

# Monitoring Indoor Activity of Daily Living using Thermal Imaging: A Case Study

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**Abstract**—Monitoring indoor activities of daily living (ADLs) of a person is subjected to dependency on sensor type, power supply stability, and connectivity stability without mentioning artifacts introduced by the person himself. Multiple challenges have to be overcome in this field, such as; detecting the precise spatial location of the person, and estimating vital signs like an individual's average temperature. Privacy is another domain of the problem to be thought of with care. Identifying the person's posture without a camera is another challenge. Posture identification is a key in assisting detection of a person's fall. Thermal imaging could be a proper solution for most of the mentioned challenges. It provides monitoring both the person's average temperature and spatial location while maintaining privacy. In this research, an IoT system for monitoring an indoor ADL using thermal sensor array (TSA) is proposed. Three classes of ADLs are introduced, which are daily activity, sleeping activity and no-activity respectively. Estimating person average temperature using TSAs is introduced as well in this paper. Results have shown that the three activity classes can be identified as well as the person's average temperature during day and night. The person's spatial location can be determined while his/her privacy is maintained as well.

**Keywords**—Activity monitoring; activities of daily living (ADLs); thermal imaging; indoor monitoring; thermal sensor array (TSA)

## I. INTRODUCTION

Monitoring indoor activities of daily living (ADLs) can be achieved with different methods [1]–[5]. As a first step, building occupancy and estimating the number of occupying individuals should be performed. A full review for detection of building occupancy and estimating number of individuals inside a building is presented by Chen et al. [1]. In this research, a review for different systems utilizing sensor fusion for building occupancy detection is presented. A comparison between the sensors utilized is conducted as well. Another complete review for different approaches used in detecting occupancy of the buildings, counting number of individuals and tracking those individuals is introduced by Saha et al. [2]. The authors in that review, focused on two aspects, the mathematical point of view and the corresponding metrics for evaluating these approaches. They focused on the prediction and performance metrics in order to establish a benchmark system for indoor occupancy estimation. A third systematic review concerned about the ambient assisted living technologies and focusing on their impact on individuals' health is presented by Choukou et al. [6].

Inertial sensors are utilized in Voung et al. [3] to monitor the indoor wandering patterns to detect behavior disorder for people with dementia. Their preliminary experimental results have shown that their proposed solution has outperformed the existing classification algorithms based on time-series analysis with respect to accuracy and time performance. Another research in the scope of dementia is conducted by Das et al. [4], where a one-class machine learning classification approach for detecting real-time indoor elderly individual daily activity errors is proposed. Machine learning techniques with the aid of computer vision approaches are used to monitor the daily activities of elderly people in another study Chen et al. [5]. Deep convolution neural network approach is used for recognition of daily activities such as; eating, bathroom entries, sleeping and housekeeping by the work presented by Gochoo et al. [7]. The proposed deep convolution neural network is found to outperform the existing models by F1 score of 0.951. Utilizing motion sensors is one of them [8]–[10]. As in Aloulou et al. [8], an adaptive approach for plug-and-play mechanisms of motion sensors used for ambient assistive living of elderly people is proposed. The real-life deployment for the system proposed in the previous study using motion sensors is presented in Aloulou et al. [9], where the authors deployed the system in three nursing room and monitored the daily activity for elderly people for a 14 months period. The study included eight dementia patients. A pilot study for IoT deployment of a continuous real-time monitoring of elderly people using unobtrusive technology and utilizing door sensors and motion sensors as a core sensor is conducted by the same team Aloulou et al. [10]. The aim of that pilot study is to identify the health-related problems for elderly people. A complete unsupervised approach is used to detect and model the behavioral change for elderly people by the use of passive-sensing technology; such as PIR and motion sensors is presented and deployed by Hu et al. [11]. Their experimental results have shown the ability of the system to detect the following individuals' activities; namely, sleeping, outing and visiting activities in addition to individuals' health status. A recent project focusing towards assisted living for elderly people to support aging in place is presented by Choukou et al. [12]. A case study for investigating the claim of smart flooring system to detect elderly people falling is presented by Chintanu et al. [13].

Motion sensors can be used to detect if there is any motion taking place in front of the sensor. On the one hand, these sensors are effective for detecting the movement of one person, and their effectiveness increases when sensor fusion is deployed. However, they impose several limitations that can be

summarized as follows: a) they cannot detect the exact spatial location of the monitored person or even an estimate for its spatial location, b) they cannot differentiate between the steady sitting state and the no-motion state, c) they cannot be used for fall detection as they cannot obtain depth and 2D data about the person's location, and d) they do not inform about the number of individuals inside the room. Moreover, this type of sensor has another limitation is that it does not give any vital data about the person during the monitoring period.

Another option of detecting ADLs is using another physical quantity i.e., the temperature of the person [14]–[17]. Every human being can be considered as a heat source that can be detected using Thermal Sensor Array (TSA). Thus, the problem can be reduced to being only the detection of the heat distribution of the person inside the room. In other words, it is possible to track the estimated spatial location of the person inside the room by tracking his/her thermal distribution. (Fig. 1 shows the thermal 2D distribution of two heat sources as measured by a thermal sensor array).

Given the various advantages of thermal imaging, the contribution of this paper is to assess the effectiveness of a thermal sensor array for tracking a subject's indoor activities.

The paper is organized as follows: section II discusses the advantages of thermal imaging over the mentioned limitations. Section III methodology used in conducting the experiment. Results of the experiment and related discussion are introduced in Section IV. Finally, the conclusion is presented in Section V.

## II. THERMAL IMAGING TECHNOLOGY

A thermal sensor array can be used to pick up a complete capture for the thermal distribution of the room every minute and store its readings for subsequent processing [18], [19] [20]. This method has many advantages.

- First, it maintains the privacy of participating persons.
- Second, it tracks the precise spatial location of the person, giving rise to a better understanding of behavior patterns extracted from activity per spatial location.
- Third, it monitors the average temperature of the person per unit timestamp allowing for better assessment of the person's health status (e.g., if he/she is suffering from fever or relevant diseases).
- Fourth, it can track whether the person is in an upstanding posture or has lain down, using advanced algorithms that can differentiate between the thermal distribution in both cases. Upstanding posture gives more concise (confined) thermal distribution for the person, alike the horizontal or lying down position where relevant thermal distribution is much wider and scattered. This feature can also be helpful in fall detection [21].

Several researches have concluded the possibility of indoor occupancy estimation using TSA [18], [19]. They all placed TSA in a specific spatial location in the room. The person IR emission is triangulated to estimate his location as in [20]. An experimental evaluation for two low resolution thermal sensor arrays for occupancy detection is conducted by Rinta-Homi et

al. [22]. Another systematic study investigated the performance of three low resolution thermal sensor arrays in detecting the indoor occupancy with the aid of machine learning algorithms [23]. In this study, the authors conquered the challenge of detecting two individuals with low proximity to each other by the use of iterative blob filtering technique to split the blob which is larger than that of a single human being. The privacy issue is respected in [24] by using a low resolution thermal sensors to detect the occupancy and to track the individuals indoors. A study is performed to detect the presence of people indoors by means of identifying their directions with respect to a room doorway using a low resolution thermal sensor array is conducted by Perra et al. [25]. The use of thermal array sensors for detecting individuals' fall is investigated practically by the study conducted in [21].

All these presented work focused on occupancy detection and estimation only without giving attention to the person's ADL indoors. In our work the focus is on monitoring a person's ADL to deduce his behavior. Following, the methodology used in our proof-of-concept IoT experiment is discussed.

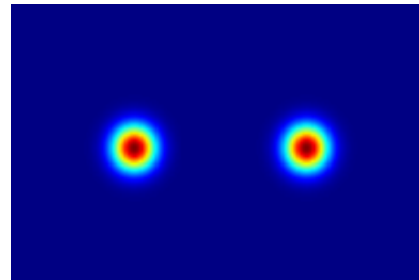


Fig. 1. Thermal Distribution of Two Heat Sources as Picked up by an Array Sensor after Interpolation.

## III. METHODOLOGY

A male person is monitored over time using a thermal sensor array to track his activity. A single person as a proof-of-concept and for feasibility is monitored. An IoT system consisting of a thermal sensor array and a processing unit to analyze the acquired data is implemented. The person's activity is monitored by tracking specific thermal image pixels related to the activity spatial locations inside the room. The temperature of the corresponding pixels in the temporal domain to construct different activity vectors/arrays for the person is tracked. Then these vectors are sent to a cloud server annotated with their relevant timestamp, where they can be stored and analyzed.

The system is deployed to monitor a single person living inside a room. The person's activity is monitored on a 24-hour basis and is classified (for this work) as three classes: the sleeping activity, the daily activity and the no-activity classes. The corresponding spatial locations at which these three activities are most likely to happen are marked on the room schematic. The bed represents the sleeping activity of the person. The working table and dining table represents the daily activity of the subject. The room schematic is presented in Fig. 2 along with the sensor located inside the room and its location with respect to the person. The activities' spatial locations are presented in Fig. 3.

The IoT system consists of MLX90641 (16x12/110°x 75°/~7m axial range) [26] which is a thermal sensor array for acquiring thermal activity and a Raspberry Pi 3B+ is used as a node. The acquired thermal frame is transmitted as a 1D-array (element-by-element) along with a corresponding timestamp via CoAP transmission protocol from the Pi to a server for subsequent data processing and analysis. Another copy from the transmitted data is stored locally on the Pi for retrieval and substitution in case of transmission failure situations. The IoT system block diagram is presented in Fig. 4. The complete process of the system is presented in Fig. 5. The experimental hardware setup is shown in Fig. 6. The next section explains the temporal thermal activity tracking algorithm.

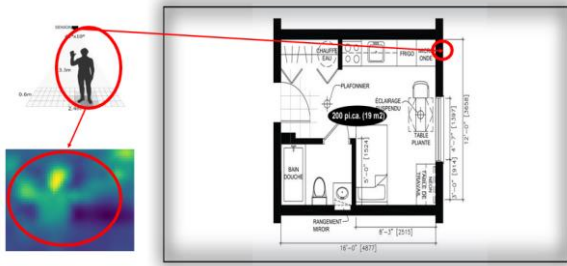


Fig. 2. Room Schematic along with its Real Photo, describing the Spatial Location of the Sensor W.R.T the Person Body.

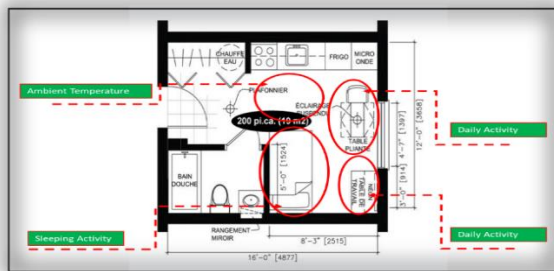


Fig. 3. Regions of Interest along with its Corresponding Activity.

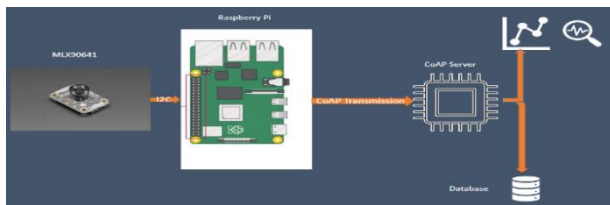


Fig. 4. Block Diagram of the Complete System.

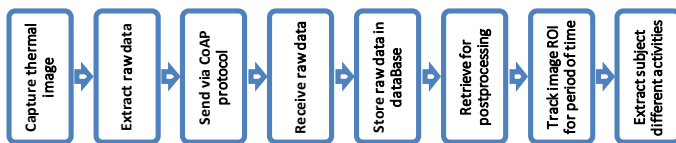


Fig. 5. Complete System Process.



Fig. 6. Complete Hardware Setup during Runtime.

### A. The Temporal Thermal Activity Tracking Algorithm

This algorithm is used to track the spatial thermal activity in the acquired image from the sensor array. It starts with tagging the corresponding pixels that are relevant to the spatial locations where the three activity classes are most likely to happen. The tagging is performed by relating specific image pixels to a location where each class of the three classes happen, i.e. for the sleeping activity class, the person is asked to lie down on the bed and a reference image is captured to identify the location of the bed and so on for the other two classes. Then the related pixels to these locations are tracked over time. This process is shown in Fig. 7.

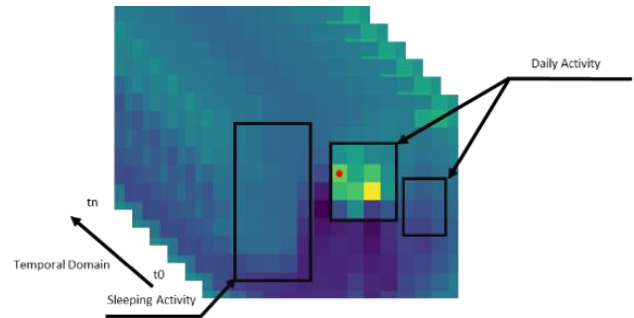


Fig. 7. Visualization of Temporal Thermal Activity Tracking Algorithm.

Each thermal activity corresponding to one of the three classes can be formulated mathematically as a 1D-array by the following formula (1):

$$A^K = [a_t^K, a_t^K, a_t^K, \dots, a_t^K], \forall t = \{0, 1, 2, \dots, T\} \text{ and } K \in \{1, 2, 3\} \quad (1)$$

Where A is the thermal activity array, t is the temporal resolution, T is the final timestamp of the monitoring period, and K is the activity class (1: Sleeping, 2: Daily and 3: No-activity).

The computational algorithm is implemented on the server side due to the limited computational resources used on the monitoring site side. The aim of this algorithm is to identify the timestamps at which each activity has started and ended as accurate as possible.

The used algorithm starts firstly by collecting the relative pixel values into 1D arrays, where each value in the activity 1D array represents the temperature value at specific timestamp in the real spatial location in the room. Each constructed 1D array ( $A^K$ ) is then differentiated to its first derivative array, this will help identify the timestamps at which there were changes along the array. If the value of the array is falling from a high temperature value to a lower temperature value, then there has been an activity at this spatial place and is now ended. This is reflected in the first derivative array as a sharp impulse in the negative direction, i.e., having a negative value. It is at this value where we identify the ending timestamp of one of the three activities done by the individual. On the contrary, if the 1D array is experiencing a sudden increase in its values from a relatively low value to a higher value, then its first derivative output should have positive impulse values indicating the start of the activity at this spatial location.

This process is ruled by a try and error threshold of  $>3C$  degrees between the no activity state and the activity state. The complete No-activity inside the room is identified when there is no activity status detected on all of the three arrays representing the thermal activity of the person on the three spatial locations tagged previously.

The computational algorithm is illustrated in the following Algorithm1.

**ALGORITHM1: IDENTIFY ACTIVITY START AND END TIME-STAMPS**

```

Input: activity1_arr[time_stamp][Temperature],
activity2_arr[time_stamp][Temperature]
Output: activity1_duration_arr[time_stamp][status], status  $\in$  {Start, End}
activity2_duration_arr[time_stamp][status], status  $\in$  {Start, End}
1 Initialization of variables:
Set act1[][]  $\leftarrow$  activity1_arr[time_stamp][Temperature],
Set act2[][]  $\leftarrow$  activity2_arr[time_stamp][Temperature]
Set derivative1_arr [][]  $\leftarrow$  empty
Set derivative2_arr [][]  $\leftarrow$  empty
Set threshold  $\leftarrow$  3C
2 if (length(act1) == length(act2))
3   for each entry in length(activity1_arr):
4     if index(entry)  $\leq$  (length(activity1_arr) - 1)
5       derivative1_arr[time_stamp][entry]  $\leftarrow$ 
act1[time_stamp][entry+1] - act1[time_stamp][entry]
derivative2_arr[time_stamp][entry]  $\leftarrow$ 
act2[time_stamp][entry+1] - act2[time_stamp][entry]
6     End
7   End
8   for each entry in length(derivative1_arr):
9     if (derivative1_arr[entry]  $\geq$  threshold )
10      activity1_duration_arr[time_stamp][Start]  $\leftarrow$  derivative1_ar
rr[time_stamp][-]
11     end
12     if (derivative1_arr[entry]  $\leq$  -( threshold ))
13      activity1_duration_arr[time_stamp][End]  $\leftarrow$  derivative1_ar
r[time_stamp][-]
14     end
15   end
16   for each entry in length(derivative2_arr):
17     if (derivative2_arr[entry]  $\geq$  threshold )
18      activity2_duration_arr[time_stamp][Start]  $\leftarrow$  derivative2_a
rr[time_stamp][-]
19     end
20     if (derivative2_arr[entry]  $\leq$  -( threshold ))
21      Activity2_duration_arr[time_stamp][End]  $\leftarrow$  derivative2_ar
r[time_stamp][-]
22     end
23   end
24 else:
25   Terminate with error message ("The duration of time-stamps and
activity does not match")
26 end

```

IV. RESULTS AND DISCUSSION

The non-interpolated image (16x12) as captured from the sensor, its corresponding interpolated image (128x176) and no-activity image are presented in Fig. 8(a), (b) and (c) respectively. The person's location inside the image is labeled by the red dot. Two different ways of sleeping activities are presented in Fig. 9.

The person's behavior for 10 consecutive days in April 2021 is monitored. Every monitored day is presented in a separate curve starting from 00:00 o'clock till 11:59 of the same day on the X-axis and the temperature on the Y-axis, except for the last day where the monitoring ended at 16:30. The orange curve represents sleeping activity and the blue curve represents daily activity for the monitored person. The first three days of monitoring are shown in Fig. 10, namely 7<sup>th</sup>, 8<sup>th</sup> and 9<sup>th</sup> April. The three consecutive days which are 10<sup>th</sup>, 11<sup>th</sup> and 12<sup>th</sup> April are shown in Fig. 11. Fig. 12 shows the person's behavior during 13<sup>th</sup>, 14<sup>th</sup> and 15<sup>th</sup> April. Finally, the last two days are shown in Fig. 13.

Sleeping activity periods, daily activity periods, no-activity periods, and missing data periods for each day are listed in Table I and are shown as a bar chart in Fig. 14. Behavior statistics such as mean value and percentage value for each activity type along the whole monitoring period are listed in Table II.

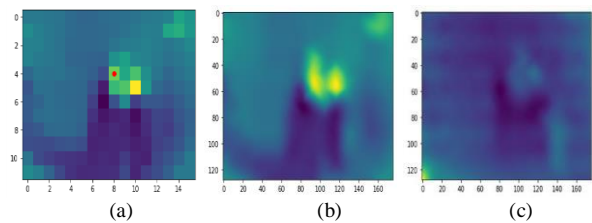


Fig. 8. (a) Non-Interpolated Image showing the Person doing his Daily Activity, (b) The Corresponding Interpolated Image, and (c) Interpolated Image showing no Activity Inside the Room.

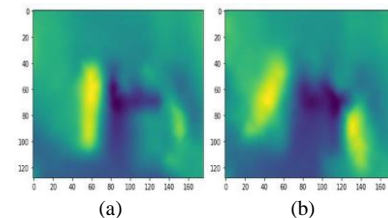


Fig. 9. Two different Sleeping Activities of the Person.

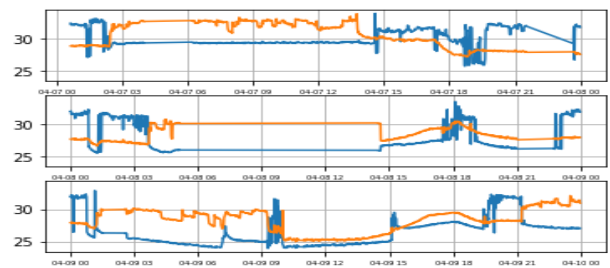


Fig. 10. Monitoring Person's behavior during 7<sup>th</sup>, 8<sup>th</sup> and 9<sup>th</sup> April.

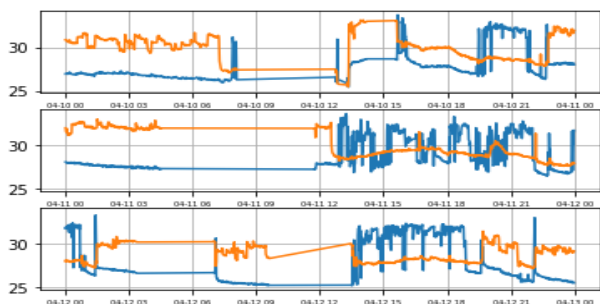


Fig. 11. Monitoring Person’s behavior during 10<sup>th</sup>, 11<sup>th</sup> and 12<sup>th</sup> April.

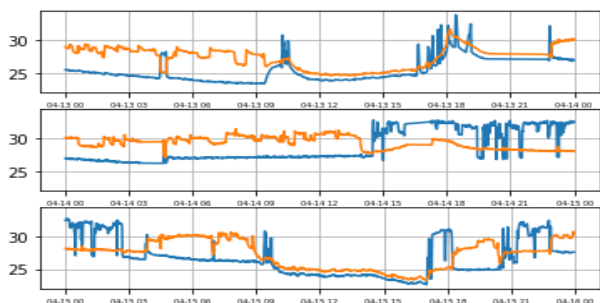


Fig. 12. Monitoring Person’s behavior during 13<sup>th</sup>, 14<sup>th</sup> and 15<sup>th</sup> April.

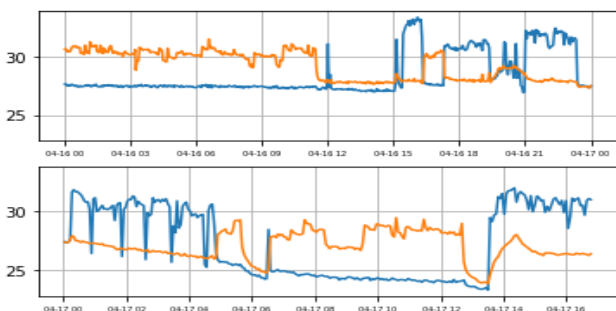


Fig. 13. Monitoring Person’s behavior during 16<sup>th</sup> and 17<sup>th</sup> April.

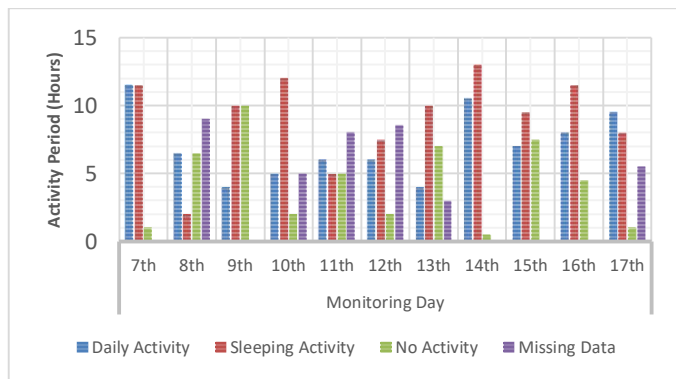


Fig. 14. Different Activity Periods for the Person’s behavior during the Whole Monitoring Period.

On each day of the monitoring period, the sleeping activity and the daily activity are observed to be contrary to each other. Both activities have a temperature difference of about 3°C degrees each day. The person’s average temperature is observed to be 32°C degrees on average during the whole monitoring period.

TABLE I. BEHAVIOR MONITORING PERIODS

Monitoring Day	Activity Period (Hours)			
	Daily	Sleeping	No-Activity	Missing Data
7 <sup>th</sup>	11.5	11.5	1	0
8 <sup>th</sup>	6.5	2	6.5	9
9 <sup>th</sup>	4	10	10	0
10 <sup>th</sup>	5	12	2	5
11 <sup>th</sup>	6	5	5	8
12 <sup>th</sup>	6	7.5	2	8.5
13 <sup>th</sup>	4	10	7	3
14 <sup>th</sup>	10.5	13	0.5	0
15 <sup>th</sup>	7	9.5	7.5	0
16 <sup>th</sup>	8	11.5	4.5	0
17 <sup>th</sup>	9.5	8	1	5.5

TABLE II. BEHAVIOR STATISTICS FOR THE WHOLE MONITORING PERIOD

Activity Type	Mean (Hours)	Percentage
Daily Activity	7.090909	0.295454545
Sleeping Activity	9.090909	0.378787879
No Activity	4.272727	0.178030303
Missing Data	3.545455	0.147727273

The most dominant activity of the person during the monitoring period is the sleeping activity as concluded from the behavior statistics in Table II with an average of 9 hours per day. Daily activity happens to be the second place with 7 hours per day, and the no activity comes in third place with about 4.2 hours per day.

Small periods of no-activity happening inside the room are inferred as a bathroom entry due to its small duration and its location between two long durations of either sleeping activity or daily activity or both of them. The person is most likely considered visiting the bathroom just after wake up. The person’s concluded bathroom visits are listed in Table III.

It is concluded from Table III that the person’s bathroom visit takes on average between 30 minutes to 60 minutes.

During the long no-activity durations exceeding one hour the person is considered out of the room, i.e., these durations are considered outing periods. On 9<sup>th</sup>, 13<sup>th</sup>, 15<sup>th</sup> and 16<sup>th</sup> long durations of no-activity at the same normal working hours are observed, hence it is concluded that the person was out for work at these periods.

TABLE III. THE PERSON’S BATHROOM VISITS

Monitoring Day	Bathroom Visit (Start / Duration [minutes])			
	7 <sup>th</sup>	14:00 / 60		
8 <sup>th</sup>	01:00 / 30			
9 <sup>th</sup>	01:30 / 30			
10 <sup>th</sup>	07:00 / 30	13:00 / 30	21:30 / 60	
11 <sup>th</sup>	17:30 / 30	22:00 / 30	22:30 / 90	
12 <sup>th</sup>	01:30 / 30	18:30 / 30	21:00 / 60	
13 <sup>th</sup>	09:30 / 30			
14 <sup>th</sup>	14:15 / 30			
15 <sup>th</sup>	03:00 / 30			
17 <sup>th</sup>	12:30 / 30			

It is also noticed that the person often goes to sleep after midnight and before 03:00 except for 8<sup>th</sup>, 15<sup>th</sup> and 17<sup>th</sup> April, where the person went to bed after 03:00. It is concluded here that the person is a night owl.

It is noticed that the person spends about 29% of its day as daily activity, 37% as sleeping activity, and 17% as no-activity or bathroom visits and outings. Missing data is about 14%.

In terms of monitoring the person's temperature, a significant decrease in the person's body temperature is observed during 12th April around 20:00 and during 17th April from 00:00 till around 05:00.

## V. CONCLUSION

In this paper a monitoring system based on thermal sensor array that can capture a person's activities of daily living (ADLs) is proposed and implemented. The monitored ADLs are classified as sleeping, daily, and no-activity at all. The experiment proves that the system enables detection of a person's spatial location indoor precisely. In addition, the experiment enables prediction for the bathroom visits and the outing and estimates the person's temperature during the whole monitoring period along with maintaining the person's privacy as well. As a future development of this experiment, there are different directions to be investigated. A first direction is the hardware experimental setup; where for covering wider field of view (FOV) an approach of TSA grid should be utilized. Another direction is, in the direction of automatic recognition of the individuals' presence inside the room, where machine learning approaches should be utilized. This is considered to automate the presence recognition and to reveal more daily activities' types. Also, machine learning techniques can help differentiate between multiple heat sources not only other than multiple human beings' presence in the room but also differentiating between different heat sources such as; the heater-on and the heater-off states in the room.

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