Human Activity of Daily Living Recognition in Presence of an Animal Pet Using Thermal Sensor Array

Abdallah Naser*
School of Science and Technology
Nottingham Trent University
Nottingham, United Kingdom
abdallah.naser2019@my.ntu.ac.uk

Ahmad Lotfi†
School of Science and Technology
Nottingham Trent University
Nottingham, United Kingdom
ahmad.lotfi@ntu.ac.uk

Junpei Zhong
School of Science and Technology
Nottingham Trent University
Nottingham, United Kingdom
joni.zhong@ntu.ac.uk

Jun He
School of Science and Technology
Nottingham Trent University
Nottingham, United Kingdom
jun.he@ntu.ac.uk

ABSTRACT

The recognition of human activities of daily living has gained increasing attention in recent years due to its potential to promote autonomy for elderly people in their own homes and its usage for security surveillance in scenarios such as supermarkets, banks, etc. Infrared thermal array has been proposed as a non-invasive device for human activity detection, which has the advantages of low-cost, low-power, and high-performance capabilities. However, most of the ambient-based sensor research has not considered animal pets, whose bodies have similar temperature to human body, that may live with the elderly people in a single inhabitant environment. This has led to a gap in the usability and deployability of such systems on a broader range. This paper proposes a filtering method for removing thermal noises, including those radiated by pets, from the acquired heat-map. Therefore, only the presence of a human in the thermal scene is considered for further activity recognition. This paper shows the possibility of using an entropy point estimate for a one-dimensional heat-map histogram as a distinctive attribute to distinguish between heat-maps of the human and animal pet with 100% achieved accuracy.

CCS CONCEPTS

• **Computing methodologies → Machine learning**; **Activity recognition and understanding**; • **Hardware → Emerging technologies**.

*Abdallah Naser is a PhD research student who has conducted the research as part of his thesis.
†Ahmad Lotfi is the corresponding author. The corresponding email address is: ahmad.lotfi@ntu.ac.uk

PETRA '20, June 30-July 3, 2020, Corfu, Greece

ACM ISBN 978-1-4503-7773-7/20/06…$15.00
https://doi.org/10.1145/3389189.3397988

KEYWORDS

Thermal Sensing; Noise Removal; Ambient Intelligence; Multi-occupancy; Independent Living; Activities of Daily Living; Image Segmentation; Entropy; Principal Component Analysis

ACM Reference Format:
Abdallah Naser, Ahmad Lotfi, Junpei Zhong, and Jun He. 2020. Human Activity of Daily Living Recognition in Presence of an Animal Pet Using Thermal Sensor Array. In *The 13th PErvasive Technologies Related to Assistive Environments Conference (PETRA '20), June 30-July 3, 2020, Corfu, Greece.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3389189.3397988

1 INTRODUCTION

Long-term care expenditures for elderly people will increase due to the increasing population of elderly people [19]. Furthermore, the acceptability of nursing homes among senior citizens is low [20]. Therefore, there is a necessity to promote autonomy among elderly people by finding new alternative solutions that provide them with independent living in their homes.

There have been numerous reported research works to help elderly people to live independently. The proposed solutions experienced notable hindrances in the deployment stage mainly due to the assumption that the home environment is occupied by a single person [5]. Homes, in reality, often contain more than one occupant, which is referred to as multi-occupancy. Furthermore, the existing solutions do not take into account pets that may live at home with the elderly people in single or multi-occupancy environments [5]. A reported study has estimated that pets are owned by 24% to 31% of UK households [17].

The research into Activity of Daily Living (ADL) recognition in a domestic environment can be categorised mainly into three types: wearable sensor-based, ambient sensor-based, and vision-based. Vision-based ADL recognition systems perform well in a multi-occupant environment. However, they may have a violation of people's privacy in the context of the home environment. By contrast, ambient sensors, such as a Passive Infra-Red (PIR), do not perform very well in multi-occupancy applications [15]. Most of the work that uses wearable sensors required from the user to carry a device. In the context of older adults, carrying a device

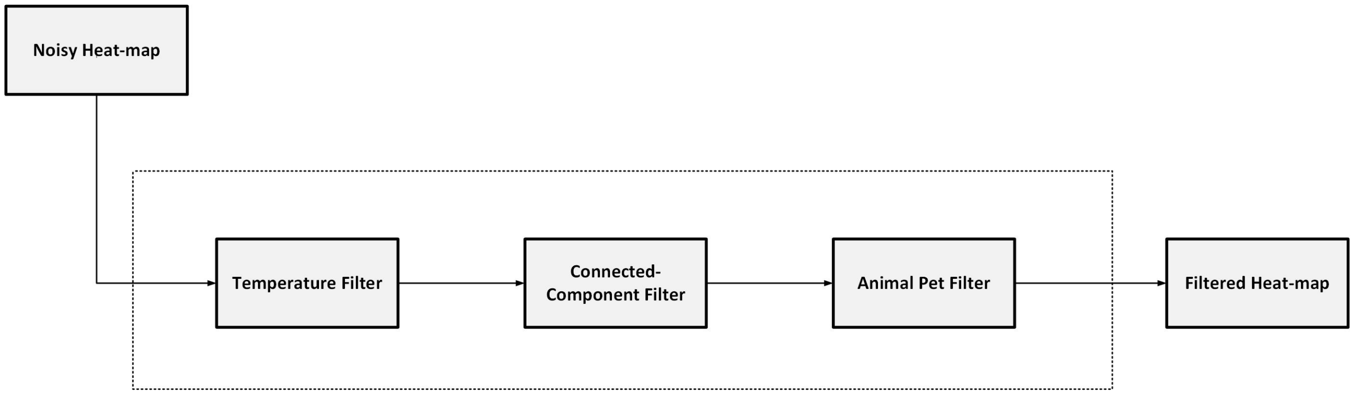

Figure 1: A schematic diagram of the proposed noise removal system.

is not convenient [8]. Further, there are difficulties in designing a wearable-based device such as energy-efficient, fabrication, and light-weight [16].

This paper is making an attempt to address the issue of identifying an occupant performing routine ADL using a Thermal Sensor Array (TSA). The proposed system is tested in the presence of thermal noise presented as an animal pet or a second occupant living with the main older adults.

This paper is organised as follows: in Section 2, a summary of the related work regarding multi-occupancy is presented. In Section 3, the proposed system architecture is explained. Results of the experimental evaluation are presented in Section 4. Pertinent conclusion are drawn in Section 5.

2 RELATED WORK

Various machine learning models based on different sensors have been used to identify ADL of the single-occupancy problem [15, 23, 23], where only one person is assumed to exist at any given time.

Using the non-invasive sensors in elderly people's home would be a solution for the privacy issue and may encourage elderly people to use such applications. One of the solutions that consider the privacy issue in a home environment is reported in [12]. In this work, entropy measures are used to determine the multi-occupancy in ADL. The target was to determine the visiting time of the elderly people in a single-occupancy environment. The authors accomplished this by comparing the entropy of binary data collected from PIR sensors in the single and multi-occupancy scenarios. This approach does not consider an animal pet as a noise factor that may change the entropy value of a single-occupancy state, which leads to a miscalculation of the visit time.

The work presented in [27] introduces a tracking algorithm for the location of residents and counting them in a home environment. Unlike other research work, this does not rely on ground-truth annotated sensor data, sensor layout, and floor plans. Other PIR-based sensing research has been shown for activity recognition [7, 10, 11, 13, 21]. However, none of these works has considered animal pets that may alter the output of any of these activity recognition systems.

Indeed, the recognition of ADL in single-occupancy or multi-occupancy with an animal pet is still an open question without using the vision sensors [4]. For instance, some work employed thermal sensors to estimate the occupancy in an indoor environment [3, 26]. However, their proposed methods did not consider animal pet and other hot objects, such as kettles, as noised factors that would results in an error in the estimation of the occupancy.

There are limited reported work using the TSA for animal detection. Authors in [14] have used a TSA with a resolution of 4×16 to detect dogs near the power equipment to protect wild animals from mutilation or being killed during haymaking. However, this work only identifies heat above the environmental temperature, but it did not perform as a fine-grained categorisation, such as human, animals or other objects.

Other solutions based on vision sensors have also been suggested for home environment [2, 9, 22, 25]. Due to privacy concerns, the acceptability of vision-based approaches is not considered high.

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

- the choice of the sensor resolution. The resolution of the proposed sensor provides high performance in maintaining the privacy and human heat-map detection.
- the novelty of segmenting a human heat-map from a noisy environment. This environment may contain objects with the same temperature as human bodies such as animal pets, higher temperatures such as a hot kettle, or even lower temperatures than the human body like environmental objects.
- the ability to adapt appropriately to an unseen indoor environment with a new temperature degree.

The experimental results also show 100% accuracy for distinguishing between human heat map and animal pet heat-map.

3 THE PROPOSED SYSTEM

A schematic diagram of the proposed system is shown in Figure 1. The system entry is a noisy heat-map that may have a human presence with other noises that may negatively affect the performance of recognising the ADL.

The first stage in the proposed system is Temperature Filter that seeks to remove all heat sources from heat-map which are not in the human body temperature range. In the Second stage, Connected-Component Filter is used to removing all heat sources within the human temperature range but represented in a relatively small volume in the thermal scene. In the third stage, an animal pet filter is used to eliminate the heat sources for objects with a high resemblance to humans, such as an animal pet. A detailed description of these functional stages will be given in the subsequent Sections. At last, the system outputs a filtered heat-map with the possible human presence.

The proposed filters aim to keep the presence of human while removing any other noise factors. By doing so, the recognition of ADL can be achieved without considering the static or moving objects with a similar temperature of humans, such as hot kettles or animal pets.

3.1 Temperature Filter

This filter aims to remove any heat source that does not have a temperature similar to that in humans. Non-human heat sources can be objects with a specific temperature identical to the temperature of the home environment, such as chairs or high-temperature objects compared to human temperatures such as a hot kettle.

Our previous research [18] has found that the acquired human temperature by the proposed sensor can be any value in the range of $27°C$ and $33°C$. The reason behind this range is due to the fact that the human body covered with clothes has a lower temperature than the exposed parts. The temperature filter can be applied by checking each FIR in the gathered heat-map if it is in the human temperature range using the following formula:

$$y = \begin{cases} x & \text{for} \quad 27 <= x < 33 \\ 0 & \text{otherwise} \end{cases} \qquad where \quad x = FIR \tag{1}$$

To illustrate the proposed filtering system, consider the heat-map presented in Figure 2 (a). The result of applying the temperature filter on the heat-map is depicted in Figure 2 (b). The temperature filter removes all heat sources whose temperatures are below or above human body temperatures, such as the background of the thermal scene.

3.2 Connected Component Filter

The aforementioned temperature filter can remove any heat noise whose temperature is not in the range specified above, for example, a hot kettle. However, the temperature filter will not be effective in removing other thermal noise that has a similar human temperature, such as a kettle with warm water. The proposed connected component filter in this section aims to eliminate thermal noise based on the size of the occupied area of the heat map instead of using only temperature values.

The first step of this filter is to localise each object in the heat map. After that, the 8-connected algorithm [6] is applied to find each connected-component in the heat-map as the second step. The idea behind this algorithm is to cluster each object based on the connectivity of its intensity values. Two "pixels"[1] whose edges or corners are reaching with each other are considered belonging to the same object. In other words, Pixel belongs to the same object if they have the same intensity and are connected along the horizontal, vertical, or diagonal direction.

[1]The concept of the pixel is borrowed from computer vision taking into account the intensity values in a heat-map.

The third step is to measure its size in order to determine whether or not the calculated size of the binarized heat-map belongs to the human class. Figure 2 (c) shows a binary image of the heat-map after applying the temperature filter. The reason behind binarizing the heat-map is to have the same pixel intensity for each object in the image. In this paper, any connected-component with less or equal to 30 pixels is considered as noise to be removed.

3.3 Animal Pet Filter

The purposes of the temperature and the connected-component filters were twofold:

(1) eliminating thermal noise with a temperature different from human temperature;
(2) eliminating thermal noise similar to human temperatures but with smaller sizes.

In this section, an animal pet filter is introduced to eliminate animal pets from the resultant heat-map of the previous steps. The target of this filter is to remove the thermal noise radiated by animal pets, whose bodies have similar temperature to human body temperature and are with relatively larger sizes than the threshold specified in the connected-component filter above.

Figure 3 shows the proposed flow diagram of the proposed animal pet filter. The input of this filter is the heat-map, which indicates as the region of interest (ROI) after applying the above filters. The filter classifies each ROI into an animal pet or human based on two different feature extraction methods:

The first approach, using Principal Component Analysis (PCA) with 95% of the variance. PCA is a linear technique for a dimensional reduction based on a linear mapping of the data from high-dimensional space to a lower-dimensional space. Mathematically, PCA is an orthogonal linear transformation that transforms the data to the greatest variance as a new coordinate system using the scalar projection of the data to lie on the first coordinate, which is referred to as the first principle component. The second greatest variance on the second coordinate, and so on. The transformation is described by a set vector of weights $w_{(k)} = \left(w_1, \ldots, w_p\right)_{(k)}$ that transform each row vector $x_{(i)}$ of a data matrix X with column-wise zero mean to a new vector of principal component scores $t_{(i)} = (t_1, \ldots, t_l)_{(i)}$, where each of the p columns represents a specific kind of feature (in this paper, represents each heat-map), and each of the n shows a different iteration of the experiment. The individual variables $(t_1, \ldots, t_l)_{(i)}$ of t computed by:

$$\begin{aligned} &t_{k(i)} = \mathbf{x}_{(i)} \cdot \mathbf{w}_{(k)} \\ &\text{for} \quad i = 1, \ldots, n \quad \text{and} \quad k = 1, \ldots, l \end{aligned} \tag{2}$$

In order to maximise variance, the first weight vector has to satisfy:

$$\mathbf{w}_{(1)} = \underset{\|\mathbf{w}\|=1}{\arg\max} \left\{ \sum_i (t_1)^2_{(i)} \right\} = \underset{\|\mathbf{w}\|=1}{\arg\max} \left\{ \sum_i \left(\mathbf{x}_{(i)} \cdot \mathbf{w}\right)^2 \right\} \tag{3}$$

and

$$\mathbf{w}_{(1)} = \arg\max \left\{ \frac{\mathbf{w}^T \mathbf{X}^\mathbf{T} \mathbf{X} \mathbf{w}}{\mathbf{w}^T \mathbf{w}} \right\} \tag{4}$$

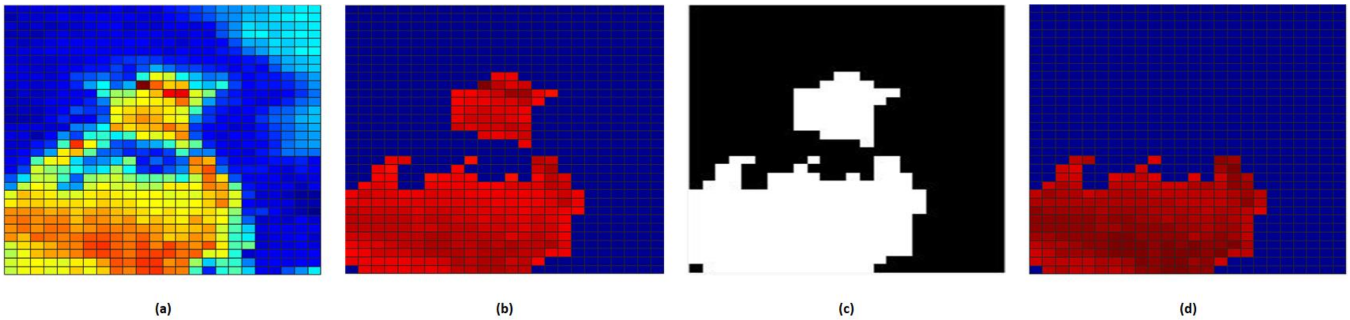

Figure 2: Human heat-map segmentation, (a) original heat-map, (b) heat-map after applying temperature filter, (c) regions of interest, (d) heat-map after animal pet filter.

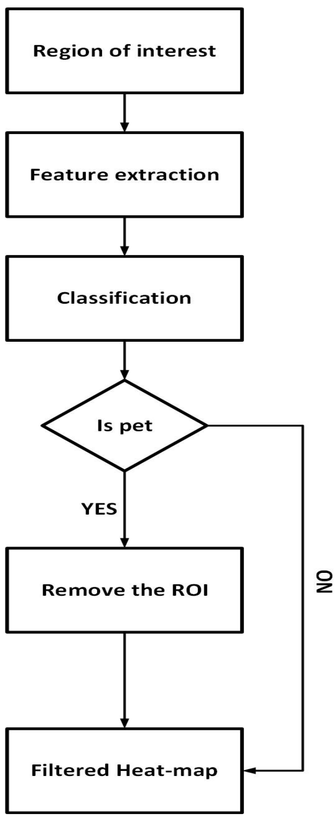

Figure 3: Flow-chart for the animal pet filter.

The principal component Kth can be found, first, subtracting the first $k-1$ components from X

$$\hat{\mathbf{X}}_k = \mathbf{X} - \sum_{s=1}^{k-1} \mathbf{X}\mathbf{w}_{(s)}\mathbf{w}_{(s)}^{\mathrm{T}} \tag{5}$$

Second, extract the maximum variance from the new matrix by finding the weight vector:

$$\mathbf{w}_{(k)} = \underset{\|\mathbf{w}\|=1}{\arg\max} \left\{ \left\| \hat{\mathbf{X}}_k \mathbf{w} \right\|^2 \right\} = \arg\max \left\{ \frac{\mathbf{w}^T \hat{\mathbf{x}}_k^T \hat{\mathbf{x}}_k w}{\mathbf{w}^T \mathbf{w}} \right\} \tag{6}$$

By doing so, the remaining eigenvectors of $X^T X$, with most significant information, are determined by their corresponding eigenvalues. Hence, the weight vectors are eigenvectors of $X^T X$. The decomposition of X for full principal components can be given as:

$$\mathbf{T} = \mathbf{X}\mathbf{W} \tag{7}$$

In the second approach, the entropy method is used. The entropy of one-dimensional histogram of each ROI $\mathbf{X}$ is calculated:

$$H(X) = -\sum_{i=1}^{n} P(x_i) \log P(x_i) \quad where \quad n = histogram\ bins \tag{8}$$

Depending on the result of the classification stage of each extracted feature vector, the filter will remove the ROI from the heat-map, if the extracted feature vector classifies as an animal pet and will retain the ROI otherwise. Figure 2 (d) shows the result of applying this filter on the heat-map shown on Figure 2 (b).

4 EXPERIMENTAL RESULTS

4.1 Data Collection

To evaluate the performance of the proposed system, a data collection system based on MLX90640 [1] infrared thermal sensor array is used. The sensor returned the temperature of the detected objects in the Celsius scale. This sensor provides a privacy-preserving and low-cost capabilities [24]. The resolution of this sensor is a 32×24 pixels, which makes a total of 768 Far Infrared Radiation (FIR). The sensor is accessible via the I2C interface, and it is suitable for a battery-powered solution as its consumption is less than 23 mA. The sensor's operational temperature range between $-40°C$ and $85°C$ and able to measure objects with temperatures between $-40°C$ and $300°C$. The refresh rate of this sensor is between 0.5 and 64 Hz, and this makes it capable of detecting human movements.

The detected temperatures of the objects from the sensor vary depending on the distance. For instance, if the sensor is placed on a vertical position, such as on the wall, it will affect the proposed temperature filter (see Section 3.1) in distinguishing human radiation

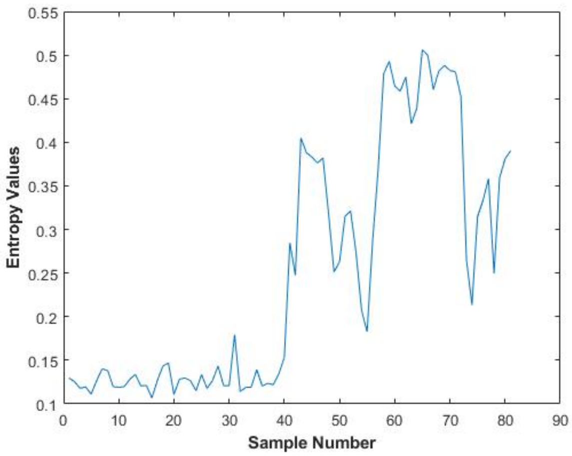

Figure 4: The entropy point estimation from heat-map histograms.

and radiations from other noised object, due to the difference in distances. Therefore, choosing an appropriate placement of the sensor in the room is an important step to get accurate results from the temperature filter method. In our system, the sensor was installed on the ceiling of the room. The reason for this installation is to ensure that the distance between the objects and the sensor is fixed in most of the residential homes. The collected data-set consists of 40 heat maps that contain human and animal pets as well as other environmental noises and a sample human presence alone. Additionally, 30 heat-maps that include hot objects and other kinds of environmental noise were included. The dataset re-sampled using cross-validation to split it into 75% for the training set and 25% for the testing set.

4.2 Animal Pet Filter

This section presents the animal pet filter classification results and their interpretations. To validate the performance of the filter, a subset of the dataset contains 81 ROIs for both the human heat-map and cat as a pet case study. Experimental investigations were conducted with four classifiers to examine the performance of the two feature-extraction methods.

From Table 1, which includes the accuracy of individual classifiers that use PCA feature vectors, it can be observed that the performance of PCA use varies based on the classifier itself. The medium KNN classifier gives the lowest performance with an accuracy of 50%, cosine KNN 75%, Naive Bayes 95%, and SVM achieved the best performance among them with an accuracy equal to 100% in distinguishing between a cat and human heat-maps.

Figure 4 shows the entropy estimation of the $1 - D$ histogram for mentioned subset data-set. The first 40 samples in the Figure belong to the cat class, while the remaining 41 belong to the human class. It can be observed that cat heat-maps entropy estimates are lower than human heat-maps. The assumed reason for entropy is low in animal pet heat-maps compared to humans is the animal pet does not have a variation in their body temperatures. However,

Table 1: Results of human and animal pet classification using PCA.

Classification Algorithm	Accuracy
Medium KNN	50.0%
Cosine KNN	75.0%
Naive Bayes	95.0%
SVM	100.0%

Table 2: Results of human and animal pet classification using entropy point estimation.

Classification Algorithm	Accuracy
Medium KNN	100.0%
Cosine KNN	100.0%
Naive Bayes	100.0%
SVM	100.0%

humans do have as a result of wearing clothes in some parts of their bodies. Table 2 shows the result of using the same classifiers used with the PCA method. The four classifiers provided 100% accuracy in classifying heat-maps into pet and human classes.

5 CONCLUSIONS AND FUTURE WORKS

This paper proposed a novel framework to solve the problem of recognition of the human presence in the activity of daily living by eliminating different noise factors, for example, animal pets, using the TSA sensor. The framework in non-invasive and low-cost. At the same time, using the proposed methodology and sensor leads to a robust recognition framework of human activity that is not sensitive to the presence of animal pets or other warm objects.

The framework includes the stages of a temperature filter, a connected-component filter and an animal pet filter. The results indicate that the combination of such filters as well as the entropy-based feature extraction, all choices of various kinds of classification methods result in a very good performance. Also, if the PCA method is chosen as the feature extraction, the SVM method should be used to guarantee a good classification result.

In our data-set, the human presence is collected while they are standing. Future work can be extended to recognise different human activities such as standing, sitting, and sleeping using thermal sensing.

REFERENCES

[1] [n. d.]. Far Infrared Thermal Sensor Array. https://www.melexis.com/en/product/MLX90640/Far-Infrared-Thermal-Sensor-Array Accessed: 2019-12-19.

[2] Athanasios Bamis, Dimitrios Lymberopoulos, Thiago Teixeira, and Andreas Savvides. 2010. The BehaviorScope framework for enabling ambient assisted living. *Personal and Ubiquitous Computing* 14, 6 (2010), 473–487.

[3] Alex Beltran, Varick L Erickson, and Alberto E Cerpa. 2013. Thermosense: Occupancy thermal based sensing for hvac control. In *Proceedings of the 5th ACM Workshop on Embedded Systems For Energy-Efficient Buildings*. ACM, 1–8.

[4] Asma Benmansour, Abdelhamid Bouchachia, and Mohammed Feham. 2015. Multioccupant activity recognition in pervasive smart home environments. *ACM Computing Surveys (CSUR)* 48, 3 (2015), 1–36.

[5] Asma Benmansour, Abdelhamid Bouchachia, and Mohammed Feham. 2016. Multioccupant activity recognition in pervasive smart home environments. *ACM Computing Surveys (CSUR)* 48, 3 (2016), 34.

[6] CC Cheng, GJ Peng, and WL Hwang. 2009. Lossy Coding of Images and Video-Subband Weighting With Pixel Connectivity for 3-D Wavelet Coding. *IEEE*

Transactions on Image Processing 18, 1 (2009), 52.
[7] Diane J Cook. 2010. Learning setting-generalized activity models for smart spaces. *IEEE intelligent systems* 2010, 99 (2010), 1.
[8] Samundra Deep, Xi Zheng, Chandan Karmakar, Dongjin Yu, Len Hamey, and Jiong Jin. 2019. A Survey on Anomalous Behavior Detection for Elderly Care using Dense-sensing Networks. *IEEE Communications Surveys & Tutorials* (2019).
[9] Muhammad Ehatisham-Ul-Haq, Ali Javed, Muhammad Awais Azam, Hafiz MA Malik, Aun Irtaza, Ik Hyun Lee, and Muhammad Tariq Mahmood. 2019. Robust human activity recognition using multimodal feature-level fusion. *IEEE Access* 7 (2019), 60736–60751.
[10] KS Gayathri, KS Easwarakumar, and Susan Elias. 2017. Probabilistic ontology based activity recognition in smart homes using Markov Logic Network. *Knowledge-Based Systems* 121 (2017), 173–184.
[11] Munkhjargal Gochoo, Tan-Hsu Tan, Shing-Hong Liu, Fu-Rong Jean, Fady S Alnajjar, and Shih-Chia Huang. 2018. Unobtrusive activity recognition of elderly people living alone using anonymous binary sensors and DCNN. *IEEE journal of biomedical and health informatics* 23, 2 (2018), 693–702.
[12] Aadel Howedi, Ahmad Lotfi, and Amir Pourabdollah. 2019. Exploring Entropy Measurements to Identify Multi-Occupancy in Activities of Daily Living. *Entropy* 21, 4 (2019), 416.
[13] Narayanan C Krishnan and Diane J Cook. 2014. Activity recognition on streaming sensor data. *Pervasive and mobile computing* 10 (2014), 138–154.
[14] Jakub Lev, Vadym Shapoval, Jan Bartoška, and František Kumhála. 2017. Low-cost infrared sensor for wildlife detection in vegetation. *Research in Agricultural Engineering* 63, Special Issue (2017), S13–S17.
[15] Ahmad Lotfi, Caroline Langensiepen, Sawsan M Mahmoud, and Mohammad Javad Akhlaghinia. 2012. Smart homes for the elderly dementia sufferers: identification and prediction of abnormal behaviour. *Journal of ambient intelligence and humanized computing* 3, 3 (2012), 205–218.
[16] Subhas Chandra Mukhopadhyay. 2014. Wearable sensors for human activity monitoring: A review. *IEEE sensors journal* 15, 3 (2014), 1321–1330.
[17] JK Murray, TJ Gruffydd-Jones, MA Roberts, and WJ Browne. 2015. Assessing changes in the UK pet cat and dog populations: numbers and household ownership. *Veterinary Record* (2015).
[18] Abdallah Naser, Ahmad Lotfi, Junpei Zhong, and Jun He. 2020. Heat-Map Based Occupancy Estimation Using Adaptive Boosting. In *International Conference on Fuzzy Systems*. IEEE. (accepted).
[19] United States. General Accounting Office. 2002. *Long term care: aging baby boom generation will increase demand and burden on federal and state budgets*. US General Accounting Office.
[20] Susan Quine and Stephen Morrell. 2007. Fear of loss of independence and nursing home admission in older Australians. *Health & social care in the community* 15, 3 (2007), 212–220.
[21] Joseph Rafferty, Chris D Nugent, Jun Liu, and Liming Chen. 2017. From activity recognition to intention recognition for assisted living within smart homes. *IEEE Transactions on Human-Machine Systems* 47, 3 (2017), 368–379.
[22] Amitesh Singh Rajput, Balasubramanian Raman, and Javed Imran. 2020. Privacy-preserving human action recognition as a remote cloud service using RGB-D sensors and deep CNN. *Expert Systems with Applications* (2020), 113349.
[23] Daniele Riboni, Linda Pareschi, Laura Radaelli, and Claudio Bettini. 2011. Is ontology-based activity recognition really effective?. In *2011 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops)*. IEEE, 427–431.
[24] Fabián Riquelme, Cristina Espinoza, Tomás Rodenas, Jean-Gabriel Minonzio, and Carla Taramasco. 2019. eHomeSeniors Dataset: An Infrared Thermal Sensor Dataset for Automatic Fall Detection Research. *Sensors* 19, 20 (2019), 4565.
[25] Juan Serrano-Cuerda, José Carlos Castillo, Marina V Sokolova, and Antonio Fernández-Caballero. 2013. Efficient people counting from indoor overhead video camera. In *Trends in Practical Applications of Agents and Multiagent Systems*. Springer, 129–137.
[26] Ash Tyndall, Rachel Cardell-Oliver, and Adrian Keating. 2016. Occupancy estimation using a low-pixel count thermal imager. *IEEE Sensors Journal* 16, 10 (2016), 3784–3791.
[27] T Wang and DJ Cook. 2020. sMRT: Multi-Resident Tracking in Smart Homes with Sensor Vectorization. *IEEE transactions on pattern analysis and machine intelligence* (2020).