UNIVERSITY OF CALIFORNIA
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Radar and Thermal for Remote Sleep Monitoring of Breathing and Apnea

A thesis submitted in partial satisfaction
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by

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ABSTRACT OF THE THESIS

Radar and Thermal for Remote
Sleep Monitoring of Breathing and Apnea

by

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Master of Science in Electrical and Computer Engineering
University of California, Los Angeles, 2024
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Polysomnography (PSG), the current gold standard method for monitoring and detecting sleep disorders, is cumbersome and costly. At-home testing solutions, known as home sleep apnea testing (HSAT), exist. However, they are contact-based, a feature which limits the ability of some patient populations to tolerate testing and discourages widespread deployment. Previous work on non-contact sleep monitoring for sleep apnea detection either estimates respiratory effort using radar or nasal airflow using a thermal camera, but has not compared the two or used them together. We conducted a study on 10 participants, ages 34 - 78, with suspected sleep disorders using a hardware setup with a synchronized radar and thermal camera. We show the first comparison of radar and thermal imaging for sleep monitoring, and find that our thermal imaging method outperforms radar significantly. Our thermal imaging method detects apneas with an accuracy of 0.99, a precision of 0.68, a recall of 0.74, an F1 score of 0.71, and an intra-class correlation of 0.70; our radar method detects apneas with an accuracy of 0.83, a precision of 0.13, a recall of 0.86, an F1 score of 0.22, and an intra-class correlation of 0.13. We also present a novel proposal for classifying

obstructive and central sleep apnea by leveraging a multimodal setup. This method could be used to accurately detect and classify apneas during sleep with non-contact sensors, thereby improving diagnostic capacities in patient populations unable to tolerate current technology.

The thesis of Kai Antonio Del Regno is approved.

Ashley E. Kita

Aydogan Ozcan

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University of California, Los Angeles

2024

To all of my friends—

I would be nowhere without you

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CHAPTER 1

Introduction

Sleep apnea disorders are conditions in which breathing is interrupted during sleep. Untreated sleep apnea can result in daytime sleepiness, leading to a higher risk of motor vehicle and workplace accidents, as well as quality of life impacts, higher risk of cardiovascular health issues, and metabolic dysregulation, resulting in an increased risk of diabetes [EKS09]. One form of sleep apnea is obstructive sleep apnea (OSA), which occurs due to airway narrowing or obstruction during sleep [PRO11]. This is in contrast to central sleep apnea (CSA) which occurs when pauses in breathing occur due to problems with communication between the brain and muscles for respiration [ACR12]. OSA, in particular, is a tremendous public health problem that affects roughly 17% of women and 34% of men and is likely underdiagnosed [GP20]. Both forms of sleep apnea cause the affected person to have reduced breathing (hypopnea) or pauses in their breathing (apnea). These disorders are clinically defined and categorized into severities based on the apnea-hypopnea index (AHI) - the number of apnea or hypopnea events per hour of sleep [EKS09].

The gold standard for diagnosing sleep apnea disorders is polysomnography (PSG) conducted in a sleep lab [EKS09]. At-home testing with a portable monitor, known as home sleep apnea testing (HSAT), is also considered acceptable so long as the portable monitor, at minimum, measures nasal airflow, respiratory effort, and blood oxygenation. In both of these methods, signals are recorded throughout the patient's sleep and scored by a trained sleep technician according to the American Academy of Sleep Medicine (AASM) criteria. An apnea is scored if the nasal airflow signal amplitude drops by at least 90% for at least 90%

of a duration of least 10 seconds [TQB23]. Apnea may be classified as obstructive if there is continued or increased respiratory effort during the duration, as central if respiratory effort is absent during the duration, or mixed if respiratory effort is initially absent but returns while nasal airflow is still reduced. Hypopnea is scored if the nasal airflow signal amplitude drops by at least 30% for at least 90% of a duration of at least 10 seconds and the blood oxygenation desaturates by at least 4% across that duration. Respiratory-effort-related arousal is scored if there is a sequence of breaths lasting at least 10 seconds where nasal airflow decreases or respiratory effort increases, and arousal from sleep occurs [TQB23].

The AASM recommends respiratory monitoring in PSG through the use of oronasal thermal sensors for apnea identification, nasal pressure transducers for hypopnea identification, esophageal manometry or dual thoracoabdominal inductance plethysmography belts for respiratory effort monitoring; a pulse oximeter for blood oxygenation monitoring; a microphone, piezoelectric sensor, or nasal pressure transducer for monitoring snoring; an arterial, transcutaneous, or end-tidal PCO2 sensor for hypoventilation detection [TQB23]. We visualize salient examples of how breathing and apneas manifest on sleep lab airflow and respiratory effort sensors in Fig. 1.1. For HSAT, the AASM recommends at least a nasal airflow sensor, a respiratory effort sensor, some type of oxygen saturation sensor, and a heart rate sensor, either using photoplethysmography or electrocardiography. Optionally, they recommend a sensor for body position, a sensor for sleep/wake monitoring, and a sensor for snoring using either nasal pressure, a microphone, or a piezoelectric sensor.

A contactless method of detecting and differentiating obstructive, central, and mixed events would allow for individuals who do not tolerate contact sensors (e.g. young children and individuals with intellectual disabilities) to be assessed for sleep apnea. Sleep apnea is underdiagnosed and undertreated in these populations due to poor patient ability to tolerate current PSG or HSAT [PDA21]. A contactless method of evaluation for sleep apnea may allow for repeat studies to be performed more easily to assess how well an intervention (e.g., sleeping on one's side, using an oral appliance, or undergoing a surgical procedure) changes

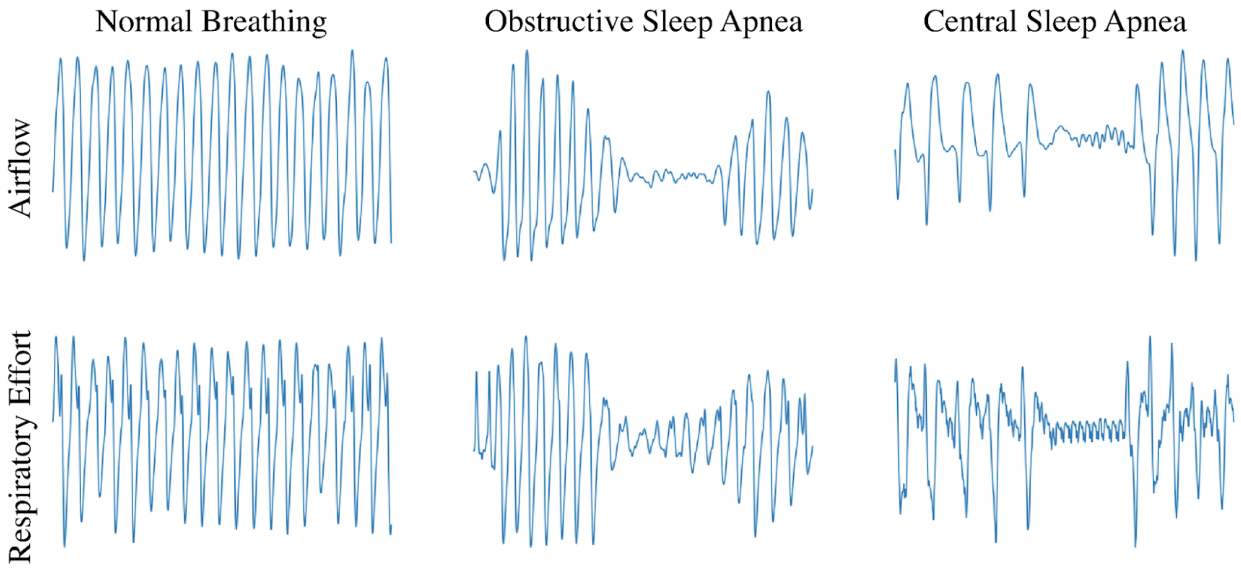

Figure 1.1: **Airflow and respiratory effort waveforms measured with sleep lab sensors depicting normal breathing, obstructive apnea, and central apnea.** During the onset of CSA, we notice anomalies in both the airflow and the respiratory effort waveforms; these anomalies manifest as attenuating factors that lower the amplitude of the two waveforms. Unlike CSA, the occurrence of OSA can be detected only through the airflow, which experiences a similar reduction in amplitude as the previous case. In comparison, the respiratory effort does not experience the same degree of attenuation for OSA.

one's sleep apnea. This would allow patients to try different management techniques and see what works best for them. Furthermore, information could be transmitted wirelessly for interpretation by a technician or automatic interpretation through the use of an analysis app. Therefore, finding alternatives to conventional sleep monitoring that are both non-contact and can be conducted in a patient's home can greatly improve patient care and speed of diagnosis. Inspired by the use of a multimodal camera+radar setup for remote vital sensing [VCA22], we investigate using thermography-based nasal airflow measurements as a replacement for the contact nasal airflow sensors and radar-based respiratory effort measurements as a replacement for chest motion sensors. We present the following contributions of

this thesis:

1. A comparison of radar and thermal modalities for remote sleep monitoring detection of breathing and sleep apnea.

2. A non-contact multimodal thermal and radar stack for detection and clinically relevant classification of apnea.

3. A dataset composed of 10 sleeping patients with hardware-synchronized thermal videos, frequency-modulated continuous wave (FMCW) radar data, and ground truth waveforms with annotations performed by a certified sleep technician at a sleep center. In addition, we open-source our data-collection framework, code base, and circuit schematics for collecting hardware-synchronized radar and thermal data, accessible at https://github.com/UCLA-VMG/NonContactApneaDetection.

Previous works are limited in scope to detecting apnea events using one clinically relevant respiratory signal, either respiratory effort or nasal airflow [MFF07, MVF09, FPM09, CLC23, HZL18, ASY22, NSN19, NHS14, XDH20, DTZ13, NGW15, RDT14, RDT15]. Our findings support the development of a comprehensive, multimodal framework for non-contact diagnosis of sleep apnea disorders which can discriminate between central apnea disorders and OSA leveraging multiple clinically relevant respiratory signals.

CHAPTER 2

Related Works

2.1 Thermography for Airflow Estimation

Thermal imaging has been explored for many medical applications including non-contact respiratory rate estimation [ZVA23, MMK18, Amm96, GHR17]. In clinical PSG, a thermistor measures nasal airflow by detecting the thermal fluctuations near the patient's nostrils due to breathing [TQB23]. These fluctuations are also visible in thermal videos of a patient's face [BYC17, CWD20, YHZ22]. Mozafari et al. decompose the videos into rank-1 tensors and perform a spectral analysis on their power spectral densities to estimate the signal [MLG22]. Szankin et al. use a slow-fast convolutional neural network [FFM19] as a regressor to estimate the airflow signal [SKR23]. Methods for estimating airflow from thermal videos have also been validated on newborns [PYG19] and preterm infants [PHV17]. In addition to the previously discussed unimodal methods, several multimodal methods have been proposed that augment low-resolution thermal videos with RGB [CHL20, KRA24] and depth [PCV17] cues for lower-cost hardware deployment.

2.2 Visual and Wireless Sensing for Respiratory Effort

Respiratory effort can be defined as the muscle movements of the chest that drive respiration [VJS18], visible to the human eye as the expansion of the chest, abdomen, and neck as the lungs fill with air. Clinically, they are detected using esophageal manometry or inductance plethysmography [TQB23]. Several video-based algorithmic [BLM18, PPM17,

GVK22, JWM15, RAR15], and data-driven approaches [CLL23, ACF15, AFP16] have been proposed to extract the respiratory effort signal. In addition to visual methods, thoracic and abdominal movements can be measured using wireless sensors, such as impulse-radio radars [KC17, ZCZ21, HKZ22], Doppler radars [ZRV12, LPE15, LTP16, GL15], and FMCW radars [LHL21, PLA21, PKL22, WZW21, PKK23]. These approaches include both algorithmic [LHL21, PLA21, LTP16, GL15, ZRV12, KC17, GYC20] and data-driven [ZCZ21] solutions to estimate the respiratory effort.

2.3 Automatic Apnea Detection

Several methods have been developed to detect sleep apneas from ground truth breathing data using wavelet features [FGA05, EAS10, Has16, AA15], neural networks (e.g., MLPs, ANNs, CNNs, and LSTMs) [FGA05, ZTG21, EAS10, YLW21] of many architectures, and envelope detection [UCL21]. Methods have also been developed to detect sleep apneas from features of heart rate waveforms [GBV10, NWC14, GCN18, GCN16].

Several methods have been developed using nasal airflow information from infrared thermography to detect apneas in conjunction with either signal processing [MFF07, MVF09, FPM09] or deep learning [CLC23, HZL18]. An et al. propose a method to detect sleep apneas using nasal airflow information from infrared optical gas imaging [ASY22]. Parallel work has also been conducted to detect apnea events from acoustic recordings [NSN19, NHS14, XDH20, DTZ13, NGW15, RDT14, RDT15], analyzing the recordings to identify breathing signals and isolate periods where the breathing stops or is obstructed. While these methods can be effective for apnea detection, to our knowledge no previous method uses non-contact measurements of both nasal airflow and respiratory efforts jointly to detect and classify obstructive and central apneas. We hypothesize that a method estimating all or most of the same relevant physiological signals as the AASM recommended contact sensors [TQB23] would provide greater accuracy and clinical grounding than unimodal methods.

Our hardware stack can be used to estimate both the nasal airflow and the respiratory effort, and this thesis builds towards a multimodal method to detect and classify apneas.

Kang et al. provide a method for detecting apnea events using a respiratory effort signal measured with an impulse-radio radar only [KKL20]. A high-quality signal is extracted by performing a range-doppler analysis, followed by a Kalman filtering operation [KC17]. Binary classifiers are then trained to predict apneas based only on this estimated respiratory effort signal [KKL20]. Akbarian et al. provide a method for detecting apnea events from near-infrared videos of patients by computing the optical flow between frames of the videos and using a convolutional neural network to classify 10-second durations of the optical flow between apneic and non-apneic breathing with technician-annotated data as supervision [AGY21]. Carter et al provide a method for detecting apnea events using both respiratory and photoplethysmograph waveforms extracted from near-infrared videos [CJV23]

CHAPTER 3

Methods

We begin by describing our hardware setup in Section 3.1, followed by breathing waveform and respiratory rate (RR) extraction in Section 3.2 and apnea detection in Section 3.3 for both the radar and thermal modalities. An overview of the process is shown in Fig. 3.2. We conclude with a description of our proposed apnea classification method in Section 3.3.2.

3.1 Hardware Setup

As part of our clinical validation, six-hour recordings of patients participating in their PSG study were captured. Our hardware setup primarily consists of a thermal camera and radar placed in the periphery of the bed, visualized in Fig. 3.1. This is in addition to the existing ground truthing equipment used in PSG studies.

A radiometrically calibrated Teledyne FLIR Boson with a 512×640 resolution was positioned to the side of the bed and aimed at the face. This choice of placement was necessitated by the constraints of existing PSG procedures. As a result, the patient's nose was not always visible; for example, if they turned to the side facing opposite the camera, their face would be obscured. Beyond these experimental constraints, as a product set, we conjecture that a ceiling-mounted thermal camera could alleviate concerns about occlusions.

We also place an AWR1443BOOST FMCW radar beside the thermal camera and in the periphery of the patient, next to the bed. Similar placement constraints exist for the radar; however, unlike the thermal camera, the radar is not adversely affected by the orientation of

the patient. We balance attenuating factors from lateral position shifts and elevation offsets by operating the radar with all 3 transmitters and 4 receivers enabled. This allows us to perform beamforming post-acquisition and improve the SNR.

A synchronization signal was sent via an Arduino microcontroller to align the ground truth signals recorded by the external hardware used in contemporary PSG studies, as well as triggering the thermal and radar sensors at a 30 Hz rate. The alignment was performed on the vital sign recordings, as well as other ground truth labeling obtained from the PSG and technicians involved with the sleep study. A full-night or split-night PSG was recorded and annotated by a trained sleep technician in accordance with AASM guidelines [TQB23].

3.2 Breathing and Respiratory Rate (RR) Estimation

While both thermal cameras and radars yield RR estimates, they do so by sensing slightly different physical phenomena. Thermal cameras monitor intensity changes, while radars track the instantaneous displacement of the chest (and/or the abdomen) to produce a breathing signal. From this breathing signal, we can easily extract the breathing rate by performing a bandpass filter, windowing the signal, and picking the frequency which maximizes the power spectral density. This type of processing is commonplace in vital sign estimation [BYC17, ZCZ21, VCA22]. This allows us to evaluate the accuracy of the breathing rate estimation over time.

3.2.1 Airflow and RR from Thermography

The breathing rate information in thermal videos of a patient's face is primarily located in a small region below the nostrils caused by temperature changes during inhalation of room temperature air or exhalation of warm air from the lungs. Therefore, all videos of patients are manually cropped to a tight region around the nose as shown in Fig. 3.2. A simple approach taken by prior works [CWD20, BYC17] collapse the video to obtain a 1D temporal

signal, $x[t]$, by spatially averaging each frame. This is followed by filtering operations to limit frequencies to the accepted range of breathing rates. However, this approach does not translate perfectly to our setting because we do not have control over patient motion, which severely degrades the signal. Since motion and disturbances can be modeled as spikes or delta functions, we can compensate for them by averaging the derivative signal over a $N = 25$ frame window following by a derivative operation to remove low frequency trends. We found that this operation dampens artifacts from motion as well as compensates for any spurious calibrations that the thermal camera requires. The operation can be written as:

$$y[t] = \frac{1}{N} \sum_{i=-\lfloor N/2 \rfloor}^{\lfloor N/2 \rfloor} x[t+i] - x[t+i-1]. \tag{3.1}$$

We further detrend the signal $y[t]$ with a high-pass filter, and the resulting signal is our non-contact estimate of the nasal airflow signal.

3.2.2 Respiratory Effort and RR from Radar Sensors

To extract respiratory effort information from radar recordings, we begin with the fast-slow matrix and transform to a range matrix using the Fast Fourier Transform. We then beamform all range bins using a standard Bartlett beamformer, which has been employed in previous works on vital sign monitoring [PKK23, WZW21] effectively. The beamforming step helps to increase the SNR, since the patient is not always located at the $0, 0$ azimuth/zenith angle of the radar, and the patient position can change during sleep. Once the beamformed range matrix is constructed, the first step is to find the primary range bin that a person is located in. This is usually chosen as the range bin with the maximum power [ASD19]. However, this assumes that the patient is the main object in view, which is not always the case in a sleep monitoring setting where the radar is placed on the side of the patient. We improve upon this by taking a window of range bins, M, around the maximum power range bin and choosing the range bin with the maximum SNR. We calculate the SNR of of the ith

unwrapped range bin, $x_i[t]$ as:

$$\alpha_i = \frac{\sum_{f \in F_{signal}} |X_i[f]|^2}{\sum_{f \in F_{noise}} |X_i[f]|^2}, \tag{3.2}$$

where $X_i[f]$ is the DFT representation of $x_i[t]$, F_{signal} is a small set of frequency bins centered around the frequency bin that contains the most power in the range of $0.1 - 0.5$ Hz, and F_{noise} contains the remaining frequency bins in the breathing frequencies. The final breathing signal, $y[t]$ is:

$$y[t] = \alpha_{i^*} \cdot x_{i^*}[t]. \tag{3.3}$$

where $i^* = argmax_i\ \alpha_i$. We additionally process this signal with Eq. (3.1) to also help with motion and phase unwrapping artifacts.

3.3 Sleep Apnea Detection

We employ an envelope detection algorithm for detecting sleep apnea events remotely using a thermal camera or a radar sensor. We refrain from the using the Hilbert Transform because of its poor robustness to noise outside narrow bands [CNS14]. We instead opt to detect critical points in the signal and process them for continuous predictions of the lower and upper envelopes of the signal. In addition to envelope detection, motion detection is crucial in order to filter out false positives.

3.3.1 Envelope Detection

After filtering for motion, we extract the breathing signal as described in Section 3.2. To find the envelope of the derivative-smoothed breathing signal, s, we need to determine its extrema by finding all the points where the sign of the derivative changes. This results in many extrema being detected, most of which are artifacts caused by local extrema which are not at the peaks of the true breathing signal. We employ a sliding window with width chosen to be approximately $\frac{1}{2}$ of the period of a typical breathing signal, and filter out peaks in this

window which are less extreme than the most extreme peaks; this leaves us with a set of the most extreme peaks as seen in Fig. 3.2. In some instances, significant amounts of patient motion can hinder the data quality of the thermal camera due to the lack of visibility of nasal airflow from the nose of the patient, leaving peaks which remain in this set. To combat this, we designed a peak-based motion detection algorithm.

A common way patient motion manifests itself in the breathing signal is in the form of singular high-magnitude peaks that significantly alter the envelope of the thermal signal. In order to filter out these peaks, for each key point, we compute the average distance to its K nearest neighbors and filter out signal chunks surrounding the key points whose distance metrics are unusually high. That is, given an array of peaks, $s[p] \in \mathbb{R}^P$ with P local minima or maxima, the set of detected motion peaks is given by:

$$\left\{ s[i] \mid \frac{\sum_{k=i-\frac{K}{2}}^{k=i-1+\frac{K}{2}} |s[k+1] - s[k]|}{K} > \beta = 2.5 \right\} \tag{3.4}$$

We determine the values of K and the threshold β heuristically by observing a set of signals known to be motion-corrupted and a set of signals known to be free of motion artifacts, and adjusting until only known motion peaks are detected as motion peaks.

Once we filter out unwanted local extrema, a continuous version of the lower and upper envelopes of the signal is constructed from the minima and maxima respectively via linear interpolation. We then use the envelope difference normalized by its mean for apnea detection. This normalized envelope difference is then thresholded to produce a binary prediction, with the threshold selected by cross-validation. However, since most patients in the dataset did not have apneas, we could not perform this cross-validation across subjects.

Several data-driven methods [YSN20, FGA05, VGD19, ZTG21, YLW21, AA15] also exist for detecting sleep apneas from contact-based respiratory signals. However, due to the limited size of our non-contact dataset, we cannot replicate machine-learning driven algorithms.

3.3.2 Sleep Apnea Classification

Differentiating between OSA and CSA is difficult with access to only one modality. However, the reader may notice in Fig. 1.1 that during a CSA, both the respiratory effort and nasal airflow signals decrease in amplitude, while for OSA, only the nasal airflow decreases in amplitude. We propose leveraging this observation to perform sleep apnea classification using both the thermal and radar modalities, where the remote sensors replace the nasal airflow and respiratory effort sensors, respectively. Classification then reduces to simple boolean algebra. Given the apnea predictions from radar, $a_{Radar}(t)$, and thermal, $a_{Thermal}(t)$, (where $y(t) = 1$ and $y(t) = 0$ denote apnea present and no apnea present, respectively), then we can formula CSA and OSA classification as:

$$a_{CSA}(t) = a_{Radar}(t) \cdot a_{Thermal}(t) \tag{3.5}$$

$$a_{OSA}(t) = a_{Thermal}(t) \cdot (1 - a_{Radar}(t)) \tag{3.6}$$

Figure 3.1: **Our experimental hardware setup consisting of a thermal camera, a radar module, and data-processing auxiliaries located in a sleep lab.** In this particular setting, we have placed the thermal camera and the radar to the right of the bed. Our setup also includes a microcontroller that is connected to the existing in-lab PSG hardware. This microcontroller sends pulse trains that can be used to synchronize the ground truth annotations with the captured recordings.

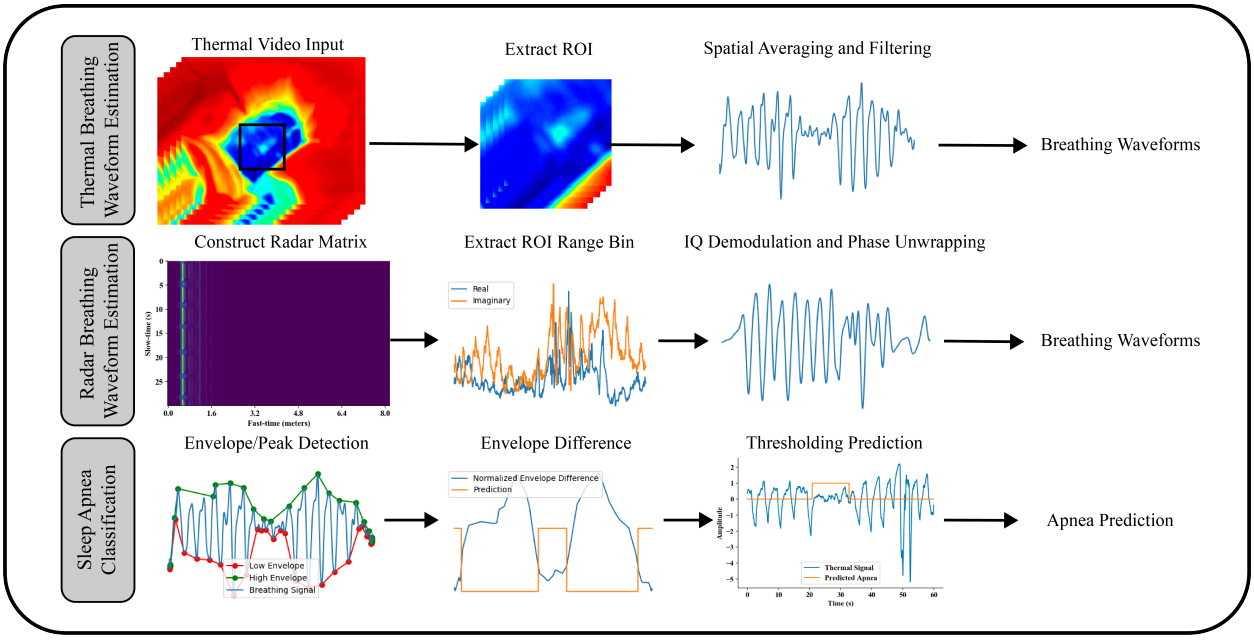

Figure 3.2: **Proposed pipeline for breathing detection from the radar and thermal modalities, followed by subsequent apnea detection.** First, we crop the frames acquired from the thermal camera (top) to focus only on the region near the nose. Then, we perform a global spatial averaging operation to collapse the video into a single time-series sequence, which, when filtered, gives us the breathing waveforms. For the radar (middle), we perform a standard Range-Doppler analysis to identify the approximate location of the patient, i.e., within a window of range bins. Once identified, we take an SNR-based weighted average of the extracted range bins to obtain breathing waveforms, which can then be filtered to increase waveform quality. Finally, we employ an envelope detection algorithm (bottom) to extract the upper and lower envelope, which can then be analyzed to detect anomalous regions on the waveform, i.e., regions with apnea.

CHAPTER 4

Results

4.1 Dataset Details

10 patients with suspected OSA undergoing full-night or split-night PSG were enrolled in this study. Of these patients, 1 was diagnosed with mild OSA ($5 \leq AHI \leq 15$), 3 were diagnosed with moderate OSA ($15 \leq AHI \leq 30$), and 1 was diagnosed with severe OSA ($AHI \geq 30$). The patients provided their written informed consent in accordance with our Institutional Review Board permissions, and all methods were performed in compliance with relevant guidelines and regulations of the University of California, Los Angeles. This study was approved by the UCLA Institutional Review Board, IRB#21-000018.

In our dataset, we discarded one patient's data due to synchronization error and another patient's data due to improper setup of the thermal camera. We also discarded periods of the recordings where the patients' noses were not in the frame of the thermal video. The entire dataset contains 20 hours and 25 minutes of synchronized thermal videos, radar recordings, and ground truth PSG recordings. Of the patients in the final dataset, two patients had sleep apnea events during the valid recording periods.

When calculating metrics in Table 1, we over-sampled 1-minute-long chunks of the data twenty times for every 5 minutes of data, resulting in an over-sampled dataset that is 59 hours 40 minutes long. Using our motion detection algorithm, we classified that 34 hours and 42 minutes of data in the over-sampled dataset do not contain significant levels of motion.

Table 4.1: Performance of Breathing Rate Estimation.

Method	**MAE**	**RMSE**	**MAPE**
Alizadeh [ASD19]	4.91	6.97	32.56%
Our Radar	1.90	3.95	14.45%
Chan [CWD20]	3.17	5.21	20.58%
Our Thermal Method	**1.58**	**3.45**	**11.88%**

4.2 Results

4.2.1 Breathing Estimation Evaluation

We present quantitative results of breathing estimation in Table 4.1 as well as in a Bland-Altman plot in Fig. 4.3. We also show qualitative results of the estimated breathing waveforms in Fig. 4.1. We find that the thermal modality outperforms the radar in breathing rate estimation. We hypothesize that this is due to reflections from the 77 GHz radar being specular. This can lead to a reduced signal when a patient's chest is not perpendicular to the radar's optical axis. We also find that our radar smoothing and SNR weighting scheme, Section 3.2, improves upon prior breathing estimation methods [ASD19].

4.2.2 Sleep Apnea Detection

We demonstrate the qualitative results in Fig. 4.1. Overall, from Table 4.2, we found that thermal imaging provides more robust sensing of apneas than the radar when accounting for motion. While the radar was able to achieve the highest recall, it suffered from low precision. We believe that this is due to the sensitivity of the radar wave's phase to movement. Even small movements can cause changes in the amplitude of the signal, resulting in false positives. Using motion detection and handling is advantageous as it allows us to filter out parts of the signals that have anomalies due to patient motion. The motion handling algorithm removes

Table 4.2: Performance of Sleep Apnea Detection

Method	Accuracy	Precision	Recall	F1	ICC
Radar	0.88	0.12	0.84	0.21	0.14
Radar excl. motion samples	0.83	0.13	**0.86**	0.22	0.13
Thermal	0.90	0.19	0.79	0.31	0.26
Thermal excl. motion samples	**0.99**	**0.68**	0.74	**0.71**	**0.70**

adverse distribution shifts to the distribution of local maxima and minima that make up the envelope of the signal, causing our algorithm to classify false-positive apnea events. Furthermore, our motion handling algorithm is not only limited to our apnea detection algorithm but can also be used to inform other apnea detection or breathing rate estimation algorithms about the presence of motion and allow for proper handling. However, motion detection comes with the tradeoff of possibly discarding sleep apnea samples. For the final results, we used a threshold of 0.4 for thermal and 0.5 for radar for the motion detection algorithm and a window size of 23 for the upper and lower envelopes.

Two patients had apnea events in the valid recording period. The first participant had 20 ground truth apneas (1 OSA and 19 CSA): 18 of the apneas were predicted by the thermal camera data and 16 of the apneas were predicted by the radar data by our algorithm. The second participant had 7 ground truth apneas (1 OSA and 6 CSA): 2 of the apneas were predicted by the thermal camera data and 4 of the apneas were predicted by the radar data. predicted apneas on the thermal camera data.

4.2.3 Sleep Apnea Classification

We also demonstrate an application of using both radar and thermal modalities for apnea classification between OSA and CSA. In Fig. 4.2, we can see an example of OSA and CSA from our dataset classification according to Eq. (3.5) and Eq. (3.6). Due to the small number

of OSA and CSA examples in our dataset, we can only show qualitative multimodal results of OSA and CSA classification.

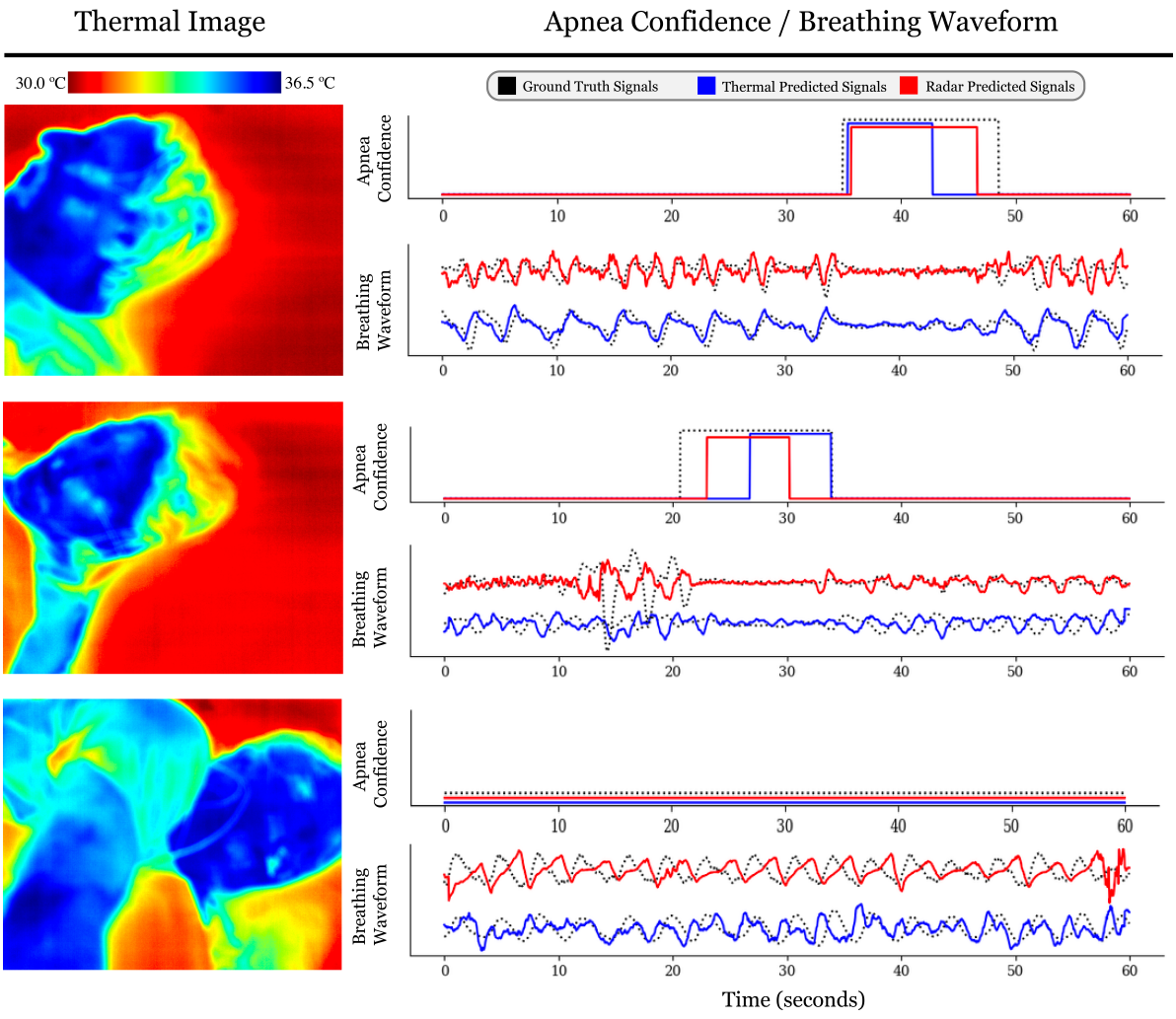

Figure 4.1: **Our apnea confidence scores and breathing waveforms are estimated from our thermal and radar recordings for several apnea events.**

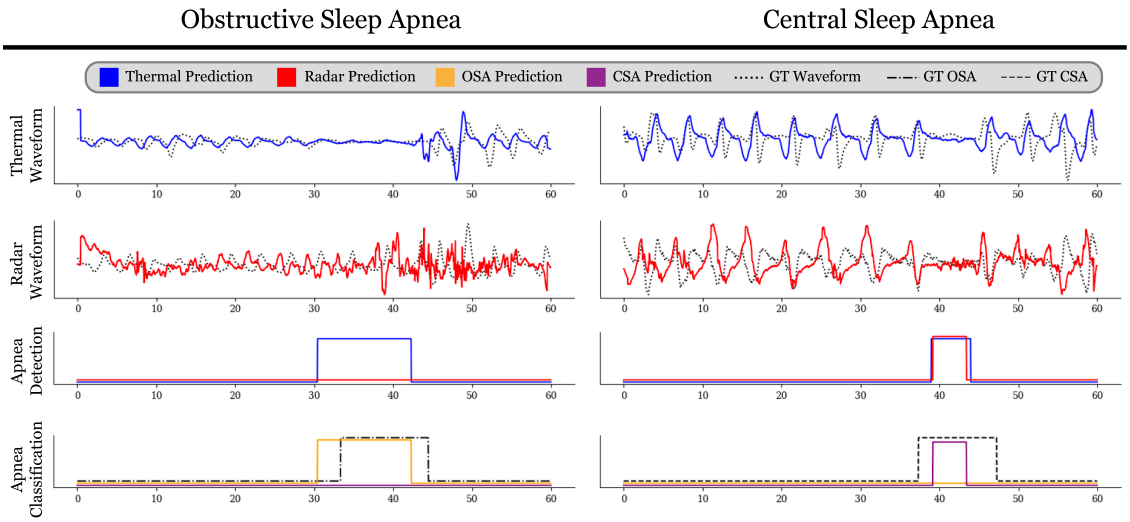

Figure 4.2: **A qualitative comparison between how obstructive and central sleep apnea appear to the radar and thermal modalities.** The thermal modality reduces in amplitude for both OSA and CSA, but the radar modality reduces in amplitude only for CSA. This distinction can be used to classify between OSA and CSA in a multimodal setup using radar and thermal. Apnea classification can then be performed by applying Eq. (3.5) and Eq. (3.6) with filtering of detections that are too short.

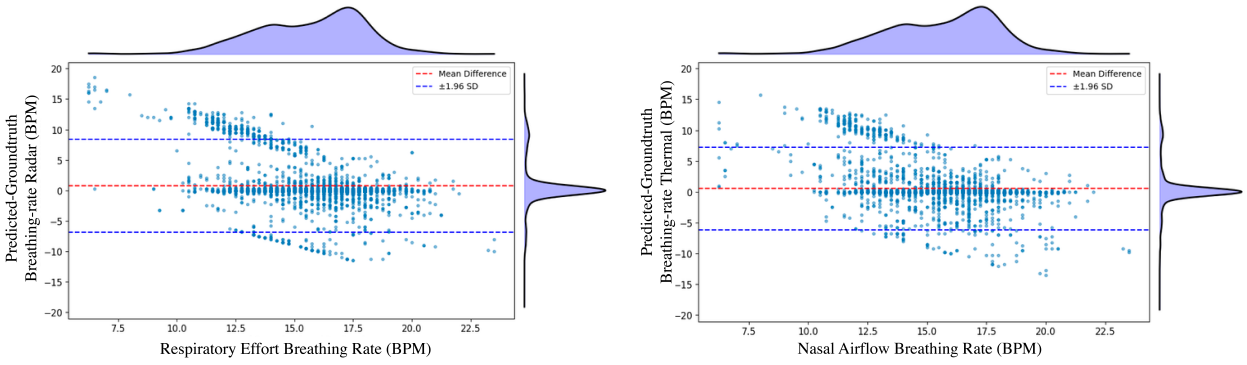

Figure 4.3: **Bland-Altman plot for breathing rates estimated by our radar (left) and thermal (right) modalities.**

CHAPTER 5

Conclusion

5.1 Limitations

Like other non-contact methods for apnea detection, we utilize previous work to estimate the relevant physiological signals which are normally measured using contact methods. We inherit all the limitations of this previous work, including errors due to noise and motion artifacts [MLG22, YHZ22, SKR23, BYC17, CWD20] or the presence of other signals [KC17]. Additionally, as previously stated in Section 3.2, extreme sleeping positions can obscure the nose from the thermal camera, the modality found to be crucial for apnea detection. While remote sensing has the potential to benefit patients, it is still a new technology that warrants further studies to understand generalizability and fairness [Kad21] of the technology to diverse patient populations.

Non-contact methods have been developed to remotely measure SpO2. The most common method to achieve remote SpO2 extraction is through two NIR cameras with different wavelength sensitivities. Typically, these methods first detect a remote-photoplethysmography signal [VCA22, WWZ20, CKK20, PLP23, LHJ23, CM18, CHA24], followed by application of the ratio-of-ratios method [CCC13, NRK14]. This general framework has been applied in several instances [MTW23, VVW18, TWR22, SWC24, HZL18] with various algorithmic innovations to extract a better remote photoplethysmography signal. Other work also detects SpO2 using spectroscopic methods with a multi-aperture camera [RM07, RMK08, IAS15]. While SpO2 is an important vital sign for sleep monitoring, we determined that we would re-

quire custom ground truth SpO2 measurement hardware to implement a noncontact method. This would have been incompatible with our data collection procedures as it would require our hardware to contact the patients. Therefore, since blood oxygenation is a criterion for hypopnea classification, hypopnea detection using completely non-contact methods is outside the scope of this thesis. However, it may be possible to use relaxed criteria to score hypopneas, omitting the blood oxygenation information.

5.2 Future Work

Further work is needed to verify the efficacy of multimodal fusion for classification between types of sleep apnea. We emphasize the need for more high-quality datasets for non-contact apnea detection, especially multimodal datasets. Furthermore, we hope that in future work, we can incorporate novel or previously developed non-contact blood oxygenation methods to enable full non-contact monitoring. Further work is also needed to study the efficacy of non-contact apnea detection and classification on pediatric and infant populations, which are most affected by the limitations of current contact technology.

5.3 Conclusion

We propose a novel method of contactless nasal airflow and respiratory effort estimation of apnea to function as a real-time drop-in replacement for existing contact sensors. We verify the performance of these methods using data collected from patients with suspected sleep apnea. We demonstrate that these methods can be used to detect sleep apnea events and even potentially distinguish between some obstructive and central apnea events. We hope that this thesis can contribute to the development of a portable, repeatable, non-contact diagnostic tool for populations underdiagnosed with sleep disorders due to their inability to access or tolerate current PSG and HSAT diagnostics.

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