Learning Human Behaviour Patterns by Trajectory and Activity Recognition

Letícia Fernandes[1], Marília Barandas[1] and Hugo Gamboa[1,2]
[1]*Associação Fraunhofer Portugal Research, Rua Alfredo Allen 455/461, 4200-135 Porto, Portugal*
[2]*Laboratório de Instrumentação, Engenharia Biomédica e Física da Radiação (LIBPhys-UNL), Departamento de Física, Faculdade de Ciências e Tecnologia da Universidade Nova de Lisboa, Monte da Caparica, 2829-516 Caparica, Portugal*

Keywords: Human Behaviour, Pattern Recognition, Anomaly Detection, Ambient Assisted Living, Probability Density Function, Clustering.

Abstract: The world's population is ageing, increasing the awareness of neurological and behavioural impairments that may arise from the human ageing. These impairments can be manifested by cognitive conditions or mobility reduction. These conditions are difficult to be detected on time, there is a lack of routine screening which demands the development of solutions to better assist and monitor human behaviour. This study investigates the question of what we can learn about human behaviour patterns from the rich and pervasive mobile sensing data. Data was collected over 6 months, measuring two different human routines through human trajectory analysis and activity recognition comprising indoor and outdoor environment. A framework for modelling human behaviour was developed using human motion features, extracted with and without previous knowledge of the user's behaviour. The human patterns were modelled through probability density functions and clustering approaches. Using the learned patterns, inferences about the current human behaviour were continuously quantified by an anomaly detection algorithm where distance measurements were used to detect significant changes in behaviour. Experimental results demonstrate the effectiveness of the proposed framework that revealed an increased potential to learn behavioural patterns and detect anomalies.

1 INTRODUCTION

The increase in life expectancy leads to the ageing population growing worldwide. According to United Nations (United Nations, 2017), the global population over 60 years is expected to double in 2050. As a consequence, common health conditions associated with ageing and that affects human behaviour, such as physical declining, psychological and cognitive alteration are increasing.

Physical declining of elderly people is observed through the decrease of walking speed, mobility disability that is associated with falls and difficulty in performing activities of daily living. Whereas, cognitive alterations, that includes cognitive ageing, dementia and depression are more difficult to be detected in early stages of the disease (Jaul and Barron, 2017). For example, early symptoms of dementia, may not be detected by doctors in periodical visits, given that there is a lack of routine screening. The role of the caregiver is very important for the early diagnosis of these health conditions. However, a significant portion of these people live alone (Evans et al., 2016), and it may be difficult to either detect and monitor the disease, leading to its progression. Thus, a reliable tool for learning more about the person's daily living, helping the diagnosis and following up these impairment, is needed. The assessment of human behaviour is the basis for understanding people's needs and problems, helping them improve their lives. With the widespread of technology, specifically smartphones, it is possible to recognise human motions and to monitor human daily routines, since they possess multiple accurate sensors to better assist humans in a cost-effective and unobtrusive way.

2 RELATED WORK

In the past years, studies are approaching the challenge of learning human motion patterns and anomalies detection on those patterns.

Zheng et al. (Zheng et al., 2019) proposed a heuristic method combining Dynamic Time Warping

Fernandes, L., Barandas, M. and Gamboa, H.
Learning Human Behaviour Patterns by Trajectory and Activity Recognition.
DOI: 10.5220/0008953902200227
In *Proceedings of the 13th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2020) - Volume 4: BIOSIGNALS*, pages 220-227
ISBN: 978-989-758-398-8; ISSN: 2184-4305

(DTW) and Earth Mover's Distance (EMD) to understand tourist mobility through the measurement of trajectory similarity. The resulting method proved to be accurate and noise resistant. A study conducted by Tomforde et al. (Tomforde et al., 2018) developed models to learn the user's behaviour in a health enabling living environment equipped with multiple sensors. The user's location and activity sequences were detected and used to train two multinomial Hidden Markov Models (HMM) with the normal course of the user's days. The resulting log-likelihood of the HMM were modelled into a Kernel Density Estimate (KDE) to signalise a deviation from the expected normal behaviour pattern. Rahim et al. (Rahim et al., 2015) developed a context-aware change detection model using machine learning and statistical models. The authors created a HMM to detect anomalies in sequences of daily activities in an ambient assisted living. To detect behavioural changes related to the time duration and frequency of activities, a statistical model measuring gaussian distribution of activities was used. Suzuki et al. (Suzuki et al., 2007) proposed an unsupervised learning method to learn motion patterns and detect anomalies by the analysis of human trajectory recorded in a real store by cameras.

Although there are some studies in the literature about modelling human behaviour, the people's behaviour changes are often hard to quantify. Moreover, the aggregation of both activity recognition and trajectory analysis remains relatively unexplained. Furthermore, most of the studies that found patterns by activity recognition rely on the installation of sensors around the home, which presents higher installation and maintenance cost compared to the use of smartphone sensors that are going to be used in this study. Finally, the possibility to detect and quantify anomalies in humans routines by continuously learning daily patterns will be evaluated.

3 PROPOSED METHOD

The developed framework for modelling human motion behaviour patterns exploits the human motion by trajectory and activity recognition, effectively capturing both indoor and outdoor environment. The following subsections are divided into the three framework steps. The first step (Section 3.1) describes the methods applied for the feature extraction along each day, the second step (Section 3.2) uses the extracted features from a set of days to learn patterns, and the last step (Section 3.3) describes the process for anomaly detection using the previously detected patterns and features from a specific day.

3.1 Feature Extraction

The extraction of relevant features of human motion patterns comprises features extracted with and without previous knowledge of the user's behaviour, depending on the available information.

3.1.1 Without Previous Knowledge

The extracted features from human behaviour without previous knowledge refers to all features that may be extracted without any previous annotation. Extracted features can be grouped by the type of information source used and are divided into the outdoor trajectory, Dead Reckoning (DR) and locomotion activities.

The outdoor trajectory is extracted through Global Positioning System (GPS). Since GPS accuracy is reduced near buildings, a threshold based algorithm was developed to overcome GPS inaccuracies and remove GPS outlier points with inconsistent velocities.

From the corrected GPS signal, the following features were computed: mean and maximum velocity (m/s), mean and maximum altitude variation (m), walking distance (m) and walking time (min).

To learn mobility patterns that can not be measured using GPS measurements, DR techniques were used to extract metrics from the step detection and its estimated length. The DR algorithm implemented in this framework was developed by (Guimarães et al., 2016). The output features from this algorithm were: number of steps and mean step length (m).

For the recognition of locomotion activities such as *walking*, *standing*, *walking up* and *walking down*, a machine learning classifier was used. For this recognition a Decision Tree (DT) classifier was implemented using only accelerometer and barometer signals, re-sampled to 30 Hz and segmented into equal-sized 5 second windows. The feature extraction process was based on Time Series Feature Extraction Library (TSFEL) library [1] and the selected features (Standard deviation of acceleration magnitude, barometer linear regression, mean y-axis acceleration, the total number of peaks of x-axis acceleration and standard deviation of y-axis acceleration) arise from the implementation of a Feed-Forward Feature Selection (FFFS) algorithm using 10-fold cross-validation. The DT classifier ended up with an accuracy of 90.2%.

Regarding the extracted features using this locomotion classifier, its predictions are used to calculate the percentage of time each activity is being performed. This percentage is calculated by equation 1.

[1] Available in https://github.com/fraunhoferportugal/tsfel (visited on 03/09/2019)

$$t_{activity}(\%) = \frac{\Delta t_{activity}}{\Delta t_{route}} \times 100 \quad (1)$$

Where $\Delta t_{activity}$ represents the activity duration along all route and Δt_{route} correspond to the route duration. Thus, the output features are the percentage time of each locomotion activity: walking (%), standing (%), walking up (%) and walking down (%).

3.1.2 With Previous Knowledge

Feature extraction with previous knowledge occurs when there is previous knowledge about the user, such as, the location and complex activities.

Location, in indoor environments, is used to understand the user's room preferences that may be associated with routine activities. In this study, a room-level indoor location solution with a fast deployment, that relies on Wi-Fi Received Signal Strength Indicator (RSSI) measurements to recognise in which room the user is located, was implemented. The training process starts with recording data in each room separately. Using the unique IDs from Access Point (AP) and the corresponding signal strength, a statistical classifier is trained and the prediction step is based on the highest probability. The algorithm output includes the labels of the predicted rooms over time. Thus, it is possible to extract some relevant metrics for finding patterns in human behaviour, namely: Times of Interest (TOI) (min), corresponding to the time spent in each location, and number of times the user goes into each room.

The recognition of complex activities involves a deeper knowledge about the user being studied. For this reason, depending on the user and also on the characteristics of the routine being analysed, a personalised training process is required. For this training process, a set of activities is selected, and the user must perform each activity several times beforehand. Alternatively, during his/her routine the annotation of activities can be done and used for training after a few days. The output features from classifier are the duration, in minutes, of each performed activity.

HMM is an effective method for finding patterns (Rabiner, 1989). In this study, HMM are used to evaluate the probability of a given sequence of locations and/or activities. A multinomial HMM was implemented using a number of hidden states that lead to the highest Bayesian Inference Criterion (BIC) value (Jeebun et al., 2015). Recurring to HMM the following features were extracted: activity sequence log-likelihood and location sequence log-likelihood.

3.2 Pattern Discovery

The pattern discovery step consists in modelling patterns in human behaviour using the extracted features with and without previous knowledge through probability density functions and clustering approaches.

Kernel Density Estimate was used to model each extracted feature, as the probability density function of the extracted features is unknown. KDE was firstly defined by Rosenblatt (Rosenblatt, 1956) and Parzen (Parzen, 1962), the kernel estimate is given by the sum of the kernel function K placed at each point of the dataset, as it is defined in equation 2.

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right) \quad (2)$$

Where n is the number of points in the dataset, h is the bandwidth and K is the kernel function centred on X_i with width h. The K used in this study was a Gaussian function. The method defined by Silverman (Silverman, 1982) was used for calculating the optimal bandwidth (h).

This method was designed to be independent of the features being used, and all features from the Feature Extraction step were equally modelled with KDE. Thus, the process of adding more features to model a specific routine can be easily introduced in this framework without changing the pattern discovery method. Depending on the intrinsic characteristics of each feature for a specific user, the modelling process may need more or less days to learn the pattern of the feature.

Although the majority of features can be modelled using KDE, other patterns can be learned using spatial information. For this purpose, clustering methods are used to find patterns in an unsupervised way, relying on trajectory similarity and Points of Interest (POI).

Trajectory similarity is measured using DTW (Zheng et al., 2019). Once trajectory distance is measured, a distance matrix is computed to feed as input to a Hierarchical Density-based spatial clustering of applications with noise (HDBSCAN) for grouping trajectories into clusters (Zhang, 2018), with a minimum cluster size of 3. This method is suitable for this pattern discovery since the final number of clusters is unknown and it is capable of dealing with clusters of different densities.

Points of Interest are locations of interest. In this study, a POI is defined as the location where the user stands for the minimum time of 1 minute and occurs in at least 3 different days, within a radius of 50 meters. For the assessment of these locations, the standing predictions of the locomotion classifier combined with time and spatial information were used.

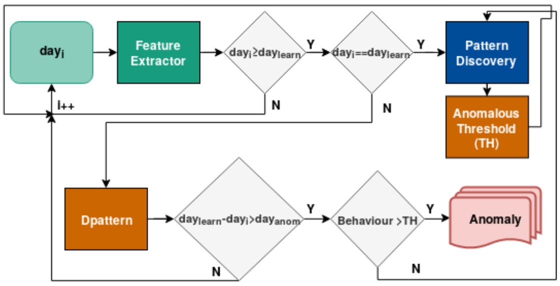

Figure 1: Learning patterns continuously and anomaly detection fluxogram.

Density-based spatial clustering of applications with noise (DBSCAN) clustering method (Kumar et al., 2006) was implemented for POI detection.

3.3 Anomaly Detection

Once motion patterns were defined, the next step of this framework aimed to detect anomalies on those patterns. Figure 1 represents the process of anomaly detection. Firstly, features are extracted from each day and the behavioural pattern is only defined after a predefined number of days (day_{learn}). When day_{learn} is reached, the pattern is learned and the threshold to detect an anomaly defined. The following days are evaluated by measuring the distance of each day to the pattern. To detect an anomaly, the anomalous decision is computed through the evaluation of a predefined number of consecutive days (day_{anom}). Therefore, only if the mean distance along the day_{anom} days are above the threshold an anomaly was detected.

The threshold is initially defined considering the learned behaviour until day_{learn}, and continuously updated along the days. However, if an anomaly is detected, the anomalous distances are not considered to the model pattern, neither for threshold definition.

Assuming that a specific feature is well modelled through KDE, we can use the density values from KDE to assess the feature probability given a predefined feature value. To transform density values to distance values, we normalised each distribution by its maximum density value. Therefore, the KDE distance ($KDE_{distance}$) is a scale from 0 to 1 and we can assess the level of deviation from pattern through a quantitative measure given by $d_{fi} = 1 - KDE_{distance_i}$. To combine several features and return an overall level of anomaly a global distance ($Dpattern$) is computed by a weighted arithmetic mean. $Dpattern$ is computed by Equation 3, where d_{fi} is the distance to the pattern of each feature i in a total of n features and w_{fi} are the corresponding weights. Thus, we can define a weight for each feature to measure the anomalous behaviour.

$$D_{pattern} = \frac{\sum_{i=0}^{n} d_{fi} \times w_{fi}}{\sum_{i=0}^{n} w_{fi}} \quad (3)$$

The anomalous threshold was defined by equation 4, where all behaviours (b) correspond only to normal behaviours.

$$TH = 1.1 \times max(b_0, b_1, ..., b_m) \quad (4)$$

Thus, only the distances to behaviour that are higher than 10% of the maximum behaviour distance of the trained model would account as anomalies.

4 EXPERIMENTS

Two different human routines were acquired over a period of 6 months to analyse human behaviour patterns addressing different challenges ranging from unsupervised human motion features to the recognition of complex activities and their sequence in indoor and outdoor environment, using the developed framework. Data was recorded using a smartphone positioned on the user's wrist, including accelerometer, gyroscope, magnetometer, barometer, sound, GPS and Wi-Fi sensors. The placement of the device was carefully chosen to be sensitive enough to perceive human motions in order to recognise predefined complex activities that need to be monitored. In real life application, the smartphone should be replaced by a bracelet or smartwatch comprising the needed sensors to perceive human motion behaviour.

4.1 Human Mobility on Daily Walks Dataset

This dataset was recorded by User 1 to extract mobility patterns during the outdoor daily walks of the user, including more than 30 hours of acquisition time with normal user behaviour. Aside from the normal routine days acquired in this dataset, it also comprises days with planned anomalies reflecting a human that starts to express reduced mobility, corresponding to 3 hours of anomalous behaviour.

4.1.1 Motion Patterns

The motion patterns were obtained through KDE, trajectory clusters and POI.

Kernel Density Estimate: Using this dataset, the feature extraction without previous knowledge includes features from outdoor trajectory, DR and locomotion activities. These extracted features were all modelled through KDE.

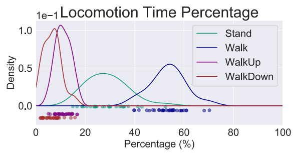

Figure 2: Percentage time distribution while standing, walking, walking up and walking down coloured in green, blue, purple and brown respectively.

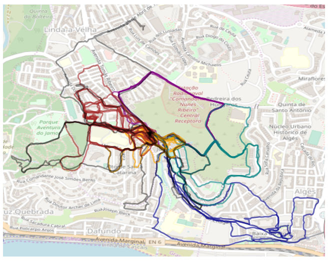

Figure 3: Representation of the trajectory clusters by spatial similarity.

The modelled locomotion percentage time distribution is presented in Figure 2. Through the analysis of these distributions, it is obvious that the user's most common locomotion mode is *walking*, although the user also stops during the daily walk. Although less commonly, *walking up* and *down* also make part of routine of this user, filling under 20% of the daily walking.

Regarding walking time and distance from GPS data, and number of steps and mean step length from DR, it was possible to validate the estimated distance values between GPS measurements and step detection algorithm, since the number of steps follows the same behaviour of the distance walked by the user.

Trajectory Clusters: A total of 5 clusters were found in this dataset (see Figure 3) coloured in blue, brown, orange, purple and green. The black trajectories correspond to the ones that are not similar to any of the found trajectory clusters.

Points of Interest: A total of four POI were discovered in User 1 routine, and their locations can be visualised in Figure 4. Since these POI were not annotated, it was asked to the user to validate the obtained POI. All POI represent meaningful locations to the user, being the blue POI the user's home, the orange POI the supermarket and the purple and green POI two gardens where the user usually stops.

4.1.2 Anomaly Detection

The previous subsection describes how patterns are discovered considering all normal days of a user's daily routine. However, for anomaly detection, the rules described in Figure 1 are applied. The number of 14 days was set to the minimum learning period to learn each feature pattern (day_{learn} = 14) and 5 consecutive days were used to predict an anomaly (day_{anom} = 5). For $Dpattern$ all feature weights were assigned to one, but weight optimisation should be considered in future work. Depending on the user and on the selected features, the minimum number of days used to learn the human pattern can not completely describe the real user behaviour, but since the pattern model is updated daily, the patterns will become more robust along the days. Thus, anomalies will be detected considering the previous normal days.

Figure 4: Illustration of the locations that correspond to the user POI.

The case study for anomalies detection, based on human mobility on daily walks dataset, concerns a user that starts to face reduced mobility. The planned anomalies were directly related to mobility, thus, User 1 during the anomalous days started to walk slowly and to perform shorter trajectories in less challenging paths. The extracted patterns that are more adequate for the detection of reduced mobility are the ones that are directly related to the user's mobility, namely the locomotion percentage time, the number of steps, mean step length, walking time, walking distance, mean and maximum velocity and mean and maximum altitude variation distributions.

In Figure 5, a representation of the distance of each day to the pattern, as well as the anomalous threshold value along days is shown. As the behaviour is defined within a range of 5 days, each distance represented correspond to the mean distance to the pattern regarding 5 days. The anomalous threshold is only defined after the pattern is learnt, which occurs after 14 days. On day 19 the behaviour starts to be evaluated, considering the behaviour of the last 5 days, according to the previous pattern and the defined threshold. The pattern and the threshold are continuously updated unless an anomaly is detected. Comparing the detected anomalies and the ground truth (red region), day 19 and 23 were incorrectly assigned as a planned anomaly. The anomalous behaviour of both days occurred due to a distinct user's locomotion behaviour that lead to a large anomalous distance. Specifically, day 19 was a raining day, so the performed walk was shorter than usual, leading to a large anomalous distance. Day 32 was not correctly

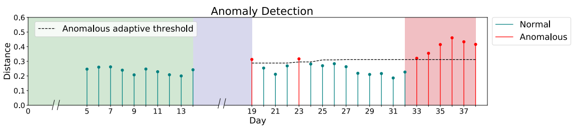

Figure 5: Representation of the anomaly detection results. The x-axis correspond to the days of the user's behaviour and the y-axis to the distance to the pattern. The green and red stem correspond to normal and anomalous days, respectively. The streak line defines the anomalous adaptive threshold. The green region correspond to the distances for first defining the pattern and the threshold, the blue region correspond to the day_{anom} and the red region is the ground truth of the anomalous days.

detected as an anomaly, which is acceptable since it considers the behaviour of the last 5 days that were normal, so the mean distance tends to be reduced.

4.2 Morning Daily Living Routine Dataset

This dataset aims to evaluate the behaviour motion patterns of the User 2, focusing on the indoor environment. Thus, we are interested in knowing the activities performed by the user comprising complex activities of his/her daily living and the user's location in a room-level.

The indoor location relying on room level recognition used data records from each room of the user's house. The implementation of a statistical classifier regarding the Wi-Fi RSSI of the unique IDs from several AP lead to an accuracy of 93.6%.

For the recognition of complex activities, namely *making the bed, washing the dishes, cooking, eating* and *brushing teeth*, separated activities from routines were acquired for training the classifier and the accuracies of various machine learning classifiers were evaluated. For the training process, the user was asked to record data while performing each of the morning activities. The train set was composed of 15 repetitions of each activity, and the test set was composed by the annotated activities during 54 days of the morning routine. For this recognition, data from the accelerometer, gyroscope, magnetometer, barometer and microphone smartphone sensors was acquired. Data was resampled to 30 Hz and the magnitude of tri-axial sensors was calculated. A resample exception was applied to microphone since a sampling frequency of 8000 Hz is needed to detect small sound variations. For this recognition problem, a window size of 20 seconds was chosen, together with a 30% overlap to enhance relevant features of the activity that may be overshadowed by partitioning the signal into fixed size windows. The features were extracted using TSFEL library and a FFFS using 10-fold cross-

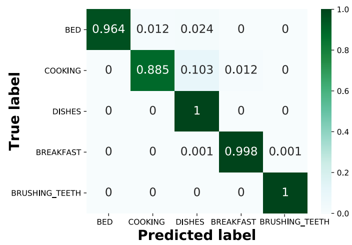

Figure 6: Normalised confusion matrix for morning activities classification, using RF classifier, after post-processing.

validation was applied. The K-Nearest Neighbor (KNN) classifier was the one that achieved the highest accuracy (92.5%) comparing to DT (89.7%), Random Forest (RF) (90.6%), Naive Bayes (NB) (62.9%) and AdaBoost (ADA) (88.5%).

In order to improve these results, a post-processing was applied to the prediction labels comprising two stages. Firstly, the indoor location classifier was combined with the complex activity recognition to ensure that an activity is being performed in the expected room. Secondly, using a window size of 60 seconds the classifier predictions are replaced by majority voting. After the post-processing, the RF classifier obtained the highest accuracy (98.1%) using the following features: mean y-axis acceleration, mean z-axis magnetometer value, and mean gyroscope magnitude. The normalised confusion matrix using RF after post-processing is presented in Figure 6.

HMM were implemented in this dataset to evaluate the probability of a given sequence of activities and locations performed by the user. The sequence of activities is important for the evaluation of the cognitive behaviour of the user, as a sequence that is too different from the usual sequences performed by the user may be an alarm situation. All 5 activities from morning activities classifier were used to learn activities sequence. The number of hidden states was estimated through BIC, resulting in 2 hidden states. Thus, the model was trained using 2 hidden states and the activities sequences performed by the user during 34 days. Regarding location sequence, the number of hidden states was also 2 and the HMM was implemented from both true labels and predictions.

4.2.1 Motion Patterns

The morning daily living dataset is evaluated only in indoor environment. The extracted features include the duration of activities (Figure 7) and the time spent in each location. These features were all modelled into a distribution using KDE, allowing to learn the user's behaviour in terms of indoor environment.

Focusing on the activity duration distribution (Figure 7), the predicted distributions present lower du-

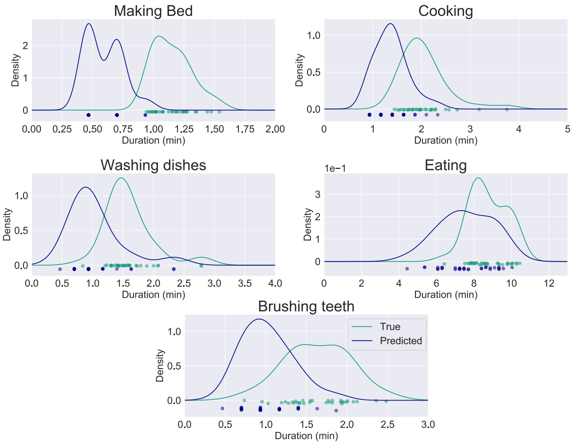

Figure 7: Representation of five features modelled into a distribution using KDE. The green and blue distributions are generated using the true and predicted activities labels, respectively.

ration compared to the true ones, which can be explained by the following reasons: firstly, the post-processing performed to the classifier prediction results discard some predictions by a majority voting window, if the discarded predictions belong to the beginning or end of the activity, correct predictions may be discarded reducing the activity duration; secondly, the annotated duration of the user's activity tends to be longer than the actual execution of the activity since the user first annotates the start of the activity, then performs it, and finally annotates the end of the activity. The gap between true and predicted activities duration will not affect the learned behaviour and consequently the planned anomalies detection, since the classifier behaviour is consistent between activities and for further predictions, its behaviour will be similar.

The HMM activities (Figure 8) illustrates the resulting log-likelihood of a trained HMM using activity sequences of true and predicted activity sequences, modelled using a KDE. Although the KDE distributions using the true and predicted labels are not exactly the same, both distributions include two peaks corresponding to the two most likely activity sequences. The shift between both distributions is due to the random processes of the HMM, and will not affect the anomaly detection since the resulting log-likelihood is dependent of the trained model.

4.2.2 Anomaly Detection

The current dataset was designed to detect anomalies on someone starting to experience dementia behaviour. For this purpose, the anomalies planned on the user's routine are related to dementia behaviour (Jaul and Barron, 2017), regarding absence

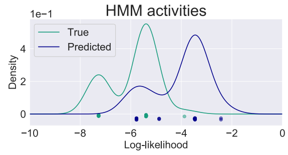

Figure 8: Representation of the log-likelihood distributions for true and predicted activities sequences, in green and blue, respectively.

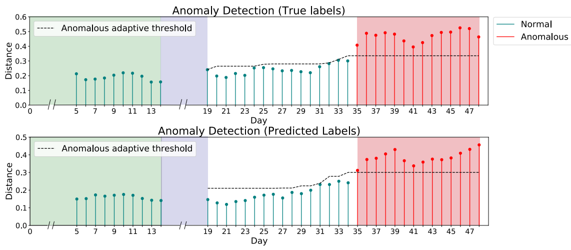

Figure 9: From the top to the bottom is represented the anomaly detection using the true and the predicted labels.

of activities that reflect the user's difficulty or disinterest in performing the activity, activity sequences that are not common on the user's normal behaviour and increased stay in certain home divisions that may be indicative that the user is feeling depressive. For anomaly detection, only the features that may characterise this behaviour were accounted for, namely the activity sequence probability, duration of each activity, TOI, number of entries per location and inactivity percentage time.

Using the fluxogram from Figure 1, day_{learn} was set to 14 and a range of 5 days (day_{anom}) for anomaly detection was used. The $Dpattern$ weights were set to one. Figure 9 illustrates the results for anomaly detection along 48 days of the user's routine. Comparing the results of the anomaly detection using the true and the predicted labels, despite the overall distances being different, the developed algorithm correctly predicts the planned anomalous days of the user behaviour that starts in day 35.

5 CONCLUSIONS

The lack of routine screening of the ageing population is a serious concern, since routine alterations and difficulty on performing certain daily activities are some of the common symptoms of cognitive impairments. Thus, the main contribution of this study was the development of a framework for learning human behaviour patterns.

The developed framework includes three main steps. The first step consists in the human behaviour feature extraction. This study has a wider perspective about human behaviour feature extraction than the reviewed literature. For instance, (Zheng et al., 2019) and (Suzuki et al., 2007) only focuses in human trajectory, (Tomforde et al., 2018) considers both location and activities sequences but no time information is extracted to model behaviour. This study extracts an extensive list of features from human behaviour, comprising time and frequency information from the trajectories and activities of the user. The second part investigates the usage of the extracted features for understanding and discovery of human patterns. Similarly to the study conducted by Rahim (Rahim et al., 2015), this study uses statistical models for the estimation of human behaviour patterns and anomaly detection. However, instead of a gaussian distribution, this study uses a KDE to define the probability density function since behaviour features may not follow a gaussian distribution as it was verified on the behaviour features acquired during this study. Finally, an anomaly detection algorithm was introduced to detect abnormal behaviour. Experimental results demonstrate the effectiveness of the proposed framework that revealed an increase potential to learn behavioural patterns and detect anomalies considering different case studies. This study may be a key insight for monitoring elderly daily routines as well as marketing analysis, security and tourism management.

Although the developed study revealed promising results there is still room for improvement that can be addressed in the future. Firstly, the framework should be tested in more users, including different anomalous behaviours. Then, the distance to the pattern can be improved by a weight optimisation and parameterization process based on the intrinsic characteristics of each feature. This way, strongly correlated features will have lower influence on the anomaly detection. The weights should be learned according to real case scenarios. For instance, it can be studied which features are more affected considering different anomalous behaviours, and the weights learned accordingly. The framework can also be improved by an automatic detection of the number of days needed to learn the pattern. Finally, the smartphone used for data acquisition should be replaced by a smartwatch or bracelet containing the sensors embedded in a smartphone.

REFERENCES

Evans, D., Price, K., and Meyer, J. (2016). Home Alone With Dementia. *SAGE Open*, 6(3):1–13.

Guimarães, V., Castro, L., Carneiro, S., Monteiro, M., Rocha, T., Barandas, M., Machado, J., Vasconcelos, M., Gamboa, H., and Elias, D. (2016). A motion tracking solution for indoor localization using smartphones. In *2016 International Conference on Indoor Positioning and Indoor Navigation, IPIN 2016*, pages 1–8. IEEE.

Jaul, E. and Barron, J. (2017). Age-Related Diseases and Clinical and Public Health implications for the 85 Years Old and Over Population. *Frontiers in Public Health*, 5:1–7.

Jeebun, S., Ballgobin, R., and Al-ani, T. (2015). Optimal Number of States in Hidden Markov Models and its Application to the Detection of Human Movement. *University of Mauritius Research Journal*, 21:438–469.

Kumar, V., Tan, P.-T., and Steinbach, M. (2006). Cluster analysis: basic concepts and algorithms. In *Introduction to data mining*, pages 488–568.

Parzen, E. (1962). On the Estimation of Probability Density Functions and Mode. *Ann. Math. Statist*, 33:1065–1076.

Rabiner, L. R. (1989). A Tuturial on Hidden Markov Models and Selected Applications in Speech Recognition. *Proceedings of the IEEE*, 77(2):257–286.

Rahim, A., Forkan, M., Khalil, I., Tari, Z., Foufou, S., and Bouras, A. (2015). A context-aware approach for long-term behavioural change detection and abnormality prediction in ambient assisted living. *Pattern Recognition*, 48(3):628–641.

Rosenblatt, M. (1956). A Central Limit Theorem and a Strong Mixing Condition. *Proceedings of the National Academy of Sciences*, 42(1):43–47.

Silverman, B. W. (1982). Kernel density estimation using the fast Fourier transform. *Applied Statistics*, 31(1):93–99.

Suzuki, N., Hirasawa, K., Tanaka, K., Kobayashi, Y., Sato, Y., and Fujino, Y. (2007). Learning motion patterns and anomaly detection by human trajectory analysis. In *Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics*, pages 498–503.

Tomforde, S., Dehling, T., Haux, R., Huseljic, D., Kottke, D., Scheerbaum, J., Sick, B., Sunyaev, A., and Wolf, K. H. (2018). Towards Proactive Health-enabling Living Environments: Simulation-based Study and Research Challenges. In *31th International Conference on Architecture of Computing Systems*, pages 1–8.

United Nations (2017). World Population Ageing 2017 - Highlights (ST/ESA(SER.A/397). Technical report, Department of Economic and Social Affairs, Population Division, New York.

Zhang, D. (2018). *Periodic Pattern Mining from Spatio-temporal Trajectory Data*. PhD thesis, James Cook University.

Zheng, W., Zhou, R., Zhang, Z., Zhong, Y., Wang, S., Wei, Z., and Ji, H. (2019). Understanding the tourist mobility using GPS: How similar are the tourists? *Tourism Management*, 71:54–66.