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Recognition of Activities of Daily Living from Topic Model

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Abstract

Research in ubiquitous and pervasive technologies have made it possible to recognise activities of daily living through non-intrusive sensors. The data captured from these sensors are required to be classified using various machine learning or knowledge driven techniques to infer and recognise activities. The process of discovering the activities and activity-object patterns from the sensors tagged to objects as they are used is critical to recognising the activities. In this paper, we propose a topic model process of discovering activities and activity-object patterns from the interactions of low level state-change sensors. We also develop a recognition and segmentation algorithm to recognise activities and recognise activity boundaries. Experimental results we present validates our framework and shows it is comparable to existing approaches.

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Keywords: Activity discovery; Activity recognition; Pattern Analysis; Probabilistic Latent Semantic Analysis ;

1. Introduction

Activity discovery and recognition of the elderly in the home environment has been identified as a major research area due to the increase in the aging population[1]. This research area typically monitors Activities of Daily Living (ADL) by capturing how these activities are performed to provide support to the elderly and cognitively impaired[2,3]. The use of wireless sensor networks which include state-change sensors has proven to be promising due to their low cost, ease of installation and most importantly being non-intrusive[4]. Attaching these state-change sensors to objects in the home environment gives a reflection of object interactions and use and subsequently the ongoing activity. For example, if sensors tagged to Fridge, Cooktop and Microwave are activated, *Breakfast* could be the recognised activity. On the other hand, it could suggest *Breakfast* as the most probable activity from the observation of Fridge, Cooktop and Microwave which describes the activity-object pattern or relatedness. The process of recognising activities from the object interactions and use requires; First, pre-processing captured sensor data into segments which reflects an activity. Second, discovering the activities and the underlying activity-object patterns. The challenge therefore is discovering

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the activity themes which these object interactions represent and further use them to recognise ADL. To this end, we propose an activity recognition framework built on an activity discovery process and a recognition and segmentation algorithm. We discover the activity topics and the activity object patterns using the topic model Probabilistic Latent Semantic Analysis (PLSA). The activities topics and the activity-object patterns are then used to develop an activity recognition and segmentation algorithm. The PLSA developed by Hoffman[5] makes the assumption that there are hidden themes or latent topics which have associations with the words contained in a corpus of documents. In our activity discovery context, we conversely assume that latent activity topics would have associations to observed sensor data which corresponds to the words and the activity topics correspond to the latent topics of the PLSA. In summary, this paper makes three main contributions:

- We propose the use of the topic model Probabilistic Latent Semantic Analysis PLSA to discover activities topics and activity-object patterns.
- We also propose an activity recognition and segmentation algorithm using the discovered activities topics and activity-object patterns.
- We validate the performance of the framework by carrying out experiments.

The remainder of the paper is organized as follows. Section 2 provides an overview of the related works, while Section 3 describes the proposed activity discovery approach. Section 4 provides experimental results based on the Ordonez dataset[6] which we used to validate our proposed framework. Section 5 concludes this paper.

2. Related Work

The proposed framework builds on previous done in the area of ADL recognition. So many research efforts have been made in field of activity recognition to discover and recognise human activities like[4,7,8,9,10]. These efforts have seen researchers explore probabilistic techniques[11,12,13,14], logic[15] and ontological methodologies[8,16,17] within the process of ADL classification. Tapia et al[14] used the Nave Bayes on features captured by wireless sensors to recognize activities of interest. Although they achieved accuracy up 83%, they failed to automatically partition sensor sequences which they did manually. Researchers made attempts using Hidden Markov Models (HMM) approach on sensor networks. Patterson et al[12] applied the HMM on data from wearable sensors and objects tagged with RFID. Kasteren et al[18] in their work used the HMM and Conditional Random Fields CRF on dataset recorded using a wireless sensor network. The performances from both classifiers were compared in the process. Philipose et al[19] proposed a technique of recognising activities from web mined data. In their work, they used a sliding window method to partition their sensor data. Although these approaches were unsupervised, they failed to consider the activity boundaries for recognition and activity durations. Our work uses the Probabilistic Latent Semantic Analysis which is a probabilistic topic model requiring words x documents matrix input in a *bag of words* format. Probabilistic topic models inspired by the text and natural language processing community have been applied to discover and recognise human activity routines in Zheng and Lionel[20], Hammid et al[21]. But the work we propose in this paper, extends our initial work Ihianle et al[22] by the inclusion of the recognition and segmentation algorithm and it is similar to Huynh et al[13] and Katayoun and Gatica-Perez[23]. Huynh et al[13] applied the *bag of words* model of the Latent Dirichlet Allocation (LDA) to discover activities like dinner, commuting, office work etc. The process involved activity discovery of partitioned sensor segments of each time window. Also an LDA topic model approach was applied by Katayoun and Gatica-Perez[23] to discover routines from mobile phone data. While Huynh et al[13] used wearable sensors attached to the body parts of the user, Katayoun and Gatica-Perez[23] captured their data from a single mobile phone by the user. While it is not feasible to use only a single mobile phone or phones as in Katayoun and Gatica-Perez[23] to capture low level every day ADL, our work uses multiple state-sensor tagged to every day home objects to capture object use and user activities in the home setting. Our work also significantly differs from Katayoun and Gatica-Perez[23] and Huynh et al[13] with the development of the recognition and segmentation algorithm which we use on our test subset to recognise activities. We also use this algorithm to recognise boundaries where an activity starts or ends.

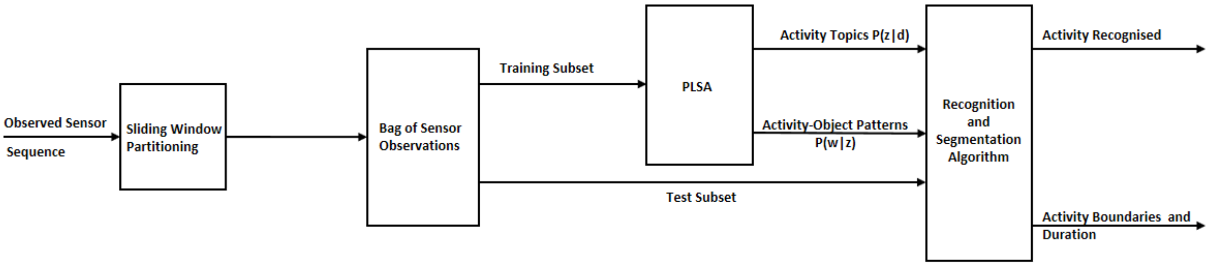

Fig. 1. An overview of our framework

3. Activity Recognition Approach

Activities are carried out by the interactions of objects within various locations in a home environment. Specific objects tend to be used in specific places for routine activities following patterns which are common to the user. In most cases, certain objects in specific locations have been known to be linked to particular activities. For the approach we propose through this framework we use the Ordonez dataset[6]. This dataset was generated using a set of simple state-change sensors installed in two different home environments. The non-intrusive nature of binary sensors suits the privacy and acceptability of the home occupants whilst object interactions are ongoing for activities. The Ordonez dataset has eight different ADLs labelled as *Sleeping*, *Toileting*, *Leaving*, *Spare Time/TV*, *Showering*, *Grooming*, *Breakfast*, *Lunch*, *Dinner*, *Snack*, and *Idle* activity which corresponded to times when no significant activity took place. Eight sensors used to capture object interactions has been annotated as object names for the two houses. Given this dataset, we aim to discover the underlying activities and then recognize them progressively along their timelines. Towards this, we form a *bag of sensor observations* from a continuous 60 seconds partitions of the sensor data. We use the topic model Probabilistic Latent Semantic Analysis (PLSA) to discover the underlying activity topics and the activity-object patterns. Further, we use the discovered activity topics and activity-object patterns to develop an algorithm for activity recognition and segmentation. An overview of the framework is as illustrated in Figure 1.

3.1. Bag of Sensor Observations

The PLSA as a generative classification approach which requires a corpus of documents made of constructed *bag of words*. In the context of activity recognition from binary sensors, we construct a *bag of sensor observations* which corresponds to the *bag of words*. For the *bag of sensor observations*, we partition the dataset of sensor observations into sequences using a sliding window of 60 seconds intervals to form a sensor-segment matrix. We also set the observed sensors to be represented as aliases such as Seat (S), Basin (B), Bed (A), Microwave (M), Cupboard (C), Fridge (F), Cabinet (N), Toilet (T), Shower (Sh) etc. to be encoded onto the partitioned sensor sequences.

3.2. The Probabilistic Latent Semantic Analysis PLSA

The aim of the activity and pattern discovery process is to determine the activity-object relatedness or patterns and the activity topics. This process takes advantage of the Probabilistic Latent Semantic Analysis (PLSA) topic model assumption that there are hidden themes or latent topics which have associations with the words contained in a corpus of documents. It involves the use of *bag of words* in the corpus of documents which are generatively classified to latent themes or topics[5]. We conversely apply this assumption to the activity discovery context that latent activity topics would have associations with the features of sensor data or objects in the partitioned sequences of the *bag of sensor observations* described in section 3.1 above. The documents are presented in the form of sensor sequences $d_1 ... d_D$ composed of co-occurring sensor data observations along their timelines. If D is composed of sensor sequences $d_1 ... d_D$, d_i would be made of sensors represented as $x_{i1} ... x_{in}$ from X sensors of $x_1 ... x_n$. The PLSA assumes that a latent activity topic z from topics $z_1...z_k$ can be classified from $d_1...d_D$ as contained in D i.e for a sensor x_i contained in $x_{i1}...x_{in}$. there is a marked probabilistic relationship with the activity topic z. In principle, there is a joint probability over D x X such that a conditional independence assumption that d and x are independently conditioned on the state of the associated activity latent topic. The proposed framework is trained to infer activity topic probabilities by the iterative Expectation Maximisation (EM) algorithm. The first step, Expectation (E step) computes the posterior probabilities of the latent variables P($z_i|d_i$) from the activity topic probabilities P(z_i) and the conditional probabilities of the sensors given the activity topics P($x_i|z_i$). The Maximisation (M step) updates the parameters from the E step by computing the new values for P(z_i) and P($x_i|z_i$). The posterior inference of the EM iterative process can be computed from P($z_i|d_i$) for each d_i. This computes the activity topic from the given sensor sequence. P($x|z$) computes the probability of the sensors given activity topics. In the context of pattern discovery, the sensors or objects linked an activity topic is computed from P($x|z$) and this defines the activity-object pattern. Modelling an activity for recognition would rely on P($x|z$) to define the compositional object usage that are linked to specific activity topic and P($z|d$) defines the activity topics therein. The learning process of the proposed framework involves dividing the dataset into training subset (90%) and test subset (10%). The EM posterior inference is used on the training subset and then progressively on the test subset. Based on the training subset inference, we use P($x|z$) and P($z|d$) for activity recognition and segmentation algorithm.

3.3. Recognition and Segmentation Algorithm

To recognize activities in a stepwise and continuous manner from objects observed, we developed a recognition and segmentation algorithm. As sensors are observed progressively, P($x|z$) determines the activity group an objects belongs to. For a non-interleaving set of activities, a stream of observed sensor data can also be segmented using this activity-object pattern P($x|z$). The co-occurrence of certain objects linked to an activity along a timeline can be used to determine activity boundaries as illustrated in Figure 2. With the association of their temporal attributes, activity durations is computed and activities with same or similar objects interaction distinguished.

Input: Observed Sensors: $x_1...x_n$
Sensors Start Time: $t_{s1}...t_{sn}$
Sensors End Time: $t_{e1}...t_{en}$
Activity Topics: $z_1...z_k$

Outputs: Activity Boundaries, Activity Durations, Activities

Begin
Read Observed sequences $x_1...x_n$
for x_{1i} P($x|z$) for Activity topic z_i **do**
x_{2i} next adjacent object ϵ P($x|z$) for Activity topic z_i
If x_{2i} not ϵ P($x|z$) for Activity topic z_i
then Boundary detected
Duration: $t_{e1i} - t_{s1i}$
return: Activity z_i, Boundary, Duration
End

Algorithm: Activity-Object Pattern Enhanced Recognition and Segmentation

4. Experimental Process and Evaluation

In this section we present result, performance and evaluation of our proposed framework. We have used the dataset by Ordonez et al [6]. Table 1 show the details of the dataset and ADL instances.

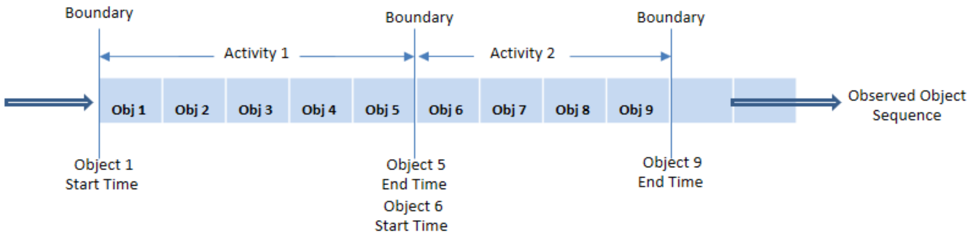

Fig. 2. Segmentation and boundary determination from observed object data

Table 1. ADL composition in the Dataset.

Activity	Ordonez A	Ordonez B
Sleeping	39.10%	35.58%
Toileting	0.76%	0.55%
Leaving	8.32%	17.41%
Spare/TV	42.32%	28.98%
Showering	0.54%	0.24%
Grooming	0.73%	1.42%
Breakfast	0.63%	1.02%
Lunch	1.59%	1.30%
Dinner	0.00%	0.38%
Snack	0.05%	1.33%
Idle	5.61%	1.42%

4.1. Experimental Process

The experimental process followed the steps outlined in section 3 on the dataset: Construction of the *bag of sensor observations* , activity topics and activity-object patterns discovery using the PLSA and development of the recognition and segmentation algorithm. Further, we performed activity recognition on the dataset and then evaluated the performance of the framework. To test the learning process, the dataset was divided into training and test subsets. The training subset was then used to learn new trace activities in the test subset. Furthermore, the performance based on accuracy and precision were determined using the true positives TP, true negatives TN, false positive FP and false negatives FN. Further experiments were also carried out to determine the impact of number of topics and patterns to the proposed framework. To evaluate the performance of the algorithm, we compute the percentage of Accurately Recognised Activity Boundaries (ARAB) from the accurately recognised boundary B_a, real boundaries B using equation below:

$$\text{ARAB} \ = \sum_{i=1}^{B} (\dot{B}_a * 100)/B \tag{1}$$

4.2. Results.

Applying 8 activity topics, the topic model process discovered activities as illustrated in Figure 3. Although there were evidence of confusion from same and similar object interaction, we believe results obtained are significantly comparable.

Based on the activity discovery process, activity topics 1,2,3,4,5,6,7 and 8 corresponds to *Toileting*, *Grooming*, *Sleeping*, *Leaving*, *Showering*, *Make Food*, and *Spare Time/TV*, respectively for House A. Also, Topics 1,2,3,4,5,6,7 and 8 corresponds to *Leaving*, *Spare Time/TV*, *Make Food*, *Showering*, *Sleeping*, *Grooming*, *Make Food* and *Toileting*,

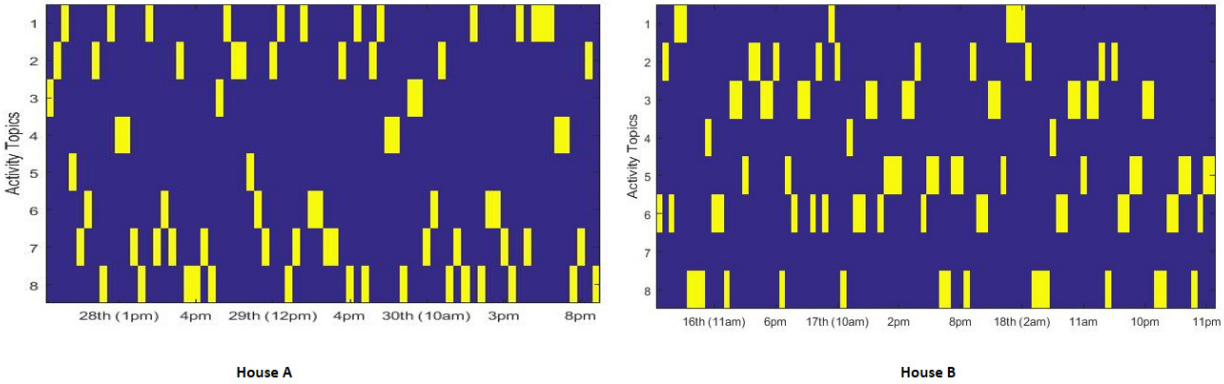

Fig. 3. Discovered Activity Topics for Ordonez House A and B

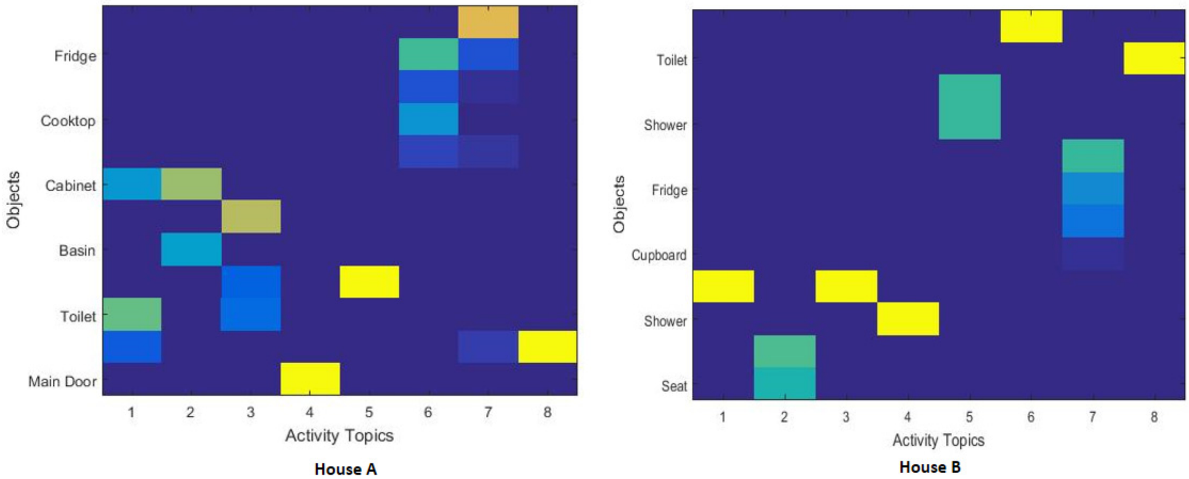

Fig. 4. Activity-Object Pattern P(x|z) for House A and B

respectively for House B. *Make Food* for Houses A and B corresponds to *Breakfast*, *Lunch*, *Dinner* and *Snack*, due to same and similar object interactions from Fridge, Cupboard, Cooktop, Microwave and Kitchen Door for House B. To discriminate and distinguish these activities, we associated them to their time stamps e.g. *Make Food* for AM times corresponds to *Breakfast* and between 12.00 and 3.00pm for *Lunch* and afterwards *Dinner*. *Snack* had no specific time. With the activity-object pattern illustrated in Figure 4, we implemented the activity recognition and segmentation algorithm. The recognition results and performance of the framework is given in table 2. Activities *Spare Time/TV*, *Toileting*, *Shower*, *Leaving* and *Sleeping* performed significantly well due minimal false positives. Of particular interest are *Breakfast*, *Lunch*, *Dinner* and *Snack*. These activities were recognised with significant false positives arising from same and similar object interactions. This impacted on their performance causing confusions and ambiguities. Discriminating them by associating the activities to their time stamps improved recognition for *Breakfast* and *Dinner* but *Lunch* and *Snack* were poor due to time stamps that were not specific. *Dinner* was not an activity in House A.

4.3. Segmentation Algorithm Performance

With regards to the recognised activity boundaries, Figure 5 illustrates the performance of the recognition and segmentation algorithm for House A and B. The average performance for House A was significantly better than for

Table 2. Experimental Results.

Activity	House A Accuracy	Precision	F1	House B Accuracy	Precision	F1
Sleeping	100	100	100	100	100	100
Toileting	100	100	100	80	80	88.9
Leaving	100	100	100	100	100	100
Spare/TV	100	100	100	85.7	85.7	92.3
Showering	58.3	53.8	70	61.5	66.7	76.2
Grooming	67.4	70.5	80.5	64.6	68.9	78.5
Breakfast	80	100	88.9	71.4	83.8	83.3
Lunch	57.1	66.7	72.7	57.1	66.7	72.7
Dinner	NA	NA	NA	50	57.1	66.7
Snack	55.6	62.5	71.4	54.5	60	70.6
Average	79.8	83.7	87.1	72.5	76.8	82.9

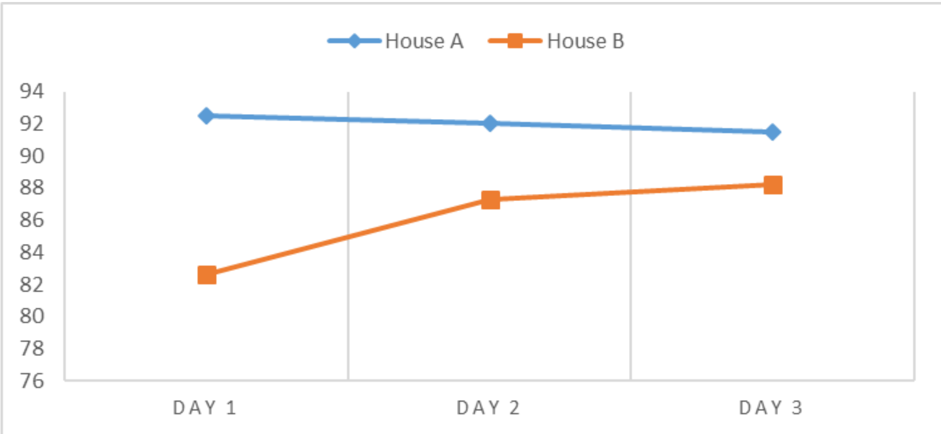

Fig. 5. Accurately Recognised Activity Boundaries

House B. The performance for House B was as it is due to noise arising from the frequent observation of Living Door and Kitchen Door which in most cases led to increased false positives for House B for the recognised activities.

4.4. *Impact of Number of Topics*

With the experiments conducted, the evidence of same or similar object interactions could result to high false positives. We further analysed the impact of different topics for the activity discovery process. We evaluated the performances of the activity discovery process for different topic numbers 7, 8 and 9. Given this, it was evident that 8 activity topics performs best for the dataset. This can be largely attributed to the shared object interactions for *Grooming* and *Shower* and *Breakfast*, *Lunch*, *Dinner* and *Snack*. The use of 8 activity topics converges these six set of activities to two set of activities which can be distinguished using their temporal patterns.

4.5. *Limitations*

In the paper we have shown that through topic models ADL can be recognized, but this work has a number of limitations. The foremost of these is that the dataset was captured in a controlled environment. Not all objects in the home environment were tagged making the set of activities discovered as finite as against real life situations which normally involves infinite amount of unrelated activities. Another limitation is that we have predefined and chosen the number of topics parameter which should have been automatically determined to cover the infinite number of activities as they unfold.

5. Conclusion

In this paper, we presented ADL recognition from sensor data using the PLSA topic model. We used the PLSA to discover activity topics and activity-object patterns. It is also noteworthy to state that the process of activity discovery uses constructed *bag of sensor observations* from partitioned sensor sequences to form a corpus of sensor documents which are assumed to have latent themes corresponding to activity topics. The resulting activity topics and activity-patterns were then used to develop a segmentation and activity recognition algorithm. The performance of the proposed framework suggests good and significant results which is comparable. Although our work used dataset captured from wireless binary sensors tagged to objects, we feel it is appealing given the non intrusive nature of these sensors, their cost, the easiness to which they can be handled and the number of objects capable of being tagged with them. We would like to extend our work by incorporating mobile phone data to binary sensor data for activity recognition.

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