

Use of Thermal Sensor Data for Personalised Mood Detection in Activities of Daily Living (ADLs)

Alexandros Konios¹[0000-0001-5281-1911], Matias Garcia-Constantino²[0000-0002-3420-0532], Idongesit Ekerete²[0000-0003-4072-7178], Mustafa A. Mustafa³[0000-0002-8772-8023], Irvin Hussein Lopez-Nava⁴[0000-0003-3979-9465], and Yulith V. Altamirano-Flores⁵[0000-0002-6350-1780]

¹ Department of Computer Science, Nottingham Trent University, Nottingham, UK

² School of Computing, Ulster University, Belfast, UK

³ Department of Computer Science & COSIC, The University of Manchester & KU Leuven, Manchester, UK & KU Leuven, Belgium

⁴ CICESE (Centro de Investigacion Científica y de Educación Superior de Ensenada), Ensenada, México

⁵ Universidad de Castilla-La Mancha, Spain

alexandros.konios@ntu.ac.uk, {m.garcia-constantino, i.ekerete}@ulster.ac.uk, mustafa.mustafa@manchester.ac.uk, hussein@cicese.edu.mx, Yulith.Altamirano@uclm.es

Abstract. Ambient sensors have been typically used in Human Activity Recognition (HAR) to monitor the activities of people and to detect unusual activities that may affect a person's wellbeing. The main advantages of ambient sensors are that they are not intrusive and do not require the user to charge them periodically. Thermal sensors are a type of ambient sensor that provides temperature data from the environment in which they are placed, allowing to identify a thermal representation of elements that produce heat, such as people, animals or hot objects. In most cases, the focus of HAR research is on the physical health of people, not on their mental health. This paper presents an investigation on the use of thermal sensor data from people performing Activities of Daily Living (ADLs) to identify mood in a personalised way. Thermal data was collected from 15 participants performing the ADLs of preparing and drinking a hot beverage in 7 sessions. At the start of each session participants reported their mood. Classification results were produced for each participant using the Support Vector Machines (SVM) model in 10-Fold Cross Validation (CV) and in 80/20 split. The average accuracy values obtained of 0.9123 (80/20) and 0.9233 (CV), and of Cohen's Kappa Coefficient of 0.8375 (80/20) and 0.8574 (CV) are promising for a thermal sensor personalised mood detection approach.

Keywords: Activities of Daily Living, Activity Recognition, Ambient Sensors, Thermal Sensors, Mood, Machine Learning, Healthcare.

1 Introduction

In recent years there has been an increased use of Internet of Things (IoT) sensors and solutions at home by the general public in the form of virtual assistants (i.e. Amazon Alexa and Google Home) and sensors to automate daily tasks such as controlling heating and lights of home environments. These types of sensors used at home are considered ambient sensors because they are attached to objects in the environment with which the user interacts (e.g., kitchen, bathroom, home appliances). Ambient sensors are not intrusive and do not require the user to charge them periodically, however, for their more optimal functioning they need to be well placed in the environment and within an adequate setting. In addition to ambient sensors being more widely used, there has also been a widespread use of wearable sensors, that can be worn by users in parts of their body or in their clothes, in the form of smartwatches and fitness trackers. Wearable sensors can be used to monitor and collect data regardless of the location of the users; however, users are responsible for their correct use and for charging the battery of the sensors [1].

The use of ambient sensors, to improve the quality of life of their users, has not been limited to support with the automation of daily tasks, as it has also been widely used in healthcare to monitor the health and wellbeing of people [2]. An indicator typically used by health professionals to assess if a person can live on their own independently is on how well they perform Activities of Daily Living (ADLs), which are categorised into basic and instrumental. Basic ADLs are those required to manage basic physical needs such as having functional mobility, personal hygiene, and dressing. Instrumental ADLs include more complex activities related to the ability to live independently in the community such as housekeeping, meal preparation and medication management. The detection of abnormal behaviour while performing ADLs can be an indicator of a progressive health problem taking place (dementia, osteoporosis, arthritis, etc.) or the occurrence of a hazardous incident (falls, burns, cuts, food, or smoke intoxication, etc.) [3]. In terms of mood, there have been studies showing how they affect how people perform ADLs [4][5]. Note that in many studies in the literature the focus is on elderly people with dementia, but mood can also affect how healthy people of different age groups perform ADLs.

In that sense, this study investigates the use of thermal sensor data from people performing ADLs to identify mood in a personalised way based on individual patterns. This work builds upon prior research efforts in which the focusses were abnormal behaviour identification in ADLs [6][7][8][9][10], and privacy concerns in the context of IoT-based ADLs [11]. The approaches considered in [8] and in [10] used Petri nets to model and verify the ADLs of preparing and drinking a hot beverage and preparing pasta. The approach presented in [6] is based on the temporal analysis of ADLs to identify abnormal behaviour. In [9], the approach presented in [6] is extended by considering the sequential aspects of the ADLs in addition to the temporal aspects and using Cumulative Distribution Function (CDF) to provide accurate and reliable results regarding the presence of abnormal behaviour. Privacy issues and potential countermeasures in the context of IoT-based ADLs for abnormal behaviour detection were investigated in [11]. In [7], an initial approach using just accelerometer

data for activity recognition in the context of ADLs was presented. The methodology presented in this paper expands on previous work that investigated mood detection while performing ADLs based on: (i) accelerometer data [12], and (ii) ambient sensors (thermal and contact) [13].

The main contribution of this work includes the proposal and evaluation of a thermal sensor-based solution for personalised mood detection using Support Vector Machines (SVM) with linear kernel classification model. This research involves the analysis of thermal and mood data collected from multiple sessions of participants performing the ADL of preparing and drinking a hot beverage to determine if mood classes can be effectively identified by using only thermal sensors for the typical ADL considered. The remainder of this paper is organised as follows: Section 2 presents the related work in the areas of activity recognition using ambient sensors and mood data. Section 3 describes the environment setup, and the data collection. Section 4 describes the methodology proposed for personalised mood detection, and Section 5 presents the results obtained. Finally, Section 6 presents the conclusions.

2 Related Work

Detection of people’s mood in everyday life within smart environments could support their wellbeing and mental health by reinforcing positive moods and alerting people of negative moods to seek assistance. The sensors typically used in smart environments are categorised to ambient (attached to objects in the environment with which the user interacts [6][16]) and wearable (worn by users in parts of their body or on clothes [14][15][1]) ones. As the investigation on the use of both ambient and wearable sensors in conjunction for mood detection is beyond the scope of this paper, the focus in this section is on research concerned with the use of thermal sensors as the ambient sensor used and mood detection.

In [17], a framework for mood recognition based on Long Short-Term Memory (LSTM) recurrent neural networks is presented. LSTM networks are a type of artificial neural network architecture designed to capture and analyse sequential data effectively. The approach presented in [17] is trained on relevant mood-related data (physiological signals or behavioural patterns), and it recognises and predicts mood states using LSTM recurrent neurons. The work is a contribution to the affective computing research area with the use of advanced neural network architectures.

The use of thermal sensors has been frequently used to detect stress, depression, and moods and emotions in general. While the terms “mood” and “emotion” are usually used interchangeably, there are key differences between them, for instance, emotions are considered to last from seconds to minutes, while moods last from minutes to hours. The study presented in [18] presents a method to detect stress in real time using facial thermal image analysis. Data was collected from 20 healthy participants using a FLIR SC7600 thermal IR imager with noise-equivalent temperature difference of 17mK and with a sample rate of 30 frames. The Region of Interest (ROI) of the thermal device used was the face of the participants. In addition to using the thermal sensor, participants were asked to use a chest strap heart monitor while a series of

emotional stressors were given to participants followed by a 45-minute recovery period. In [18] thermal imprints extracted from participants by magnification method significantly changed during the emotional stressors.

In the study presented in [19], thermal and hyperspectral imaging methods were used to detect stress remotely. The results reported in [19] indicated patterns in temperature regions of the forehead of participants characteristic to the types of stressors. Cross *et al.* [20] presented a multimodal sensor platform which included high-resolution electro-optical and mid-wave infrared (WMIR) cameras as well as a millimetre-wave radar system to detect stress in 32 participants. Facial data from participants was segmented into 29 non-overlapping segments. Results in [20] were reported as very satisfactory with classification of physical versus psychological stressors being greater than 90%.

Dharma *et al.* [21] proposed an approach using a Deep Neural Network (DNN) to predict four states (normal, and of depression (mild, moderate or severe)) using thermal images from people. The results reported were positive with an accuracy of 96.61% for ResNet101 and 96.55% for MobileNetV2. The authors of [21] mentioned that environmental temperature could have affected their results. In [22], Nayak *et al.* presented a non-contact framework based on thermal and visual facial imaging for the classification of four affective states (stress, depression, anxiety or healthy) during Human-Computer Interaction. A cascaded Convolutional Neural Network (CNN) was used to ensemble cues from visual and thermal facial images, and a Hidden Markov Model (HMM) was used to cluster a sequence of emotional states. There were 51 participants in their study. The results reported in [22] were indicated as promising.

An approach for emotion recognition using thermal images of faces was presented in [23]. The four regions of the face were divided into four classes and into eight regions, with four ROI. Results for the Optimised Probability Density Function (OPDF) proposed approach [23] were presented for average colour image, average infrared image and for the proposed optimised method, which had the highest accuracy classification values. In [24], feature based data analysis on thermal images is used for emotion recognition. Spatial and spectral aspects of histogram-based feature descriptors (34 in total) and a set of classifiers for thermal emotion are investigated. Results reported in [24] had the highest accuracies for emotion recognition with PHOG (Pyramid of Histogram of Oriented Gradients).

3 Environment Setup and Data Collection

The ADLs considered for the data collection and analysis are “preparing and drinking a hot beverage” with the variants of coffee and tea. These ADLs are typically performed by people regardless of their health status and they are based on the ones used in [25], where they were modelled using ontologies.

3.1 Environment Setup

The kitchen environment in which the data for the ADLs was collected was the one at the smart kitchen in the Pervasive Computing Research Centre (PCRC)¹ at Ulster University (see Fig. 1).

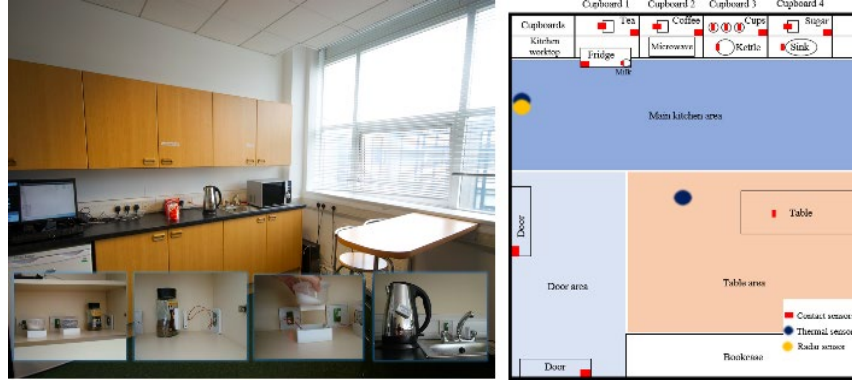


Fig. 1. (a) Main area of the smart kitchen, and (b) smart kitchen layout showing placement of contact, thermal and radar sensors.

Data was collected using three types of ambient sensors (contact, thermal, and radar) and one wearable sensor (accelerometer). Contact sensors were attached to objects with which the participant had interaction in the kitchen while performing the ADLs considered for this study: doors, cupboards, refrigerator, cups, containers (tea, instant coffee, sugar, and milk), and location areas (kitchen worktop, table, and sink). The contact sensors used were the NEXA LMST-606, which combine wireless transmitters and magnetic switches. The signals from the contact sensors have two possible states (on or off), and they were monitored and collected by the sensor data platform SensorCentral [26] for further processing and analysis. The timestamps from the state changes in the contact sensors were used to calculate duration times of stages in the ADLs. In Fig. 1b, the contact sensors are represented as rectangles divided into two parts that can be separated ('on' state) or joint ('off' state). Accelerometer data was collected using a Shimmer² device, which includes a 3-Axis Freescale accelerometer and can record and transmit data in real time. Accelerometer data was collected at a sample rate of 51.2Hz with a sensitivity range of $\pm 1.5G$ and streamed via Bluetooth. The Shimmer device was worn by participants on the wrist of their dominant hand using a band while they performed the ADLs. Details of the data collection, pre-processing of the radar sensors are beyond the scope of this paper and will be addressed comprehensively in future work.

The two thermal sensors used to collect thermal sensor data from participants were the Heimann GMBh model HTPA32 and they were placed in two different parts of

¹ <https://www.ulster.ac.uk/research/topic/computer-science/pervasive-computing>

² <http://www.shimmersensing.com/>

the kitchen to reduce any possible Restricted Field of View (FOV) when capturing the data. The thermal sensors used have a resolution of 32x31, a 90° by 86° field of view that provides a coverage area of 6m by 6m, and a sample rate of 10Hz. The first thermal sensor was mounted in the ceiling of the kitchen in a central position where it could identify the three main kitchen areas where participants' presence could be detected (main kitchen area, table area, and areas around the doors). It was placed on the ceiling because it provided coverage of the kitchen area and because it was for the purpose of a controlled laboratory data collection. The second thermal sensor was attached to a tripod and placed in a corner of the kitchen close to the worktop to provide a different perspective of how the ADLs were performed. Note that this study considers only data from the thermal sensor placed on the ceiling of the kitchen.

For both thermal sensors one sample (thermal image) per second was collected. The rationale of using thermal sensors in this study instead of other ambient sensors or video cameras was mainly to protect the privacy of the participants and of potential users of the proposed approach because thermal images collected do not have enough resolution to be considered as privacy invasive.

3.2 Participants

Fifteen participants were recruited for this project following some specific selection requirements related to their age, gender, and health. Although half of the number of participants were recruited with respect to previous related works by the authors [6] [9], there were more sessions performed per participant. This was to investigate a more personalised version of the proposed approach. The inclusion criteria were: (i) over the age of 18, (ii) below the age of 60, and (iii) willing to participate. The exclusion criteria were individuals with a mental or physical condition because the focus of this initial approach was on healthy individuals. The participants were from 18 to 45 years old. This age group was selected because most of the people at these ages are usually healthy and can also exhibit behaviour that could potentially reveal progressive or temporary health issues [27]. Also, for the experiments conducted, male and female participants were considered, as the behaviour exhibited usually differs [28], which could disclose useful information about the way in which the ADLs are executed and about the time they last. It was considered that age and gender could indicate abnormal behavioural patterns that could be linked to medical conditions or hazards [29]. Thus, the generated sample of the 15 participants consists of 7 males and 8 females, the youngest and older of whom are 22 and 43 years old respectively.

3.3 Activities of Daily Living (ADLs) and mood

To investigate the behaviour of the participants, two ADLs have been considered, the preparation of coffee or tea. These two activities were chosen since they can exhibit multiple or similar occurrences during a typical day of a person or can be met as part of other daily activities, such as breakfast, lunch, or dinner. For the execution of these two activities, the participants had the initiative with respect to how they could prepare their drink and the time they would spend drinking it. Note that preparation

and drinking time are variables specific to each person that can support in finding personalised patterns and behaviour that deviate from them. The only restrictions imposed on the participants regarding the completion of the activity were: (i) each participant can prepare only one drink, (ii) coffee/tea should be drunk at the table, and (iii) the cup is placed in the sink after finishing the drink.

Prior to performing the ADL, the participants were asked 6 questions related to their well-being and mood: (i) “do you feel stressed?”, (ii) “do you feel tired?”, (iii) “are you thirsty?”, (iv) “are you hungry?”, (v) “how busy are you right now?”, and (vi) “what is your current mood?”. The possible answers for the first five questions were in this range: “Not at all / Not much / Slightly / Fairly / Extremely”. The possible answers for the question about their mood were based on the moods considered in [30]: “Excited / Happy / Calm / Tired / Bored / Sad / Stressed / Angry”. Note that the self-reported answers from the participants had a one-to-one correspondence with their sessions, that is, one participant response per session.

4 Methodology

The main stages of the ADLs performed were: (i) enter kitchen, (ii) prepare beverage, (iii) drink beverage, and (iv) exit kitchen. The timestamps collected from the contact sensors were used to calculate the durations of each of the ADLs’ main stages, which varied across the different sessions for all participants. Note that while there was variety in the durations of performing the ADLs’ stages per participant, in all cases the durations of the “enter kitchen” and “exit kitchen” stages lasted much less than the preparing and drinking stages. From the results presented in [12], the accelerometers were effective in characterising some of the activities involved in the stages such as a walking, opening the kitchen door and taking sips from a cup. The rationale for considering the durations from participants to perform the ADLs and each of the stages involved was to investigate if there was a relation of spending more or less time performing the same ADL with the participants’ self-reported mood before starting the data collection for each session. The sessions for each participant took place on different days and at different times of the day.

For the work presented, the data collected from the thermal sensor was not analysed as images using image processing and analysis techniques, instead 1,000 features were extracted from each image collected. Hence, the extracted features were handled in tabular form. The resulting dataset was comprised by 1,004 columns (image size, image width, image height, 1,000 extracted features, and mood class), and 73,025 rows, with each row corresponding to a thermal image for a specific second during a participant’s session. The contact sensor timestamps were used to segment the dataset into 15 datasets, one for each participant, containing the extracted thermal features and mood classes for each of the 7 sessions that each participant performed. Thus, in each row of the datasets, extracted thermal features were associated with a mood class based on the participant. Note that the number of rows in each of the 15 individual datasets varied according to the duration in which the participants performed the ADLs in each session.

The Support Vector Machine (SVM) with linear kernel classifier was used considering the limited number of classes in total (8) and their distribution as reported by the participants. Other aspects considered for using SVM as the classifier were the amount of data and its computational processing performance (producing results in a reasonable amount of time compared to other classification models). In a previous work [13], SVM with linear kernel was amongst the four classification models that produced the best accuracy results with averaged extracted thermal features after Bayesian Generalised Linear Model (BGLM), Multi-Layer Perceptron (MLP) and Random Forest (RF).

The evaluation metrics were accuracy and Cohen’s Kappa Coefficient using: (i) 10-Fold Cross Validation, and (ii) 80/20 split (80% of the data for training and 20% for testing). The rationale of using 10-Fold Cross Validation instead of other cross-validation techniques such as LOSO (Leave-One-Subject-Out) was that typically k-fold cross validation approaches are more appropriate to train a model on a large dataset, which is the case of our dataset. While the number of rows is 105, the 1,018 columns of features add complexity in the training of the model. A technique like LOSO would be more appropriate to be used on a smaller dataset. The use of an 80/20 split on the training and testing data respectively was chosen because it is a commonly ratio used in the literature for classification, and it is another mean to compare the results obtained with 10-Fold Cross Validation. Accuracy was selected as evaluation metric to have a baseline to which we could compare other results obtained with a personalised approach using data from ambient sensors. Cohen’s Kappa Coefficient was considered as evaluation metric because of its reliability in comparison to just using accuracy.

5 Results

Classification results for personalised mood detection per participant are presented in Table 1. The highest classification results were obtained for participant P6 with accuracy values of 0.9867 (80/20) and 0.8991 (CV), and of Cohen’s Kappa Coefficient of 0.9783 (80/20) and 0.9822 (CV). On the other hand, the lowest classification results were obtained for participant P3 with accuracy values of 0.7590 (80/20) and 0.7823 (CV), and of Cohen’s Kappa Coefficient of 0.6093 (80/20) and 0.6466 (CV). Note that in the case of participants P3 and P6, the number of mood classes is 4. Interestingly, for participants P8 and P9, which only reported two mood classes across their ADLs performing sessions, the results were not the highest considering that SVM typically performs well in binary classification.

Table 1. Classification results using the SVM classifier for the each of the participants’ datasets which comprised extracted thermal features from 7 sessions.

Participant	Gender	SVM with Split 80/20		SVM with 10-Fold Cross Validation	
		Accuracy (%)	Cohen’s Kappa Coefficient	Accuracy (%)	Cohen’s Kappa Coefficient
P1	Male	0.9592	0.9069	0.9645	0.9190

P2	Male	0.9369	0.8571	0.9445	0.8752
P3	Female	0.7590	0.6093	0.7823	0.6466
P4	Male	0.9363	0.9028	0.9443	0.9150
P5	Female	0.9582	0.9432	0.9683	0.9569
P6	Male	0.9867	0.9783	0.9891	0.9822
P7	Male	0.9183	0.8642	0.9280	0.8801
P8	Male	0.9330	0.8290	0.9423	0.8543
P9	Female	0.8735	0.7403	0.8849	0.7636
P10	Male	0.9037	0.7519	0.9087	0.7660
P11	Female	0.9068	0.8492	0.9197	0.8698
P12	Female	0.8562	0.7189	0.8701	0.7497
P13	Female	0.9508	0.9261	0.9581	0.9373
P14	Female	0.8529	0.7549	0.8808	0.7989
P15	Female	0.9525	0.9299	0.9633	0.9458

For most participants, the accuracy and Cohen’s Kappa Coefficient results obtained were high, with average accuracy values of 0.9123 (80/20) and 0.9233 (CV), and of Cohen’s Kappa Coefficient of 0.8375 (80/20) and 0.8574 (CV). These results are promising for a thermal sensor personalised mood detection approach considering the simplicity of the solution in a real-world environment, which is not as computationally intensive as other solutions. For instance, other solutions might use large amounts of thermal images that would require more computational processing. In terms of mood variation based on gender there were no significant differences between male and female participants. The only aspect to note, considering the small sample, is that only female participants report mood states of “Stressed” and “Bored”. Most mood states reported were “Happy”, “Calm” and “Tired”, with the first two having a positive connotation and the last one a neutral or negative. It may have been the case that participants, conscious that they were observed during the data collection, self-reported in most cases positive or neutral mood states.

6 Conclusions

This paper presented an investigation on the personalised use of thermal sensor data from people performing ADLs to identify mood. In this study the large dataset used in our previous studies was divided so that there were individual datasets per participant which included the extracted thermal features and mood classes for each of the sessions. From the 15 participants, the number of mood classes considered varied between 3 and 4 for 13 participants, and only for 2 participants there were 2 classes. The relatively low number of classes and low amount of data was one of the main reasons the SVM with linear kernel classifier was utilised. Another reason was its computa-

tional processing performance, in which results were produced in a reasonable amount of time compared to other models.

For most participants, the accuracy and Cohen’s Kappa Coefficient results obtained were high, with average accuracy values of 0.9123 (80/20) and 0.9233 (CV), and of Cohen’s Kappa Coefficient of 0.8375 (80/20) and 0.8574 (CV). Cohen’s Kappa Coefficient was used as an evaluation metric in addition to accuracy because of its reliability. In future studies, other evaluation metrics such as F1-score and AUC (Area Under the ROC curve) will be used. The classification results obtained with thermal data from 7 sessions per participant are considered as promising because in a real-world environment it would be possible to detect mood in a more reliable and personalised way with data collected more often or continuously.

Future work will consider using other classification models on the individual thermal datasets from participants performing ADLs in 7 sessions to investigate how well they perform compared to SVM and a possible trade-off between high accuracy results and computational processing performance. It will also be explored the use of Deep Learning techniques on a spectrogram representation of the thermal data collected which could be compared to this thermal extracted features-based approach for mood detection. As the approach is meant to be a personalised one, for future work the duration of the ADLs per participant will be used to set personalised thresholds to indicate has spent “too long” or “not that long” while performing an ADL, which could indicate instances of abnormal behaviour occurring.

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