Analysis of Accelerometer Data for Personalised Mood Detection in Activities of Daily Living

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***Abstract*—This paper proposes a novel approach to identify moods in Activities of Daily Living (ADLs) using accelerometer sensor data from 15 participants over 7 sessions each. Monitoring ADLs and detecting moods are of particular importance due to the potential life-changing consequences. The ADL considered relate to preparing and drinking a hot beverage, and they were segmented into four sub-activities: (i) entering kitchen, (ii) preparing beverage, (iii) drinking beverage, and (iv) exiting kitchen. The accelerometer was attached to the participants' wrist, and prior to collecting the data, they were asked about their current mood. Two approaches were considered in the analysis according to the moods reported by the participants (happy, calm, tired, stressed, excited, sad, and bored), firstly using all trials, and secondly using a balanced sample of data. A set of statistical, temporal, and spectral features were extracted from acceleration data, and personalised classification models were built and evaluated using the Random Forest algorithm. The experimental results showed that the average F-measure for all personalized classifiers was 0.75 (σ 0.20) considering all data, and 0.76 (σ 0.22) using balanced data. The best classification results were obtained with the "preparing" and "drinking" activities, and with the "happy", "calm", and "stressed" moods. This suggests that the use of accelerometers, such as those incorporated into smartwatches or activity trackers, may be useful in detecting moods in ADLs.**

***Index Terms*—Activities of Daily Living, ADLs, Activity Recognition, Accelerometer, Mood, Sensors**

I. Introduction

In general, the detection of abnormal behaviour in Activities of Daily Living (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.) [21]. Therefore, monitoring ADLs and detecting moods is of particular importance due to the potential life-changing consequences that could result from not acting timely. Sensors are typically used to monitor ADLs [15]. Using sensors that can be placed within the environment and in appliances of interest, as opposed to wearable sensors, has the main advantage of not being intrusive for the users [24]. The use of wearable sensors, on the other hand, has the main advantage that data can be collected in any location where users are, regardless if they are at home or outside [26]. The popularisation of fitness trackers and smartwatches could result in their adoption and familiarisation by people from different backgrounds, not just athletes, and in the collection of data for a longer period of time [12].

The main contribution of the approach presented is the use of accelerometer to identify moods in ADLs based on machine learning models. This is a first step towards a more personalised approach focused on individual profiles using sensor and mood data for the detection of abnormal behaviours in ADLs. Further steps will include considering data from other sensors, and collecting data over a longer period of time. In this case, the sensor data used is from accelerometer sensors, which are a type of wearable sensor, but the use of data collected with other sensors (contact, thermal and radar), will be analysed subsequently. To our best knowledge, the use of sensors (ambient and wearable) in conjunction with well-being and mood data has not been widely investigated. Moreover, this type of approach could provide a better insight into the role that well-being has in the way people perform their daily activities and if they might influence their performance.

This work continues the research presented in [6], [7], [13], [18] and [8]. In [6], Petri nets were used to model and verify ADLs (preparing and drinking a hot beverage (tea or coffee), and preparing pasta. The approach presented in [7] is based on the temporal analysis of ADLs in order to identify abnormal behaviour. In [13], the approach presented in [7] is extended by considering the sequential aspects of the actions that are part of each ADL 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 [18]. In [8], an initial approach using just accelerometer data for activity recognition in the context of ADLs was presented. The current work also considers the ADL of "preparing and drinking a hot beverage" with the variants of tea, coffee and hot chocolate. This work proposes in the first instance the analysis of accelerometer data for detecting moods stated by the users during ADLs. In detail, the main contributions of this work are: (i) propose and evaluate personalised models to recognise different moods, and (ii) analyse in which ADLs it is possible to better recognise such moods. In this way, it would be possible to obtain a personalised assessment of events that deviate from the normal way in which people perform their ADLs.

The work involved the analysis of accelerometer and mood data collected from the sessions performed 7 times by 15 participants in terms of: (i) one dataset comprised of 105 sessions, and (ii) one dataset per user comprised of 7 sessions each. The dataset collected includes data from a number of sensors (contact, thermal, accelerometer and radar) for each user, which provides a granularity for the analysis of the data from different perspectives. This paper mainly focuses on the analysis of the collected accelerometer and mood data.

The remainder of this paper is organised as follows: Section II presents the related work in the areas of activity recognition using accelerometer sensors and mood data. Section III describes the environment setup considered for the data collection, the participants, and the aspects involved in performing the ADLs. Section IV presents the proposed approach and Section V discusses the data analysis and the evaluation of the results. Finally, Section VI presents the conclusions.

II. Related Work

Activity recognition using sensors is typically classified in terms of wearable sensors versus ambient sensors. Wearable sensors can be worn by users in parts of their body or on clothes [1], [19], [25]. Ambient sensors are attached to objects in the environment with which the user interacts (e.g. kitchen, kettle, cup, cupboard) [7], [11]. The use of both wearable and ambient sensors for activity recognition in ADLs to detect and predict abnormal behaviour has been well investigated in the literature. The mood data collected from participants while they perform activities can provide more insight for the detection of abnormal behaviour and building profiles that allow a personalised data analysis. This section presents related work that involve accelerometry and mood domains.

In [27], a mood recognition framework using smartphones and wearable sensors is presented for structured self-reporting of mood from users in an office environment. In this case, the participants use a smartphone app called Healthy Office to collect mood data at different intensity levels, and wearable devices to collect physiological (heart rate, pulse rate and temperature) and accelerometer data. The moods considered in the mood classification model are: excitement, happiness, calmness, tiredness, boredom, sadness, stress and anger. The results reported by [27] are described as promising as their classifiers performed better than the baseline on a relatively small dataset (4 participants over 11 working days resulting in 44 mood data points and 352 hours of sensor data).

The system presented in [10] is used to detect three different emotional states (neutral, stress and excitement) from participants by using the accelerometer sensor built-in on a smartphone and is based on eight different sitting positions. Data was collected from 20 participants. While the authors of [10] report that the results are not satisfactory, the use case of mood detection using accelerometers is interesting and could lead to an improved implementation. The PAM (Personalized Ambient Monitoring) project introduced in [2] makes use of accelerometry for the classification of activity levels in the context of patients with bipolar disorder. In this case, the objective is to distinguish different basic activities and activity levels in normal controls from data collected by participants wearing an accelerometer sensor. The personalisation aspect used in [2] is of particular interest as it is acknowledged that each patient has particular needs.

In [16], the MoodMiner framework is introduced to analyse three different moods (displeasure, tiredness and tensity) in people's daily life. MoodMiner uses data collected from smartphone's built-in sensors (acceleration, light, ambient sound, location, call log, etc.) to extract human behaviour patterns. The results obtained by [16] from 15 participants using the smartphone over 30 days show that it is possible to evaluate and determine a daily mood using the proposed framework, however it is acknowledged that a personalised approach could result in an improved performance.

The study presented in [17] is focused on using unobtrusive monitoring technology, in the form of accelerometers, to study mood changes during office hours and the related factors (social activity and non-sedentary patterns) that could have influenced the changes. The moods considered in the study are: cheerful, sad, tensed, fatigued, energetic, relaxed, annoyed and friendly. In addition to using accelerometers, the participants completed mood questionnaires in the beginning, in the middle and at the end of each working day. The results obtained by [17] from 9 participants over 7 working days indicate that mood changes are highly correlated with both social interactions and non-sedentary work style.

In [20], three physical activities measured by an accelerometer worn on the left hip are compared, and mood is examined to see its correlation to physical activity in pregnant women. The group of participants comprised 12 pregnant women recruited during their first trimester and 12 non-pregnant women over 7 months. The moods considered are: tension, depression, anger, vigor, fatigue and confusion. The results presented by [20] were obtained using a two-factor mixed model ANOVA and show that healthy women who maintain an above average level of physical activity during the second and third trimesters can enjoy mood stability.

The main limitation of the works covered in this section is having a personalised approach in detecting moods using accelerometer data. The only approach that had a focused approach was the one presented in [2]. Thus, our work contributes with an initial personalised mood detection approach based on accelerometer data.

III. 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 usually carried out in the kitchen and are based on the ones used in [5], where they were modelled using ontologies. The environment in which the data for the kitchen ADLs was collected is the one at the smart kitchen in the Pervasive Computing Research Centre (PCRC)[1] at Ulster University (see layout in Fig. 1).

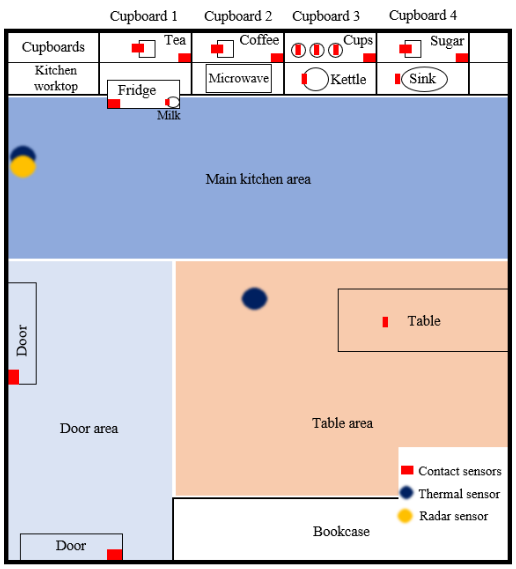


Fig. 1: Smart kitchen layout at PCRC.

Sensor data was collected from four types of sensors: (i) contact sensors, (ii) thermal sensors, (iii) radar, and (iv) accelerometers. The contact sensors were attached to objects with which the user has interaction in the kitchen in the context of the ADLs considered in this paper: doors, cupboards, refrigerator, cups, containers (tea, coffee, chocolate, sugar and milk), and location areas (kitchen worktop, table and sink). The contact sensors combine wireless transmitters and magnetic switches. The signals from the contacts sensors have two possible states (on or off) and are monitored and collected by SensorCentral [22], a sensor data platform, 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). The colour codes in the legend indicate to which objects they are attached. Details of the data collection, preprocessing and analysis of the thermal sensors and radar are beyond the scope of this paper and will be addressed comprehensively in future work.

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

Fig. 2: Shimmer accelerometer device.

A. Recruiting Participants

Fifteen participants were recruited for this project following some specific selection requirements related to their age, gender and health. Note that due to the personalised nature of the proposed approach, half of the number of participants were recruited with respect to previous related works by the authors [7], [13], however, in this case there were more sessions performed by participant. The inclusion criteria was: (i) male and female, (ii) over the age of 18, (iii) below the age of 60, and (iv) willing to participate. The exclusion criteria was: (i) 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 the majority of the people at these ages are usually healthy and can also exhibit behaviour that could potentially reveal progressive or temporary health issues [23]. Also, for the experiments conducted, both genders were considered, as the behaviour exhibited usually differs [9], which could disclose useful information about the way in which the ADLs are executed and also 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 [14]. Following the aforementioned criteria, 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. The number of participants per age range was as follows: 10 were between 18 and 30, 4 were between 30 and 40, and one over 40.

B. Defining the Activities of Daily Living

To investigate the behaviour of the participants, two ADLs have been considered, the preparation of coffee and tea respectively. These two activities were chosen due to the fact that 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 volunteers had the initiative with respect to how they could prepare their drink and the time they

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

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

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. Consequently, each participant was able to repeat any preferred actions, but it is assumed that the participant could only use the ingredients and equipment that were available for the activity (i.e. coffee, tea, sugar, milk, cups and kettle). The order in which all these items would be used was exclusively dependent on the participant's will. 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.

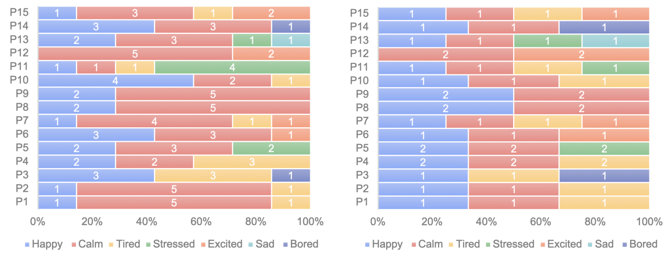
A general scenario was followed by the participants to prepare their drink: each participant had to first enter the kitchen using one of the doors, prepare the preferred drink, sit at the table to drink it, leave the cup in the sink when the participant finishes its drinking and finally exit the kitchen. This scenario was introduced because the activity steps which the participants follow to perform the ADLs can be traced more accurately, thus supporting the data analysis process.

Taking into account the initiative of the participants and the number of items used in each of the activities, the construction of all the paths (i.e. different sequences of actions) that can be potentially followed for the successful completion of each activity gives more than a hundred different ways for the preparation of each drink. Thus, if the repetition of some actions (steps) occur, then this number may increase exponentially. For instance, an initial calculation of the total number of unique sequences of steps/action (i.e. paths) showed that there exist around 120 different ways to perform the coffee or tea activity respectively (including no repetition of actions). Prior to the 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 was based on the moods considered in [27]: "Excited / Happy / Calm / Tired / Bored / Sad / Stressed / Angry". Unlike the approach presented in [27], the intensity of the moods was not considered, just which mood the participants related more before performing the ADL.

IV. Methodology

In the present work only accelerometer data was used to train and evaluate models to automatically classify the mood reported by the subjects in each trial. It is a supervised classification task in which the moods reported by the participants are the classes, and each trial, or instance, was segmented into subsets corresponding to four activities: (i) Entering kitchen, (ii) Preparing beverage, (iii) Drinking beverage, and (iv) Exiting kitchen.

The proportion of the moods according to the trials for each participant is presented in Fig. 3a, and it is distributed as follows: Happy (31%), Calm (33%), Tired (16%), Stressed (7%), Excited (9%), Sad (2%), and Bored (3%). As it can be seen, the number of trials for the Happy and Calm classes represents practically two-thirds of all the data (64%), so it is an unbalanced class task. As an alternative, it was proposed to sub-sample the data to adjust for minority class for each participant, e.g., for Participant 1 (P1), whose Calm class contains most of the data, only one of the trials is considered to be balanced with the Happy and Tired classes (see Fig. 3b).



(a) Original dataset (b) Sampled dataset

Fig. 3: Number of trials considering original unbalanced dataset (3a), and sampled balanced dataset (3b).

Both datasets, original (unbalanced) and sampled (balanced), were divided into four activities ("Entering" with a mean duration among all participants of 7.3s (σ = 1.3), "Preparing" with 124s (σ = 39), "Drinking" with 274.2s (σ = 243.5), and "Exiting" 13.6s (σ 8.5)), because each one has different movement characteristics and duration times, e.g. walking activities with relatively short duration compared to the other two activities. In addition, the data for each activity was segmented into 1-second windows and each segment was considered an instance of the activity.

A set of features were extracted from the segmented data of linear acceleration, in the X, Y, and Z axes; also considering the total acceleration, also known as the magnitude of the acceleration, i.e., $XYZ = sqrt(x^2 + y^2 + z^2)$. The resulting feature vector includes 160 statistical, temporal, and spectral features [3], for each of the time series (X, Y, Z, XYZ). The parameters established for the feature extraction function were: $sampling\_frequency = 50$, and $windows\_size = 50$, i.e., 1-second segments with 50 frames each.

These feature vectors in combination with the Random Forest inference algorithm were used to train the classification models of participants' moods. A Random Forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the feature vector and uses averaging to improve the predictive accuracy and control over-fitting [4].

Due to the high inter-subject variability when carrying out activities of daily living, particularly in the scenario presented, it was decided to train one classifier per participant considering the unbalanced and balanced datasets. F-score, or F-measure, was used to evaluate the classifiers. This metric combines precision and recall into a single metric by taking their harmonic mean.

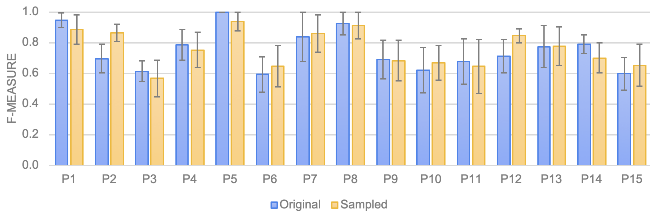


Fig. 4: Overall performance by subject.

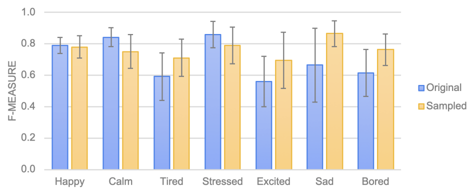


Fig. 5: Overall performance by mood.

V. Results

The average classification result of the four activities per participant is shown in Fig. 4. In general, the performance averages of all classifiers are more than 0.6, even for four participants (P1, P5, P7, and P8) exceeding 0.8. On average, classification results using the balanced dataset are slightly higher, however, the average dispersion is lower for the unbalanced dataset. The best overall result was scored for Participant 5, whose reported moods were Happy, Calm, and Stressed; the worst was for Participant 3 with Happy, Tired, and Bored.

Regarding the average results by mood (Fig. 5), only three of them were close to 0.8: Happy, Calm, and Stressed, with the first two being the classes with the highest number of instances; on the other hand, the Stressed class only contributed 7% of the total data. In this case, using the balanced dataset was superior in the average of the central tendency measure (Sampled: 0.76 (σ = 0.22) vs. Original: 0.70 (σ = 0.25)) and lower for dispersion than using the unbalanced dataset. It must be highlighted the increase in performance in minority classes, with the exception of the Stressed class.

If we analyse the results grouped by activity in detail, it is possible to notice a performance improvement when balancing the data. Tables I and II show the results obtained for each mood by activity using the original dataset and the sampled dataset, respectively. In both cases, the activities of "Preparing" and "Drinking" score the best results, while the other activities are at least 2 decimals below. The activity with the best average result was "Preparing" using the sampled dataset, in which all moods were classified with an F-measure greater than 0.9. On the other hand, the activity with the worst result was "Entering" using the original dataset, note that three of the seven moods obtained extremely low results, and even no instance of Sad was correctly classified. The Stressed and Sad moods have the best performance for the "Preparing" and "Drinking" activities, regardless of the dataset. The biggest improvement when balancing the data was for the "Exiting" activity, highlighting the increase in the Bored, Tired, and Excited moods. Finally, Fig. 6 presents the overall performance by activity, with the best performance being achieved by the "Preparing" and "Drinking" activities.

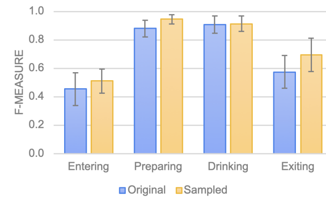


Fig. 6: Overall performance by activity.

VI. Conclusions

This paper presented an approach to identify personalised moods based on the analysis of accelerometer data from Activities of Daily Living (ADLs). The accelerometer and mood data considered was collected from 15 participants over 7 sessions each in which the ADLs performed were preparing and drinking a hot beverage (coffee or tea). The ADLs were divided into: (i) entering kitchen, (ii) preparing beverage, (iii) drinking beverage, and (iv) exiting kitchen. The moods considered were: happy, calm, tired, stressed, excited, sad, and bored. Since the original dataset was very unbalanced, a sampled dataset was generated for the data analysis. Both datasets were then divided into four activities and had statistical, temporal and spectral features extracted.

The personalised classification models were built using the Random Forest algorithm, and evaluated with the F-measure metric. Experimental results show that the average F-measure for all personalized classifiers was 0.75 (σ 0.20) considering all data, and 0.76 (σ 0.22) using balanced data. The best classification results were obtained with the "preparing" and "drinking" activities, and with the "happy", "calm", and "stressed" moods. This suggests that the use of accelerometers, such as those incorporated into smartwatches or activity trackers, may be useful in detecting moods in ADLs. Future work will consider using thermal and radar data collected in the same sessions, as well as data from the other questions about their well-being.

Acknowledgements

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TABLE I: Original dataset (unbalanced)

Activity	Happy	Calm	Tired	Mood Stressed	Excited	Sad	Bored	**Average** (std)
Entering	0.70	0.70	0.26	0.76	0.10	0.00	0.65	**0.45** (0.32)
Preparing	0.89	0.93	0.89	1.00	0.75	1.00	0.69	**0.88** (0.12)
Drinking	0.87	0.96	0.80	1.00	0.80	1.00	0.92	**0.91** (0.09)
Exiting	0.71	0.78	0.41	0.68	0.59	0.66	0.20	**0.57** (0.20)

TABLE II: Sampled dataset (balanced)

Activity	Happy	Calm	Tired	Mood Stressed	Excited	Sad	Bored	**Average** (std)
Entering	0.62	0.46	0.40	0.63	0.17	0.80	0.50	**0.51** (0.20)
Preparing	0.93	0.90	0.93	0.98	0.91	1.00	0.96	**0.94** (0.04)
Drinking	0.87	0.93	0.85	1.00	0.89	1.00	0.86	**0.91** (0.06)
Exiting	0.71	0.72	0.66	0.55	0.82	0.66	0.73	**0.69** (0.08)

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