Detecting Bed Occupancy Using Thermal Sensing Technology: A Feasibility Study

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Abstract. Measures of sleep and its disturbances can be detected by monitoring bed occupancy. These measures can also be used for alerting of bed exits or for determining sleep quality. This paper introduces an unobtrusive approach to detecting bed occupancy using low resolution thermal sensing technology. Thermal sensors operate regardless of lighting conditions and offer a high level of privacy making them ideal for the bedroom environment. The optimum bed occupancy detection algorithm was determined and tested on over 55,000 frames of 32×32 thermal sensor data. The developed solution to detect bed occupancy achieved an accuracy of 0.997. In this approach the location of the bed and the location of the participant is considered by classification rules to determine bed occupancy. The approach was evaluated using thermal sensor and bed pressure sensor data. Future work will focus on automatic detection of the bed location and improving the system by further reducing the false positives caused from residual heat.

Keywords: Thermal sensor · Bed occupancy detection · Bed pressure sensor · Contactless sleep monitoring · Background subtraction · Residual heat

1 Introduction

Polysomnography (PSG) and Actigraphy are considered the current gold standard in objective sleep monitoring and provide measures of sleep such as total sleep time and sleep quality [1]. PSG requires the physical attachment of obtrusive sensors to the body and is therefore normally conducted within a sleep clinic [1, 2]. Actigraphy is the continuous monitoring of movement levels by a watch-like device worn on the wrist which generates sleep metrics to aid in diagnosis of sleep disorders [3]. Actigraph devices range from medical grade devices to general wellness devices [4]. Medical grade actigraphy devices offer a high level of precision and are therefore very costly, while wellness monitoring actigraphy devices are less accurate and more affordable [4]. There are numerous commercially available unobtrusive sleep monitoring solutions based on Actigraphy such as: the Fitbit Inspire HR, a smartwatch device; Sleep Time: Cycle Alarm Timer, a smartphone app; and Withings Sleep Tracking Mat, a bed pressure sensor, to name but a few [5–7].

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The aim of movement-based sleep monitoring devices, such as the wearables mentioned above, is to generate objective measures of sleep. These measures are typically combined to determine sleep quality and detect sleep disturbances. One such sleep monitoring metric is Bed Occupancy [8, 9]. Developing a metric which can accurately measure the current bed occupancy status can be used to provide a range of measurements in terms of sleep quality and sleep disturbances. In addition to bed occupancy status, many other metrics can be generated from this data such as the total time spent in bed, the timing of bed entry and exits, in addition to the number of bed exits each night. A major cause of bed exits during the night is Nocturia (i.e., waking during the night to urinate), which are recorded causes of sleep disorder and daytime fatigue in elderly [10]. Long-term sleep monitoring generates significant records of data in which patterns can be deduced and therefore deviations from these patterns can be detected as an indication of early illness [11]. Furthermore, a bed occupancy status metric can also be used to issue alerts of bed exits to caregivers, and to sound a bed exit alarm for those most at risk from falls.

The aim of this paper is to evaluate a novel unobtrusive approach to determine bed occupancy duration using low resolution thermal sensing technology. This approach is validated against the gold standard measurement from a pressure sensor and measurement from a human observer. The implementation of logical rules is proposed as a solution to limiting the effects of residual heat on the bed occupancy detection algorithm. The system is designed to produce a bed occupancy log, of which the bed occupancy duration can be determined. The bed occupancy duration determined by the thermal sensor-based system will be compared to that of the bed pressure sensor and the human observer. The contribution of this research is the development a thermal sensor-based system to detect bed occupancy from a ceiling installed thermal sensor. The remainder of this paper is structured as follows: Sect. 2 provides a detailed overview of related work, highlighting the advantages, applications, and challenges, of thermal sensing. Section 3 provides a discussion of the materials (i.e., sensor and dataset) and methods (i.e., data-preprocessing and labelling, background subtraction, and others) used in this approach to detect bed occupancy. Section 4 presents the results from of this approach to detecting bed occupancy and determining bed occupancy duration. Section 5 provides a discussion on the findings and limitations of this approach, while Sect. 6 presents the conclusions.

2 Related Work

Sleep monitoring research has largely focused on the use of actigraphy devices to detect sleep states. The use of actigraphy to detect movement and infer sleep was evaluated against simultaneously collected PSG data [12]. The sleep and wake states determined by the actigraphy device were evaluated and achieved an accuracy and sensitivity of 0.86 and 0.96, respectively, while specificity was 0.32. The low specificity arose from periods spent motionless while awake being determined as time spent asleep due to the absence of movement. Furthermore, several issues have been identified with wearable sleep monitoring technologies. Liu *et al*. discovered that wear discomfort resulted in discontinued use, and that continuous tracking was inhibited by limited battery life [13]. Wearable technologies are not considered appropriate for monitoring those living with certain diseases, such as late-stage dementia.

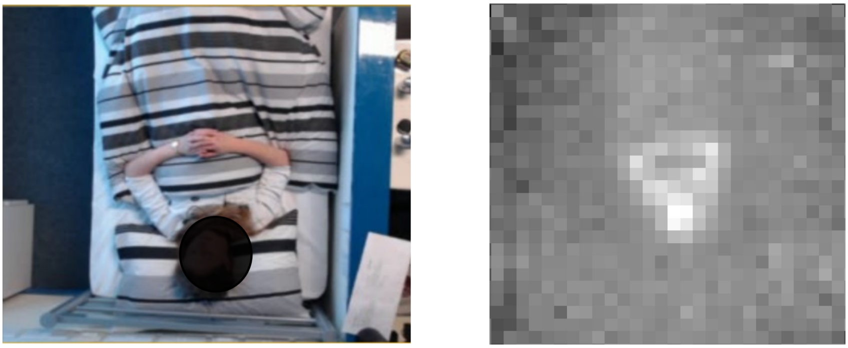
In recent years, the area of sleep monitoring research has focused on developing automatic, low cost, unobtrusive sensor-based systems suitable for long-term monitoring [14]. Most recent non-wearable movement-based systems designed to monitor sleep and bed occupancy include bed pressure sensors, smartphones, and cameras, including RGB (Red Green Blue), NIR (Near Infrared), and Thermal. Most bed pressure sensors are mats which incorporate a mesh of pressure sensors [15]. Bed pressure sensors can be discretely installed under the mattress out of view. Pouliot *et al.* developed a clinical user interface to view bed occupancy metrics, such as the number and timing of bed entries and exits, generated using an under-mattress pressure sensor [8]. Similarly, Taylor *et al.* generated several bed occupancy metrics and observed patterns in bed occupancy, distinguishing days of under sleeping and oversleeping, using an under-mattress pressure sensor [9]. Alternatively, a pressure sensor can be installed under the leg of the bed. Such a set-up detected the activity of lying-in bed with an accuracy of 0.93 [16]. Compared to actigraphy, bed pressure sensors offer the advantage of being an ambient sensor and therefore do not require contact with the user nor do they require being charged. Nam *et al.* referred to the physical and mental burden of bed pressure sensor users to ensure they are correctly positioned directly on top of the mat [17]. Like wearable devices, bed pressures sensors can also be limited by sensor placement. During an overnight two-subject data collection experiment by Jones *et al.*, one subject did not lie directly on top of the pressure sensor therefore inhibiting the data collection for 5 of the 7.5 h [18].

Ambient sensor types including thermal sensors can overcome these limitations, and therefore researchers have looked at visual sleep monitoring solutions. A near-infrared camera-based solution was developed to detect movement body and determine sleep quality [19]. Activity levels were estimated from high-resolution (640 $\times$ 480) images and compared to actigraphy and PSG. The infrared-camera based approach achieved a slightly improved accuracy of 0.921 when compared to the actigraphy achieved accuracy of 0.912. As this approach uses high-resolution images it is fundamentally limited by privacy invasion as the participants can be identified.

To avoid such privacy concerns, Eldib *et al.* used a low-resolution 10-piece dual 30 $\times$ 30 visual sensor network-based system to detect motion patterns to analyze sleep [20]. The visual sensor network was installed into the living space (minus the bedroom) of one elderly participant for 10 months. This system could estimate sleep duration and achieved an accuracy of 0.8 with an absolute error range of 40 min. The ground truth in this study was provided from a sleep diary which is error-prone due to perception and memory. In the given study, the sleep diary was not completed for two weeks of the study as the participant had forgotten. This system's functionality is limited by the lighting conditions, as around 20% of the sleep durations were overestimated due to the participant standing without turning the lights on. Some nightly bathroom visits were also missed due to the participant not using the light. Thermal sensors offer advantages over RGB cameras and IR cameras as they operate regardless of lighting conditions.

Thermal imaging cameras have also been applied to several areas of sleep monitoring. Murthy *et al.* used a FLIR thermal image camera alongside PSG to monitor airflow and detect sleep apnea events by tracking the nostrils of participants during sleep in a clinical setting [3]. Sleep data were collected from 27 participants for 1–2 h. The thermal imaging system missed 3 of 167 epoch breathing events therefore resulting in a missed detection rate of only 1.8%. Thermal imaging camera systems do provide some user privacy as only humans can be identified as opposed to human individuals.

To further limit invasiveness a very-low resolution thermal sensor (32 × 32) may offer a benefit in terms of human identification, as presented in Fig. 1(a). This study aims to monitor bed occupancy and determine bed occupancy duration using a very-low resolution thermal sensor. Monitoring the temperature data of thermal images, biological temperature readings and a thermal sensor can be used as an alternative to actigraphy [21]. Madrid-Navarro *et al.* found that skin temperature was a good indicator of sleep fragmentation and was therefore presented as a solution to the fundamental limitation of actigraphy [22]. Similarly, Tamura *et al.* concluded that the bed surface temperature data could be used to detect movement and infer sleep duration [23]. Both studies however, used sensors which required contact with the participant or the bed, whereas in the current study a contactless thermal sensor solution is proposed. Such ceiling mounted thermal sensors often have a Field of View (FOV) capable of monitoring activity in and around a double-sized bed, therefore eliminating the need for numerous sensors.



(a) (b)

Fig. 1. (a) A 320 × 240 RGB frame and (b) the corresponding 32 × 32 greyscale thermal frame.

Contactless thermal sensors have been used for a broad range of human activity monitoring and detection. Shetty *et al.* developed a system to track participants within 8 × 8 thermal sensor data [24]. Taha designed a people counting system to detect participants entering or exiting a room using a 4 × 4 ceiling mounted thermal sensor [25]. Liang *et al.* used a 32 × 32 wall mounted thermal sensor to detect participant movement and falls [26]. The detected movement was then categorized as a fall or non-fall movement. Synnott *et al.* [27] developed a system to detect and monitor sedentary behavior using 16 × 16 thermal sensor data. Burns *et al.* [28] fused two 32 × 31 thermal sensor data to recognize kitchen activities.

Contactless thermal sensing has also been applied to sleep activity detection and monitoring. Taniguchi *et al.* developed a system to detect human posture using two 16 × 16 thermal sensors [29]. One thermal sensor was mounted to the wall and the other mounted to the ceiling. The system was able to detect transitions from ‘walking’ to ‘lying in bed’ with an accuracy of 0.889. This study focused on recognizing the transition or microevents between actual events. For example, exiting the bed is made up of four pose transitions: lying on the bed; sitting on the bed; sitting on the edge of the bed; standing beside the bed; walking. The mean accuracy of these four pose transitions is 0.889. Taniguchi *et al.* also detected falling transitions using the same set up [30]. This system was able to detect a transition from 'sitting on the bed' to 'falling from the bed' with a mean accuracy of 0.958 and a transition from 'walking' upon bed exit to 'falling' with a mean accuracy of 0.789. Again, this study focuses on detecting the microevents between actual events.

Asbjørn and Jim used a ceiling mounted 80×60 thermal sensor and ultrasonic sensor to recognize bedside events [31]. Participant location was detected using thermal data, while participant posture was detected using thermal and ultrasonic data (i.e., the number of centimeters to the nearest object). Sitting on the bed achieved a recognition rate of 0.753 while lying on the bed achieved a recognition rate of 0.881. Bed entry and exit events were detected with an accuracy of 0.987 and 0.966, respectively. The bed entry and exits events were recognized by analyzing the participants location and posture, the nearest object distance reading, and the number of changed pixels from the previous frame, across 10 consecutive frames. Our approach to detecting bed entry and bed exit events is designed to be computationally inexpensive while relying on low-resolution thermal data alone. This system was also capable of detecting 'Area Entry' and 'Area Exit' events. Area entry is detected when heat enters the sensor FOV, while area exit is detected when heat leaves the sensor FOV. The area entry events were detected with an accuracy of 0.961, while area exit events were detected with an accuracy of 0.955. Both area entry and exit events suffered from false positive and false negative readings, suggesting the systems performance could have been limited due to thermal noise.

Unlike other visual sensors such as an RGB camera or depth camera, thermal sensor systems must also incorporate a way to reduce or eliminate the effect of residual heat [32]. A study conducted by Lee *et al.*, investigated different types of residual heat, including analyzing the residual heat left from a single fingertip touch visible to a thermal camera [33]. Residual heat is generated from human body heat conducting to the surface it is in contact with and this heat may remain for an extended period of time [32, 33]. For example, after sleeping in bed overnight, the accumulated residual heat could potentially make it more difficult to differentiate the human from the residual heat [32]. Alternatively, after exiting the bed, the residual heat signature could be very similar to that of the participant lying on the bed [31]. Therefore, the effects of residual heat on detecting bed occupancy must be clarified and resolved to prevent false positives [32].

Kuki *et al.*'s system to determine the number of humans in an office environment was susceptible to the effects of residual heat [34]. Once participants had left their chair, the revealed residual heat was inaccurately determined to be a human. Consequently, 7 logical rules based on temperature and change in temperature, and heat source shape and movement were incorporated into the system, to differentiate between humans and residual heat in every frame of thermal data. This system suffered greatly from missed estimations at 51.4%, whereas the over estimation rate was only 7.5%, illustrating a reduction of false positive readings due to residual heat.

In [31] a background subtraction algorithm was designed to incorporate a residual heat disposal algorithm. This algorithm works by tracking the individual temperature of each pixel. If the pixel temperature is reducing at a steady rate, it is detected as residual heat and removed from the foreground. The performance of this algorithm is difficult to analyze due to limited discussion of factors such the time spent in bed to generate residual heat or the number of participants in the study.

This study will investigate the effects of incorporating logical rules to limit false positives resulting from residual heat. Compared to the technique implemented by Kuki *et al.*, this system will be more computationally inexpensive as only one logical rule will be used to determine a 'bed exit' and 'bed landing area exit' [34]. Only once this condition has been met, a logical value will then negate the effects of residual heat, as the heat source within the bed will be ignored by the bed occupancy algorithm. Compared to the technique in [31] this technique has been designed to be computationally inexpensive therefore only one logical value will be tracked across each frame compared to 4,800 pixels.

To summarize, researchers have considered visual bed occupancy and sleep monitoring solutions. In [19] Liao *et al.* used a near-infrared camera-based system to detect body movement and achieved an accuracy higher than actigraphy, when compared to PSG. To limit the invasiveness of such visual solutions a very low-resolution thermal sensor will be evaluated as an approach to monitoring bed occupancy. This study aims to develop a bed occupancy metric which can accurately detect presences within a single bed while participants are using a duvet. This study aims to develop a bed occupancy duration metric, derived from the bed occupancy metric, which accuracy determines bed occupancy duration compared to a bed pressure sensor. This study aims to evaluate the implementation of logical reasoning to distinguish participants from residual heat as an approach to limiting the false positives resulting from residual heat upon bed exit, the implementation of logical reasoning to distinguish humans from residual heat will be evaluated. The contribution of this research is the development a thermal sensor-based system to detect bed occupancy from a ceiling installed thermal sensor.

3 Materials and Methods

This Section details the materials and methods used by the bed occupancy detection algorithm. Firstly, the dataset collection protocol is detailed. Next, the data labelling and data pre-processing methods are presented. Finally, the methods used by the system to determine bed occupancy are explained.

3.1 Thermopile Array Sensor Setup

The thermal sensor used in the current study was a Heimann HTPA32 $\times$ 32 Infrared Thermopile Array Sensor, which has a 32 $\times$ 32 resolution, a 90-degree FOV and an ambient temperature range of -20 to 85 °C. The thermal sensor, power cable and ethernet cable were installed onto a frame, providing a birds-eye view of the bed area. The frame height was set to the standard ceiling height of 240 cm. The sensor generated temperature data with a frame rate of 7.8 Hz which is transmitted via UDP using Heimann Sensor HTPA ArraySoft v.1.28 and stored in a. txt file.

3.2 Data Collection

Ethical approval of this research was granted by Ulster University Research Ethics Filter Committee. The experiment involved collecting 20 examples of bed occupancy data from 5 participants. The participants were made up of both male and female aged 24–45. Each participant performed the activity with a target bed occupancy duration of 1 min, 3 min, 5 min, and 10 min. The data collection resulted in a total of 55,529 frames of thermal data. The participants were instructed to follow the experimental protocol: Enter the room, closing the door behind them; approach the bed; pull back the duvet, get into the bed, and cover up with the duvet; on alarm, pull back the duvet, get out of the bed replacing the duvet; exit the room and close the door. The participants were free to move within the bed throughout the bed occupancy. A researcher was present inside the room and started the timer for the specified time once the participants had entered the bed.

To provide a reference for comparison of the determined bed occupancy duration, a Tynetec bed pressure sensor (Model No. ZCS844) was installed between the mattress and bed frame. The pressure sensor creates a bed occupancy log, providing timestamped logical values representing either an “in bed” or “not in bed” status. The first instance of each status is noted, and the duration of bed occupancy is calculated.

3.3 Data Pre-processing

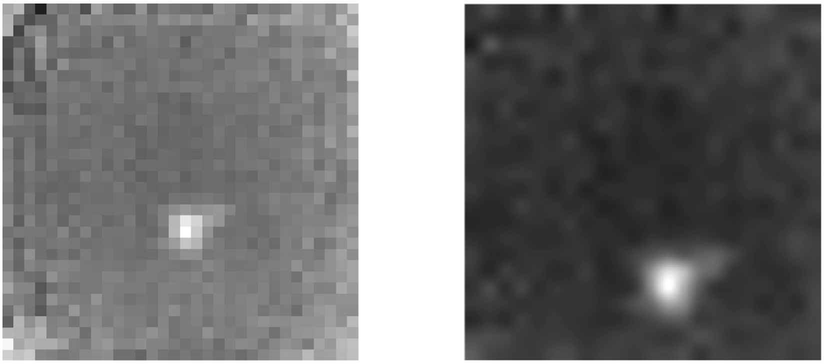
The thermal sensor data were imported into MATLAB and each instance was manipulated into a 32 $\times$ 32 matrix of temperature readings. To remove any fisheye distortion around the edge of the frame, the matrix of temperature readings was cropped with a 5 pixel-width perimeter, resulting in a resolution of 22 $\times$ 22. This matrix is converted into an intensity image (i.e., a greyscale image) containing values ranging from 0 (i.e., black) to 1 (i.e., white) before being rescaled by a factor of 10, resulting in a 220 $\times$ 220 matrix, as illustrated in Fig. 2. A bicubic interpolation method was used as it resulted in smoother and more defined images compared to the nearest-neighbor or bilinear interpolation methods.

3.4 Data Labelling

Each frame of thermal data was manually labelled ‘in bed’ or ‘not in bed’ by the researcher to provide ground truth values to measure the classification performance. The thermal data were visualized as a greyscale image with the bed location superimposed, as depicted in Fig. 3. The thermal frames were labelled 1 if the participant’s blob, or more than 50% of the participant’s blob, was within the location of the bed. Conversely, thermal frames were labelled 0 if the participant’s blob, or more than 50% of the participant’s blob, was outside the location for the bed.

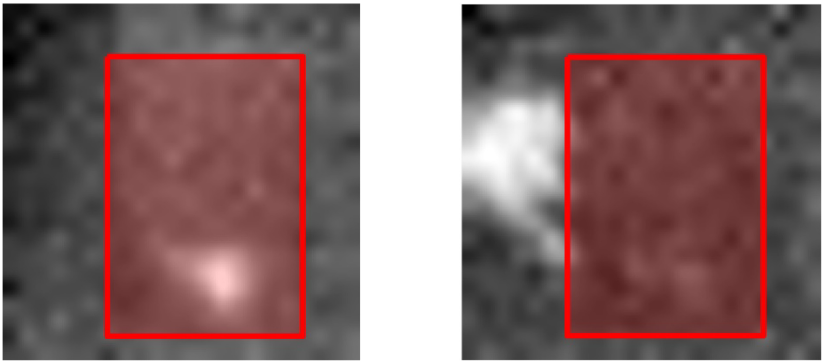
3.5 Background Subtraction

The greyscale image is then segmented using a determined temperature threshold value for heat source identification. The aim of the background subtraction algorithm is to segment the hottest pixels within the frame of thermal data which may be representative



(a) (b)

Fig. 2. A 32 × 32 greyscale image of thermal data (a). White represents the hottest pixels while black represents the coldest. The image is rescaled to a 220 × 220 greyscale thermal image (b).



(a) (b)

Fig. 3. Thermal frames used in the labelling processing - visualized as greyscale images with the bed location superimposed. Labels include 'in bed' (a) and 'not in bed' (b).

of a human heat source, while any other undesired sources of heat (such as from radiators, hot water bottles, or temperature drifts) are discarded and remain within the background. The temperature difference between the human body and the background reading is used for successful image segmentation.

Pixels with a value larger than the selected threshold are determined to be foreground pixels and are assigned the logical value of 1, which make up a white blob representing the participant. Pixels with a value smaller than the set threshold are determined to be background pixels and are assigned the logical value of 0. The resulting image is called a binary mask, presented in Fig. 4 (right).

3.6 Blob Detection and Tracking

The remaining white blobs within the binary mask are detected and properties are calculated for each. Blobs with a surface area of less than 20 pixels are filtered out of the

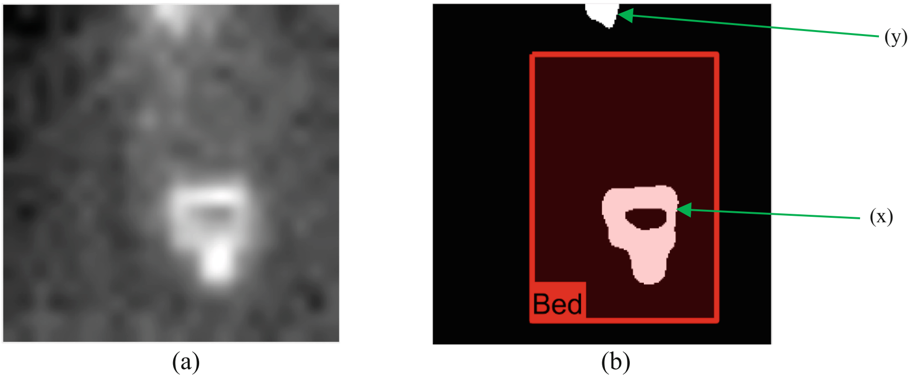


Fig. 4. A 220 × 220 greyscale thermal frame (a) and corresponding binary mask (b). The participant (x) and researcher (y) heat signatures are segmented using thresholding. The bed location is predefined and labelled. The participant is in the bed with their arms folded above the blanket. (Color figure online)

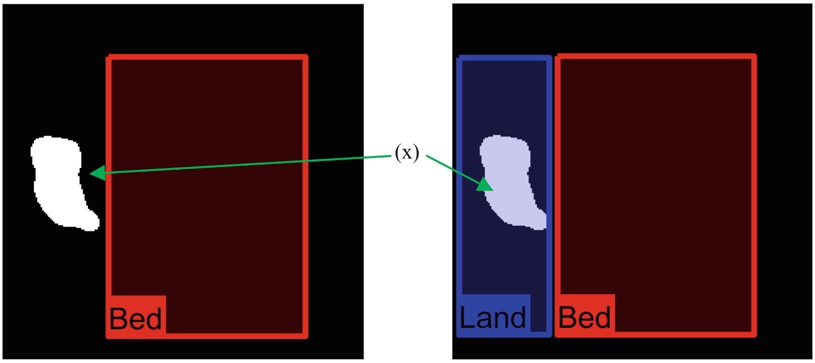
foreground and removed from the binary mask. A surface area of 20 pixels or more was determined as it allowed for successful segmentation of blobs representing a human head while preventing minor noise (e.g., a radiator) from being segmented. The centroid of each detected blob is determined, returning an x- and y-coordinate of the centre of mass of the blob within the binary image. The blob centroids are calculated and stored so that the participant's current location and previous location can be determined.

3.7 Region of Interest Identification

The location of the bed is predefined using a rectangular Region-Of-Interest (ROI). To determine the bed position within the frame of thermal data, heat emitting elements were placed on each corner of the mattress and the defined ROI encompassed these pixels. This was performed during the setup phase. The bed location is illustrated in Fig. 4 as a red rectangle.

3.8 Logical Reasoning

Logical reasoning is applied to distinguish residual heat from the participant. Using the bed ROI, bedside events such as entering the bed and exiting the bed can be identified. Including an ROI encompassing the area along the side of the bed where participants enter and exit the bed as the "landing area", means bedside events of entering the bed landing area and exiting the bed landing area can also be identified. The bed "landing area" is illustrated in Fig. 5 (right) as a blue rectangle. Once the logical steps of exiting the bed and exiting the bed landing area is identified, any remaining heat in the bed is assumed to be residual heat. The logical reasoning algorithm was designed so that is could be included or excluded in the bed occupancy algorithm for performance evaluation.



(a) (b)

Fig. 5. Two binary masks of thermal data. The participant (x) has approached the bed. The bed location is predefined with a red rectangular ROI (a) while the bed "landing area" location is predefined with a blue rectangular ROI (b). (Color figure online)

3.9 Bed Occupancy Detection

The information obtained from both objects (i.e., ROI and blob) is used to determine if the participant is in or is not in bed. To detect presence within the bed, a timestamped logical value is returned for each frame of the timeseries data depending on if the blob's centroid coordinates are within the ROI or not. Timestamps of the first instance of an "in bed" status and the first instance of an "not in bed" status are recorded, and the bed occupancy duration is calculated for each sample of data. The bed occupancy duration determined by the system is compared to the gold stand measurement from the bed pressure sensor and the measurement from the human observer. To assess the performance of the bed occupancy detection algorithm evaluation metrics of accuracy, precision and recall are calculated.

4 Results

This Section presents the finding from this study. The performance of the bed occupancy detection algorithm with and without logical reasoning is provided in Table 1.

The measured bed occupancy duration for each target duration determined by the thermal sensor, pressure sensor and human observer is provided in Fig. 6.

4.1 Bed Occupancy Detection

The bed occupancy detection algorithm susceptible to the effects of residual heat achieved an accuracy of 0.969 and a precision of 0.964. The precision is affected by false positives, in this case, resulting from the residual heat in the bed. With logical reasoning incorporated to limit the effects of residual heat, the bed occupancy detection algorithm achieved an improved accuracy of 0.997 and a precision of 0.997.

Table 1. Performance statistics of the bed occupancy detection algorithm.

Performance measures	Bed occupancy detection	
	Without LR*	With LR
Accuracy	0.969	0.997
Precision	0.964	0.997
Recall	1	1

*Logical Reasoning

4.2 Bed Occupancy Duration

A comparison between the bed occupancy duration determined from using a thermal sensor, pressure sensor and human observer is shown in Fig. 6. Mean occupancy time refers to the mean (average) duration of which bed occupancy was detected across each sample of data, for each set target duration. A one-way ANOVA ($F(2, 57) = 0.0024$, $p = 0.9975$) determined there were no statistically significant differences amongst the methods, therefore illustrating that the system performed closely to gold standard measure from the bed pressure sensor.

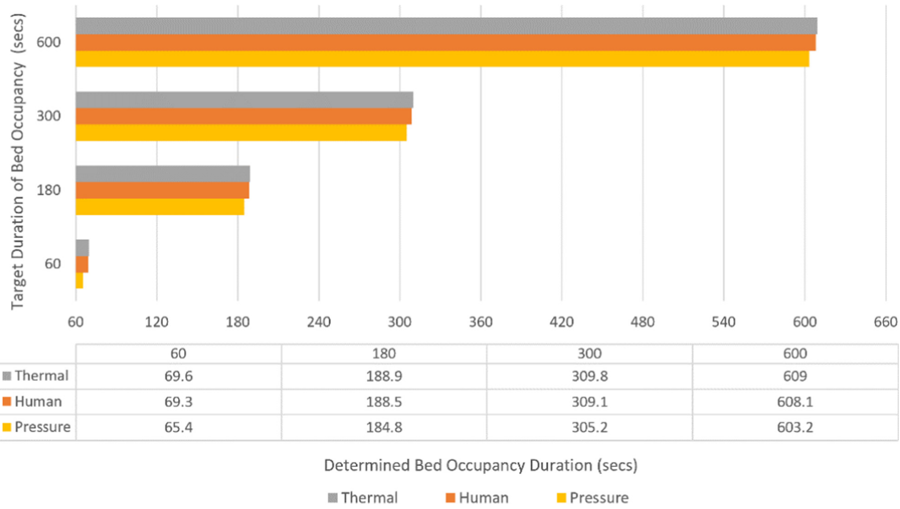


Fig. 6. A graph showing the mean duration of bed occupancy determined by a thermal sensor, a pressure sensor and human observer. The data table is included.

5 Discussion

The bed occupancy detection algorithm with and without logical reasoning achieved a recall of 1 as no false positives were returned. This result illustrates the effectiveness of the thermal sensor data pre-processing methods, as only the human heat signatures are segmented as the foreground in images. The system only suffered from the false positives resulting from the residual heat, as was to be expected. Without logical reasoning, the system returned 1,968 false positives, reducing to 185 frames with the inclusion of the logical rules. Without the rules, the system returned false positives on all frames with residual heat after the participant exited the bed, until the residual heat temperature was less than that of the temperature threshold in the background subtraction algorithm. Whereas, with the rules, the system only returned false positives until the participant remained in contact with the residual heat on the blanket and/or mattress.

The thermal sensor consistently provided a longer duration of detected occupancy time by an average of 0.6 s ($\pm$0.24 s), compared to the human observer. This increased duration can be explained due to the residual heat on the blanket. Once the blanket becomes the same temperature as the participant it is therefore segmented as foreground pixels on the binary mask and merges with the blob of the participant. Therefore, as the participant is replacing the blanket after they have exited the bed and entered the landing area, the heat source from the participant and the heat signature from the residual heat are combined into one large foreground blob, in turn returning a false "in bed" status until the participant drops the blanket (i.e., approximately 0.6 s).

The thermal sensor consistently provided a longer duration of detected occupancy time by an average of 4.7 s ($\pm$0.68 s), compared to the pressure sensor. A large portion of this duration can be explained as the thermal sensor returns an "in bed" status once the centroid of a given heat source is within the bed location, whereas the pressure sensor returns an "in bed" status once weight has been registered on the centre of the bed. Similarly, on exiting the bed, the pressure sensor returns a "not in bed" status once body weight has been removed from the centre of the bed, whereas the thermal sensor returns a "not in bed" status once the blanket has been replaced on the bed and the heat source centroid is outside of the bed location. This variation in operation is also illustrated by the duration difference determined by the human observer. The pressure sensor consistently provided a longer duration of detected occupancy time by an average of 4.1 s ($\pm$0.47 s), compared to the human observer.

5.1 Limitations

Whilst the results are promising, this study is not without limitations. The data on which the system was tested was collected in one environment, therefore all participants used the same bed and blanket, in the same location of the room. Consequently, uncertainty remains regarding the system's performance across other sleeping environments and with varied blanket tog/thickness. Similarly, each sample of data contained the same scenario which consisted of only one bed enter and one bed exit with a short bed occupancy duration, thus the system's performance cannot be inferred for detecting bed occupancy long-term, for example, across a number of nights incorporating many bed entry and exits. The logical reasoning algorithm is also currently limited to a single occupant environment as the performance has not been evaluated in situations where another participant approaches and leaves the bed, such as in a caring situation.

The performance of this system may also be limited across different climates and weather conditions as all data were collected over a short time frame in which the weather conditions remained similar. Likewise, the system has not been tested on a range of clothing and therefore the performance may differ when very thick clothing is worn. With thicker clothing the surface temperature of the participant may appear cooler. Finally, the most fundamental limitation to the use of thermal sensing to detect bed occupancy is that heat sources can be obscured by blankets. Therefore, if the blanket is pulled up to cover the face and whole body, the system would result in a false negative as the human heat source cannot be detected.

6 Conclusions

This paper has presented a contactless approach to detecting bed occupancy using low-resolution thermal sensing timeseries data. This approach achieved the highest accuracy of 0.997 and precision of 0.997 in detecting bed occupancy. The algorithm developed in this study was capable of producing a bed occupancy log to determine the overall bed occupancy duration. The thermal sensor system consistently provided a longer duration of detected bed occupancy by an average of 4.7 s when compared to a pressure sensor and 0.6 s when compared to a human observer. The finding of this study demonstrates that the inclusion of logical reasoning to differentiate participants from residual heat improved the accuracy of the bed occupancy algorithm by 0.28, from 0.9694 to 0.9974. This study demonstrates the capabilities of a low-resolution ceiling-mounted thermal sensor to detect bed occupancy and determine occupancy duration within a bedroom environment.

It is thought that this approach could be integrated as part of a movement-based sleep monitoring system within care homes, in which bed exits and periods of restfulness can be detected for the purpose of caregiver alerts. To facilitate this, numerous metrics (such as ‘bed enter time’ or ‘number of bed-exits’) must be generated from the thermal binary images. Therefore, the focus of the future work is creating accurately represented foregrounds within the binary images.

The future work begins with updating components of the background subtraction algorithm as the current algorithm was designed to work on the collected bed occupancy data. Currently the average background temperature reading, used in the background subtraction algorithm to determine the threshold value, updates where no humans are detected in the frame. The longest example of bed occupancy recorded lasts 10 min whereas bed occupancy in the real world could be expected to be the typical sleep time of 8 h. Therefore, to ensure real world viability the background average background temperature should be closely tracked, and the threshold value continually updated. A residual heat detection and removal algorithm will also be integrated into the background subtraction algorithm. Finally, future work focuses on investigating a machine learning approach to detecting bed occupancy on a larger and more diverse dataset.

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