Heat-Map Based Occupancy Estimation Using Adaptive Boosting

Abdallah Naser, Ahmad Lotfi, Junpei Zhong and Jun He
School of Science and Technology
Nottingham Trent University
Nottingham, United Kingdom
Email: abdallah.naser2019@my.ntu.ac.uk, {ahmad.lotfi, joni.zhong, jun.he}@ntu.ac.uk

***Abstract*—There is a growing demand for efficient and privacy-preserving intelligent solutions in a multi-occupancy environment. This paper proposes a non-contact scheme for occupancy estimation using an infrared thermal sensor array, which has the advantages of low-cost, low-power, and high-performance capabilities. The proposed scheme offers an accurate human heat segmentation technique that extracts human body temperature from a noisy environment. It is shown that the proposed system can detect the empty occupancy state after utilising the segmentation technique with an accuracy of 100%. By using adaptive boosting, it is shown that the system is capable of measuring the non-empty occupancy with an overall accuracy of 98.2%**

***Index Terms*—Thermal Sensing, Occupancy Estimation, Ambient Intelligence, Multi-occupancy, Independent Living, Activities of Daily Living, Image Segmentation, Adaptive Boosting**

I. Introduction

Intelligent technological solutions applied to the home environment have a significant potential impact on solving important problems of independent living. For example, smart homes may help elderly people to live their lives with less reliance on others to help them with activities of daily living [1]. However, there exist notable difficulties to deploy these solutions. Specifically, most research in the field of human activity modelling and predicting abnormal behaviour in smart homes are based on the assumption of a single inhabitant environment [2]. Homes in reality often contain more than one occupant. For instance, in the United States, the average number of individuals per household is more than 3.14 people per home [3]. Therefore, there is a need for a new functional layer to detect and determine the number of people in a given area, which is referred to as **occupancy estimation**. Furthermore, occupancy estimation is also valuable in other areas, such as the energy efficiency of buildings, safety, and many other vital applications [4].

The systems based on the visual sensors perform well in the occupancy estimation problem. But the trade-off between privacy and performance of these sensors used in the field of Ambient Intelligence is another vital hindrance to escalating the deployment of smart solutions in the broader range. For instance, a high-performance human presence detection sensor like a camera may have violation to people's privacy in the context of smart homes. By contrast, a very high privacy sensor, such as a Passive Infra-Red (PIR) sensor does not perform very well in multi-occupancy applications [1]. This is because the PIR sensor can only detect the human body movement but fails to distinguish individual occupants and subsequently estimate the number of people.

This paper is concerned with the problem of occupancy estimation. As mentioned above, the occupancy estimation is a more complex problem than the occupancy detection. This is because the system is not only able to discover the human presence but also to determine the number of people in the sensor environment in estimating occupancy. Specifically, this research aims to realise it by designing a high-performance, non-intrusive, cost-efficient, and well privacy-preserving occupancy estimation system for the smart environment based on a far infrared thermal sensor array. Also a data-driven learning method is implemented to achieve great performance in the occupancy estimation.

This paper is organised as follows: in Section II of this paper, a summary of the related work regarding occupancy estimation in the smart environment is presented. In Section III, the methodology and the proposed system architecture is explained. Section IV explains the proposed system phases. Results of the experimental evaluation are presented in Section V. Section VI concludes the paper.

II. Related Work

Several different solutions have been proposed to estimate the number of occupants in an indoor environment using different sensing methods [5]. However, only a few occupancy estimation systems have been proposed using a thermal sensor array [4]. The authors in [6] integrated a thermal sensor array with 8×8 resolution and a PIR sensor to estimate the occupancy for heating, ventilation, and air conditioning control. They used the PIR sensor to detect the empty occupancy, and a thermal sensor array to determine the number of people. Their system was tested to estimate up to 3 people. However, their proposed method may not work correctly when the person is inactive for a long time, such as sleeping. In this case, the likelihood of classifying human radiation as the background radiation increases.

Authors in [4] have used a 4×16 thermal sensor array to estimate the occupancy. They removed the background infrared using the per-pixel and standard deviation values for a short occupancy period, then the K* algorithm [7] was applied to estimate the occupancy. They were able to achieve

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82.56% accuracy. It is reported that they were able to handle a prolonged period of occupancy by using a complex scaling algorithm. However, using per-pixel and standard deviation values to remove the background is probably not the best solution, because when a newer object with a higher temperature than the human body enters the sensor environment, the system may view the human body as radiation from the background, which results in an error in estimation.

The authors in [8] have proposed a system for tracking the elderly using High-performance Wireless Sensor Network Node (iMote2) sensor with Enalab camera board in smart homes. In their work, they were able to estimate the number of occupants by calculating the peaks within the histograms. Furthermore, the system also uses the PIR sensor to detect the occupancy in some areas of the home. This makes their system complicated, and privacy concerns are raised here due to the use of the camera too. Other previous works have similar concerns for using the camera in people-counting for indoor applications such as [9], [10].

Other solutions based on wearable sensors have also been suggested. But the designs of wearable sensors are inconvenient to most of the users. For instance, [11] integrated the PIR sensor with active radio frequency identification (RFID) tags to estimate the occupancy. The main limitation of this work is that users must have these tags wherever they go in the smart environment.

One of the new solutions that take the privacy issue into consideration in a smart home is reported in [12]. In this work, the authors measured the entropy of binary data collected from PIR sensors to discover the visiting time in a single-occupancy environment. The authors find that if entropy at a particular time is high, the number of house occupancy is larger than one. However, their solution was simply to predict that the house contains more than one person, which means that there is no real-time estimation of the number of people in the house.

A multimodal system for occupancy measurement is proposed in [13]–[15]. They used various environmental sensors to detect the occupancy, such as CO2, CO, lighting, temperature, movement, humidity, and acoustics sensors. The use of multiple sensors increases its accuracy, but they can only operate in a highly controlled environment and not a real home environment. This is because the authors of these papers assumed that ventilation does not affect the estimate of room occupancy. In fact, ventilation changes the CO2 and humidity level of the room, thus changes the projected occupancy estimate [6].

The work of [16] used heterogeneous sensors with neutrosophic (an extension of intuitionistic fuzzy logic) for occupancy detection without counting the number of people in a given place. The classification results were obtained by Random Forest (RF), Linear Discriminant Analysis (LDA), and FUzzy GEnetic (FUGE) algorithms.

The proposed solution in this paper differs from previous works. The differences are in

- the choice of the sensor resolution;
- inclusion of a computational method to segment human heat-map from the background of the environment (an environment may contain objects such as a kettle with the same as body temperature of higher);
- the choice of the classification method, and
- the ability to adapt appropriately to an unseen indoor environment with a new temperature degree.

The experimental results have shown 100% accuracy for empty occupancy estimation and 98.2% for occupancy estimation of up to four people.

III. Methodology

A flow-chart of the proposed system is depicted in Fig.1. The proposed system is composed of a data collection stage, an image histogram-based pre-processing, a conditional layer to predict the empty occupancy state, and the Adaptive Boosting technique in the classification phase. A detailed description of these functional phases are provided below. At first, a brief description of the characteristics of the Infrared Thermal Sensor Array is provided.

A. Infrared Thermal Sensor Array

The Infrared Thermal Sensor Array is used as an ambient sensor to measure the circumference temperature in a specific area. In this research, the MLX90640 sensor [17] has been used. This sensor is a 32×24 pixel IR array, which makes a total of 768 Far Infrared Radiation (FIR). The sensor can be accessed via the I2C interface, and its current consumption is less than $23\,mA$. This consumption makes it suitable for even a battery-powered solution. The refresh rate of this sensor is between 0.5 and $64\,Hz$, and this makes it capable of detecting swift human movements.

B. General Framework of the Proposed System

The proposed system architecture for occupancy estimation is following a similar pattern as most of pattern recognition systems, but for the analysis of occupancy estimation using a non-contact thermal sensor array and its deployment in a real environment, it is important to take the characteristics of the infrared thermal sensor array. For the case, the thermal sensor array is not light sensitive compared to the visual sensors. However, they are sensitive to environmental temperature. Therefore, it is essential to develop a systematic framework that depends on the type of sensor per itself.

As shown in Fig.1, in the pre-processing stage, the system removes all heat sources from the acquired heat-map scene except for human infrared. This results in a zero matrix for the view of empty human existence. Accordingly, the system predicts the vacant occupancy if the sum of the pixel values is zero. Otherwise, the system will use the classification model described in section IV-C to forecast the number of people in the scene.

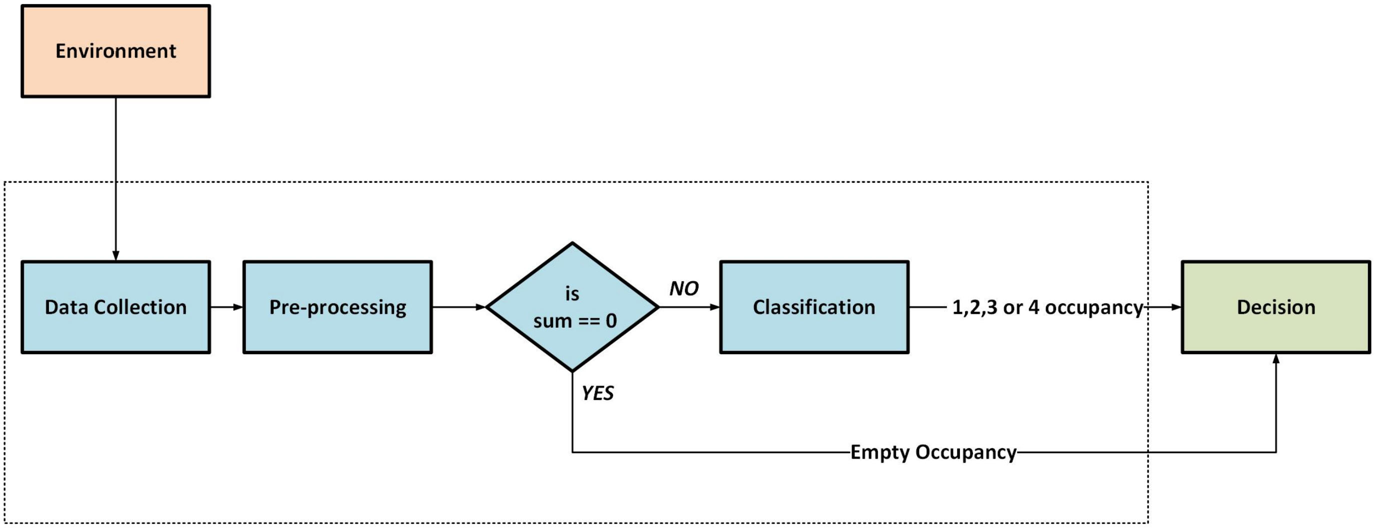

Fig. 1: Flow-chart for the proposed occupancy estimation system.

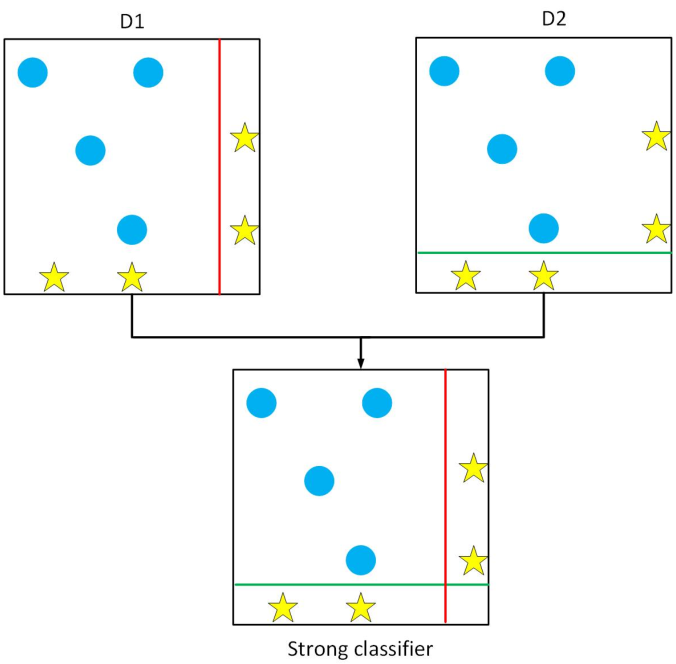

Fig. 2: An illustration of adaptive boosting applied to a binary classification problem.

C. Adaptive Boosting

There are several classification techniques to deal with the problem of occupancy estimation. Boosting algorithms are one of these possible methods that seek to boost the accuracy of a given learning algorithm by converting weak learners to strong learners [18]. In this context, a weak learner means a classifier that performs relatively poor in classification and is slightly better than random guess. In contrast, a strong learner can label the testing examples more accurate than the weak classifiers.

In Adaptive Boosting (AdaBoost) [19], the weak learners

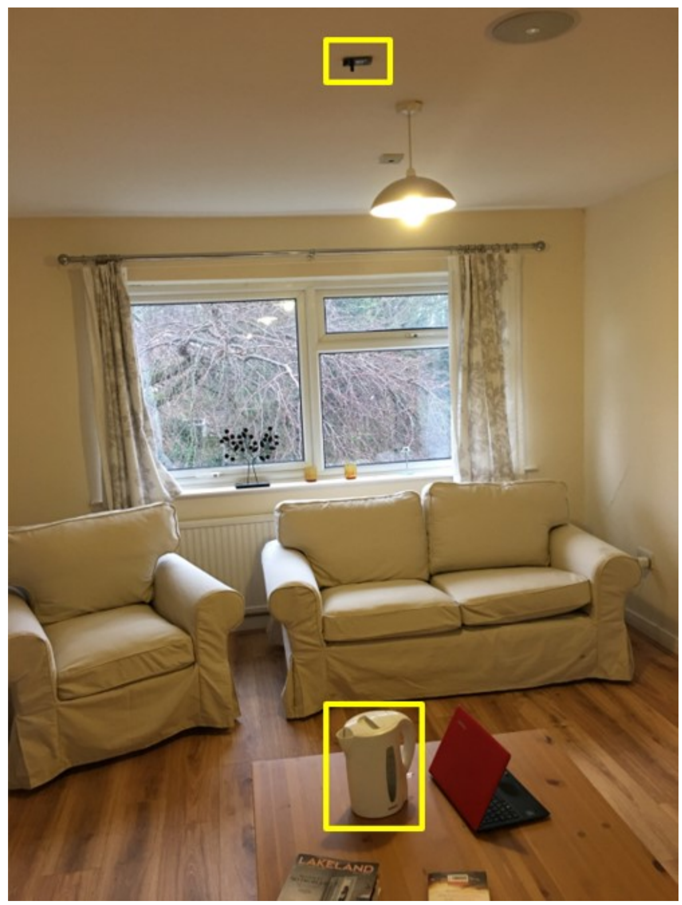

Fig. 3: Acquiring the heat-map of a warm object.

are decision trees with a single split, referred to as the decision stump. The prediction model in AdaBoost improved through training the weak learners sequentially. Each of these weak learners aims to correct its predecessor. The weights of the

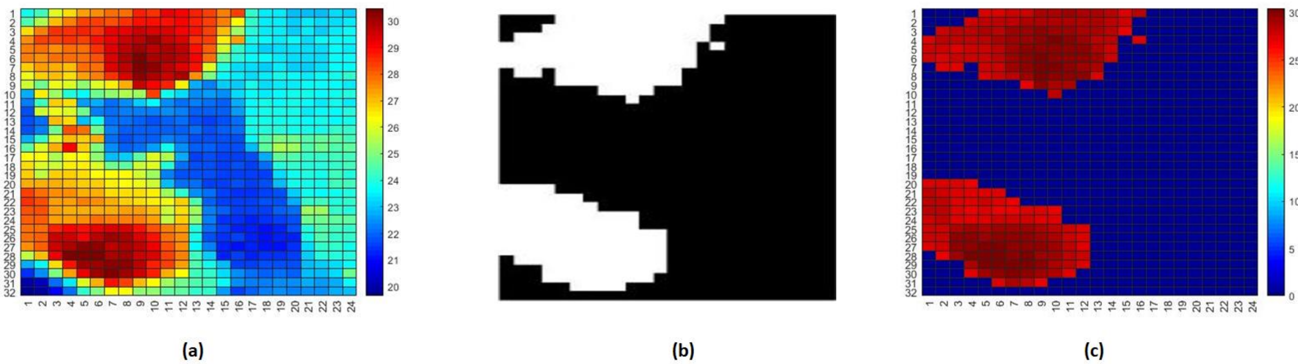

Fig. 4: Human heat-map segmentation, (a) original heat-map, (b) mask, (c) object of interest.

observations in the first decision stump are equal. In the next iteration, the incorrect observations that were inaccurately classified in the previous round carry more weights than the true classified observations to force the weak learner to focus on the hard samples in the training set.

Fig. 2 shows an illustration of a simple binary classification problem using AdaBoost. The first decision stump (D1 and D2) separates stars from circles. In this separation, there are two misclassified stars. These incorrectly rated stars will carry more weights than others to feed the second learner. Combining these two learners leads to a strong final classifier that correctly classifies the objects.

IV. Occupancy Detection and Estimation

In this section, details of the gathered data, pre-processing and classification phases are presented below.

A. Data Acquisition

To evaluate the performance of the proposed system, a data collection system based on MLX90640 infrared thermal sensor array in a domestic environment is used. The sensor returned the temperature of the captured objects in the Celsius scale.

To choose an appropriate placement of the sensor in the room is an important step to get accurate results. For instance, placing the sensor on a vertical position, such as on the wall, will affect the proposed pre-processing method in distinguishing human radiation and other radiations of noise due to the different distances, so the temperature of the environmental objects changes respectively. For this experiment, one sensor was installed on the ceiling of the room as shown in Fig 3. Since the heights of the ceiling are similar in most residential homes, the distance between the sensor and the objects is generally fixed in different residential buildings. It means that the pre-processing technique described in the following section should work well for most of the home environments. The data-set consists of six different states: an empty occupancy scene, the human existence scenes with the number of 1 to 4 persons and a scene with noise.

B. Pre-processing

Objects in the thermal scene are categorised as either noise or an object of interest. This research found that the human temperature can be any value within $27°C$ and $33°C$ using the proposed sensor with the consideration of the following factors:

- the distance between the sensor on the ceiling and objects on the floor;
- the body covered has a lower temperature than the exposed parts.

In this way, the pre-processing stage can filter noise is any other objects that has a certain temperature similar to the indoor environment temperature, such as chairs, tables, etc. or an object with the temperature higher than the human's temperature such as a hot kettle.

As such, the human heat-map in the original thermal scene which is shown in Fig 4(a) is segmented by applying the mask obtained by the possible human presence in the original thermal scene. The mask is calculated by looping through all the values of the thermal matrix and filter those values out of the range to obtain a binary mark as shown in Fig. 4(b). Then the mask is multiplied by the original thermal scene. The resulting image about objects of interest process is shown in Fig. 4(c). Hot objects are also considered in this research. Fig. 3 shows a hot kettle placed in the sensor environment where we collected the data-set. The proposed system was able to remove such kind of smaller objects as a result of the empty human heat environment.

C. Classification

The system can detect the empty occupancy class by calculating the summation of the temperature values from the pre-processed heat-map. If the summation of a given heat-map is zero, the system will predict an empty occupancy class. Otherwise, the system will use a classification model that uses AdaBoost.M2 algorithm (Algorithm 1) to predict the number of people in the heat-map in a holistic approach. AdaBoost.M2 is one of the extensions of AdaBoost to a multi-class problem [19] in which Y is a multiple-class label.

Algorithm 1 AdaBoost.M2: an extension of the original AdaBoost algorithm - an ensemble technique to create a strong classifier from a number of weak classifiers.

Input: 1) Sequence of N of samples $\{(x_1, y_1), \dots, (x_n, y_n)\}$ with labels $y_n \in Y = \{1, \dots, k\}$
2) Distribution D over the N samples
3) Weak learning algorithm **WeakLearn**
4) Integer T specifying number of iterations

Initialize: The weight vector: $w^1_{i,y} = D(i)/(k-1)$, where $i = 1, \dots, N, y \in Y - \{y_i\}$.
for $t = 1, 2, \dots, T$ **do**
$\quad q_t(i,y) = \frac{w^t_{i,y}}{\sum_{y \neq y_i} w^t_{i,y}}$
$\quad D_t(i,y) = \frac{W^t_i}{\sum_{i=1}^{N} W^t_i}\ (y \neq y_i)$
$\quad$ Call **`WeakLearn`**. $\triangleright$ Providing it with the distribution D, and label weighting function q_t; return a hypothesis $h_t : X \times Y \to [0,1]$
$\quad \epsilon_t = \frac{1}{2}\sum_{i=1}^{N} D_t(i,y)\left(1 - h_t(x_i, y_i) + \sum_{y \neq y_i} q_t(i,y) h_t(x_i, y)\right)$ $\triangleright$ Calculate the psudo-loss of h_t.
$\quad \beta_t = \epsilon_t/(1-\epsilon_t)$
$\quad w^{t+1}_{i,y} = w^t_{i,y} \beta_t^{\frac{1}{2}(1+h_t(x_i,y_i)-h_t)(x_i,y)}$ $\triangleright$ Set the new weights vector, for $i = 1, \dots, N, y \in Y - \{y_i\}$
end for

Output: $h_f(x) = \arg\max_{y \in Y} \sum_{t=1}^{T} \log \frac{1}{\beta_t} h_t(x,y)$

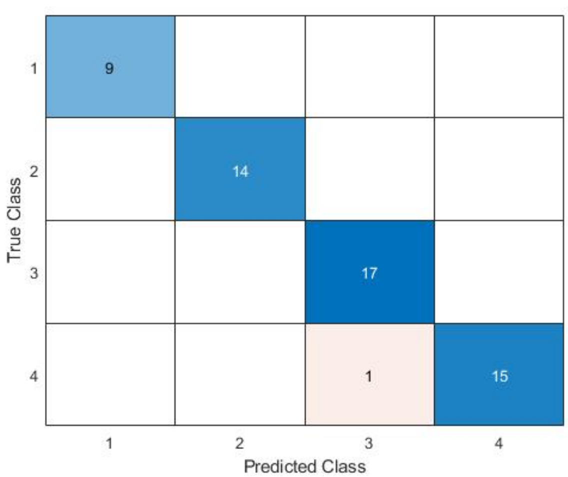

Fig. 5: The Confusion Matrix for the proposed Classification model.

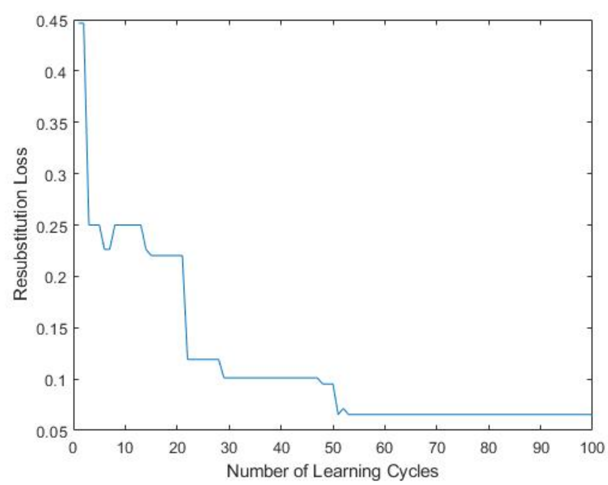

Fig. 6: The cumulative resubtition losses for the proposed classification model.

AdaBoost.M2 is described in Algorithm 1. The n-th training set for AdaBoost.M2 contains the pre-processed heat-map x and the class label y as a pair (x_n, y_n). The possible number of occupancy belongs to the set Y. The distribution $D_t(i,y)$ is maintained over the training set and is updated according to the output of each iteration's classifier on the training set. Misclassified training samples carried more weights than those truly classified in the next iteration. By doing so, the update rule is designed to guarantee upper bounds on the training and generalisation error rates. In each iteration t, a new classifier is trained with respect to the distribution D_t. In non-empty occupancy estimation, the scores of individual classifiers are weighted summation of the classifier's training error, to give the final output.

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

This section presents the experimental results and their interpretations. The collected dataset contains 220 samples. These samples are taken from single and multi-occupancy scenarios.

A. Experiment 1: Adaptive Boosting in Occupancy Estimation

The purpose of this experiment is to examine the effectiveness of the classification model described in Section IV-C. In this validity, the data set divided into 75% for model training and 25% for the testing stage.

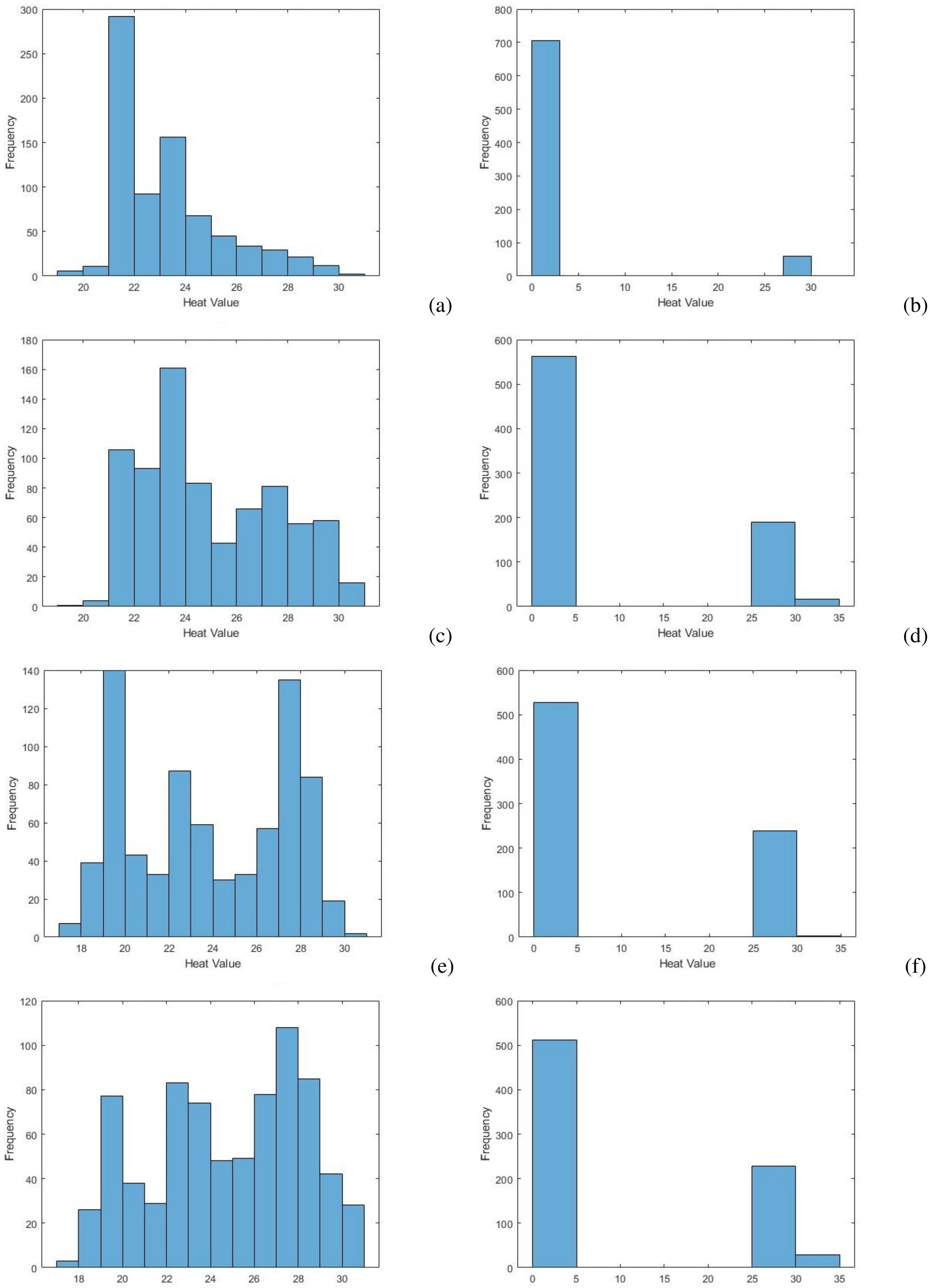

Fig. 7: Heat-map Histograms of different occupancy states, (a) single occupancy prior pre-processing, (b) single occupancy post pre-processing technique, (c) two people prior pre-processing, (d) two people post pre-processing, (e) three people prior pre-processing technique, (f) three people post-processing, (g) four people prior pre-processing, (h) four people post-preprocessing.

Fig. 5 shows the visualisation of the performance of the classification model. Each column of this matrix represents the predicted number of people in the scene, while each row represents the instances in an actual class. The system achieves 100% accuracy for predicting the number of people up to three. The only misleading rating was one in classifying the class “four” as class “three”. The overall accuracy of the system to estimate the number of people from one to four people was 98.2% and 100% for empty occupancy.

Fig. 6 shows the resubstitution loss of the boosting classification ensemble. Looking more closely, this graph indicates that when the number of decision trees in the trained classification ensemble increases, the resubstitution loss decreases.

B. Experiment 2: Image Histogram Analysis in Occupancy Estimation

The objective of this experiment is to examine the use of the histogram in occupancy estimation. Fig. 7 shows multiple histograms of different numbers of people in the sensor environment before and after applying the pre-processing technique described in Section IV-B. As shown in Figs. 7(b), 7(d), 7(f), and 7(h), the segmentation technique succeeds in dividing the heat values into two segments. The first segment is the noise represented in the zero value. The second segment shows human radiation. Another remarkable insight drawn from the segmented heat-map-based histograms is the ratio between noise, and human temperature varies with the number of people. In other words, with more people in the sensor environment with zero value at a lower frequency. Therefore, it is possible to use the ratio between the noise and the human temperature after applying the segmentation technique to estimate the occupancy.

Figs. 7(f) and 7(h) show that when the number of people increases in the sensor scene, the Inter-class similarity increases accordingly. This makes it difficult to estimate the occupancy by only looking at the ratio between noise and human heat in the aforementioned histograms. Considering the proportion of human heat per itself in addition to the ratio between human heat-map and noise segments can be useful in the case of inter-class similarity.

VI. CONCLUSION

This paper proposed an occupancy estimation scheme that uses thermal based sensing. Also, a computational method to segment human heat-map from the background of the environment is presented. The resolution of the used sensor is 32×24 in a grid pattern. This research shows the possibility of using the proposed segmentation technique and the image histogram to estimate the number of people in a specific area. Further, an investigation of the usage of adaptive boosting in determining the occupancy is described. Importantly, the proposed system is capable of predicting the empty occupancy state directly after using the proposed pre-processing technique.

Based on the achieved results, It can be concluded that the use of the adaptive boosting with the thermal sensor array in occupancy estimation is an accurate method of classification to help with the occupancy estimation in an ambient intelligent environment. Future work can be to consider other noise factors that affect the performance of estimating human occupancy such as animals pet.

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