} = n/a$, $n_F = n/a$	2048 uniformly distributed Force sensing array (FSA) sensors.	HoG features.	Deep neural networks.	3, prone excluded.	98.06%.
Yousefi *et al.* (2011).	n_T = 6, $\hat{m} = n/a$, $n_F = n/a$	2048 uniformly distributed Force sensing array (FSA) sensors.	Eigenspace projection of the pre-processsed pressure images.	K nearest neighborhood.	5, prone excluded.	97.7%.
Pouyan *et al.* (2013).	n_T = 20, $\hat{m} = n/a$, n_F = 160	2048 uniformly distributed FSA sensors.	Posture binary signature.	K nearest neighborhood.	8, prone excluded.	97.1%.
Huang *et al.* (2017).	$n_T = n/a$, $\hat{m} = n/a$, n_F = 360	6 modules containing a matrix of FSR sensors each.	Resistance values.	Template matching by minimum mean squared error.	3, prone excluded.	96.1%.
Metsis *et al.* (2011).	n_T = 3, $\hat{m} = n/a$, n_F = 1800	256 uniformly distributed FSA.	Pressure values and pressure images central moments.	Hidden Markov Model.	3.	90.40%.
Hsia *et al.* (2009).	n_T = 8, $\hat{m} = n/a$, $n_F = n/a$	2048 uniformly distributed FSA sensors.	Kurtosis and Skeweness of pressure distribution.	Support vector machines.	5, prone excluded.	83.5%.
Hsia *et al.* (2008).	n_T = 2, $\hat{m} = n/a$, $n_F = n/a$	16 FSR sensors distributed in the upper region.	Kurtosis and Skeweness of pressure distribution.	Bayes.	3.	78.7%.
Prone and supine postures are identified as two separate classes						
Enokibori & Mase (2018).	n_T = 19, $\hat{m}$ = 42.89, n_F = 448	3200 uniformly distributed pressure sensor.	No feature extraction.	Deep neural networks.	4.	97.1%.
Xu *et al.* (2015).	n_T = 14, $\hat{m} = n/a$, n_F = 1848	uniformly distributed FSR.	Vertical and horizontal projection of pressure distribution.	K nearest neighborhood.	6.	90.6%.
Liu *et al.* (2014).	n_T = 14, $\hat{m}$ = 27.78, n_F = 3360	8192 uniformly distributed FSR.	Spatial and body part features.	Minimum class residual classifier.	6.	83.02%.
Mineharu *et al.* (2015).	n_T = 10, $\hat{m}$ = 22.6, n_F = 270	1768 uniformly distributed pressure sensors.	Spatial features.	Support vector machines.	9.	77.14%.
Our method.	n_T = 12, $\hat{m}$ = 27.35, n_F = 1116	**1728 uniformly distributed FSR sensors.**	**HoG + LBP features.**	**FFANN.**	**4 most common postures, prone included.**	**97.9%.**

Table 2.2 presents an exhaustive comparison of the obtained results to the state-of-the-art works that claim to be unobtrusive and use the same acquisition hardware, i.e., pressure sensor mattress.

In order to unify the evaluation criterion, from each of the presented works, the classification accuracy value has been calculated using the usual formula $\frac{TP+TN}{TP+TN+FP+FN}$, where TP, TN, FP, and FN are the true positive, true negative, false positive, and false negative predictions, respectively. While evaluating the results of the proposed methods, it is important to take into consideration two criteria that reflect the compromise facing researchers:

1. Is the method able to identify at least the 4 common postures, i.e., prone, supine, left, and right lateral, i.e., identifying prone and supine postures separately? Given the body shape similarity on the mattress between supine and prone, the proposed methods have whether merged these two classes into one during the classification task, or discarded the prone posture as a class to be identified.

2. Is the obtained classification precision rate high enough to rely on? Although there is no consensus on a standard threshold value to determine whether a classification precision rate is reliable, when comparing classification methods, a straightforward rule can be adopted: the higher rate the better performance.

By looking at Table 2.2, one can understand the compromise researchers have been facing in this classification task. It is noteworthy that classifying prone and supine positions separately such as in (Liu *et al.*, 2014; Mineharu *et al.*, 2015; Xu *et al.*, 2015) has yielded relatively lower classification precision rates when compared to merging the two classes in one class, or excluding prone posture such as in (Hsia *et al.*, 2009,0; Huang *et al.*, 2017; Metsis *et al.*, 2011; Pouyan *et al.*, 2013; Yousefi *et al.*, 2011). The proposed method has been able to identify prone and supine positions separately, while yielding the highest classification precision rate (97.9%) when compared to previous works, despite the multilevel differences between each one of the compared methods, such as the number of sensors used in the acquisition, the feature selection and classification method.

It is noteworthy that the body tissues being exposed to long-term pressure and damage when the subject is lying on his back, are different to the ones when is lying in a prone posture, making the classification of prone and supine postures separately, i.e., as two different classes, a mandatory

step in pressure ulcer prevention schemes. On the other hand, almost the same body tissues are exposed to long-term pressure when the subject is lying in different variants of a specific one of the four postures considered in this paper, making the classification of these variants as separate classes, an inconsequential step in the prevention of pressure ulcers.

Since the proposed method has been developed using a relatively limited number of subjects, i.e., 12, the generalization performance could be reduced if the system was tested on a much larger database. Moreover, the system has not been tested under special conditions, such as on subjects who underwent limb amputations, or subjects lying in spurious positions that are not variants of the 4 proposed postures, e.g., an important part of the body or limbs are not covering the pressure sensor mattress.

For application in clinical settings, the proposed system could be used in a quasi-real time acquisition, in which data is continuously processed. For instance, x minutes blocks of pressure images data-streams are continuously fed to the classifier. x could be adapted depending on the application, based on the required monitoring time-resolution, and how critical the patient's situation is. History logs of the classified postures are then fed to a function that draws a four levels curve, a level for each posture in order to keep the patient's posture history. Patient's posture history can help health professionals keep track of the least posture adapted which helps in the decision taking process such as body repositioning to avoid the development of ulcers. An output alarm could be sent to the central workstation at each time the same posture is encountered for more than a threshold of a certain amount of time, that could be adapted depending on the application. The output trigger could be used in several uses, such as sending alarms or messages for the health professionals in order to allow remote monitoring.

Regarding employment costs, the proposed system could significantly improve care, reduce the required human resources, and make it easier to remotely monitor patients, with a relatively low cost solution. For instance, purchasing such a system include a computer workstation, a pressure sensor mattress, and a local connection.

Hence, with the right choice of posture classes, the adopted pre-processing, feature selection, classification learning, and the nested cross-validation, our method provides a solution to overcome the challenge of compromising accuracy and including prone posture in the classification task, giving a promising solution to make unobtrusive sleeping posture identification using bed pressure sensor mattress reliable.

2.6 Conclusion and future perspectives

Pressure bed ulcers have a serious impact on the patients, requiring a specialized care procedure that causes a burden on the health-care systems in terms of professional and material resources and costs. While the presented work does not offer a comprehensive solution to the problem, it presents a potential technique to make a fundamental step towards prevention, i.e., posture classification, automated and requiring less resources. And most importantly, making the data acquisition step less obtrusive for the patient on two levels, 1) acquiring physiological data without causing discomfort or imposing constraints on the patient, and 2) preserving patient's privacy by substituting cameras with textile pressure sensors embedded in the bed-sheet. The easy-to evaluate classifier is able to identify 4 different HBLPs with a high predictive accuracy and a validated generalization performance.

Ulcer prevention has barely advanced over the past decades and the techniques adopted in the majority of clinical and residential units are still insufficient. Therefore the field has open issues and needs more research efforts. Future works will aim for acting according to diagnosis. Hence using the proposed method, feeding a central monitoring station with the classification results or an automated feedback system with body pressure mapping, and consequently changing posture or redistributing pressure, respectively.

Moreover, the proposed methodology has a potential use in several other medical fields that requires in-bed posture identification such as non or partial anesthetic surgical procedures, orthopaedic applications, and medical imaging techniques.

CHAPTER 3

KALMAN FILTERING FOR POSTURE-ADAPTIVE IN-BED BREATHING RATE MONITORING USING BED-SHEET PRESSURE SENSORS

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3.1 Abstract

BR is one of the vital signs used in physiological monitoring. Conventional methods to calculate BR consist in attaching wired canula/thermistor on the buco-nasal area to measure air-flow, which induces mild to severe subject discomfort to the subject. Abdominal/thoracic belts are also used to detect breathing movements whereas esophageal pressure is the gold standard to measure breathing effort. In this paper, we validate the consistency of BR monitoring in healthy adult subjects using bed-sheet pressure sensors. We demonstrate throughout the paper that this approach could be used interchangeably with respiratory belts which have been approved for medical use by the AASM, providing a more convenient solution for both subjects and health professionals. In this vein, we reconstruct the breathing movements signal then compute the BR over 30 seconds time windows. A ten-sinusoidal model-based extended Kalman Filter was used to adaptively estimate the breathing movements signal from the body pressure distribution data. The model is posture-specific, i.e., the model's parameters are optimized based on the detected posture. An ANN model was used to detect four bed postures to perform the optimization step accordingly. Recordings were conducted on 12 healthy adults (mean age $\approx 27 \pm 5$ years) to acquire data with the pressure mattress and a conventional respiratory belt placed on the abdomen region, used as a reference. To validate the proposed method as a surrogate measure, a BA analysis has been performed on both pressure sensor and respiratory belt data, and the linear

relationship has been evaluated using Pearson Correlation Coefficient (PCC). A high inter-rater agreement rate, with an average maximum of 1.93 BrPM of difference, and a confidence interval of 95%, along with a strong linear relationship of 95.8% on average between the two methods have been interestingly obtained. With such results for measuring BRs for the different postures, we show and discuss the consistency of the proposed method and the potential usage in medical applications requiring respiration monitoring.

3.2 Introduction

BR is one of the physiological vital signs to measure during patient monitoring in clinical applications. Medical technologies have been proposed to monitor breathing such as belts, cannulas, and thermistors (AL-Khalidi, Saatchi, Burke, Elphick & Tan, 2011b). For instance, end-tidal carbon dioxide levels are measured with capnometry, which is used for both detecting BR and hypoventilation. Depending on the application, these methods suffer from cumbersome sensors and apparatus that constraint the monitoring, the subject's comfort, and the professional's operation (Folke, Cernerud, Ekström & Hök, 2003). Alternatives to the conventional measures have been proposed in order to make the process of breathing monitoring less obtrusive. For instance, the measuring device should satisfy certain criteria such as 1) allowing the unprovoked and natural behavior of the subject, like body and limb movements and tosses, 2) requiring less direct contact with the body, and 3) reducing the number of sensors and cables worn by the subject (Folke *et al.*, 2003; Matar *et al.*, 2018). The monitoring of alternative physiological behaviors such as the volume of the abdomen to infer breathing movements in lying positions, adds new types of noises to the acquired signals during unobtrusive respiration monitoring, such as the impact of the posture on the abdominal volume magnitude. A large spectrum of non-invasive methods of breathing monitoring can be found in the literature (Folke *et al.*, 2003). Current techniques include respiratory belts, cameras, accelerometers, and infra-red sensors (Matar *et al.*, 2018; Ranta, Aittokoski, Tenhunen & Alasaukko-oja, 2019). The acquisition methods, technologies and processing algorithms employed to monitor breathing are briefly reviewed in this section.

1. Airflow sensing-based: devices that quantify airflow by measuring temperature, humidity, acoustic and carbon dioxide through the bucco-nasal area.

2. Volume, movement, and tissue composition sensing-based: devices that quantify volume or volume change mechanically or optically such as strain gauge transducers, mutual inductance, magnetometers, and sensors in a mattress, cameras, wireless and radar devices and all types of plethysmographs, e.g., transthoracic impedance, inductance, and fiber-optic plethysmography.

3. Blood gas sensing-based: devices that measure the gas composition of the blood, they include: pulse oximetry and end-tidal carbon dioxide measurement.

Respiratory inductance plethysmographs (RIP) have been proposed, implemented and clinically validated by researchers as a surrogate measurement method of the exchanged air volume to monitor inhalation and exhalation phases (Fiamma, Samara, Baconnier, Similowski & Straus, 2007). During RIP, the breathing induced volume change in the abdominal region is measured. Similar acquisition approaches for the same target measure have been proposed in the literature (AL-Khalidi *et al.*, 2011b). In the same line of research, several methods have been proposed to track respiration activity using bed sheet embedded pressure sensors. Bed pressure sensors have been proven to be able to track several physiological behaviors such as respiration, activity level and body movements (Azimi, Gilakjani, Bouchard, Bennett, Goubran & Knoefel, 2017; Gilakjani, Azimi, Bouchard, Goubran & Knoefel, 2018; Harada, Sakata, Mori & Sato, 2000; Jones, Goubran & Knoefel, 2006; Liu, Huang, Xu, Zhang, Stevens, Alshurafa & Sarrafzadeh, 2015; Samy, Huang, Liu, Xu & Sarrafzadeh, 2014). However, the existing methods have still not yet successfully produced a reliable BR estimation for the four different bed postures due to the following challenges and shortcomings:

- **Improper selection of sensors**: that lack adaptability to the subject's behavior, or are sensitive to body movements. These methods consist of selecting all sensors on the mattress and then summing pressure values to reconstruct the respiratory signal (Samy *et al.*, 2014),

or choosing a pre-defined and fixed area on the mattress (geometrical methods), on which the abdominal region or the head is more likely to be (Harada *et al.*, 2000).

- **Lack of validation**: researchers have been validating their proposed methods using the PCC to assess the relationship with a reference method such as belt measures (Azimi *et al.*, 2017) , or by self validating using auto-correlation without using any reference method (Jones *et al.*, 2006). Although the information that linear relationship to the reference method is bound to give, no insights on the precision, or distance to truth can be given using this metric. Another concern regarding validation, is that researchers have been only considering true positive respiratory counts detection and ignoring false negatives, which is likely to give optimistic results that do not reflect the practical percentage of true detections, which leads to under- or over-estimating the counts, giving a less reliable BR (Harada *et al.*, 2000).

- **Posture limitations**: researchers have whether ignored the posture effect on the respiratory-induced abdominal volume changes or restricted the posture changes during the data acquisition phase of their experiments (Azimi *et al.*, 2017; Gilakjani *et al.*, 2018). It is known that the relationship between the measured quantity, e.g., pressure distribution, and the breathing effort signal represented by the thoracic volume change is subject to different types of added noises and variations depending on factors such as the body posture on the mattress, the regions of the body whos movements represent the most the respiration, and added limb and body movements that interfere with the respiratory induced pressure-volume changes. Moreover, researchers have limited the possibility of subjects to change postures during experiments or have totally ignored the notion of posture, which influences the ability to have posture-specific, and adaptive results with regards to BR computations (Azimi *et al.*, 2017; Gilakjani *et al.*, 2018).

We mitigate each of the aforementioned challenges by proposing solutions in the processing steps throughout our method. The objective of this paper is to validate the consistency of BR monitoring in healthy adult subjects using bed-sheet pressure sensors. We aim as well to demonstrate using the Bland Altman (BA) plotting technique, that the proposed method could be used interchangeably with respiratory belts which have been approved for medical use by the

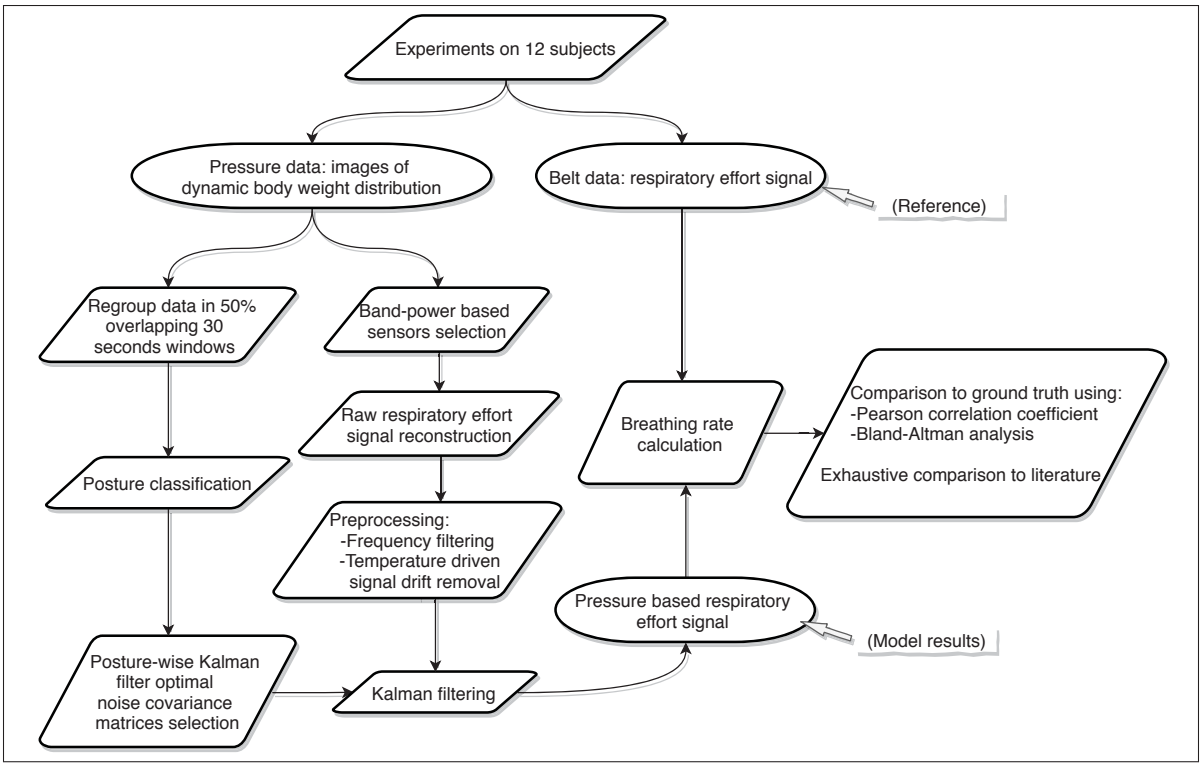

Figure 3.1 Work-flow diagram of bed pressure ulcer prevention using a pressure sensor mattress

AASM, providing a more convenient breathing monitoring solution for both subjects and health professionals. The main contribution of this work is to propose and evaluate a posture-adaptive approach to unobtrusively monitoring of BRs using a high spatial and temporal sampling of the body pressure during sleep. This elastic textile pressure sensors is placed under the individual's bed-sheet and a signal processing will allow to monitor the respiration without constraining the subjects's movement, without any direct contact or sensor on the body.

The whole contribution can be summarized as follows:

- Adaptively select pressure sensors corresponding to body regions involved in respiratory induced pressure changes and movements.

- Adaptively isolate and remove noises added by the subject's body and limb movements to avoid interference with the breathing signal.

- Estimate and reconstruct the breathing movements signal using pressure data with a multi-sinusoidal model based extended Kalman filtering.
- Adaptively select Kalman filter error and measurement noises depending on the posture of the subject on the bed.
- Adaptively derive BR over 30 seconds time windows using the reconstructed signal's spectrum analysis.
- Validating both deviation and correlation with respect to the reference method.

Section 3.2 gives a brief introduction and review of unobtrusive breathing monitoring literature, along with the contribution and objective of this paper. We develop the methodology adopted to build the BR prediction model and test it in section 3.3. We show and discuss the obtained experimental results in section 3.4. In section 3.5, a conclusive observation based on the obtained results is given, and future perspectives and open research areas are highlighted.

3.3 Methodology

The work-flow diagram presented in figure 3.1 shows the methodology we used in general steps. Experiments were conducted on 12 healthy adults subjects to generate the pressure and belt data. Using the pressure data, pixels corresponding to the sensors involved in sensing the breathing activity were adaptively selected to reconstruct the raw breathing movements signal. Signal drift was removed, and frequency filtering was applied to remove unwanted frequencies. An ANN posture classifier was then used to detect posture, in order to adaptively select the Kalman filter parameters based on the detected posture. BRs were then calculated from both kalman filtered pressure sensor signal, and belt signal. The present section details hardware specifications, and the steps adopted to acquire, pre-process, and analyze the data along with how the prediction model was built and its parameters were initialized.

3.3.1 System hardware

A pressure sensor mattress and a respiratory belt have been used simultaneously for data acquisition. The pressure sensor mattress used is Tactilus® made by Sensor Products Inc (Sensor Products). It consists of a rectangular bed-sheet containing a 2-dimensional matrix of 64 × 27 textile made piezoresistive pressure sensors covering a total area of 1.95 x 0.863 m. The mattress has a sampling frequency of up to 35 Hz and is connected to the workstation with a USB cable or a Wi-Fi module for a wireless connection.

Several types of sensors, including piezo-electric, inductive, and capacitive, have been used in the literature to monitor volume changes in such medical applications (Gal, 2011; Hoskuldsson & Gudmundsson, 2015). The respiratory belt used our experiment is TN1132/ST made by AD instruments (AD Instruments, 2019). It consists of an textile made belt that contains a capacitive sensing element. The output voltage of the system is linearly proportional to changes in the length of the sensing element. During inhalation, the abdominal volume increases leading to an increase of the belt placed around this area, followed by a decrease in abdominal volume and belt length during exhalation, leading to an increase in voltage proportional to the volume change during inhalation and a decrease during exhalation. The belt sensor TN1132/ST has been used and validated in research as a consistent measurement technique of the breathing movements signal, and further has been used to calculate more specific parameters such as the exchanged breathing volume (AD Instruments, 2019; Chalaye, Goffaux, Lafrenaye & Marchand, 2009). Its built-in signal pre-processing module and interface through the Lab-chart software, helps removing induced noises during the experiments, which improves accuracy of detection. The device is accessible, easy to deploy, and gives accurate measurements. The TN1132/ST is widely used in research with references in more than 152 peer reviewed scientific articles (AD Instruments, 2019).

3.3.2 Experimental protocol

The conducted set of experiments has been certified as ethics-compliant. 12 healthy adult subjects (2 females and ten males), mean age ≈ 27 ± 5 years, have participated in the experiments. Weight and height inter-subject variability were intentionally high, to preserve a generalization performance regarding body pressure images on the mattress. Hence, subjects' body weights and heights varied between 110 and 286 lbs, and 5 feet 1 inch and 6 feet 1 inch, respectively. Gender unbalance are generally of no effects on the data, knowing that men and women have similar body shape and weight distribution except for few variations slightly detectable in prone position (Matar, Lina & Kaddoum, 2019). Subjects were recorded in 4 different postures for 5 minutes each: dorsal, prone, left and right lateral. Before the experiments started, subjects were instructed to breathe normally during the acquisition, without trying to control the pace or depth of their breathing. Breathing activity was monitored with the belt and the pressure sensor mattress simultaneously.

During the experiments, the subjects were lying on the pressure sensor mattress covering the bed, while wearing the respiratory belt around the umbilical region of their body. To make sure that different variants of a specific posture were recorded, specific instructions were given to subjects regarding the body and limbs orientations on the mattress during the recording in a way that a high inter-subject variance is preserved for a specific posture, e.g., subject 1 lied on his right side with his body curled and legs folded, while subject 2 lied on his right side with his body and legs straight. An overall 12 variant of each of the 4 postures were recorded, combining different limb and body position and orientation on the mattress. The dynamic body pressure distribution on the mattress and the abdominal volume were acquired simultaneously with the two systems at a unified 11 Hz sampling frequency. The 11 Hz sampling frequency was chosen based on empirical trials, and the literature's recommendations (10-11 Hz). Lower sampling frequencies led to a poorer signal quality. The selected 11 Hz frequency we chose was in compliance with previous methods that used the same sampling frequency (Jones *et al.*, 2006).

3.3.3 Dataset

The belt's respiratory signal and the mattress's pressure distribution data were saved using AD instruments' PowerLab and the Tactilus software. For the pressure data, 3D matrix was created for each of the 12×4=48 recordings to save the pressure distribution data in a way that each matrix contained the 64×27 2D pressure images stacked along the third dimension of a length of 5×60×11=3300 frames. The respiratory signal data for each of the 48 recordings was saved in a 1x3300 1D array. Belt data was saved separately using a different 1D array containing the breathing movements signal for each of the 48 recordings.

3.3.4 Data pre-processing

Band-power computation: out of the 1728 pressure sensors embedded in the mattress, only some are involved in acquiring pressure information that is related to the abdominal volume change due to the breathing activity. We performed a frequency analysis in a pre-defined breathing frequency band to select pressure sensors that will be used to derive the breathing signal. The signal band power of each pressure sensor that has positive pressure values (i.e., is under the subject's body) is calculated on frequency band using the Welch power spectrum density (PSD) estimation in the [0.14-1] Hz range as recommended by an observational studies that included young adults (Garde, Karlen, Ansermino & Dumont, 2014). The Welch method has been widely used to estimate PSDs of non-stationary signals (Lin & Qu, 2000). Time-windows in which the band power frequencies are calculated have a 30 seconds length and a 50% overlap. For each 30-seconds window, a band power map was computed for the pixels that correspond to the sensors under the subject's body.

Sensors selection and signal computation: only the pressure sensors that have a band-power value lying in the 95^{th} percentile were selected when computing the raw signal. For instance, at each acquisition frame, the pixel values corresponding to the selected sensors were algebraically summed to form the signal. In the next paragraphs, we describe how the resulting signal is

pre-processed to improve its quality, then is fed to a Kalman filter to reconstruct the breathing signal.

Signal's logarithmic drift compensation: usually before the acquisition, the mattress surface is at room temperature. When the acquisition begins, an increase of the temperature occurs in the mattress region under the subject due to the body's temperature (Meyer, 2008). This temperature increase gradually occurs over a period of 5 to 10 minutes, according to several simulation trials we conducted before data collection. Such increase is more likely to occur at the beginning of the recording, and during posture changes or body movements that involve changing contact areas between the mattress and the body. The temperature increase in such situations is induced in a new area of the mattress, that is at room temperature initially, and becomes in contact with the body that is at a higher temperature. Such temperature change affects the pressure sensors' sensitivity to pressure, and a logarithmic drift is seen in the time-series output pressure values leading to a logarithmic drift in the computed raw signal (Meyer, 2008). A polynomial curve fitting method was adopted to eliminate this logarithmic drift before we calculate the sum of the individual signals selected by the band-power method (Mecozzi, 2014).

Frequency-based signal filtering: the obtained signal was then filtered using a third order Chebychev band pass filter with a bandwidth of [0.15-0.6]. The bandwidth was chosen to make all the respiratory activity frequency range detectable, based on a review of related research literature (Zhihao Chen,Doreen Lau, 2014). The bandpass filtering was performed to remove 1) the high-frequency components present in the signal due to the acquisition hardware noise, and 2) the constant bias or the lower frequencies induced by slow movements which do not correspond to breathing activities, or low frequency pressure variations caused by temperature variation such as blanket use.

3.3.5 Breathing movements signal prediction model

The motion-induced breathing movements signal $s(t)$ can be modeled as a multi-sinusoidal contribution (George, Vedam, Chung, Ramakrishnan & Keall, 2005; Lujan, Larsen, Balter & Ten Haken, 1999), thus:

$$s(t) = \sum_{i=1}^{N} A_i \sin(2\pi f_i t + \Phi_i) + b_1.t + b_0, \tag{3.1}$$

where $s(t)$ is the signal model of the abdominal volume change induced by respiration, N is the number of frequencies f_i; A_i and Φ_i are the corresponding amplitudes and phases of the sinusoidal components, respectively, and b_1 and b_0 are the linear and constant drifts, respectively.

The Kalman filter is governed by two equations:

1) The first describes the relationship l between $\mathbf{C}_k$ and $\mathbf{C}_{k-1}$ given a process noise $\mathbf{V}$ (Eq. (3.2)). $\mathbf{V}$ represents the error on the assumptions made when modelling the signal.

$$\mathbf{C_k} = l(\mathbf{C_{k-1}}, k) + \mathbf{V}_{k-1}, \tag{3.2}$$

where $\mathbf{C}_k$ is the sinusoidal components vector at instant k containing the states variables: amplitudes A_k, frequencies f_k, and phase shifts Φ_k of the sinusoids, and the coefficients $b_{0,k}$ and $b_{1,k}$ which represent the constant and linear drifts of the signal over time.

Ramrath, Schlaefer, Ernst, Dieterich & Schweikard (2007), random drift could describe the variation of the amplitudes and frequencies, but the phase shift could be modeled as a function of the last frequency state added to a random variation, and the linear drift c_1 varies randomly as the constant drift c_0 depends on the last c_1. Equation (3.3) shows the relationships between

these states in two consecutive instants.

$$
\begin{aligned}
(A_k)_i &= (A_{k-1})_i + (V_{k-1})_{3(i-1)+1} \\
(f_k)_i &= (f_{k-1})_i + (V_{k-1})_{3(i-1)+2} \\
(\Phi_k)_i &= (\Phi_{k-1})_i + 2\pi(f_{k-1})_i \Delta t + (V_{k-1})_{3i} \\
b_{0,k} &= b_{0,k-1} + b_{1,k-1}\Delta t + (V_{k-1})_{3N+1} \\
b_{1,k} &= b_{1,k-1} + (V_{k-1})_{3N+2}
\end{aligned}
\tag{3.3}
$$

Where Δt is the time difference between two consecutive measurements. For instance, the states transition between two consecutive instants can be expressed as:

$$
\underbrace{\begin{bmatrix} (A_k)_i \\ (f_k)_i \\ (\Phi_k)_i \\ b_{0,k} \\ b_{1,k} \end{bmatrix}}_{\mathbf{C}_k} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 2\pi\Delta t & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} (A_{k-1})_i \\ (f_{k-1})_i \\ (\Phi_{k-1})_i \\ b_{0,k-1} \\ b_{1,k-1} \end{bmatrix}}_{l(\mathbf{C}_{k-1},k)} + \underbrace{\begin{bmatrix} (V_{k-1})_{3(i-1)+1} \\ (V_{k-1})_{3(i-1)+2} \\ (V_{k-1})_{3i} \\ (V_{k-1})_{3N+1} \\ (V_{k-1})_{3N+2} \end{bmatrix}}_{\mathbf{V}_{k-1}}
\tag{3.4}
$$

Let the pre-processed respiratory signal extracted from the pressure sensor mattress be p. 2) Inspired by the respiratory signal model shown in Eq. (3.1), the second equation of the Kalman filter is the measurement equation, that describes the relationship between the states components C_k and the measurement p as follows:

$$
\mathbf{p}_k = \underbrace{\sum_{i=1}^{N} A_k^{(N)} \sin(2\pi f_k^{(N)} \Delta t + \Phi_k^{(N)}) + b_{1,k}\Delta t + b_{0,k}}_{d(\mathbf{C}_k,k)} + \omega_k,
\tag{3.5}
$$

where ω is the measurement noise that combines hardware and pre-processing induced noises, and $d(\mathbf{C}_k, k)$ is the measurement model, that maps the measurements to the model's state

variables. $\mathbf{V}_k$ and $\mathbf{w}_k$ are considered to follow zero-mean gaussian multivariate distributions, uncorrelated, and their respective covariance matrices are $\mathbf{Q}_k$ and $\mathbf{R}_k \in \mathbb{R}^{(3N+2)\times(3N+2)}$.

In order to model the non-linear relationship between the measurement p_k and the states components (Eq. (3.4)), the extended version of Kalman filtering is used. It consists of replacing $l(\mathbf{C}_{k-1}, k)$ and $d(\mathbf{C}_k, k)$ by their respective jacobians matrices $\mathbf{L}_{k-1} = \frac{\delta l}{\delta \mathbf{C}}\Big|_{\mathbf{C}_{k-1|k-1},\Delta t,k-1}$ and $\mathbf{D}_k = \frac{\delta d}{\delta \mathbf{C}}\Big|_{\mathbf{C}_{k|k-1},\Delta t,k}$. Hence the transition matrices $\mathbf{L}$ and $\mathbf{D}$ can be expressed as stipulated in Eq. (3.6). and Eq. (3.7), respectively, where $\mathbf{L}_k \in \mathbb{R}^{(3N+2)\times(3N+2)}$, $\mathbf{D}_k^{\mathbf{T}} \in \mathbb{R}^{(3N+2)}$, and $i, j = 1, ..., 3N + 2$.

$$(\mathbf{L}_k)_{i,j} = \begin{cases} 1, & \text{if } i = j \\ \Delta t, & \text{if } i = 3N + 1, \,\&\, j = 3N + 2 \\ 2\pi\Delta t, & \text{if } i = j + 1, \,\&\, i \equiv 0 \bmod 3 \\ 0, & \text{otherwise} \end{cases} \tag{3.6}$$

$$(\mathbf{D}_k)_i = \begin{cases} \sin(2\pi(\mathbf{C}_k)_{i+1}\Delta t + (\mathbf{C}_k)_{i+2}), & \text{if } i \equiv 1 \bmod 3 \,\&\, i \leq 3N \\ 2\pi\Delta t(\mathbf{C}_k)_{i-1} cos(2\pi(\mathbf{C}_k)_i\Delta t + (\mathbf{C}_k)_{i+1}), & \text{if } i \equiv 2 \bmod 3, \,\&\, i \leq 3N \\ (\mathbf{C}_k)_{i-2}\cos(2\pi(\mathbf{C}_k)_{i-1}\Delta t + (\mathbf{C}_k)_i) & i \equiv 0 \bmod 3 \,\&\, i \leq 3N \\ 1, & \text{if } i = 3N + 1 \\ \Delta t, & \text{if } i = 3N + 2 \end{cases} \tag{3.7}$$

Hence, at instant k, for a time-window of δ samples, the prediction function could be expressed as:

$$\hat{s}_{k+\delta} = \sum_{i=1}^{N} A_k^{(N)} \sin(2\pi f_k^{(N)}(1 + \delta)\Delta t + \Phi_k^{(N)}) + b_{1,k}\Delta t + b_{0,k} + \omega_k \tag{3.8}$$

3.3.6 Parameters selection and initialization

We describe in this subsection the parameters selection procedure concerning N, $\mathbf{Q}$ and $\mathbf{R}$, and the initialization applied to A, f, and Φ.

We set a fixed value of $N = 10$ that minimized the average Kalman RMS for each of the 4 postures, allowing up to 10 components to be taken into consideration, such as small irregularities or ripples.

As the relationship between posture changes and the amplitude variation of the reconstructed respiratory signal does not remain the same, including new types of noises both in the model and the measurement, the model and measurement noise matrices are selected according to the posture. We note $\mathbf{Q}$ and $\mathbf{R}$ the noise covariance diagonal matrices. Let q and r be the coefficients values to be multiplied by the unit matrices to form $\mathbf{Q}$ and $\mathbf{R}$ respectively. Hence a batch optimization procedure has been performed on each of the subjects for each of the four postures, in order to determine the optimal values of q and r for each of the postures using an exhaustive search. In order to detect posture to perform the q and r selection optimization, a batch of pressure distribution frames in a 30 seconds epochs window is selected, posture is identified in each of the frames, then the posture having the most votes out of the 4 is selected as the corresponding posture for the current 30 seconds window. Then based on the identified posture, Kalman filter parameters are selected and initialized accordingly to reconstruct the breathing movements signal, in order to derive BRs.

In order to mitigate the effect of posture change on the relationship between the breathing activity and the dynamic pressure distribution, we need to identify the posture, and adaptively choose the right Kalman filter parameters, i.e., $\mathbf{Q}$ and $\mathbf{R}$. In a previous work, we built an ANN posture classifier using body pressure distribution data (Matar *et al.*, 2019). The model was trained on a dataset of 1116 pressure distribution frames collected as follows: from each of the 12 subjects, 23 frames were collected for each of the 4 postures. In order to preserve inter-frames variance and the generalization performance of the classifier, subjects were given specific instructions during the experiments to lay on the bed in different variants of each of the 4 postures. For

instance, one of the prone posture variants was: right arm down (below shoulder), left arm up (beside the hip), right leg unfolded, and left leg folded, or one of the right posture variants was arms and legs folded, and curled up body. Also, orientation and location of the body on mattress have been varied, e.g., body on the far left, far right, or body in a diagonal position relatively to bed. The used ANN classifier consisted of a single hidden layer with 30 hidden nodes. The training of the ANN classifier was done using the scaled conjugate back-propagation technique with the CE as an evaluation criteria of the error. A feature vector containing the HoGs and LBPs features. The feature vector, initially having a size of 579, was reduced to 46 using the singular value decomposition based PCA, with an explained variance of 95%. Nested cross-validation with an exhaustive outer loop has been applied to maintain both good prediction accuracy and generalization performance. Hence, the algorithm takes as input the body pressure distribution images and returns a label corresponding to one of the four state-of-art bed postures, i.e., *prone*, *dorsal*, *right*, and *left lateral*. Prior to Kalman selection parameters, the ANN classifier model was used to classify each of the postures in a 30 seconds windows, and votes were given to each of the 4 postures. The posture having the most number of votes was chosen as a posture for the 30 seconds window, which allows to even improve classification performance by avoiding small mis-classification probabilities, i.e., less than 3% for each of the four postures.

The raw respiratory breathing movements reconstructed as described in section 3.3.4 is used to calculate the power spectrum density over a training window of M=30 samples. The first 10 most dominant frequencies, i.e., the frequencies having the highest amplitudes in the spectrum, are set as initial values for f_i, $i = 1, ..., 10$. The corresponding amplitudes A_i were initialized as the average signal amplitudes for the 30 samples window, and the corresponding phases Φ_i as zero.

3.3.7 Validation methodology

We detail in this subsection the approach we adopt in order to validate the proposed model.
A conventional respiratory belt plethysmograph was used as a reference for validation during the experiments. In order to compare our system to the plethysmograph, we derived BRs using both

Table 3.1 Testing confusion matrix of the ANN posture classifier

		Target class			
		Supine	**Prone**	**Right**	**Left**
Output class	**Supine**	96.8%	0.0%	0.0%	0.0%
	Prone	0.0%	99.2%	1.0%	0.0%
	Right	3.2%	0.8%	99.0%	3.3%
	Left	0.0%	0.0%	0.0%	96.7%
	Testing prediction accuracy: 97.9%				

systems based on the following procedure:

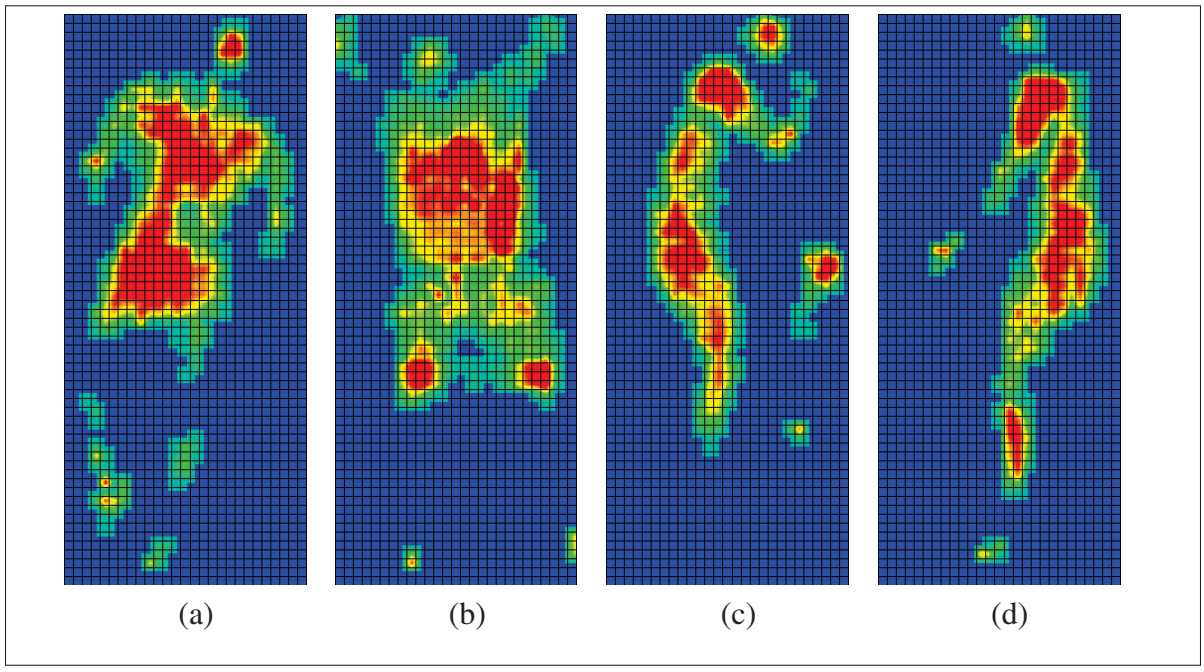

Figure 3.2 Body pressure distribution images of 4 postures:
supine (a), prone (b), left (c), and right (d)

The Fast Fourrier Transform (FFT) based power spectrum density was computed from the Kalman filtered breathing movements signals derived from the pressure sensor system and the

belt. The computation was performed on 30 seconds windows for each of the 12 subjects, with a total recording length of 5 minutes, for each of the 4 postures, i.e., for each posture, a total of $\frac{5}{0.5} \times 12 = 120$ BR value for pressure data, and 120 for belt data to be compared. The comparison between the two set of values was done using two metrics: 1) the PCC, that reflects the linear correlation between the two measurements. Although giving insights about linear relationship and how the measurement varies with respect to each others, the PCC does not show the difference of the values measured, and is not recommended to be used for evaluating the comparability between two measurement methods. Hence, 2) we use BA plots: BA analysis is a well-established method of assessing agreement between two measurement methods in order to validate if they could be used interchangeably without leading to practical problems (Bland & Altman, 1986; Mantha, Roizen, Fleisher, Thisted & Foss, 2000).

3.4 Experimental results and discussion

In this section, we present and discuss the resulting parameters that were selected during the experimentation, along with the obtained simulation results, and compare our results to state-of-art studies addressing unobtrusive BR monitoring using bed-sheet pressure sensors.

The considered bed postures are shown in figure 3.2. Different variants of the same posture have been recorded in the dataset, where the body and limbs orientation and location on the mattress have changed between frames belonging to the same posture. The testing confusion matrix of the used ANN posture classifier is presented in table 3.1 (Matar *et al.*, 2019). A relatively high true positive rate has been obtained when testing the model on new data, showing its accurate classification performance. We additionally performed a Cohen's Kappa calculation in order to assess the reliability of the results and ignore the agreement by chance, we obtained a $\kappa = 97.14\%$, reflecting the high intended agreement. The advantage of using this classifier is its high classification accuracy and its ability to separately classify prone and supine postures using both body

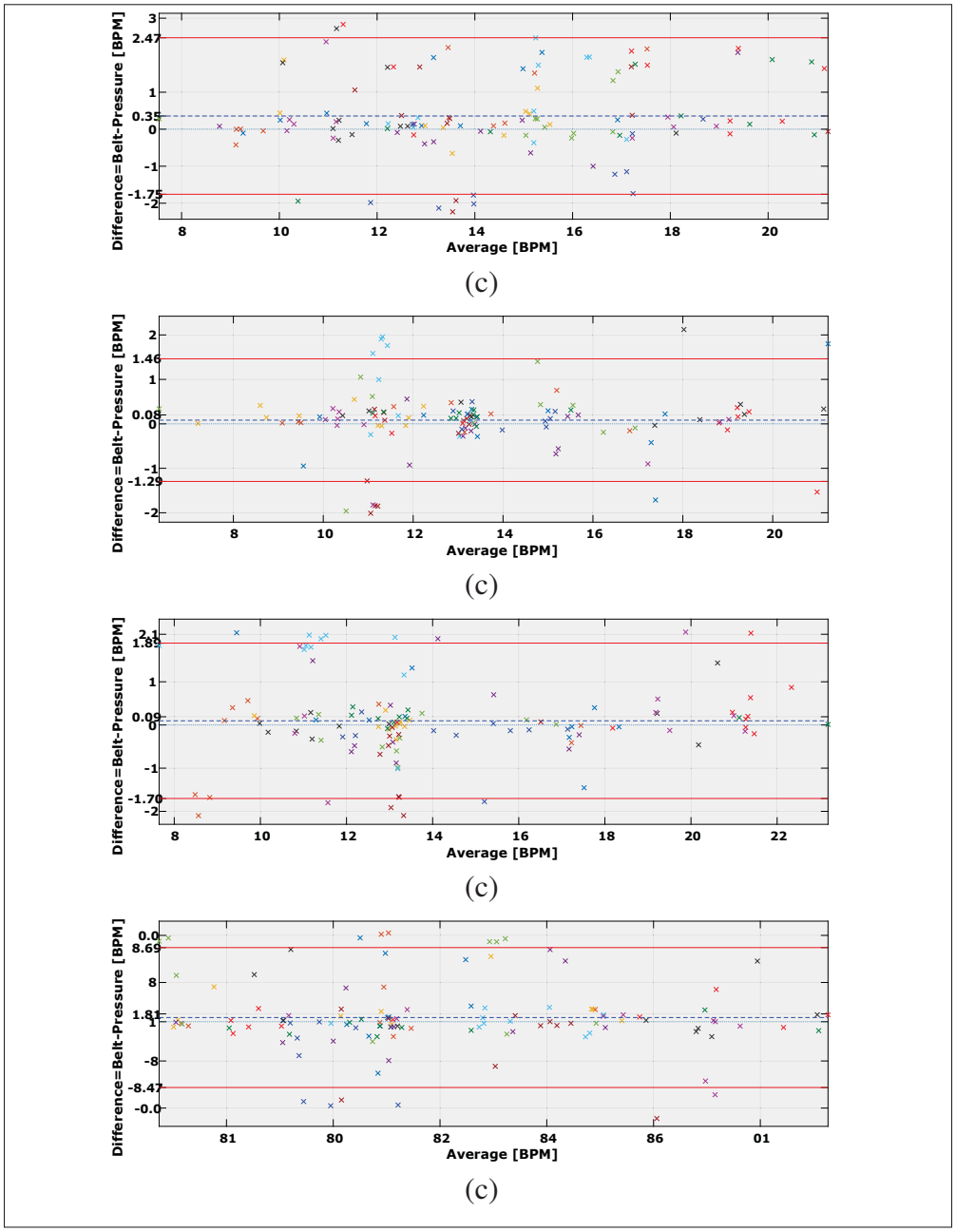

Figure 3.3 BA plots for the BRs calculated over 30 seconds windows for the 12 subjects (a color per subject) lying in each of the 4 postures

shape and weight distribution by extracting both HoG and LBP feature vectors (Matar *et al.*, 2019).

Table 3.2 Posture-wise optimal q and r coefficients

	Dorsal	**Prone**	**Right Lateral**	**Left Lateral**
q	0.76	0.98	0.58	0.31
r	0.93	0.58	0.69	0.27

Table 3.2 presents the results of the exhaustive search technique used in order to find an optimal choice of the value of both model and measurement noise matrices for each of the 4 detected postures ,i.e., the ones that minimize the RMS value. Different ranges of RMS values have been obtained for each of the postures with a relatively different extensity between minimum and maximum RMS values.

The obtained differences between the optimal q and r values can be theoretically explained for both **Q** and **R** matrices as follows: the error made on the assumption of modeling the respiratory signal using a multi-sinusoidal model is indeed not the same for the 4 bed postures. For instance, the variation of the body pressure distribution on mattress differs between right lateral and prone positions, where the direct contact with the mattress is larger in the latter and the detected changes are more pronounced, which explains the changes in both model and measurement noises.

The BA plots of the BRs derived from both measurement systems for the 12 subjects lying in each of the 4 postures: supine (a), prone (b), left (c), and right (d) are illustrated in Figure 3.3. This plot shows for each of the four postures, for each of the 12 subjects (a color per subjects), the difference between the derived BR values using belt and pressure sensor mattress. The Line of equality (LOE) line shows the constant value, at which the two measurements are equal or have zero differences. The mean difference line $\bar{\mathbf{d}}$ shows the average difference value between the two measurements. The LOA lines show the upper and lower limits of agreeements, which were clinically predefined to set the maximum allowable differences between the two measurement methods. The lower and upper LOAs are expressed as: $\bar{\mathbf{d}} - 1.96.S_D$, and $\bar{\mathbf{d}} + 1.96.S_D$, respectively, where S_D is the standard deviation. Although the clinically accepted inter-rater limits of difference between two BRs measurement methods lie around ±

Table 3.3 Existing methods that focus on breathing monitoring during sleep using bed pressure sensors

Author name, year	**Dataset**	**Pressure sensor type**	**Methodology**	**Validation**	**Number of identified postures**	**Results**
Jones *et al.* (2006).	n = 2, adults, t_T = 13 hours.	24 fiber optics sensors, distributed on 24 x 90 cm.	Data driven clustering of 24 RR estimations.	No validation to a a reference method.	Unspecified.	Average reliability: 88%.
Azimi *et al.* (2017).	n = 1	72 sensors, uniformly distributed from head to hip.	- PCC. - Minimum-Variance Distortionless Response (MVDR).	Validation of the correlation to belt with regression.	1: supine.	- PCC: 97.16 %. - MVDR: 96.7 %.
Gilakjani *et al.* (2018).	n = 2, adults, t_T = 13 hours.	24 fiber optics sensors, distributed on 24 × 90 cm.	Movement detection, movement suppression, and sensor selection.	Validation with belt. Comparison to (Jones *et al.*, 2006).	1: supine.	- Average reliability: 75.92 %. - Best average PCC to belt (SNR-max method): 73.4 %.
Samy *et al.* (2014).	n = 7, t_T = 50 hours.	8192 pressure sensors, distributed on 125 × 250 cm.	Sum of all pressure values, and frequency filtering.	Validation with belt.	Unspecified.	No quantitative results given.
Liu *et al.* (2015).	n = 12	8192 pressure sensors, distributed on 125 × 250 cm.	Torso localization, respiratory signal extraction, and peak detection.	Validation of TP RC with visual inspection from video recordings.	3. No posture change allowed.	Average percentage of breaths detection: 97.63 %.
Our method	n = 12, $\hat{m}$ = 27.35 ± 5.39	1728 uniformly distributed pressure sensors	Posture based Kalman filtering + BR computation	Comparison of BR results to belt using: - PCC - BA analysis	4, supine and prone included, posture adaptive RR estimation	Average PCC: 95.78%. Average BR deviation with 95% CI: 1.76 BrPM

5 BrPM (Parker, Weir, Rubio, Rabinovich, Pinnock, Hanley, McCloughan, Drost, Mantoani, MacNee & McKinstry, 2016), we decided to narrow this agreement limit to around 2.5 BrPM in order to aim for more accuracy and consistency in the evaluation of the two measurement values. As shown in the plots, the average derived BR values range from 6 and 23 BrPM, while the maximum difference between the two sets of values, on a 95% of a confidence interval, is around 2.47 BrPM, with an average of 1.93 BrPM. It is noteworthy that the $\bar{\mathbf{d}}$ line is relatively close to the LOE, and that the LOE lies exactly in the middle distance between the two LOA

showing that the absolute differences are approximately equally spreaded around the equality line. The strong agreement between the two methods can be also regarded by inspecting the data points spreading with respect to both the upper and lower limits of agreements. For instance, the fact that the majority of the data points lie between these two limits shows that the difference between the BR calculated from the two methods is bound to have a maximal value of 2.5 BrPM, which is an acceptable value that lies within inter rater agreement according to clinical practices (Parker *et al.*, 2016). Previous methods of unobtrusive breathing monitoring using modalities such as ZigBee have obtained a 95% of around 10 BrPM, which makes this method far more accurate (Hillyard, Luong, Abrar, Patwari, Sundar, Farney, Burch, Porucznik & Pollard, 2018). The same given remarks apply for each of the four BA plots of the BR derived from the two methods for the subjects lying in the four postures, as illustrated in figure 3.3 (a), (b), (c), and (d).

Table 3.4 PCC values calculated on the BRs derived from the two measurement methods for each of the four postures

PCC	**Dorsal**	**Prone**	**Right Lateral**	**Left Lateral**
	93.51	96.29	97.61	95.69

The PCC values for each of the four postures are shown in table 3.4. With at least 93.51% of PCC value, and a mean of 95.78%, the table shows the strong linear relationship between the two sets of BR values, showing that our method of unobtrusively monitoring BR is highly linearly correlated to the reference measurement.

A high agreement, and a high linear correlation, both established by the BA analysis, and by the PCC calculation, respectively, show that the two methods could be used interchangeably for the derivation of the BR. Being less obtrusive, more autonomous and convenient, and more suitable for home use than the belt, the pressure sensor mattress is a reliable alternative to BR monitoring.

Under-sampling the number of sensors used in the mattress by half introduced a bias, resulting in an average maximum difference of BRs of 2.72 BrPM, instead of 1.93 BrPM when using the

full sensors matrix. The posture detection was slightly affected by the under-sampling operation, with a reduction of the average detection accuracy of 0.3%. We choose to use the full pressure sensor matrix to the system, in order to preserve the minimal BrPM difference between the belt and pressure sensor mattress.

It is noteworthy that, regardless of the posture, the measurements from both methods remained comparable and consistent, which shows the posture-specific adaptive behavior of the proposed model. This is due to both the posture recognition procedure implemented, and the sensors selection used to reconstruct the breathing signal.

Table 3.3 shows an exhaustive review of the existing methods that focus on breathing monitoring using bed pressure sensors, along with our method. In order to establish a set of comparison criteria between the methods, it is crucial to take into account some considerations that will be discussed in the subsequent sections.

3.4.1 Posture-adaptivity:

Tosses form an integral part of body movements on bed, which makes it important to validate the ability of the model to estimate BRs while the subject is lying in the four postures due to the dependence of the breathing induced pressure changes with the lying posture (Matar *et al.*, 2018,1). It is one of the main challenges that researchers have been facing for several reasons, mainly, the ability to classify supine and prone postures separately while having a high classification accuracy. This is a question we addressed in a previous work, by combining weight and shape information in the classification task, which allowed us to deal with this problem and propose a posture-adaptive BR estimation model. As shown in table 3.3, previous works have either considered only one posture in the validation, or 3 postures at most (Liu *et al.*, 2015), excluding supine posture due to the shape similarity induced confusion with the prone posture.

3.4.2 Clinical validation:

Model validation has to meet clinical validation criteria. Some of the previous works have whether missed validation to a reference method (Gilakjani *et al.*, 2018), or validated with respect to belt but gave no quantitative validation results (Samy *et al.*, 2014), and others gave only used PCC correlation, that shows that the methods are linearly correlated (Azimi *et al.*, 2017). Other methods validated with a percentage of detection breaths, giving no insights on the correlation or linear relationship with a reference method used, neither on the false negative and false positive detections, comparing only the total number of detection over a time window with the reference method (Liu *et al.*, 2015). In our paper, we derive the inter-rater agreement on BR estimation by calculating the difference between our method and the conventional belt system, and we show that the results are clinically accepted (Parker *et al.*, 2016).

3.4.3 Inter-subject variance:

Body shape and weight distribution vary between different subjects, and hence, could have an impact on the dynamic pressure distribution on the mattress. It is therefore important to clinically validate the model on different subjects in order to grant a relatively high generalization performance of the BR estimations. Previous works have validated their models with respect to 1 or 2 subjects, except for (Samy, Huang, Liu, Xu & Sarrafzadeh, 2014), and (Liu *et al.*, 2015), where 7 and 12 subjects were recruited, respectively. In our experiments, we recruited 12 subjects, and made sure that equal recording duration was performed.

3.4.4 Pressure sensor mattress choice:

it is an important choice that could affect the prediction model due to the acquisition of incomplete images of the subject's body. This incomplete information does not allow the system to take into account limb movements or body parts that are not covered by the mattress region, which makes movement suppression and body posture recognition harder. For instance, previous works have used pressure sensor mattresses that covered a part of the body, mainly between head and hip

(Azimi *et al.*, 2017; Gilakjani *et al.*, 2018; Jones *et al.*, 2006). Some researchers however, used a very dense sensor matrix i.e., more than 8000 sensors distributed over the mattress region (Liu *et al.*, 2015; Samy *et al.*, 2014) . In the benchmark stage of our project, we made sure that the whole mattress area is covered, with a sufficient number of sensors to allow us to have reliable predictions for both posture and BRs.

3.5 Conclusion and future perspectives

Monitoring breathing activity is a vital procedure for a wide range of medical applications. We described and evaluated a new unobtrusive approach to monitor the BR using a bed-sheet pressure sensors. The main contributions of this work consist in: unlike literature works, 1) adaptively selecting and isolating the sensors reflecting breathing activity in the raw signal reconstruction step, which reduces added noise and unwanted body movements pressure changes, and 2) considering the posture effect in the model's optimization step, which reduces posture induced noise on the pressure-sensed abdominal volume changes. We validated the obtained results to a belt sensor used as a reference using the BA plotting technique. We compared the proposed method to state-of-the-art methods in the literature using several comparison criteria, while presenting the validation procedure adopted and whether the posture was accounted for in the experiments or not. Unobtrusive breathing monitoring using a pressure sensor mattress, could be a potential solution for both home and clinical use. We demonstrated throughout the paper that with proper signal processing, a pressure sensor mattresses could be used interchangeably with respiratory belts. For information regarding the investment, a clinical unit has to made to acquire the system, the reader could refer to the manufacturer's website (Sensor Products). The system requires no after-sale recurring expenses or periodic maintenance. The hardware consists in a pressure sensor mattress, and a processing station to execute the model. The software consists in the developed algorithm installed on the station and a control interface. The connection between the mattress and the station can be accomplished using the Wi-Fi communication module or the USB cable, which makes the application wider in several clinical places, e.g., where Wi-Fi is not allowed, or a cable-less connection is required. The system could be used both in clinics or

in the subject's place as no clinical intervention is required during the data acquisition step. The system could be used in parallel with other medical devices or sensors attached on the body. The mattress contains elastic FSR sensors, powered by a low voltage (5 Volts), thus no potential physical harm or discomfort could be induced by the mattress.

Future work has to focus on extending the proposed method on further applications such as whole nights recording during polysomnographic procedures, which would give a push towards a wider use of such unobtrusive hardware in applications such as sleep monitoring, hospital environment, police custodies, elderly houses and at home for elderly and people with disabilities. In addition, future steps would be addressing special clinical conditions such as gross body movements that influence the signal's quality for certain categories of patients. Moreover, customizing the method to specific applications could optimally leverage its outcomes and serve the medical community.

CHAPTER 4

DEEP-LEARNING BASED UNOBTRUSIVE SLEEP STAGES CLASSIFICATION USING BED-SHEET PRESSURE SENSORS

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4.1 Abstract

Objective: A variety of deep learning studies for automatic sleep stages classification exploit data measured through conventional signal acquisition techniques, mainly PSG. In the light of broad evidence demonstrating the potential of autonomic nervous system (ANS) based physiological changes to be bio-markers for sleep stages identification, we propose to extend this understanding to the yet-unexplored field of unobtrusive sleep studies using bed-sheet pressure sensors. **Methods:** We present a sleep stages classification method using data acquired using bed-sheet pressure sensors placed under the subject. An automated feature extraction step is performed using three dimensional convolutional neural networks (3D-CNN). **Experiments:** A whole-night recording experiments during sleep using PSG and bed-sheet pressure sensors are conducted on 12 healthy adults subjects. A team of sleep technologists labeled the data based on the American Academy of Sleep Medicine (AASM) scoring manual, giving a sleep stage classification for each 30 seconds epochs. We propose a supervised deep learning architecture, which we train, validate and test using this labeling. We compare the obtained performance to state-of-the-art methods of unobtrusive sleep stages classification using bed-sheet pressure sensors. **Results:** For a classification between 3 classes, namely Rapid Eye Movement (REM), non-REM (NREM), and wake, we obtained an average classification accuracy of 74.27%, a precision of 72.54%, and a recall of 62.86%, which demonstrates the relatively high

classification performance of the proposed method. **Conclusion:** Using the dynamic body pressure distribution on a mattress, it is possible to identify sleep stages. **Significance:** We argue that the proposed method could be a step towards unobtrusive sleep studies that require less resources allocation. We give recommendations and practical steps for future endeavors seeking to bring contributions to unobtrusive sleep studies using bed-sheet pressure sensors.

4.2 Introduction

Sleep studies are overnight tests that allow sleep professionals to monitor the brain and body states during sleep. Over the last decades, PSG defined the clinical standard of studying sleep as it has shown the promise of providing a reliable estimation of hypnogram, which is the cycling diagram of sleep stages. Sleep stages are cyclic states in which specific physiological functions occur (Douglas, Thomas & Jan, 1992a). The sleep architecture is formed by different sleep stages, each characterized by specific physiological changes such as breathing irregularities or body paralysis in REM stage. There exist 4 sleep stages: rapid eye movement (REM), and three non-REM (NREM) stages: NREM1, NREM2, and NREM3 reflecting the progression from lighter NREM1 to deep NREM3 sleep. Despite the consistent estimation of sleep stages that PSG provides, the PSG suffers from a cumbersome acquisition protocol. For the patients, it is an obtrusive investigation that requires attaching tens of cables and sensors to the body during sleep for one or several nights, which affects the patient's comfort and the sleep quality to be evaluated (Byun, Kim, jin Moon, Motamedi & Cho, 2019). As a result, although the persistent increase of sleep disorders in the world's population, where at least one in two elderly experience disturbed sleep, an excessively low willingness to resort to medical tests is documented (Charles, Mélanie, Lynda, Hans & Chantal, 2011; Monane, 1992). Figure 4.1 illustrates the usually used sensors for signal acquisition during PSG: the brain electrical activity, eyes movements, breathing, chin and limb muscles activities, cardiac electrical activity, breathing induced chest and abdomen movements, and blood oxygen saturation are measured using EEG, EOG, spirometer, EMG, ECG, Respiratory inductance plethysmograph (RIP) or breathing belt, and oxymeter, respectively. For the health-care system, PSG requires, after data acquisition and storage, and a sleep professional

who spends hours to manually classify sleep stages by visually inspecting the recorded signals in order to build a sleep hypnogram, a diagram showing the cycling of sleep stages during sleep. Such factors made PSG an expensive test that requires a large amount of professional resources and costs, and where there are long waiting lists before exam [9].

However, and most importantly, the non-ecological aspect of PSG remains the scientific barrier to a natural sleep estimation. During a PSG investigation, the body and the brain are exposed to new conditions i.e., room, temperature, mattress, pillow, and at least 22 sensors and cables attached on the body. This prevents the sleep stages estimation and sleep evaluation in natural conditions, and leads to adding physiological biases to the test. For instance, when we evaluate the sleep quality of a subject in the PSG lab, it is most likely that the subject actually sleeps better at home, in natural conditions. The sleep, being the unique period of time where the brain is freely operating, lessening perturbations and constraints on its operation could provide unexplored information. Here comes the importance of developing an unobtrusive home sleep monitoring method that could allow to explore the unexplored aspect of natural sleep. Based on the aforementioned description of PSG, two main problems need to be addressed in the current form of sleep evaluation, where each problem is related to a different phase of the test. First, the cumbersome acquisition protocol needs to be the less obtrusive as possible. This can be accomplished by finding means of reducing the number of sensors and cables attached on the body, and try to do the test at home, where the subject's sleep is natural and more representative of the real sleep. And second, in the post-acquisition step, the sleep stage classification needs to become less time and resources consuming. This can be accomplished by developing an automatic classification method that is tested and validated with respect to PSG labeled data, which avoids sleep technicians spending hours to score a sleep night manually.

Therefore, to address the two problems, a prominent research line has came to light, aiming to make sleep tests less obtrusive by investigating several approaches, ranging from the way the physiological data is measured, to how the sleep staging is performed.

In this context, in our previous work (Matar *et al.*, 2018), we shown how researchers have explored new sensors and materials, such as cameras and actigraphy monitors, to unobtrusively

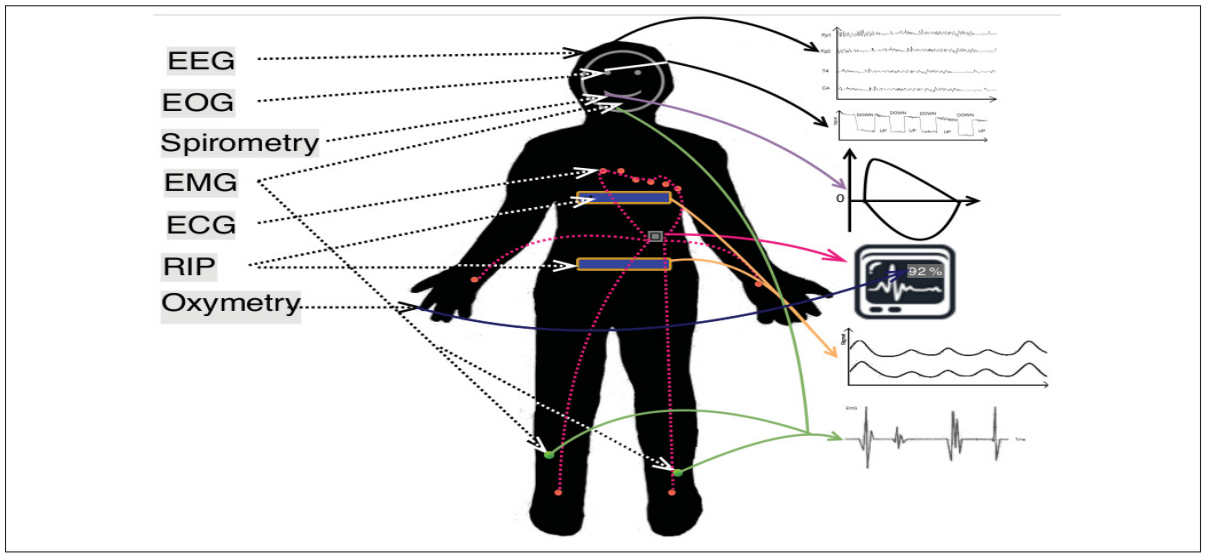

Figure 4.1 Conventional PSG acquisition protocol and sensors placement on the body

measure physiological data during sleep, and consequently reduce 1) the number of sensors and cables attached on the body, 2) the constraints on body movements during sleep, and 3) general obtrusivity for the subject being monitored. These techniques have reached industrial gates and leaded to a global sales convincing a large number of subjects the promise of having sleep stages classifications at home (Philips). The main problem of usual available techniques, as discussed in details in (Matar *et al.*, 2018), is the lack of exhaustive clinical validation with respect to the gold standard, i.e, PSG. This has been an important barrier for such methods which prevented them from being deployed in clinics and adopted as alternatives to conventional acquisition protocols, or be classified as medical devices.

On the other hand, further efforts have been made to automate the classification of sleep stages once the data is acquired using PSG apparatus (Boostani, Karimzadeh & Nami, 2017). In this vein, both, model-based methods relying on the exploration of temporal and frequency domains of physiological signals, and data-driven models using machine learning algorithms (Biswal, Kulas, Sun, Goparaju, Westover, Bianchi & Sun, 2017; Chambon, Galtier, Arnal, Wainrib & Gramfort, 2018; Mikkelsen & de Vos, 2018), have shown the promise of reliably providing an estimation of sleep stages in clinical environments. The potential application of

such systems is the deployment in a semi-automatic configuration, where the sleep professional has to approve the output of the classifier in order to make a final sleep stages classification (Anderer, Gruber, Parapatics, Woertz, Miazhynskaia, Klösch, Saletu, Zeitlhofer, Barbanoj, Hopfer-Danke, Himanen, Kemp, Penzel, Grötzinger, Kunz, Rappelsberger, Schlögl & Dorffner, 2005; Punjabi, Shifa, Dorffner, Patil, Pien & Aurora, 2015). As a good clinical validation has been accomplished, these algorithms help in the automation of sleep stages classification for the professionals; however, the main problem of these solutions is that, since the conventional PSG signals are still used in these solutions, the cumbersome acquisition protocol that PSG imposes on the subjects being monitored remains unsolved, despite the sleep stages classification task being automated.

Recent studies have started to clinically validate with respect to PSG, a number of unobtrusive sleep stages classification methods (Kalkbrenner, Brucher, Kesztyüs, Eichenlaub, Rottbauer & Scharnbeck, 2019; Rao, Ali & Cesar, 2019; Samy *et al.*, 2014). Sensors used during data acquisition include accelerometers, actigraphs, microphones, ballistocardiographs, and bed-sheet pressure sensors. With the introduction of artificial intelligence, and the ability to leverage big data in the automation of prediction and classification tasks, this research direction has gained researchers' interest. As we later discuss in section 4.4, the field remains in its early stages, and so do the presented literature results, which prevented to-date proposed methods from reaching clinical applications.

In this paper, we aim to contribute to the unobtrusive sleep stages classification field using bed-sheet pressure sensors. We propose and validate a solution that tackles both of the aforementioned problems, by reducing the acquisition protocol intrusiveness, while automating the sleep stages classification task. Instead of the cables and sensors attached on the body in the conventional PSG procedure, we placed a bed-sheet containing textile pressure sensors under the subject's bed-sheet, and monitor the dynamic body pressure distribution on the mattress. Simultaneously with the acquisition of the body pressure distribution on the mattress, a PSG recording served as a reference in order to generate sleep stages labels and supervise the model learning task. A deep ANN classifier architecture is proposed, where the classifier consists of a 3D CNN to extract

spatio-temporal features from the data, and a multi-layer perceptron for further classification. The main contribution of this paper is a validated method of unobtrusive sleep stages classification using bed-sheet pressure sensors. Other key sub-contributions can be summarized as follows:

- The simultaneous measurement and exploration of the body pressure distribution on a mattress and polygraphic signals in a sleep clinic on 12 healthy adults using bed-sheet pressure sensors and a PSG system connected according to AASM rules.
- Proposition of a new feature extraction to explore the body dynamics on a mattress in all three dimensions of a 3D-CNN, and leveraging this information in classifying sleep stages. We show the difference of considering the body physical activity and the body pressure distribution on the mattress, and we discuss the relevant information that each provides in the context of sleep stages classification.
- Designing and testing a new 3D-CNN architecture followed by an artificial deep neural network to classify sleep stages using the body pressure distribution on mattress.
- Showing state-of-the-art results in unobtrusive sleep monitoring and sleep stages classification.
- Giving key recommendations for future endeavors based on the challenges and limitations we faced in our experimentation, in order to improve and yield better results in unobtrusive sleep monitoring.

The subsequent sections are structured as follows: section 4.3 describes the methodology including data acquisition, pre-processing, and feature extraction, the learning model, and validation procedure. Section 4.4 presents the simulation trials we conducted and the obtained results. A discussion of the results and a comparison to the state-of-the-art works that are based on pressure distribution data to classify sleep stages are also presented. In section 4.5, concluding remarks and recommendations are given, along with future perspectives and open related research areas are highlighted.

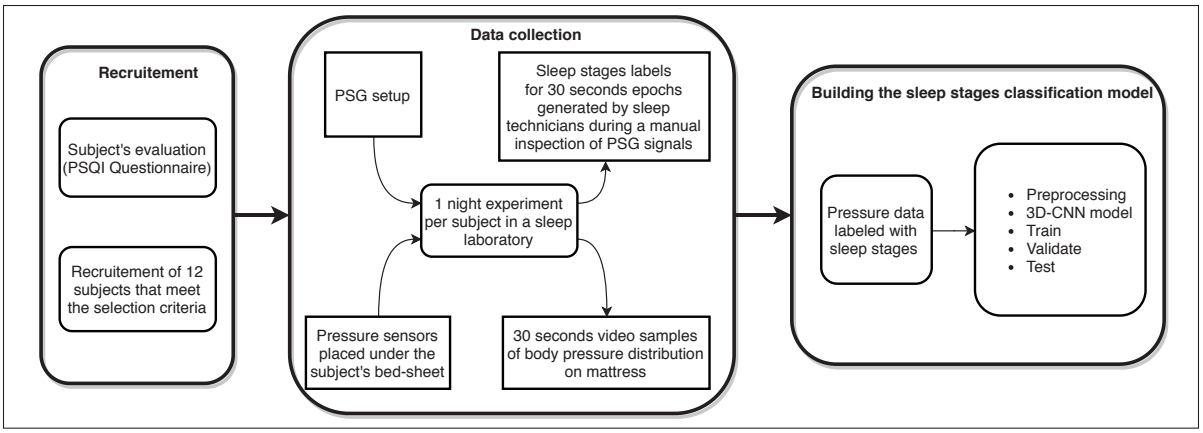

Figure 4.2 Work-flow diagram of unobtrusive sleep stage classification using bed-sheet pressure sensors

4.3 Materials and methods

The work-flow that leaded to the proposed model design and validation is illustrated in a diagram in Figure 4.2. The proposed model uses a 3D CNNs applied on a dataset of body pressure distribution on mattress. The data was collected in a PSG procedure where the body pressure distribution was measured simultaneously. The proposed model is trained, validated, and tested on never-seen data recorded from new subjects. In this section, we describe the methodology and materials used in the proposed method, namely subjects selection and recruitment, data collection, preprocessing, model design and selection, and criteria selection for results comparison to state-of-the-art methods.

4.3.1 Subjects recruitment

As the aim here was to prove the existing correlation between body and limb movements, and breathing activities with sleep stages, 13 healthy adults were recruited to sleep a whole night at the center for advanced research of sleep medicine in order to collect the data. For instance, a data with healthy sleep patterns prevents learning biased or alternated hypnograms, affecting training and validation of the model. A certificate of ethics (Number: 2018-1481) was obtained from the ethics committee of the *hôpital Sacré-Cœur de Montréal* hospital. Subjects were excluded

if they were younger than 18 or older than 45, having sleep, psychological or neurological disorders, and under medication. Prospective subjects had to go through a screening interview at least one week before the experiment in order to assess their sleep quality and make sure they were admissible. During the interview, subjects answered the The Pittsburgh sleep quality index (PSQI), a standard self-rated questionnaire which we used to assess sleep quality and disturbances in subjects over the last week (Buysse, Reynolds, Monk, Berman & Kupfer, 1989). Only subjects that had no sleep disorders in general or disturbances over the last week were included to participate in the experiment. Selected subjects were asked to keep normal physical activity and eating habits, and reduce as much as possible caffeine and alcohol intakes. To make sure that sleep quality is maintained regular and normal, one week before the experiments, subjects had to answer daily morning and evening questionnaires to describe their day and night, regarding sleep, physical activity, irregular somnolence, fatigue, caffeine, and alcohol intakes. Because the experiment consisted of a one night sleep per subject, this night served both for screening and recording. For instance, due to a sleep disordered breathing, one of the subjects had during the experiment, the collected data was excluded from the study, and the data of the 12 remaining subjects was stored for processing.

4.3.2 Materials and experimental procedure

PSG and bed-sheet pressure sensors were used in the whole night experiments in the sleep clinic as follows:

Bed-sheet pressure sensors: placed under the subject, the bed-sheet pressure sensors is used to measure the dynamic evolution of the body weight distribution on the mattress. The bed-sheet pressure sensors used is Tactilus® made by Sensor Products Inc (Sensor Products). It consists of a rectangular bed-sheet containing a 2-dimensional matrix of 64×27 textile made piezoresistive pressure sensors covering a total area of 1.95 x 0.863 m. The mattress has a sampling frequency of up to 35 Hz, where 8 Hz was used in the acquisitions. The mattress is connected to the workstation with a USB cable or a Wi-Fi module for a wireless connection. The software interface allows to export data in various file formats including comma separated values (CSV)

files.

PSG: the PSG system used is Xltek® Brain Monitor Amplifier by Natus® technology (Natus). The system allows 50 electrodes inputs to be recorded simultaneously. The sampling rate we used was 512 Hz, According to the recommendations of the American Society of Sleep Medicine (AASM), and the data acquisition protocol adopted in the laboratory, the following signals were recorded in order to be able to label sleep stages for every 30 seconds epoch (Berry *et al.*, 2018):

- **ECG**: measures the cardiac activity. Two standard ECG electrodes were applied in a modified lead II format adopted in the Einthoven triangle, i.e., one electrode is placed under the right collarbone and one near the left hip.

- **EEG**: measures brain activity, which is the main biomarker for tracking wakefulness, bursts and sleep stages. 8 glued scalp electrodes were used in the following referenced montage: F3-A2, F4-A1, C3-A2, C4-A1, O1-A2, O2-A1.

- **EOG**: measures eye movement to identify the onset of sleep by monitoring slow eye movements that occur with the transition to NREM1 stage. In addition, EOG data is used for the characterization of REM sleep stage, also called paradoxical sleep, where rapid eye movements take place. Two electrodes are placed 1 cm above the outer canthus of one eye, and 1 cm below the outer canthus of the other. The placement distance of the 2 electrodes must be the same with respect to each eye canthus (symmetrical).

- **Chin EMG**: determines the level of muscle tone, which significantly decreases during REM sleep and can also be reduced with the onset of sleep. This channel also provides additional information on the movements and excitation levels of patients and can be useful for distinguishing the artifact in other channels. Here, 3 chin EMG electrodes were used: 1 at the center of the chin and the other 2 on each side ± 2 cm away from the center electrode.

- **Legs EMG**: additional causes of sleep disorders that need to be identified and treated are periodic limb movements during sleep (PLMS). These movements are often visually detectable during the monitoring process of the anterior tibial muscles which allows to determine the severity of the disorder by quantifying the rate of movements as well as the

correlation with EEG awakening. We recorded leg EMG to exclude subjects having PLMS from the study as we intend to collect data from sleep disorders-free subjects. A PLMS index greater or equal to 10 per hour associated with micro-arousals lead to discarding the data of the subject. Here, 2 EMG electrodes were placed longitudinally on the anterior tibial muscle of each leg and secured with tape.

- **Flow and snore sensor**: used during standard PSG to monitor breathing, and specifically the occurrence of events such as respiratory effort related arousal (RERA), apneas, and hypopneas. 1 oronasal thermistor, as well as a cannula on the nose, were placed at the nostrils entrance. The apnea-hypopnea index (AHI) is the average number of apneas and hypopneas per hour of sleep. An AHI greater or equal than 15 per sleeping hour leads to an exclusion of the subject from the study. Apneas were measured using the oronasal thermistor and the hypopneas using a canula.

- **Respiratory belts**: used to calculate RERAs and assist the detection of other sleep-related breathing events such as helping determine the nature of apnea events, when they occur, and whether they are central, obstructive, or mixed. One belt is placed around the rib cage under the armpits and the other around the abdomen at the level of the umbilicus (belly button).

- **Microphone**: records sounds associated with snoring behaviors. Snoring can be an indicator of sleep disordered breathing (SDB) disorders. A snoring microphone was attached on the neck.

- **Pulse oxymeter**: measures oxygen saturation in the blood (spO2). SpO2 helps detect a drop of oxygen level in the blood which could be the result of apnea or hypopnea events or other sleep breathing problems. A spo2 sensor was attached on the index finger. Fs = 25 Hz.

- **Camera**: records a continuous visual display of the patient sleeping with no lights using infrared sensing.

Subjects wearing their usual sleep clothes, slept one night each between 7 and 9 hours, with an an average of 7 hours and 41 minutes ± 24 minutes per subject. During the night, data was

collected and stored simultaneously using the bed-sheet pressure sensors and the PSG systems. A sleep professional monitored the real-time progress of the experiment in order to make sure that the recording went as planned, and that special events are reported in a subject-specific experiment report.

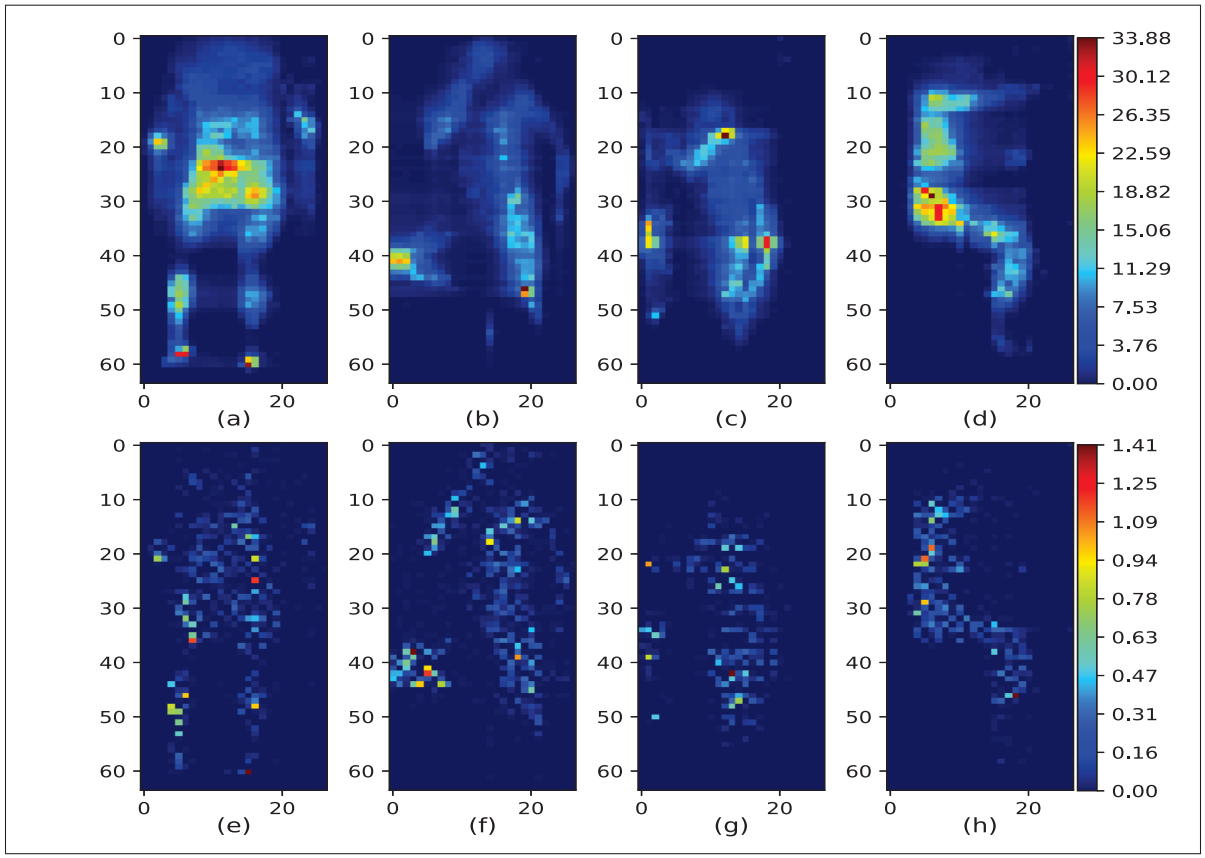

Figure 4.3 Pressure images in the first row and differences of pressure images in the second row for dorsal (a), prone (b), right (c), and left (d) positions. Image dimensions are in pixels, and colorbar unit is PSI

Subjects were allowed to use the toilet during the night, after being disconnected from the PSG system by the sleep professional. In order to form the so called hypnogram, a sleep professional inspected the collected PSG data and classified sleep stages during the night by giving a numerical value corresponding to one of the 4 categorical labels: light sleep (NREM1 & NREM2), deep sleep (NREM3), REM, Wake, or Interruption (disconnection from PSG), to

each 30 seconds time segment. Pressure data and PSG labels were extracted and stored in csv file formats and stored for processing.

4.3.3 Data pre-processing

Table 4.1 shows statistics related to both the physiology and sleep parameters of the 12 subjects included in the experiment. The parameters shown are age, sex, height, weight, body mass index (BMI), sleep latency (SL: the number of minutes subjects took to switch from being awake to falling sleep), TST (the number of minutes subjects spent in bed), and the sleep efficiency (SE: evaluated as the ratio between the time slept and TST).

Table 4.1 Average age, height, weight, BMI, SL, TST, SE calculated for the 12 subjects

Metric	**Value (Mean ± standard deviation)**
Age (years)	24.1 ± 3.78
Sex	6 males, 6 females
Height (m)	1.694 ± 0.10
Weight (Kg)	67.89 ± 10.41
BMI (Kg/m^2)	23.62 ± 3.05
Sleep latency (Mins)	16.8 ± 23.59
TST (Mins)	461.25 ± 24.27
Sleep efficiency (%)	91.88 ± 7.64

Data were collected and stored in 30 seconds windows separated intervals called epochs. The stored data was cleaned by removing epochs where the subject was not, for some reason, on the mattress and/or disconnected from the PSG for the complete epoch. In order to account for future unseen data processing, an automatic cleaning method was implemented to remove the epochs that have been labelled by the sleep professional as interruption and, epochs where the sum of pressure values given by the $64 \times 27 = 1728$ sensors was less than 10% of the sum of presssure corresponding to an average body weight, i.e., 255 PSI. Due to the hardware nature of the bed-sheet pressure sensors, and random mattress folding, very low pressure values can still be detected even if the subject is not on the mattress, which explains the aforementioned

10% threshold value, in order to rise the good detection of a body on the mattress. Overall, 40 epochs were removed from the data during the cleaning phase. The clean data contained a total of 11525 epochs. Due to imperfections in the sampling frequency setting of the pressure sensor mattress, the number of frames per epochs varied between 231 and 240. To unify the epochs' third dimension in order to use unified convolution operations, we retained only the first 231 frames of each epoch for analysis. Hence, each epoch, or sample consists of a 30 seconds of data, namely a (231 x 64 x 27) 3D matrix or video containing 240 pressure images stacked along the third dimension, and a categorical label indicating the epoch's sleep stage.

The clean dataset consisted of 11640 samples, with an average of 970 ± 51 sample per subject.

Dynamic body pressure distribution gradient images:

The main physiological behaviors that we aim to quantify and explore in this work are the breathing activity and the dynamic body state which includes body and limb movements, acceleration, or absence of movements. The collected pressure data contains two dimensional images of the body over time stacked in the third dimension. Therefore, only the third dimension gives information about the variation of the body pressure distribution over time, while the first two dimensions give information about the posture on the mattress. Considering the fact that the body posture feature doesn't have the sleep stages discriminating power that breathing and physical activity (such as breathing movements and body and limbs movements) have, we chosen to use the three dimensions to explore body dynamics in the following way: the difference between consecutive pressure images was calculated to form the new pressure data-set. Such information represents for each pixel value $p(t, x, y)$, where the t is the frame number from 1 to 230, x and y are the pixel locations on the mattress, represents the velocity of movements, or the first gradient $\dot{p}(t, x, y)$. The new data set contains epochs of 230 frames (difference between consecutive 231 frames). Hence the resulting data consists of two dimensional images containing the amplitude and location of the pressure variation, hence movement on the mattress, including the body, limbs, and breathing-related chest area. The pressure amplitude variation of these images stacked in the third dimension is the second order gradient, or the acceleration, that represents the variability of the detected movements over time, which further helps explore the

dynamic aspect of the body over time. As a result, the new data-set provides information on the physical activity in three dimensions, and is ready to be explored using the 3D-CNN in order to form higher dimensional feature maps and classify sleep stages accordingly. Figure 4.3 shows pressure images in the first row and differences of pressure images in the second row for dorsal, prone, left, and right positions. As depicted in the image, depending on posture, the highest pressure areas in the pressure images are usually associated to pelvic and/or shoulders. However, it is not the case for pressure difference images, whereas the highest pressure areas correspond to the chest and limb areas, where movement occurs most frequently, i.e., breathing induced activity and limb movements.

4.3.4 Network architecture

We propose a 3D-CNN model for sleep stages classification using differences between consecutive images of the body pressure distribution on the mattress. The architecture consists of multiple 3D convolutional layers used for spatio-temporal feature extraction, followed by a deep neural network made of multiple dense layers, and a three classes soft-max activation function for classification.

Data is fed to the network in a 3 dimensional matrices format representing 30-seconds samples of pressure images. Let a data sample be $X \in \mathbb{R}^{s,k,d,r,c}$, where $s = 12$ is the number of subjects, k is the number of video samples per subject, $d = 230$ is the number of pressure differences frames per sample, $r = 64$ is the number of rows, and $c = 27$ is the number of columns in a frame. Figure 4.4 shows an illustration of the network. Several network architectures were tested to obtain a relatively high performance based on the obtained accuracy metrics in the validation and testing.

The model consists of three convolutional stages.

The output shape of each layer is illustrated in table 4.2, where None represents the variable number of samples (epochs of 230 frames), a,b and c the volume size, and d the number of layers in (None,a,b,c,d) notation. While each stage has its own number of 3D-CNN kernels (16, 16, and 32 respectively), a unique architecture was adopted for the three convolutional stages, which

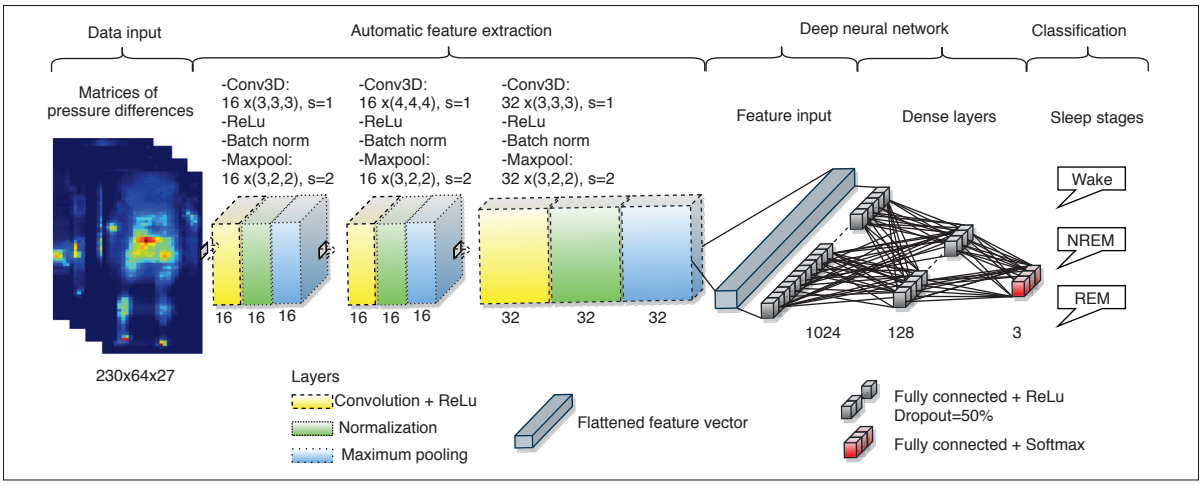

Figure 4.4 Classification network's architecture: 3D-CNN + deep ANN layers

can be described as follows: three dimensional filters with a $(3 \times 3 \times 3)$ kernel size, a stride of $(1 \times 1 \times 1)$, and a same padding were used to extract spatio-temporal feautres. A rectified linear unit (ReLU) was used as the activation function given by (He, Zhang, Ren & Sun, 2015):

$$f(x) = max(0, x)$$

. The main advantage of using ReLU lies in its ability to bypass the vanishing gradient problem in the optimization step, and where a faster convergence is more likely to occur.

A batch normalization was applied on the activation function's output. In a batch normalization procedure, each batch of data is normalized by subtracting its mean and dividing by the square root of its co-variance for each of the batch samples. Batch normalization was shown to improve and speed-up the learning process while having a slight regularization effect as it adds some noise to each layer, which reduces over-fitting. In addition, batch normalization allows each layer to change its weights more independently from other layers (Ioffe & Szegedy, 2015). A three dimensional maximum pooling layer was added after the normalization layer. Maximum pooling consists of down-sampling the input feature by binning over striding windows in order to make assumptions and extract features while lowering the data dimensionality. A maxpool

Table 4.2 Detailed summary of the output shapes of the classification network's layers

Layer (type)	**Output Shape**
InputLayer	(None, 230, 64, 27, 1)
conv3d_1	(None, 230, 64, 27, 16)
batch_normalization_1	(None, 230, 64, 27, 16)
max_pooling3d_1	(None, 115, 32, 14, 16)
conv3d_2	(None, 115, 32, 14, 32)
batch_normalization_2	(None, 115, 32, 14, 32)
max_pooling3d_2	(None, 58, 16, 7, 32)
conv3d_3	(None, 58, 16, 7, 32)
batch_normalization_3	(None, 58, 16, 7, 32)
max_pooling3d_3	(None, 29, 8, 4, 32)
flatten_1	(None, 29696)
dense_1	(None, 1024)
activation_1	(None, 1024)
batch_normalization_4	(None, 1024)
dropout_1	(None, 1024)
dense_2	(None, 128)
activation_2	(None, 128)
dropout_2	(None, 128)
dense_3	(None, 3)
activation_3	(None, 3)

size of $(3 \times 2 \times 2)$, a strides of $(2 \times 2 \times 2)$, and a same padding are used. The output of the convolutional layers is flattened into a feature vector and fed to a three layers fully connected neural networks having 1024, 128, and 3 nodes, respectively. Each node of the fully connected layers is connected to a ReLU activation function, and a 50% dropout layer. Dropout layers randomly select a percentage of the hidden nodes in a layer while ignoring the remaining nodes. Dropout layers have a regularization effect as they ensure that every data point is used in the training of a random subset of the hidden neurons. Hence, for a specific layer, the network is trained by averaging an ensemble of individual neural networks, instead of the whole layer nodes in a single network. The final stage of the classifier consists of a three nodes output layer followed by a softmax activation function for classification of the three sleep stages, i.e., REM, NREM, and wake.

Table 4.3 Model training parameters and computational resources

Weights initialization	**Convolutional/ Dense layers**	**Xavier uniform**
Batch size	Training/Testing	4
GPU	Brand Memory Number	Nvidia Tesla P100 12 GB HBM2 4
CPU	Brand Memory Frequency Number	Intel® Xeon® Processor E5-2650 v4 123 GB Ram 2.2 GHz 6
Loss function	Type	Categorical CE Focal loss: γ Class-weighted: α
Early stopping	Patience Monitored value Stopping threshold	10 Validation loss 0.001
Optimizer	Name Learning rate Beta 1 Beta 2	Adam 0.001 0.9 0.999

4.3.5 Model training

The network's learning parameters and the computational resources used for the training are shown in table 4.3. Xavier uniform initialization was used to initialize the weights of the convolutional and fully connected layers at the beginning of the training. The Xavier uniform initialization consists of drawing random samples from a uniform distribution within $-l$ and $+l$, where $l = \sqrt{\frac{6}{f_{in}+f_{out}}}$, f_{in} and f_{out} are the number of input and ouput units (Glorot & Bengio, 2010). A batch size of 4 samples was used in the training to fit the available computational capacity. We used four Nvidia Tesla P100 graphical processing units (GPUs), with a memory of 12 GB HBM2 each, and six Intel® Xeon® Processor E5-2650 v4 central processing units (CPUs) rated at 2.2 GHz, with a 123 GB-RAM of memory.

The loss function used to adjust weights during training is the categorical CE function:

$$-\sum_{c=1}^{3} y_{o,c} \log\left(p_{o,c}\right) \tag{4.1}$$

where o is the current observation, c is the class, $y_{o,c}$ is equal to 1 if the classification is correct and 0 if not, and $p_{o,c}$ is defined as follows:

$$p_{o,c} = \begin{cases} p & \text{if } y_{o,c} = 1 \\ 1 - p & \text{otherwise} \end{cases} \tag{4.2}$$

where $p \in [0, 1]$ is the predicted probability that observation o belongs to class c. Two weighting factors $\alpha_{o,c}$, and $\left(1 - p_{o,c}\right)^{\gamma}$, were added to the loss function presented in equation (4.1). $\alpha_{o,c}$ is the class weight factor, used to equalize the weight of the three classes which is imbalanced due to the non-equal number of instances between the three classes in the data-set. For a given class, $\alpha_{o,c} = \frac{n_\beta}{n_c}$, where n_β is the number of instances in the classes having the largest proportion of instances, and n_c is the number of instances in the current class c. $\left(1 - p_{o,c}\right)^{\gamma}$ allows to further reshape the loss function in order to down-weight samples that are easily classified (obvious), and give more weight to harder samples, hence giving a higher chance for these samples to be accurately classified. The resulting loss function is written as follows:

$$-\sum_{c=1}^{3} -\alpha_{o,c} \left(1 - p_{o,c}\right)^{\gamma} \log\left(p_{o,c}\right) \tag{4.3}$$

Following training trials and literature recommendations, we used $\gamma = 2$ (Lin, Goyal, Girshick, He & Dollar, 2017). An early stopping technique was adopted as a regularization step in order to help prevent over-fitting. The validation loss was monitored over the model training procedure, and the model was told to stop learning when loss on the validation set has decreased by less than 0.001 over 10 epochs, even if the training loss is still decreasing. In such areas in the loss function, the loss is likely to stay stable or even increase if not stopped (Girosi, Jones & Poggio, 1995). The optimizer used to minimize the loss function is Adam (Reddi, Kale & Kumar, 2018). According to Goodfellow *et al*, Adam's algorithm combines the advantages of other

optimization algorithms and is generally robust to the choice of hyper-parameters (Goodfellow, Bengio & Courville, 2016).

4.4 Experimentation results and discussion

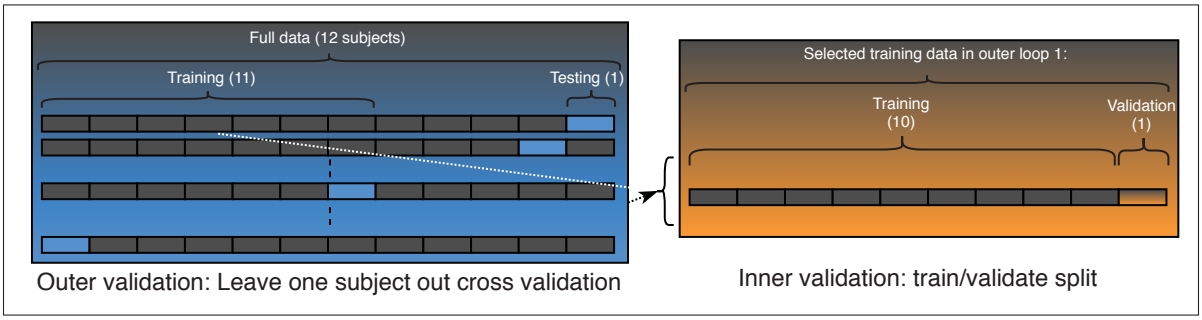

Figure 4.5 Leave one subject out cross validation scheme

In order to train, validate and test the model, the data was split into three subsets: training, validation, and testing sets. The subject label is preserved in the training process in order to make sure that the network model's performance is validated and tested on never-seen subjects. The validation scheme is illustrated in figure 4.5. Leave one subject out cross validation (LOSOCV) was used, where twelve different data splits were used to train and test the model, leaving one subject for testing. In each data split, one out of the eleven subjects' data used for training was used for validation in order to optimize the model's parameters on a new subject's data. This validation paradigm was shown to evaluate the model's generalization performance where the obtained classification results are not subject dependent (Arlot & Celisse, 2010).

In order to calculate the average performance of the classifier, percentage confusion matrices were calculated for each of the LOSOCV splits, then the average confusion matrix was calculated by multiplying the average percentage confusion matrix by the average number of sample per subject. An overall average classification accuracy of 74.27% was obtained, with a precision of 72.54% and a recall of 62.86%, showing the relatively high classification accuracy of the proposed method. In order to assess the reliability of the results, and take into account the agreement by chance, we performed a Cohen's kappa calculation. The obtained testing Cohen's

Kappa coefficient was 45.4% which reflects a moderate intended agreement (Landis & Koch, 1977).

In the following paragraph, we compare the obtained results to the literature. We class literature methods of unobtrusive sleep monitoring in two categories: 1) general monitoring methods, which include sensors such as actigraphs, microphones, accelerometers, and ballistocardiographs, and 2) bed-sheet pressure methods, that compare more to our method. To the best of our knowledge, one research paper has presented a method for the unobtrusive classification of sleep stages using bed-sheet pressure sensors. Precisely, Samy *et al* have interestingly used bed-sheet pressure sensors to estimate sleep stages using handcrafted features (Samy *et al.*, 2014). They manually calculated the respiration rate, respiration rate variability, number of leg and body movements, posture, and body orientation features for each 30 seconds epoch. The extracted features were fed to the classifier in order to estimate three sleep stages Wake, REM, and NREM. Before comparing and discussing our and their approach, we briefly present the results. Table

Table 4.4 A comparative table showing the average confusion matrix we obtained, and the precision and recall values using our method and those obtained by Samy *et al.* (2014) for two-stages and one-stage classifications

		Predicted					
		Wake	NREM	REM	**Our Precision**	Precision by Samy et al: 2 stages classification	Precision by Samy et al: 1 stage classification
Actual	Wake	59.34	25.40	1.82	**69.41%**	87.84%	79.41%
	NREM	48.99	540.27	131.66	**75.10%**	27.45%	7.84%
	REM	7.642	36.71	117.97	**73.12%**	55.88%	23.52%
	Our recall	**51.75%**	**89.85%**	**46.98%**			
	Recall by Samy et al: for 2 stages classification	100%	38.18%	17.43%			
	Recall by Samy et al: for 1 stage classification	96.17%	10.61%	5.97%			

4.4 illustrates the average testing confusion matrices using LOSOCV, obtained by Samy *et al* for Support vector machines (SVM) based (a) two stage, and (b) one stage classification, and (c) for the confusion matrix we obtained using the approach proposed in this paper. Moreover, detailed evaluation metrics are given i.e., precision and recall values for each of the classes. Due to the different sample size considered for each subject, percentage confusion matrices were first calculated for each of the LOSOCV splits, before being averaged and multiplied by the average number of samples per subject.

As shown in table 4.4, a better overall classification performance was obtained, and a less severe precision and recall disparity between classes due to the data's class-imbalance. In order to understand the results, we show: the number of the subjects recruited in the data n_S, the ratio of the number of males and the number of females r_{MF}, the data size represented by the total number of recording hours collected from all subjects n_H, the bed-sheet pressure sensors type and density, i.e. number of sensors embedded in the mattress, the feature extraction technique, the classification method, and the obtained results: accuracy, precision, and recall. It is noted that the results presented in table 4.4 correspond to the SVM algorithm presented in table 4.5. Table 4.5 presents a comparison of method along with the obtained results for both general and bed-sheet pressure sensors including our method.

By comparing bed-sheet pressure sensors methods, as shown in the table, we were able to get a relatively better accuracy, precision, and recall on average for the three classes classification with a validation on approximately double the recording hours and the number of recruited subjects, and using $\approx \frac{1}{5}$ of the number of pressure sensors.

A more detailed discussion on bed-sheet pressure sensors methods is presented in the next section in order to cover the criteria presented in table 4.5. Samy *et al* conducted experiments on 7 subjects, with 4 males and three females, and a total of 50 recording hours. Since we believe that a larger data-set is better for the model's generalization performance, in our experiments, we recruited 12 subjects, 6 males and 6 females, and approximately the double or a total of 92.5

recording hours. We used a 1728 FSR bed-sheet pressure sensors, which is approximately $\approx \frac{1}{5}$ the bed-sheet pressure sensors used by Samy *et al*.

Table 4.5 A comparison of the proposed method to the state-of-the-art methods that use pressure sensor mattresses to classify sleep stages. n/a : metric not available, n_S : number of subjects, r_{MF} : number of males over number of females, and n_H : total number of recording hours contained in the data

Author, year	Data	Acquisition hardware	Feature extraction	Classification method	Number of classes	Accuracy	Precision	Recall	Cohen Kappa
General methods									
Kalkbrenner *et al.* (2019).	n_S = 53, r_{MF} = 1.65, n_H = 22207,	Actigraph abdominal belt & neck microphone	30 hand-crafted cardio-respiratory and movement features	Linear discriminant analysis	3	76.3%	*n/a*	*n/a*	0.42
Rao *et al.* (2019).	n_S = 4, r_{MF} = 0.66, n_H = 186,	Fit-bit wrist accelerometer	1D-CNN + bi-LSTM	Deep ANN	4	63%	*n/a*	*n/a*	*n/a*
Rao *et al.* (2019)	n_S = 25, r_{MF} =*n/a*, n_H =*n/a*,	Dozee Ballistocardiograph	1D-CNN + bi-LSTM	Deep ANN	4	74%	73%	74%	*n/a*
Bed-sheet pressure sensors methods									
Samy *et al.* (2014).	n_S = 7, r_{MF} = 1.33, n_H = 50,	8192 uniformly distributed piezoresistive pressure sensors	Handcrafted features of breathing and movements	K nearest neighborhood	3	67.12%	55.9%	56.9%	*n/a*
Samy *et al.* (2014).	n_S = 7, r_{MF} = 1.33, n_H = 50,	8192 uniformly distributed piezoresistive pressure sensors	Handcrafted features of breathing and movements	Support vector machines	3	70.33%	67.7%	68.6%	*n/a*
Samy *et al.* (2014).	n_S = 7, r_{MF} = 1.33, n_H = 50,	8192 uniformly distributed piezoresistive pressure sensors	Handcrafted features of breathing and movements	Naïve Bayes	3	72.20%	70.3%	71.1%	*n/a*
Our method.	**n_S = 12, r_{MF} = 1, n_H = 92.25,**	**1728 uniformly distributed FSR pressure sensors.**	**3D-CNN**	**Deep ANN**	**3**	**74.27%**	**72.54%**	**62.86%**	**0.454**

Samy *et al* manually extracted physiological features as follows: they constructed the respiratory signal by summing all 8192 pressure values and applying a frequency filtering technique to the obtained signal, in order to compute BR and its variability. Legs movements were counted by summing pressure values only in the legs region, and applying a threshold to detect significant pressure drop or increase. Body movements were also detected and counted using the same technique by using a threshold pressure value's amplitude. 32 more physical body features were added to explore posture, and limbs location on the mattress. In our method, we make the feature extraction step automatic, with 2 steps: 1) calculating the difference between consecutive body pressure images, and 2) computing the feature vector with consecutive learnable parameters using three dimensional convolutional layers. The advantages of using this technique are: 1) more advanced hidden patterns and complex non-linearities in the data distribution can be handled and used in classifiying sleep stages efficiently, and 2) using less static features, such as posture, hips, and limbs location on mattress, and the body shape, and more dynamic features such as movements and breathing activities, and the variability of this activity during an epoch. It is indeed known that these dynamic features are much more co-varying with sleep stages than posture and limbs orientation and location on the mattress. Regarding the classification method used to output a sleep stage class using the input features, Samy *et al* have explored two data-driven algorithms: K-nearest neighborhood (KNN), support vector machines (SVM), and one model-based method: naïve bayes.

In our method, we used a 3DCNN followed by a deep ANN in order to perform the classification task. The advantages of this classification method are: 1) the data driven nature of the model, and the ability of the classifier to adapt and learn from clinical data and learn data noise and imperfections, which improves the generalization performance for future instances classification, 2) the relatively high scalability of the model; for instance, if more hours of data recording from different subjects becomes available in the future, more convolutional and fully connected layers could be added, hence more trainable parameters can be introduced, and the model could potentially have more complex classes boundaries and a better performance. These results could be applied to different kind of mattresses and different subjects due to the two respective reasons: the data is normalized with respect to its variance and not absolute amplitude, and the sleeping

paradigm and architecture is known to follow the same pattern in different subjects. Hence, training data from different mattresses and subjects could be used in order to increase the data sample size and enhance the robustness of the model. Such wide validation techniques are likely to increase the generalization performance of the algorithm and the classification precision and accuracy due to the potential increase of model complexity with bigger data sizes.

We expand the comparison to general methods of unobtrusive sleep monitoring cited in table 4.5, that use other sensors to measure the body movements and the cardio-respiratory activity. Kalkbrenner *et al* used a combination of actigraphy sensor attached to an abdominal belt and a microphone attached to the neck to collect physiological data during sleep (Kalkbrenner *et al.*, 2019). The method can be considered unobtrusive with respect to PSG, and less unobtrusive when compared to bed-sheet pressure sensors, where no cables or sensors attached to the body. Kalkbrenner *et al* used a relatively a high amount of 22207 total recording hours to validate their approach. 30 features were manually extracted that characterize cardio-respiratory and body movement features. The results obtained for the classification of NREM REM and Wake were 76.3% for accuracy, and 0.42 for Cohen's Kappa coefficient, compared to a 74.27% and 0.454, respectively, using our proposed method. Rao *et al*, proposed a method for unobtrusive sleep stages classification using a fit-bit wrist accelerometer. They used a 1D-CNN in combination with a bi-directional long short-term memory bi-LSTM for feature extraction, along with a deep ANN as classifier. The method was validated with respect to PSG on 4 subjects for a total of 186 hours of sleep recording. Although the results are preliminary, they reach a classification accuracy of 63% for 4 classes classification Rao *et al.* (2019). Furthermore, Rao *et al* used the same classifier architecture on ballistocardiography data acquired from a relatively large data-set of 25 subjects. They reported a 74%, 73%, and 74% for accuracy, precision, and recall. In both results reported by Rao *et al*, no information was provided on Cohen's Kappa coefficient to assess the intended agreement and compare the performance of the classification. An important aspect that could be noticed by inspecting the table 4.5, is that the classification performance is further improved with a larger data-set, specially when collected from a higher number of subjects. This is logically due to the increase of the data variance when increasing the number of

subjects during the training phase. The importance of data size and structure is further discussed in this section 4.5, where practical steps and recommendations are given to improve performance with data. With respect to the application, the proposed method could be further adapted to improve performance. The stored weights of the 3D-CNN and the deep neural networks classifier model could be loaded and retrained on additional data samples that could be recorded in the future. This could increase the variance of the data and improve the classification performance. However, the input dimensions of the model should be respected as described in section 4.3. Hence for body pressure distribution recording on a different bed-sheet pressure sensors, having different shape, dimensions, or sampling frequency, the data could be transformed in order to be a compatible input to the presented method. Geometrical transformations and undersampling in the three dimensions could be applied on the 3D samples corresponding to 30 seconds epochs of pressure images. In what follows, we discuss future challenges and perspectives and the steps to a wider clinical validation and use of the presented method. Although the results presented in this paper are preliminary and not yet satisfactory to claim an eventual adoption of bed-sheet pressure sensors in sleep clinics, we believe that the potential of this application is worth being widely recognized and further explored. One of the immediate needs for such sleep monitoring approach to reach clinical use lies in the data availability. More data allows the increase of the model complexity, i.e, the number of trainable parameters. For instance, increasing the classification model complexity i.e., to the conovlutional or fully connected layers, can increase the accuracy and the model's ability to have a better generalization performance and separate sleep stages more rigorously. In this vein, we believe in the potential of such method due to the ease of data acquisition. During our experiments, the bed-sheet pressure sensors was placed under the bed-sheet, not adding any constraint or discomfort to the subject undergoing the PSG test. For the future, a practical approach of gathering massive data that could be considered, is the use of bed-sheet pressure sensors to acquire pressure images during conventional PSG tests. This would not require any changes to the PSG procedure, and does not add any biases or constraints to how the data is acquired. Through this approach, as sleep professional labels sleep stages over the night, in 30 seconds epochs, where the corresponding pressure data is automatically labelled and ready to use for supervised deep learning algorithms

due to recorded time stamps. A further step is to create a platform, among the world's sleep clinics, in order to unify efforts and form an online database, where researchers can find data and bring contributions to unobtrusive sleep monitoring using the cutting-edge methods of machine learning and the collected big data.

4.5 Conclusion and future perspectives

The growing interest and emerging devices and technologies have undeniably made unobtrusive sleep monitoring a prominent research lines, in which several open research directions and challenges need to be addressed. Clinical validation and access to data are the main challenges researchers are currently facing. In this paper, we propose a new method for an automatic and unobtrusive monitoring of sleep stages using bed-sheet pressure sensors. We use the dynamic body pressure distribution on the mattress and the PSG's polygraphic signals to train a 3D-CNN artificial deep neural networks classifier. We were able to classify NREM, REM, and Wake stages with a 74.27%, 72.54%, and 62.86% average accuracy, precision, and recall, respectively. We noticed that using the pressure difference between consecutive pressure images as input to the network instead the raw pressure images considerably improves the classification performance. Although the results presented in this paper are preliminary, and not yet satisfactory to claim an eventual adoption of bed-sheet pressure sensors in sleep clinics for unobtrusive sleep stages classification, we believe that the potential of such application is worth being widely recognized and further explored. Deep learning and CNN networks have demonstrated their potential of providing a consistent and accurate classification performance when a large data-set is provided. Future work has to focus on the simultaneous data acquisition of pressure and PSG data to make a larger data-set. This can be accomplished during conventional PSG tests held in sleep clinics, where the bed-sheet pressure sensor could be placed under the subject's bed-sheet during the test, introducing no measurement biases, discomfort, or constraints to the PSG test. A promising step could be a collective online platform where sleep clinics can upload their pressure + PSG data with a description of the subject's health status, allowing researchers to apply big-data algorithms for a wider clinical validation of a more complex unobtrusive sleep stage classifier.

Finally, a potential contribution is the combination of another unobtrusive measure such as the HRV using watch actigraphy sensors, which could add relevant information to the classification sleep stages.

CONCLUSION AND RECOMMENDATIONS

The purpose of the present thesis was 1) to improve the understanding of the field of unobtrusive sleep studies and 2) to contribute to the field by proposing physiological behaviors monitoring methods during sleep using a bed-sheet containing textile pressure sensors.

Four objectives were achieved throughout this work:

The first objective was to investigate unobtrusively measurable physiological changes during sleep and review and discuss unobtrusive sleep monitoring techniques. The second objective was to provide an unobtrusive method of monitoring bed-postures using bed-sheet pressure sensors. The third objective was to provide an unobtrusive method of BR monitoring during sleep using bed-sheet pressure sensors. The fourth objective was to provide an unobtrusive method for classifying sleep stages using bed-sheet pressure sensors.

The main findings we were able to draw from this thesis can be summarized as follows:

We found that unobtrusive sleep monitoring research works have not yet succeeded to reach clinical approval due to a lack of clinical validation. We found a combination of features that involves weight and shape information in the classification of bed-posture and achieves an accuracy that is superior to what reported in the state-of-the-art works results. The method could be used in sleep applications and other applications such as ulcer prevention in hospitalized patients. We found that it is possible to reconstruct raw breathing signals using the body pressure distribution on the mattress. Moreover we showed that by building posture specific respiration models, it is possible to compensate for posture effect on the reconstructed breathing signal and provide a BR monitoring system that overcomes what is reported in the literature. We found that exploring the dynamic body pressure distribution on the mattress using convolutional neural networks and artificial deep neural networks could provide a more accurate classification performance of sleep stages then hand-crafted features.

Contributions

Conclusively, we can state the contributions brought by this thesis as follows:

Contribution 1: We presented an exhaustive literature review that provides the reader with a multidimensional perspective on both unobtrusively monitored physiological parameters and patterns, and unobtrusive sleep monitoring techniques. We were able to conclude that unobtrusive monitoring methods have not yet succeeded in obtaining a clinical approval or consensus, and consequently have not been classified as medical devices according to FDA or CE. This is due to several factors, mainly lack of validation, and access to clinical data. Based on this exhaustive review, that has been published and quoted as an original contribution in the field, we provided recommendations for specific potential research lines where we believe future endeavors should bring contributions in order to advance the field.

Contribution 2: We proposed a feature extraction method, and a classification algorithm to unobtrusively classify sleeping postures from a pressure measurement. Works in the sleep literature have not been able to successfully classify prone and supine postures separately, due to the similar shape of the body in the two postures when lying on the mattress. We based our contribution on the idea that weight distribution, or shape information, are not enough to classify prone and dorsal postures. Thus from the pressure images, we extracted the HoGss and LBP features in the aim of involving both body weight and shape information in the classification. We found that this feature extraction helped us classify prone and dorsal posture classes successfully with a high accuracy for all four sleeping postures.

Contribution 3: We proposed a method to unobtrusively monitor the BR during sleep using bed-sheet pressure sensors, while allowing and taking into consideration posture changes. When using bed-sheet pressure sensors, the correlation between breathing activity and body pressure

distribution on the mattress does not remain the same with different postures. Previous related works have not been able to successfully monitor the BR while the posture changes. We proposed a method that uses the posture detection algorithm proposed in contribution 2, in order to select the optimal parameters of a multi-sinusoidal model based extended Kalman filter that we used to reconstruct the breathing signal and compute the BR accordingly. Based on a Bland-Altman validation procedure with respect to a respiratory belt, we obtained an agreement that has not been yielded in the literature, showing that respiratory belt and bed-sheet pressure sensors could be interchangeably used in BR monitoring during sleep.

Contribution 4: In this work we developed a method for unobtrusive sleep stages classification using bed-sheet pressure sensors. We used the dynamic body pressure distribution on mattress and PSG's polygraphic signals to train and test a 3D-CNN deep neural neural network classifier. We were able to classify NREM, REM, and Wake stages with a relatively high average accuracy, precision, and recall. We noticed that using the pressure difference between consecutive pressure images as input to the network instead the raw pressure images has helped us further explore the body dynamics on the mattress, which has considerably improved the classification performance. Although the results presented in this contribution are primary and not yet satisfactory to claim an eventual adoption of bed-sheet pressure sensors alone in sleep clinics for unobtrusive sleep stages classification, we believe that the potential of this method could be further recognized by the availability of a larger data-set, which is likely to yield better and consistent results on a larger population in an ecological perspective of sleep evaluation.

5.1 Recommendations and remarks for future works

Based on what is presented in this thesis, our conclusive recommendations and remarks for future directions can be summarized as follows:

- **Clinical experimentation and database availability:** the lack of reliable data is a major issue facing two of the most crucial steps towards an unobtrusive sleep monitoring: 1) validation, and hence medical devices monitoring sleep unobtrusively, and 2) "teaching" machines to perform autonomous tasks, and lessening medical interventions and assistance requirements. A potential line of research leading to advancements in this area consists of conducting clinical experiments in order to collect physiological data during sleep. For instance, a simultaneous data acquisition using both the experimental device and the standard system i.e., PSG, is bound to give the opportunity for researchers to compare, analyze, teach machines, and validate with respect to the standard measurements leading to substantial advancements.

- **Clinical validation with respect to standards:** researchers have been focusing on proposing methods and devices for giving insights on sleep behavior leading to a larger spectrum of unobtrusive sleep monitoring techniques. However, a number of studies have shown that these techniques have been rarely validated with respect to PSG in a significant and reliable way (Roomkham, Lovell, Cheung & Perrin, 2018) and (Baroni, Bruzzese, Di Bartolo & Shatkin, 2016). Clinical validation is an inevitable phase for approving a medical device and adopting it in clinics. Hence, future efforts are bound to work on this line of research in order to validate the applicability of a broad range of existing devices and acquisition techniques.

- **Machine learning applications in unobtrusively acquired data during sleep:** this line of research consists of using the growing knowledge in machine learning techniques in the application of sleep studies. In an era where both the computation speed and deep neural networks are evolving in a tremendously fast pace, high dimensional patterns could potentially be leveraged in estimating sleep hypnograms, classifying apnea events and scoring sleep quality (Biswal *et al.*, 2017). This direction has recently started gaining researchers' interests (Chambon, Galtier, Arnal, Wainrib & Gramfort, 2018; Xia, Li, Jia, Wang, Chaudhary, Ramos-Murguialday & Birbaumer, 2015; Zhang, Wu, Bai & Chen,

2016). However, the existing works have covered the classification of sleep stages based on obtrusive and conventional data. Hence, this highlights the need to conduct similar research using autonomous physiological functions such as cardiac, breathing, and body movements activities in order to bring advancements in unobtrusive sleep monitoring.

- **Assessing conformity of the proposed techniques to norms and regulations:** it is one of the essential requirements resulting in a potential medical device. It consists of a systemic evaluation of the regulations and norms as early as during the design phase to the implementation and validation. As previously established in the thesis, the proposed unobtrusive sleep monitoring techniques have rarely succeeded in reaching industrial gates, who's outcome is a class-defined medical device. Thus a substantial work has to be done in this area in order to transfer the existing knowledge to the medical field.

- **Exploring hardware, smart clothes, wearables, and E-textiles for data acquisition** Last but not least, exploring potential and new ways of acquiring physiological data without imposing constraints on the subject is a tremendous need in the field of sleep studies. Future works needs to be done on two levels: 1) propose new methods and apparatus: although a wide spectrum of methods and devices have been proposed, proposing new solutions could make it considerably much easier for unobtrusive sleep monitoring to reach the medical field; and 2), improve the existing systems in what is related to hardware performance optimization and parameterization. This includes for instance, only improving electrodes positioning in capacitive ECG sensing eventhough by using same electrodes types, has improved potentially the signal quality and HRV analysis, leading to a better correlation with sleep stages (Dossel, Schneider & Muller, 1998).

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