Toward a holistic elderly-centred behaviour monitoring solution: Achievements and Opportunities

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ABSTRACT

Despite extensive research on human-centric domestic behaviour monitoring for various essential applications, there are still significant challenges to deploying such systems on a larger scale. One of the main obstacles is adjusting the gap between privacy, performance, and the cost of assistive technologies to support older adults living independently in their homes. For instance, while traditional vision-based sensing approaches offer high performance, they compromise human privacy in domestic environments. On the other hand, ambient sensing approaches, such as the use of Passive Infra-Red (PIR) sensors, maintain human privacy but are hindered significantly in real-world scenarios, such as multi-occupancy environments. Inspired by our previous research work, this paper proposes a holistic system approach of several functional phases that can be used together to monitor and facilitate the independence of older adults using the Thermal Sensor Array.

KEYWORDS

human behaviour monitoring, thermal sensor array; human-centred approach; abnormal behaviour detection, fall detection

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1 INTRODUCTION

There has been a growing increase in the ageing population in recent years worldwide. According to the World Health Organisation (WHO), the older adult community aged 60+ years is expected to grow from 12% of the total population in 2015 to 22% in 2050 worldwide [27]. Consequently, long-term care expenditures for older adults will increase. Furthermore, the acceptability of care homes among older adults is low [28], and generally, they prefer to continue living in their own homes. Therefore, there is an urgent need to develop new human behaviour monitoring solutions that offer older adults greater independence and enable them to live autonomously in their own homes.

The sensor technologies which could be used to acquire information related to human behaviour in a domestic home environment can be classified into three main categories:

a) Wearable-based sensors necessitate that users wear or carry a device at all times, which can be inconvenient for older adults. Furthermore, it may be even more problematic for older adults with cognitive impairments such as Dementia, as there is a high likelihood of forgetting to carry these devices. [20].
b) Ambient sensing devices such as Passive Infra-Red (PIR) sensors are installed in a home environment. Such devices preserve privacy but do not generally perform well in multi-occupancy home scenarios [19]. Other privacy-preserving device-free sensing methods, including Wireless Fidelity (WiFi), Radar, and Radio Frequency Identification (RFID), suffer from notable limitations in domestic human monitoring applications such as vulnerability to environmental interference [7, 15].
c) Vision-based sensing, for example, cameras are highly effective in real-world scenarios. However, their use in domestic environments, such as homes and care homes, raises privacy concerns as they can potentially violate the privacy of the occupants.

On the other hand, a viable and deployable solution for monitoring human behaviour in domestic settings, which is urgently needed to meet the economic and societal needs of older adults, must be acceptable to both the older adults, caregivers and the care

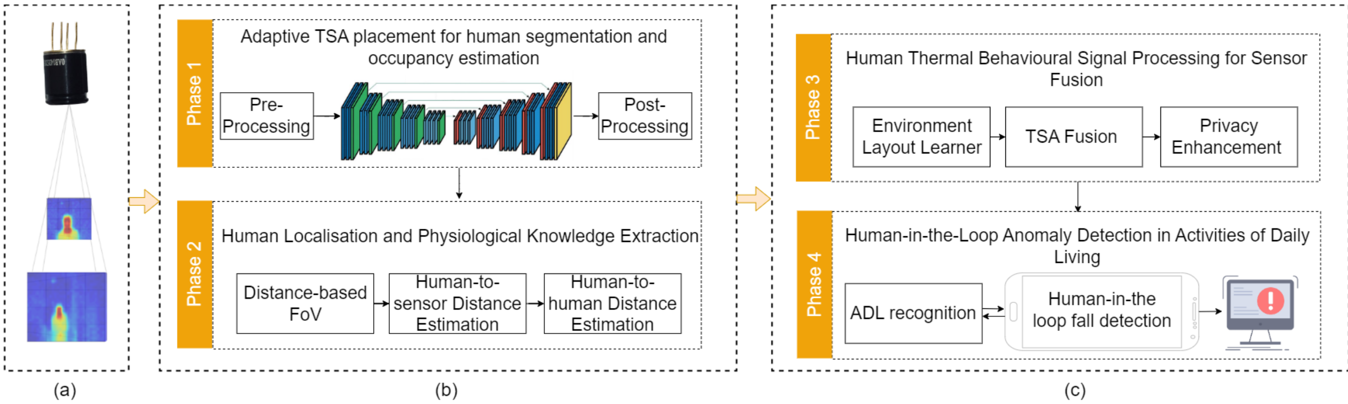

Figure 1: The proposed scheme architecture for domestic human behaviour monitoring. (a) low-resolution thermal imager for data collection, (b) monitoring human behaviour through the analysis of human physiological thermal signals, and (c) monitoring human behaviour through the analysis of human motion thermal signals.

service providers. In other words, any human-centred monitoring system for domestic use must satisfy the acceptability criteria of all stakeholders involved, which include:

- Impacts, the proposed system should contain applicable solutions that have real economic and/or social impacts,
- Privacy-preservation, the system should maintain the privacy of its users,
- Reliability, the system should be reliable to perform its tasks in realistic domestic environments that may contain more than one occupant,
- Convenience, the system should operate autonomously without interfering with normal human activities at a reasonable installation cost,
- Accountability, systems should be accountable to the users.

The aim of this paper is to outline our applicable research work on Thermal Sensor Array (TSA) for human behaviour monitoring. Hence, it is neither deployable nor impactful to propose a human monitoring system on the assumption that humans live in a single-inhabitant environment. In fact, residential homes are occupied by an average of 3.14 people per household [12]. Nevertheless, some older adults may live alone, but often have visitors such as family members, friends, and care assistants visiting their homes at certain times. This leads to a situation in which classical monitoring systems fail to operate or erroneously send abnormal alerts to the information support once more than one person has occupied the environment. On the other hand, abnormal human behaviours are unpredictable and may even be more challenging to collect actual abnormal behaviour data in a controlled lab environment. Therefore, it is essential to address a valid issue concerning the users' accountability to the system's decision in human behaviour monitoring applications.

The remaining parts of this paper are organised as follows. Initially, a scooping review and the proposed sensor for monitoring, a low-resolution thermal imager, are introduced, followed by the architecture of the proposed human behaviour monitoring system. Finally, our conclusion and further work are presented.

2 SCOPING REVIEW

The research on human-centred monitoring has been a popular and productive field, resulting in numerous publications in recent years. The number of publications on occupancy monitoring saw a significant increase, from less than 20 per year between 1981 and 2003 to over 250 in 2021 [8]. This indicates a growing demand for monitoring human behaviour in indoor settings to overcome real-world challenges, such as reducing long-term care costs for older adults and supporting their independent living. This section provides a scoping review of previous work to facilitate the understanding of the proposed holistic approach in this paper.

Human behaviour and elderly monitoring systems are essential for ensuring older adults' health, safety, and well-being. These systems use various types of sensors and algorithms to monitor the activities and behaviours of older adults, detect any anomalies or changes, and alert caregivers or family members if there are any potential health or safety concerns [22]. One of the most promising sensing technologies in human behaviour monitoring is wearable sensors. These sensors can be worn on the body and measure various parameters, such as heart rate, respiratory rate, and activity levels [9, 16, 30]. They can also detect falls or other emergencies and send caregivers alerts. Nevertheless, the success in wearable sensors has been a mix of setbacks and progress [13]. One of the technical barriers when utilising wearable sensors in human behaviour monitoring is the obstruction of feature extraction from the signal due to artefacts, body movement or respiration that need to be resolved to obtain high-quality signals [6]. On the other hand, wearable-based biosensors rely on specific body postures or on-body placement to provide reliable measurements [5].

Another promising sensing category is ambient sensing. Ambient sensors can be placed in the environment and detect various parameters, such as temperature, humidity, and motion. They can also detect changes in behaviour patterns, such as changes in sleep or bathroom use, and send alerts to caregivers or family members. This type of sensor is commonly used for domestic human monitoring, with PIR sensors being the most widely used. PIR sensors use a pair of pyroelectric sensors to detect heat energy in the environment. The sensors are located beside each other and use the changes in the signal differential between them to indicate warm object motion. The output of PIR sensors is a digital (binary) signal that either triggers new movement or does not. However, since PIR sensors cannot detect stationary subjects without motion, they cannot be used for applications involving humans in inactive states like sleep or rest. Nevertheless, PIR sensors has been proposed for various applications including ADLs recognition [14, 19], user localisation [29, 31], gait velocities analysis [1, 11], sleeping and night activities monitoring [4, 18]. Besides, PIR sensors are typically integrated with other sensors to detect the presence of human subjects, such as pressure sensor that is attached to beds or chairs, door sensor, and floor sensors [19].

In addition to wearable sensors and ambient sensing, there is vision-based monitoring. This type of monitoring use cameras to monitor the activities and behaviours of older adults. However, these types of monitoring systems may raise privacy concerns and may not be suitable for all older adults. Several studies have been reported for human-centred applications using vision-based sensors [2, 3, 10, 17]. However, the privacy concerns of vision-based sensors in domestic environments are not the only hindrances of this approach. For example, traditional cameras are sensitive to light and cannot operate in a dark environment. In contrast, thermal cameras are light-independent but are a very costly approach.

Despite the potential benefits of human behaviour and elderly monitoring systems, there are also some limitations to consider. For example, some older adults may be resistant to using these technologies, or they may find them intrusive or uncomfortable. Additionally, there are concerns about the accuracy and reliability of these systems, and there may be false alarms or missed alerts. This paper outlines our research on overcoming these issues using proper sensing technology, TSA sensors, and precise computational techniques.

3 LOW-RESOLUTION THERMAL IMAGER FOR DATA ACQUISITION

Thermal imagers are devices that detect the thermal energy emitted by objects within their Field of View (FoV) and convert it into a temperature matrix. The resulting temperature matrix is then transformed into a visual image using a colour mapping scheme. Thus, thermal imagers can be described as a means of converting radiant thermal energy into visible images. The resolution of the thermal image can be determined by the number of detector elements in the thermal imager's array. The higher the resolution, the more detector elements there are, and the more detailed the image. High-resolution thermal images are useful for detecting and identifying small temperature variations in a scene, making them ideal for applications such as medical imaging, research, and inspection. However, higher-resolution thermal cameras tend to be more expensive and may require more storage space and processing power to handle the larger amount of data they produce. A detailed empirical calibration between low- and high-resolution thermal imagers is provided in [25].

Lately, there has been a new commercial low-resolution TSA sensor that has gained growing interest in indoor human monitoring applications due to its low cost, non-contact and human privacy-preserving features. In this research, a commercial TSA sensor[1] that has a resolution of 32×24 IR array, which makes a total of 768 Far Infrared Radiation (FIR) sensors has been used. The selection of this TSA resolution was based on an empirical calibration of various thermal imagers discussed in [25]. Moreover, the TSA can be accessed via the *I2C* interface, and its current consumption is less than 23 mA, which makes it suitable for battery-powered solutions. Additionally, the sensor's refresh rate is between 0.5 and 64 Hz, which makes it capable of detecting swift human movements.

4 THE ARCHITECTURE OF THE PROPOSED HUMAN BEHAVIOUR MONITORING SCHEME

To ensure the effectiveness of a domestic human behaviour monitoring system, it is essential to consider its flexibility to operate in various domestic environments, sensor placements, and multi-occupancy scenarios. Additionally, the system's reliability should be a priority in addressing its intended purpose. For example, deploying a health-related anomaly detection system in older adults' homes that triggers alerts to a centralised information support system may pose severe problems if the system is not sufficiently reliable. A fall detection system that sends false alarms to the information system without considering the older adult's accountability could result in unreliable responses, such as sending too many ambulances. Moreover, a system designed for single-occupancy environments could inaccurately report abnormal human behaviours in the presence of a visitor.

The research methodology for the proposed human behaviour monitoring scheme is divided into two parts to ensure the above effectiveness factor in domestic human behaviour monitoring systems. The first part involves monitoring human behaviour through the analysis of human physiological thermal signals, while the second part analyses human behaviour by processing human thermal motion signals. In total, four functional phases have been proposed to enable potential human behaviour monitoring that can be applied to real-world scenarios. Figure 1(a) visualises the output of the TSAs at different FoV depths. Figure 1(b) demonstrates the first two functional phases of using the human physiological thermal signals to monitor human behaviours indoors, and Figure 1(c) demonstrates the last two functional phases concerned to analyse the human motion-based thermal signals to monitor the human behaviour.

4.1 Data Collection Scenarios

One of the identified acceptability factors for good human behaviour monitoring is convenience. To achieve this factor, the system should be user-friendly and not interfere with the users' daily activities. Additionally, it should be easy to install in various indoor environmental layouts without sensor placement limitations. The ideal monitoring scheme should allow the system's installers to choose the TSA placement based on on-site observations. Building on top of this, the proposed approach's functional phases were evaluated through comprehensive data collection with different TSA

[1]The sensor details can be obtained from the Melexis website: https://www.melexis.com/en/product/MLX90640/

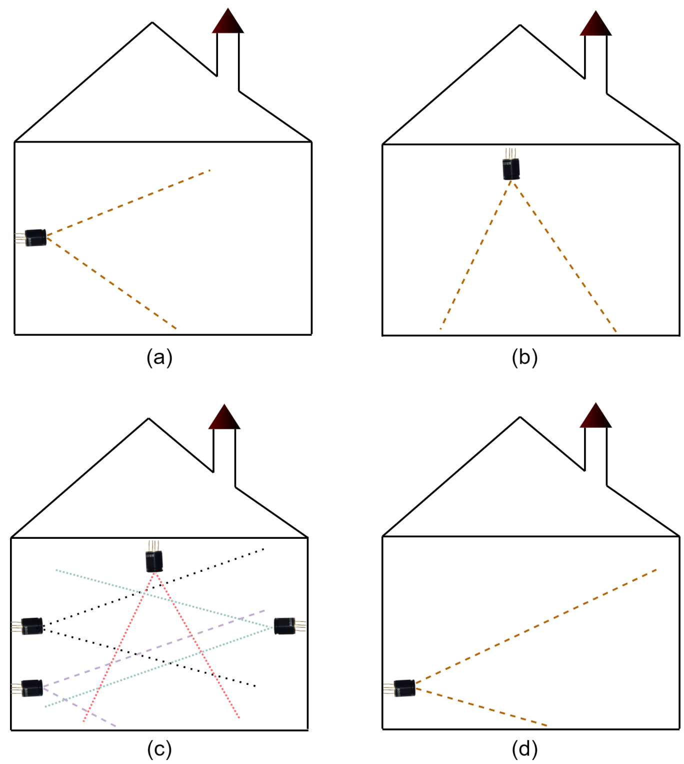

Figure 2: The scenarios of TSA placements to evaluate the performance of the proposed human behaviour approach [21].

placement scenarios, and a summary of these scenarios is presented below.

- Stage I - data collection scenarios: Two data collection scenarios were implemented to evaluate the proposed approach to assess the adaptability of the proposed human segmentation and occupancy estimation functional phase. This involved placing the TSA vertically, as shown in Figure 2(a). The second scenario involved placing the TSA on the ceiling, as illustrated in Figure 2(b).
- Stage II - data collection scenarios: Data collection scenarios were conducted in this stage for the functional phase 2, human localisation and distance estimation, with a wall TSA placement shown in Figure 2(a). This placement is more realistic for human localisation in the FoV than the ceiling placement. Hence, predicting human-to-sensor distance from a wall placement is more challenging than ceiling placement. The proposed approach was also tested with completely new and unseen data from a different TSA placement, the ceiling, as depicted in Figure 2(b).
- Stage III - data collection scenarios: this research found that low-resolution thermal images obtained from TSA have low intra-class variations and high inter-class similarities, making it difficult to identify overlapping regions through matching a comparable template image in multiple images. To validate the proposed sensor fusion functional phase, various sensor placements depicted in Figure 2(c) were employed. The first scenario involved evaluating if the movement of a person could be determined in a multi-occupancy environment using two sensors installed side by side at 90°, where there could be another person performing similar or different activities. The second scenario involved sensing interference between opposite sensor placements. The third scenario involved placing the interfering sensors at different heights on the same wall, while the fourth scenario involved placing the interfering sensors on both the wall and ceiling.
- Stage IV - data collection scenarios: the TSA sensor was placed on a short-height wall during the last stage of data collection, demonstrated in Figure 2(c). This was done to assess the efficacy of the series-based signal processing technique in detecting human ADL and identifying abnormal behaviour in the last functional phase. Additionally, the TSA was placed on the ceiling to examine the approach's ability to predict abnormal human behaviour during sleep, where individuals are typically in a horizontal position.

The following sections elucidate the aforementioned data collection scenarios by providing a summary of the technical information with regard to the functional phases of the system's architecture.

4.2 Adaptive TSA Placement for Human Segmentation and Occupancy Estimation

Careful consideration of TSA-related sensing constraints is necessary when utilising TSA to collect data. One constraint is the placement of sensors and the coverage area they provide. Previous TSA-based work suggested placing sensors on the ceiling to capture the human presence, but this can be costly and may require more sensors for larger environments. Thus, the first problem addressed in this phase is enabling the TSA sensor to segment the human presence with adaptive sensor placement accurately. Further, the system architecture accounts for multi-occupancy environments by estimating the number of human subjects in low-resolution thermal images, referred to as occupancy estimation.

In this phase, several techniques have been used to segment the human presence for low-resolution images. Specifically, a Convolutional Neural Network (CNN) has been adapted to semantic segment the human presence in low-resolution thermal images. Hence, semantic segmentation is a computer vision technique that divides an image into different regions or objects and assigns a semantic label to each segment based on its content. This allows the proposed system to accurately identify and understand an image's different components. Semantic segmentation differs from object detection as it focuses on the pixel-wise labelling of objects in an image, while object detection focuses on identifying and localising objects in an image using bounding boxes.

It is important noting that various pre- and post-processing techniques have been employed to adapt to the unique characteristics of TSA sensors. For instance, unlike camera sensors, TSA sensors are not affected by light sensitivity but are sensitive to changes in environmental temperature and have a lower resolution. Therefore, a specific set of pre-and post-processing techniques have been proposed to make the sensor output suitable for the proposed segmentation method. This first proposed system's phase is evaluated to estimate the occupancy in different sensor locations, the number of occupants, environments, and human distance with classification and regression machine learning approaches. This paper shows that the classification approach using the adaptive boosting algorithm is an accurate approach with an accuracy of 98.43% and 100% from vertical and overhead sensor locations, respectively. The detailed technical and experimental information is available in [23].

4.3 Human Localisation and Physiological Knowledge Extraction

To develop a system that monitors human behaviour in multi-occupancy environments, it is important to be able to measure human-to-sensor distance, as well as human-to-human distance. This phase proposes a new method for estimating human distances using a low-resolution TSA, with separate estimators for discrete and continuous human-to-sensor distances using classification techniques and Artificial Neural Network (ANN). The technical details of this phase are provided in [24].

This phase is applicable in vital applications like social distancing alert systems to prevent the spreading of contagious diseases. In the context of the older adults' monitoring and support, this phase will be used as a proximity monitoring scheme to track the movements of the caregiver and the older adult and measure how close they are to each other. This type of monitoring can provide valuable information about the quality and quantity of care provided to the older adult and ensure that the caregiver is fulfilling their duties and responsibilities. Tracking the movements of both parties can help identify potential issues, such as neglect or abuse, and ensure that the older adult is receiving the care they need.

4.4 Human Thermal Behavioural Signal Processing for Sensor Fusion

In this third phase of the proposed monitoring scheme, the focus is on fusing multiple TSA sensors to enable the system to learn the environment layout and identify overlapping regions between the sensors' FoVs. This is achieved through a time-series-based TSA signal processing approach, Optical Flow, which allows for a more comprehensive analysis of human behaviour over time. Hence, Optical flow is a computer vision technique used to track the motion of objects in a sequence of images or frames. It is commonly used with high-resolution images and video processing applications. However, with low-resolution thermal imagers, the use of optical flow can be challenging due to the low image resolution and limited texture information available in thermal images. Therefore, preprocessing techniques are required to use optical flow with TSA sensors. The technical details of using optical flow features with the TSA sensors to fuse multiple sensors and enhance the privacy-preserving of TSA-based Internet of Things (IoT) applications is available from [26].

One of the critical benefits of identifying overlapped regions between multiple TSAs is the improved accuracy of occupancy estimation systems. For instance, if a person is present in the overlapping region of two sensors, the system can identify this as a single person rather than two separate individuals, thereby preventing false alarms. However, it is also important to consider the impact of overlapped regions on fall detection systems. Falls are considered abnormal human behaviour, and they may occur in areas where two sensors overlap. In such cases, the system may trigger two separate fall alerts, which could be incorrect. Therefore, it is important to carefully design the fall detection system to account for overlapped regions and minimise false alarms.

4.5 Human-in-the-loop Anomaly Detection in Activities of Daily Living

To support the independent living of older adults in their own homes, it is essential to identify their abnormal behaviours before triggering an automated alert system. False alerts (false-positive) fall detection has not been addressed thoroughly in systems that report abnormal human behaviours as emergency alerts to the information support. Inspired by the results of the previous phase, this final phase is centred on examining human movement patterns in the TSA sensors output for ADL recognition and detecting abnormal behaviours. Specifically, to identify human falls during ADL and establish a fall detection system, which involves user participation to increase accountability.

A potential method of addressing the issue of false alarms in fall detection systems is by requesting that the user to confirm the fall through a mobile notification. If the user is unable to confirm or cancel the alert, such as when they are unconscious or have no access to their mobile phone, the system will automatically confirm the fall. The technical details are provided in [22] The rationale behind suggesting the smartphone as a human interaction modality to confirm the detected falls is due to the fact that most people have smartphones and would therefore be more apt to use the technology they already have rather than adding an extra cost and effort with unfamiliar modality. Besides, the proposed modality could be a feature of an existing mobile healthcare tracking application, e.g., the UK National Health Service (NHS) mobile app. However, some older adults may not have smartphones to confirm the detection of abnormal behaviour cases that require urgent responses. In this case, there are no restrictions to switching the confirmation from a mobile notification to an automated landline call to confirm or cancel the detected fall.

5 CONCLUSION AND FUTURE WORK

To conclude, this paper has presented several novel contributions of a holistic system approach towards domestic human behaviour monitoring to enhance the usability of TSA sensors in the field of Ambient Assisted Living and elderly support. The proposed monitoring scheme has overcome several major challenges and limitations from the literature associated with TSA sensors, such as static sensor placement, thermal noise, privacy, and limited inspection area by proposing a chain of novel frameworks towards a more user-accountable behaviour monitoring scheme. The preservation of privacy and the ability of the proposed monitoring scheme to operate in a multi-occupancy environment with the presence of animal pets argues in favour of significant impact on various sectors, including the healthcare sector in support of independent living of older adults in their own homes.

Future work could be conducted to explore the potential of TSA sensors for user profiling in the home environment. This could involve developing algorithms that analyse the data collected by the TSA sensors to create a profile of the user's behaviour patterns and habits over time. Such a system could provide personalised assistance and support for older adults. It could also help to identify any changes or anomalies in their behaviour that may indicate a health issue or safety concern. Additionally, user profiling could improve the monitoring system's accuracy and reliability, enabling it to distinguish between normal and abnormal behaviour more effectively.

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