Ambient and Wearable Sensor Fusion for Abnormal Behaviour Detection in Activities of Daily Living

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Abstract—**Abnormal behaviour in the performance of Activities of Daily Living (ADLs) can be an indicator of a progressive health problem or the occurrence of a hazardous incident. This paper presents an initial fusion approach of data collected from ambient (contact and thermal) and wearable (accelerometer) sensors in a smart environment to improve the recognition of the main steps of ADLs. An accurate recognition of these steps can support detecting abnormal behaviour in the form of deviations from the expected steps. The smart environment used is a smart kitchen and the ADLs considered are (i) prepare and drink tea, and (ii) prepare and drink coffee. These ADLs are deemed to have many occurrences during a typical day of a (elderly) person. The fusion approach presented considers the extraction of the most relevant features of the data collected from the two types of sensors (ambient and wearable) and the subsequent data analysis to recognise the main steps involved in the ADLs. Results show that this initial approach slightly improves the recognition of the main steps involved in the ADLs compared to the results obtained with just using data from the wearable sensors.**

Index Terms—**Activities of Daily Living, ADLs, Sensor Fusion, Data Fusion, Activity Recognition.**

I. Introduction

Activity recognition of Activities of Daily Living (ADLs) has helped in the advancement of automated sensor systems for monitoring the well-being of the elderly population. In general, the detection of abnormal behaviour in ADLs can be an indicator of a progressive health problem (e.g. dementia, osteoporosis, arthritis) taking place or the occurrence of a hazardous incident (e.g. falls, burns, cuts, food/smoke intoxication). It is acknowledged that both ambient sensors (attached to objects in the environment with which users interact) and wearable sensors (worn by users in parts of their body or in their clothes) have advantages and disadvantages. However, it is also acknowledged that, with an adequate deployment and utilisation, both types of sensors deployed together can provide more insight that could allow a better activity recognition for monitoring ADLs than if they were utilised separately. This work continues the research presented in [5], [6] and [8], in which the data analysis did not consider the fusion of the data collected from the ambient and wearable sensors used.

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The ADLs considered in this paper are variants of the main ADL "prepare and drink a hot beverage" used in [5], [6], [8]: (i) prepare and drink tea, and (ii) prepare and drink coffee. While these ADLs are deemed to have many occurrences during a typical day of an elderly person, the outputs of this research could potentially benefit abnormal behaviour detection of people from other age ranges. The main contribution of the sensor fusion approach presented is on combining and using data from different types of sensors to improve the recognition of the main steps in the ADLs that could indicate when a person successfully completes an ADL. In this context, an activity is regarded as being successfully complete if the desired output has been obtained following the typical steps defined for that activity. The granularity definition of the steps that are part of an ADL depends on how well the steps have been identified and annotated. The main steps considered for the ADLs are: (i) enter kitchen, (ii) prepare tea/coffee, (iii) drink tea/coffee, and (iv) exit kitchen. Ambient (contact and thermal) and wearable (accelerometer) sensor data was collected from 30 participants who performed the ADLs following the four main steps sequentially but with variations in the number and sequence of sub-steps involved, e.g. some participants put the milk before the tea in the cup during the "prepare beverage" step. Note that the participants had the freedom to choose which steps to carry out and the order sequence within the ADLs, which is closer to how they would perform the ADLs outside a laboratory environment.

The remainder of the paper is organised as follows: Section II presents related work in the areas of ambient and wearable sensor fusion in the context of Ambient Assisted Living (AAL) and healthcare. Section III describes the sensor system setup considered for the data collection of ADLs. Section IV describes the sensor fusion approach used. Section V presents the data analysis and the evaluation of the results obtained. Finally, Section VI presents the conclusions.

II. Related Work

Sensors used for activity recognition are typically classified as ambient and wearable sensors. Ambient or dense sensors are attached to objects in the environment (e.g. kitchen, bathroom, kettle) with which users interacts [14]. They have the advantages of not being intrusive and typically do not require users to charge them periodically. However, their main disadvantage is that they need to be well placed in the environment and within an adequate setting. Wearable sensors, on the other hand, can be worn by users in parts of their body or clothes [3], [7], [15]. While wearable sensors have the advantages of monitoring and collecting data regardless of the location of the users, some of the main disadvantages are that the users are responsible for their correct use and for charging the battery.

Sensor fusion of ambient and wearable sensors for AAL in the context of healthcare has been widely investigated in the literature. The sensor fusion approach presented in [13] considers the combination of data from three cameras (ambient sensors) with data from an accelerometer (a wearable sensor) to increase the reliability of a wireless sensor network for elderly care which has "fall detection" as its main activity recognition tasks. The authors of [13] described their approach as affordable and scalable, and reported encouraging results when used in indoor environments (hall and kitchen). A sensor fusion approach of ambient (blob-based vision) and wearable (ear-worn activity recognition) sensors is introduced in [11]. Features extracted from the vision sensor were fused with accelerometer data features extracted from the ear-worn activity recognition sensor and evaluated using a Gaussian Mixture Model Bayes classifier considering nine classes. The authors compared classification results of data from the wearable sensors with fused ambient and wearable data, and reported better results with the latter. The sensor fusion approach presented in [4] is comprised of two systems that analyse the ambient and sensor data separately considering eight activity classes. The ambient sensors considered are microphones placed around a smart home, and the wearable sensor is a circuit board with accelerometers and magnetometers worn by participants of the study. While the sensor fusion of ambient and wearable data is not reported, it is interesting the type of sensors (audio and motion) considered and their potential applications.

A multi-modal system for in home health care monitoring called EMUTEM is presented in [10]. The EMUTEM system is comprised of a wearable device to measure physiological data (heart rate, posture, fall detection, activity rate), and the following ambient sensors placed around the house: microphones, infrared sensors and domotic sensors (contact, temperature, smoke). It uses a fuzzy logic approach to integrate physiological, behavioural and medical data from ten elderly users with environmental conditions to monitor their activity in two scenarios: with and without distress. The authors of [10] state that the use of fuzzy logic allows processing high dimensional input spaces and fast detection of errors.

The work presented in [1] introduces a system for monitoring elderly people using a sensor fusion based approach comprised of video cameras as ambient sensors and accelerometers as wearable sensors. The system was tested with nine participants (four healthy and five with Mild Cognitive Impairment) aged over 65 years that performed six ADLs categorised as directed, semi-directed and undirected. Activity detection using the data

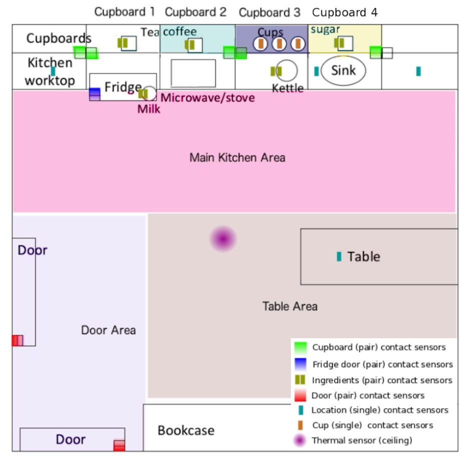


Fig. 1: Smart kitchen layout at SERG.

fusion approach (vision system and accelerometers) was gave better results compared to using only the vision system.

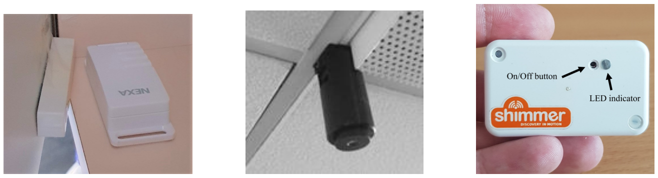
The probabilistic sensor fusion approach presented in [2] considers accelerometers as the wearable sensors, and the passive infra-red sensors and video cameras as the ambient sensors. Received signal strength indication data from the accelerometer to central access points was used to locate the participants in the environment. Twenty participants performed 20 different ADLs, each in nine rooms in a smart environment as part of the Sensor Platform for HEalthcare in Residential Environment (SPHERE) project. It was reported that the probabilistic sensor fusion approach used allowed the identification of the most useful sensor modalities for particular ADLs.

In [9], a sensor fusion approach using fuzzy spatio-temporal features for activity recognition is proposed. The wearable sensor considered is a Polar M660 smartwatch and the ambient sensors considered are: UWB-Decawave location devices, Tactigon inertial devices, Smart Things binary sensors, and Raspberry Pi gateways. There were ten ADLs performed by one participant and the data was collected as follows: location and acceleration from the participant, acceleration data from three smart objects (cup, toothbrush and fork), and binary activation data from nine static objects (bathroom faucet, toilet flush, bed, kitchen faucet, microwave, TV, phone, closet and main door). The authors reported good results and highlighted the capabilities of fuzzy scales and fuzzy temporal windows to increase the spatial-temporal representation of sensors.

III. Sensor System for Kitchen ADLs

The sensor system used is the one at the smart kitchen in the Smart Environments Research Group (SERG)[1] at Ulster University (see layout in Fig. 1). Ambient sensor data was collected from two types of sensors: contact and thermal sensors. Wearable sensor data was collected from accelerometers.

[1]https://www.ulster.ac.uk/research/topic/computer-science/centres/pervasive-computing/about



(a) (b) (c)

Fig. 2: Sensors used in this study: (a) contact sensor, (b) thermal sensor, and (c) accelerometer.

The contact sensors (see Fig. 2(a)) were attached to objects with which users interact in the kitchen in the context of the ADLs considered: doors, cups, kettle, cupboards and containers (tea, coffee, sugar and milk). The contact sensors combine wireless transmitters and magnetic switches. Their signals have two possible states ('on' or 'off') and are monitored and collected by the sensor data platform, SensorCentral [12], for further processing and data analysis. The contact sensors are represented in Fig. 1 as rectangles divided into two parts that can be separated ('on' state) or joint ('off' state).

A thermal sensor (see Fig. 2(b)) was mounted in the ceiling of the kitchen in a central position where it could identify three main kitchen areas where users' presence could be detected: (i) main kitchen area, (ii) table area, and (iii) areas around the doors (see Fig. 1). The thermal sensor has a 32x31 resolution, a $90°$ by $86°$ field of view that provides a coverage area of 6m by 6m at a height of 2.5m, and a 10Hz sample rate. Data monitored and collected from the thermal sensor is in the form of a matrix of temperatures and thermal images. The images captured by the thermal sensor do not have sufficient enough resolution to be considered as privacy invasive.

The device used to collect accelerometer data was a Shimmer[2] (see Fig. 2(c)), which can record and transmit physiological and kinematic data in real time. The Shimmer base board includes a 3-Axis Freescale accelerometer. The accelerometer was worn by the participants on the wrist of their dominant hand using a band while they performed the kitchen ADLs. Data was collected at a sample rate of 51.2Hz with a sensitivity range of ± 1.5G, streamed via Bluetooth and stored in a laptop.

IV. Information Extraction for Sensor Fusion

The sensor fusion approach considers the extraction of relevant information from each type of sensor data and their combination to improve the activity recognition of kitchen ADLs. Currently, the data collected from the contact and thermal sensors is not automatically synchronised in SensorCentral. The focus of this paper is to use a sensor fusion approach to identify the main steps of the ADLs performed: (i) enter kitchen, (ii) prepare beverage, (iii) drink beverage, and (iv) exit kitchen. The start, end and duration of these steps was manually annotated. The average and standard deviation values of the duration of the ADLs steps calculated in previous related works [6], [8] is used to segment the accelerometer and thermal data collected from the participants (see Table I).

[2]http://www.shimmersensing.com/

TABLE I: AVERAGE AND STANDARD DEVIATION OF ADLS STAGES DURATION (IN SEC.)

	Enter	Prepare	Drink	Exit	Total Time
Aver.	35.07	150.27	577.47	16.27	779.08
St. Dev.	19.26	43.93	240.28	8.09	231.99

The information extraction mechanisms used for each type of sensor are presented next.

A. *Contact sensors relevant information extraction*

The data collected from the contact sensors used is comprised, among others, of the following variables of interest: event code, sensor ID, timestamp, and name given according to the object to which the sensor was attached. The contact sensor data was stored in Comma-Separated Values (CSV) format. The data from the contact sensors provide a clear insight into the start and/or end of some steps of the ADLs. For example, an initial change of states for a kitchen door indicates the start of the "enter kitchen" step, and a consecutive change of states from the contact sensor attached to the cup indicates the step of the user "drink beverage". Note that while these inferences make sense in this context, they could also be misleading without supporting information provided by the duration of steps and by the other sensors utilised. As in previous related work [5], [6], [8], the objects to which the contact sensors are attached can provide a clear sequence of actions followed by a user, giving insights into the steps performed. For example, the sequence $\{door \rightarrow kettle \rightarrow cup \rightarrow cupboard \rightarrow coffee\}$ can be interpreted in terms of actions: $\{openDoor \rightarrow useKettle \rightarrow useCup \rightarrow openCupboard \rightarrow useCoffee\}$.

B. *Thermal sensor relevant information extraction*

The data collected from the thermal sensor can be processed and analysed in different ways. One approach is to use image vision techniques on image frames annotated on what action the user is performing to train a classifier to automatically label unseen images. The approach used here is simpler and takes into account the location of the kitchen in which the participant is performing an action. As defined in Fig. 1, the smart kitchen is divided into three main areas and the assumption is that there is clear distinction of which main steps are performed by the participant accordingly: (i) door area - enter or exit kitchen (Fig. 3(a)), (ii) main kitchen area - prepare beverage (Fig. 3(b)), and (iii) table area - drink beverage (Fig. 3(c)).
Note that, in the thermal images shown in Fig. 3, there are two blobs that can be distinguished – the participant and one of the researchers that was collecting data from the accelerometer worn by the participant on a laptop. The blob of the participant can be seen moving around the different areas of the kitchen performing certain actions and the blob of the researcher can be seen static in the lower right part of the frames. Thus, the location of participant in the different areas of the kitchen is used as a feature from the thermal images. Another useful

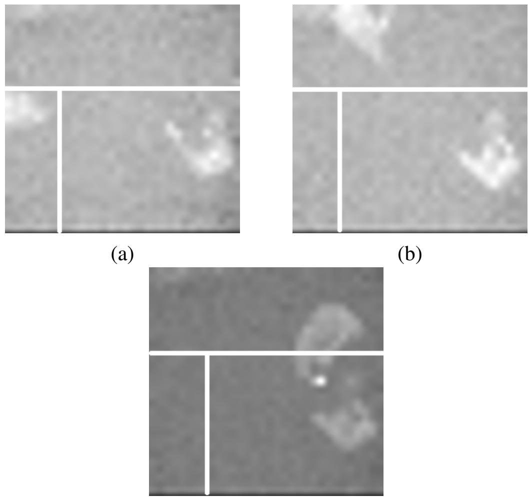


Fig. 3: Thermal sensor images of ADLs steps in smart kitchen: (a) enter/exit kitchen, (b) prepare, and (c) drink beverage.

feature from the thermal images in the context of the main ADL of “prepare and drink a hot beverage” is that the hot beverage clearly appears as a group of white pixels (see Fig. 3(c)). Thus, for example, it is possible to infer that the participant is performing the “drink a beverage” step if the blob related to the participant is closer to the table area and the identified hot beverage is inside the table area. Using the thermal images on their own it is possible to calculate how much time the participant spent carrying out an ADL step as it was collected one frame per second.

In the example sensor images shown in Fig. 3 it can be seen that the background from Fig. 3(a) and 3(b) is clearer than the background from Fig. 3(c). Possible reasons for this variation in temperature in the smart kitchen are: (i) the temperature from the kitchen window located on the right hand side of the frames, and (ii) previous immediate usage of the kitchen appliances (microwave, kettle and fridge). Previous data collection from the thermal sensor in the kitchen for other studies has shown variations on the thermal images collected possibly due to the seasonal outside temperature. Regardless of the variations in background of the thermal images, it was still possible to distinguish the blob of the participant and the group of white pixels related to the hot beverage.

In the present work, the thermal images collected are divided according to the average duration values for the ADL steps (see Table I) and labelled accordingly. As an initial sensor fusion work for these kitchen ADLs the blob detection mechanism is not fully utilised to identify the posture and direction of the participants or to use characteristics of the blobs. Instead, a basic image classification method is used considering that the steps in the ADL have been defined based on the average duration.

C. *Accelerometer relevant information extraction*

The data collected from the accelerometer worn by the participants was stored in a laptop in CSV format. A time metric is calculated from the sampling rate. A class label is added to each record in the accelerometer data according to its respective step in the ADL and then the data from each participant is aggregated in a single dataset in CSV format. The data is then cleaned by removing outlier values using median filtering, which replaces every data point in a signal by the median value of that point and a number of neighbouring points specified (in this case five points are considered). High frequency noise from the signals is removed using a fourth order Butterworth low-pass filter with a cut-off frequency set to 15Hz, considering that most human activity acceleration is represented in frequencies below 15Hz.

A five-second window is used to extract 40 features, which also include the class name. The features extracted for each axis (X, Y and Z) and the magnitude are: (i) mean, (ii) standard deviation, (iii) maximum, (iv) minimum, (v) range, (vi) RMS (Relative Mean Square), (vii) SMA (Signal Magnitude Area), (viii) median, and (ix) energy. Cross-correlation is calculated for the X-Y, X-Z, and Y-Z axes.

V. Sensor Fusion Approach and Results

This section presents how the sensor fusion was carried out for the ambient and wearable sensors considered: thermal sensor and accelerometer respectively.

A. *Activity Recognition results from only the wearable sensor*

The features extracted from the accelerometer data were used to train four classification algorithms: (i) Classification And Regression Trees (CART), (ii) Support Vector Machines (SVM), (iii) K-Nearest Neighbour (K-NN), and (iv) Naive Bayes (NB). Overall accuracy classification results (total number of correctly classified instances/total number of instances), were: (i) CART - 74.50%, (ii) K-NN - 75.16%, (iii) SVM - 72.81%, and (iv) NB - 19.48%. The accuracy classification results for each steps of the ADL are presented in Table II. In the confusion matrices for each classifier there are more incorrectly classified instances of the “enter” and “exit” steps for the CART and K-NN classifiers. The respective confusion matrices for each classifier are shown in Fig. 4. There are more incorrectly classified instances of the “enter” and “exit” steps for the CART and K-NN classifiers.

TABLE II: ACCURACY (%) CLASSIFICATION RESULTS OF ADL STEPS FOR WEARABLE SENSOR DATA.

Algorithm	Enter	Prepare	Drink	Exit	Overall
CART	78.79	97.42	94.54	76.56	74.50
K-NN	79.63	97.20	94.14	77.71	75.16
SVM	79.56	97.42	94.85	71.83	72.81
NB	22.47	96.96	91.85	27.84	19.48

As it can be seen from Table II, in general the ADL steps for which higher accuracy results were obtained were “prepare”

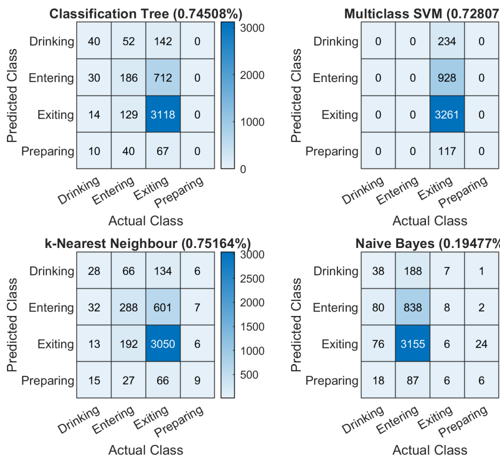


Fig. 4: Confusion matrices for the CART, SVM, K-NN and NB classifiers on wearable sensor data.

and "drink" beverage respectively, while lower accuracy results were obtained for the "enter" and "exit" kitchen ADL steps, particularly for the case of the NB algorithm. Note that while it can be observed in Table I that the "enter" and "exit" have much shorter durations on average with respect to the "prepare" and "drink" beverage steps, the relevant information extraction process would have ensured the duration differences not affecting the classification process. Another aspect to take into account is that while the accelerometer signals for the "enter" and "exit" kitchen steps are similar to each other, the "prepare" and "drink" beverage steps, on the other hand, have particular shapes and can be distinguished from each other and from the other signals. For example, the "drink" beverage step mainly involves a person holding a cup and raising his/her arm up to drink and down to put the cup back on the table successively. A possible reason why the NB algorithm performs worse than the other three algorithms is the similarity in the actions and accelerometer signals of entering and exiting kitchen.

B. Activity Recognition results from ambient and wearable sensors combined

The features extracted from the thermal data were based on the location of the participants in the kitchen areas while they performed the steps of the ADL. Blob detection was used to identify the blobs of the participants in the thermal images and to retrieve their position in the X and Y axis with respect to the images, thus their location in the kitchen. Note that the blob corresponding to the researcher who was present in the kitchen with the participants was ignored based on his location in the kitchen and considering that he did not move from that area while the participants performed the kitchen ADLs. While ignoring the location of the researcher in the kitchen helped to find the larger blob in the image, which would be of the participant at the time, in some cases other blobs caused by air of different temperature coming from the kitchen window were detected instead. In this case other features such as height or width of the blob of the participant were not considered.

The positions of the participants in the kitchen per frame were used to infer in which part of the kitchen they were at the time: door area, main kitchen area, and table area. Other features considered from the thermal images were if the users had a drink or not, which could be inferred by detecting the brightest blob in the image, typically while they were drinking the hot beverage. It was also considered if the participants were moving in the kitchen or if they were still, which would correspond to different steps of the ADL. Features extracted from the thermal data were combined to the ones extracted from the accelerometer data and this fused data was used to train the same classifiers used for just the wearable sensor data. Overall classification results were: (i) CART - 73.51%, (iii) K-NN - 72.82%, (ii) SVM - 72.11%, and (iv) NB - 27.67%. The accuracy classification for each of the steps of the ADL are presented in Table III. In the corresponding confusion matrices for each classifier, similarly to using just wearable sensor data, the classes with more incorrectly classified instances are for the "enter" and "exit" steps when using the CART, K-NN and NB classifiers. The corresponding confusion matrices for each classifier are shown in Fig. 5, where, similarly to using just wearable sensor data, the classes with more incorrectly classified instances are for the "enter" and "exit" steps when using the CART, K-NN and NB classifiers.

TABLE III: ACCURACY (%) CLASSIFICATION RESULTS OF ADL STEPS FOR FUSED AMBIENT AND WEARABLE SENSOR DATA.

Algorithm	Enter	Prepare	Drink	Exit	Overall
CART	79.93	97.56	95.53	74.12	73.51
K-NN	79.38	97.58	95.35	73.46	72.11
SVM	79.47	97.18	95.53	72.18	72.82
NB	29.78	97.07	95.53	32.91	27.67

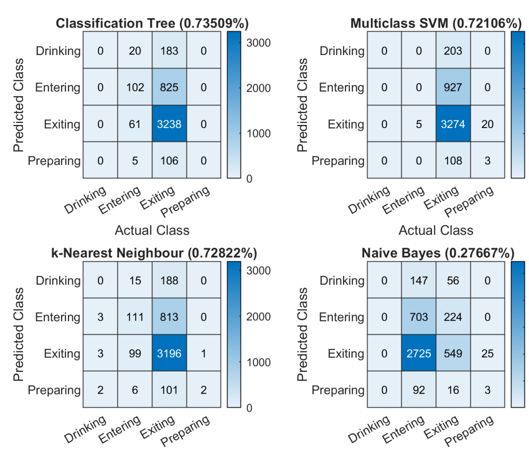


Fig. 5: Confusion matrices for the CART, SVM, K-NN and NB classifiers on fused ambient and wearable sensor data.

As it can be seen from Table III, and similarly to the results obtained from only wearable sensor data (see Table II), higher accuracy results were obtained for the “prepare” and “drink” beverage respectively, and lower accuracy for the “enter” and “exit” kitchen steps. In general, there was a minor improvement in the accuracy results when using data fused from the ambient and the wearable sensors. Note that while there was an improvement from the results of the “enter” kitchen step for the CART, K-NN and SVM algorithms, there was a decrease on the results for the “exit” kitchen step.

It is acknowledged that the feature extraction approach for the thermal features is a basic one and the reason is to have a first approach that could serve as a baseline for more comprehensive future sensor approaches resulting from this study. In this case, object detection techniques to identify the movement direction of the participants based on the posture of a person were not considered as they would have added complexity and computational time. However, the use of features related to posture and movement direction of the participants could have resulted in better results in classifying the “enter” and “exit” kitchen steps. In this work, standard classification algorithms were used based on the amount of data. The variation in the background of the thermal images (see Figs. 3(a) and 3(b)) might have contributed to the cases of low classification results.

VI. Conclusions

This paper presented an initial sensor fusion approach for data collected from ambient (contact and thermal) and wearable (accelerometer) sensors in a smart environment to improve the recognition of the main steps of the ADL “prepare and drink a hot beverage” in the variants of tea and coffee. Contact sensor data was used to automatically define the steps duration. Features extracted from thermal and accelerometer data were combined to train classifiers to recognise the steps. Results obtained using this sensor fusion approach slightly improved classification results to recognise the ADL steps in comparison of just considering wearable data. It is expected that a sensor fusion based system to detect abnormal behaviours in a kitchen for the ADL considered will identify when the user performs the respective steps involved and to detect when a user performs a different unrelated step that could lead to an abnormal behaviour.

Future work will consider including data from other sensors (contact, radar and another thermal sensor placed horizontally) that were used during the data collection. More complex and comprehensive imaging processing techniques will be considered to extract more significant features such as front and back of the participants, direction to which the participants are looking, identifying more fine grained activities (opening kitchen door, walking, sitting, drinking beverage, etc.). Deep and transfer learning techniques are planned to be used for improving this approach. Future data collections will address the temperature variations in the smart kitchen that contributed to the variation in the background of the thermal images collected.

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