Knowledge Driven Activity Recognition from Patterns of Object Use

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Abstract

The process of activity recognition of elderly individuals with cognitive impairment has made it possible to provide timely assistance and support, which in turn allows them to lead an independent life. Current activity recognition methods are based on knowledge driven techniques that require extensive modelling of the activities that need to be inferred. They follow everyday common knowledge and assumptions of object use for routine activities to model activity and object concepts capable of faulty activity recognition. The knowledge of particular object(s) which are used to perform routine activities could help enhance activity recognition. The goal of this paper is to take advantage of the object use for routine activities discovered from a topic model process to augment concepts of activity ontology for activity recognition. The experimental results obtained using the Kasteren and Ordonez datasets show it is significantly encouraging and comparable.

1 Introduction

With the rising cost of providing assistance to the elderly and the cognitively impaired, it has become imperative to consider technology driven solutions which can help provide activity recognition solutions. This area of research has attracted enormous attention and has seen efforts in the use of video [15], wearable sensors [5, 10] and wireless sensor networks [11, 16]. The use of wireless sensor networks has proven to be promising due to their low cost, ease of installation and most importantly being non-intrusive [11, 16]. Systems built to recognize and track Activities of Daily Living (ADL) of the cognitively impaired can be of significant importance in the monitoring of their well being and provision of assistive interventions. These approaches require object usage data to be classified using various machine learning techniques or modelling activities for recognition in knowledge driven approaches. The machine learning techniques works by discovering activities associated with the most probable value with regards to a set of independently observed object data. On the other hand, the knowledge driven model follows the process of developing activity recognition models following generic or everyday knowledge and assumptions of object usage for activities. In most cases, these activity recognition models are not adaptable to the user or home environment making the ability for activity recognition and tracking of health changes difficult. Building activity recognition models which does not follow prior patterns of object associations to routine activities becomes challenging. This paper aims to build a framework which relies on object use patterns to develop activity ontology for continuous and progressive activity recognition. The use of the various objects in the home environment are linked to the routine activities performed by the home user. As such, a routine activity could have specific object(s) which are used to perform them and characterises the home user's habits, lifestyle and way of performing specific activities. This paper defines the object use for specific routine activities as activity-object use patterns. To achieve an activity recognition framework which considers routine activities and their object usage with regards to the home user, this paper proposes a novel framework which utilises discovered activity-object use patterns from a topic model to augment the ontology concepts of a knowledge-driven approach to providing enhanced activity recognition. The contributions of this work are first use of the topic model Latent Dirichlet Allocation (LDA) to discover activities-object patterns and activity topics. Secondly, extend a typical generic activity ontology by modelling the discovered activity-object patterns as ontology concepts. Thirdly, perform activity recognition through experiments to validate the performance of the framework. 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 recognition approach. Section 4 provides experimental results based on the Kasteren [16] and Ordonez dataset [11] which was used to validate the proposed framework. Section 5 concludes this paper.

2 Related Work

The framework proposed in this paper purely builds on the several research efforts in activity recognition. The topic model Latent Dirichlet Allocation (LDA) and the knowledge driven ontology model have been used in this paper for activity-object pattern discovery and ontology activity model respectively. Topic models inspired by the text and natural language processing community have been applied to discover and recognise human activity routines in research works by Katayoun and Gatica-Perez [9] and Huynh et al [6]. The activity-object pattern discovery process discussed in the paper is similar to Huynh et al [6] and Katayoun and Gatica-Perez [9]. Huynh et al [6] 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 time windows. Also an LDA topic model approach was applied by Katayoun and Gatica-Perez [9] to discover routines from mobile phone data. While Huynh et al [6] used wearable sensors attached to the body parts of the user, Katayoun and Gatica-Perez [9] 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 [9] 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. This work in this paper also significantly differs from Katayoun and Gatica-Perez [9] and Huynh et al [6] with the modelling of the activity-object pattern on an ontology activity model. The framework proposed in this paper, also extends our previous works [7, 8] by the inclusion of the ontology activity model. Knowledge driven ontology models follow web ontology language (OWL) theories for the specification of conceptual structures and their relationships. OWL has been widely used for modelling human activities for recognition, which most times involve the description of activities by their specifications using their object and data properties. In ontology modelling, domain knowledge is required to encode activity scenarios, but it also allows the use of assumptions and common sense domain knowledge to build the activity scenarios that describe the conditions that drive the derivation of the activities. Recognising the activity then requires the modelled data to be fed to the ontology reasoner for classification. The authors of [3] and [4] followed generic activity knowledge to develop an ontology model for the smart home users. Whilst this approach to model activities to depending on common sense domain knowledge and its associated heuristics are commendable, they are generic and not user centric to capture events that may be abnormal or lead to report of failing health in the case of the elderly cognitively impaired. Specific personal profiles and habits have not been put into considerations just as home settings which differs with people may limit the use of these generic and reusable ontologies. They also do not follow evidenced patterns of object usage and activity evolution as they rely on generic know hows and hows to to build ontology models. The ontology activity model which forms a major part of this proposed framework relies on activity topics, activity-object patterns initiated by the user's object use. This paper also follows the temporal ontology query language [1] which provides the mechanism to integrate temporal knowledge for enhanced activity recognition.

3 Overview of Our 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 home user. For example, Breakfast in Kasteren House A could involve the use of objects like Plates Cupboard, Fridge, and Microwave in the Kitchen. The activity Breakfast in this case forms an activity-object use patterns with the objects. Given this, the activity-object use patterns could play significant role in the process of recognition of activities in the home environment. This paper aims to build develop activity ontology relying on object usage patterns for activity recognition. The LDA topic model classifies the likely object usage for specific activities i.e. activity-object use. Further, the discovered activity-object use patterns and activity topics are used as ontology concepts to develop an ontology activity model which provides the platform for a user specific activity and object use association for progressive and object based activity recognition. An overview of the framework is as illustrated in Figure 1.

3.1 Activity-Object Use Discovery

The LDA topic models is a probabilistic generative models used to analyse large collections of texts to discover hidden themes in them. It requires bag of words input constructed from a corpus of D documents to produce a set of probability distributions over words and the latent topics as output. A document is composed of sequence of X words. In the context of activity-object use pattern discovery, the dataset of observed objects corresponds to the corpus of texts, sensor segments correspond to documents and the objects correspond to the words in the corpus of texts. The choice of the LDA topic models is as a result of it popularity and robustness among other topic models [9, 13]. The bag of sensor observations corresponds to the bag of words mentioned earlier in this sub section.

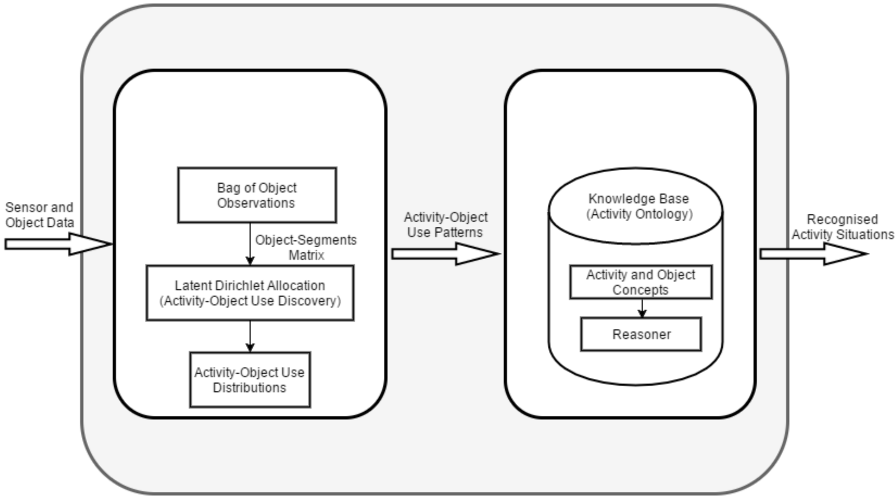

Figure 1: An Overview of the Activity Recognition Framework.
Activity-object patterns are discovered in the training phase from the classification using the LDA topic model which requires Bag of Sensor Observation inputs. An activity ontology is developed from the activity-object patterns on which activity recognition is performed using the test subset.

3.1.1 Bag of Sensor Observations

Recall that the bag of sensor observations is analogous to the bag of words of the LDA, segments of object data corresponds to the documents and the objects corresponds to the words. The bag of sensor observations is constructed by partitioning the dataset of into segments of objects along their timelines using a sliding window of choice. In this paper, we have used a 60 seconds fixed sliding window intervals for the Kasteren [16] and Ordonez [11] datasets. Observed objects were represented as aliases as in Groceries Cupboard (GC), Cups Cupboard (CC), Hall Bedroom Door (BD), Microwave (M), Pans Cupboard (PC), Fridge (F), Front Door (FD), Toilet Flush (Tf), Hall Bathroom Door (BA) etc. to be encoded onto the partitioned objects segments to form the bag of sensor observations.

3.1.2 Latent Dirichlet Allocation

Latent Dirichlet Allocation was introduced by Blei et al. [2], in which each document from the bag of words is modelled as a multinomial distribution of topics. It takes advantage of the assumption that there are hidden themes or latent topics which have associations with the words contained in a corpus of documents. It also involves the use of *bag of words* in the corpus of documents which are generatively classified to latent themes or topics. It is conversely applied this assumption to the activity-object pattern discovery context that latent activity topics would have associations with the features of objects data in the partitioned segments of the *bag of sensor observations* discussed above. The documents are presented in the form of objects segments $d_1 \dots d_D$ composed of co-occurring object data observations along their timelines. With D composed of object segments $d_1 \dots d_D$, d_i would be made of objects represented as $x_{i1} \dots x_{in}$ from X objects of $x_1 \dots x_n$. The LDA places a dirichlet prior

P($\theta_d|\alpha$) with parameter α on the document-topic distributions P($z|\theta_d$). It assumes a Dirichlet prior distribution on the topic mixture parameters θ and ϕ, to provide a complete generative model for documents D. θ describes D x Z matrix of document-specific mixture weights for the Z topics, each drawn from a Dirichlet(α) prior, with hyperparameter α. ϕ is an X x Z matrix of word-specific mixture weights over X objects for the Z activity topics, drawn from β which is a Dirichlet prior. The probability of a corpus or observed object dataset, is equivalent to finding parameter α for the dirichlet distribution and parameter β for the topic-word distributions P($x|z,\beta$) that maximize the likelihood L of the data for documents d = $d_1 ... d_D$ as given in the equation 1 following Gibbs sampling for LDA parameter estimation [2].

$$L(\alpha,\beta) = \prod_{d=1}^{D} \int P(\theta_d|\alpha) \left(\prod_{x=1}^{X_D} \sum_{z=1}^{Z} P(x_{xi}^{d}|z,\beta) P(z|\theta_d) \right) d\theta_d \tag{1}$$

Given the assumptions above, the activity-object patterns can be calculated from the equation 2 below:

$$P(x|z,\phi) = \prod_{z=1}^{Z} \prod_{x_i=1}^{X} (\phi_z^{x_i})^{n_z^{x_i}} \tag{2}$$

where $n_z^{x_i}$ is the number of times an object x_i is assigned to a topic z. In the context of a knowledge driven activity recognition, modelling activity concepts for recognition would rely on the probabilistic distribution of the objects given the activity topics. The LDA topic model, P($x|z$) computes the compositional object usage that are linked to specific activity topics. The object distributions for the activity topics similar to the schema 3 discovered through the LDA provides the activity-object patterns needed to augment activity ontology model as ontology concepts with regards to the specific object use for activities.

$$P(x|z) = \begin{bmatrix} \{x_{k1}...,x_{k1}\} & number & of & objects & are & assigned & k1 \\ \{x_{k2}...,x_{k2}\} & number & of & objects & are & assigned & k2 \\ ...... & & & .... & & & \\ \{x_{K1}...,x_{KN}\} & number & of & objects & are & assigned & k2 \end{bmatrix} \tag{3}$$

3.2 Ontology Module

The ontology module is composed of the knowledge base is a repository of information consisting of the modelled activity ontology concepts, data, rules used to support activity recognition. Just like other knowledge bases, it functions as a repository where information can be collected, organized, shared and searched. The activities and the context descriptors from the context description module are designed, developed following description logic knowledge representation and formalism and added to the knowledge base. The knowledge base is made of the , and the . The is the terminological box made of the activities and the relevant context descriptors as defined and encoded ontological concepts. The ontological design and development process gradually populates the by encoding the activities and context descriptors from the context description module as ontological concepts. The is the assertional box made of the instances and individuals of the concepts encoded in the asserted through properties which may be object or data properties. For all the terminological concepts in our , instances and individuals of these are asserted through different properties to populate our . In addition to the activity and context descriptor concepts and instances, we added temporal concepts and instances following the 4D fluent approach to allow for a realistic reflection activity evolution and transition. The resultant activity ontology created with the fusion of likely object use and behavioural information from the activity-discovery component makes it possible for activity inference. The checks the relationships between the concepts in the and also checks the consistencies in the for the individuals and instances to perform activity recognition by information retrieval. The eventual result from the information retrieval are the activities or activities situations.

Notations	Descriptions
$\sqsubseteq$	subclass of
$\exists$	Property of
$\sqcap$	Intersection
$\sqcup$	Union
$\equiv$	is an equivalent class of
$\rightarrow$	Implication

Table 1: Ontology notations used

The process of modelling an activity situation resulting from a set of sensors requires asserting all the sensors and with their times to be encoded to represent the activity situation (See table 1 for a list of ontology notations used in our analogies). If an activity situation *Breakfast* is the result of *Microwave_On* and *Fridge_On* at times *t1* and *t2* respectively, then *Breakfast* can be asserted with the properties `hasUse` and `hasStartTime` as `hasUse`(*Microwave_On*, `hasStartTime` *t1*), `hasUse`(*Fridge_On*, `hasStartTime` *t2*). The activity situation is therefore modelled as a list of the sensors and with their times ordered temporally. The example of *Breakfast* from *Microwave_On* and *Fridge_On* at *t1* and *t2* can then be encoded by the expression (5) below.

$$\begin{aligned} Breakfast \quad & \sqsubseteq ADL \sqcap \exists hasUse.\Big((Microwave\_On \sqcap \exists hasStartTime.(=,t1)) \\ & \sqcap \exists (Fridge\_On \sqcap \exists hasStartTime.(=,t2))\Big) \end{aligned} \tag{4}$$

Typically, activity situations or activities in the home environment are a result of specific objects and resources usage. To model activity situations accurately, it is important to extend generic and traditional activity ontology to include specific resources and or objects used for routine activity situations. The resulting activity-object use from the LDA forms the ontology concepts and objects use knowledge to be modelled onto the activity ontology for the specific routine activities such that:

Activities: The activity topics determined from the activity-objects use discovery and are annotated as activity concepts analogous to the activity situations in the home environment. This represents a class collection all types of activities set as $z_1 \ldots z_k$.

Objects: These represents class collection of all objects as object use describing the routine activities in the home environment set as $x_1 \ldots x_n$.

Recall P($x|z$) computes the likely objects use for each of the activity topics, then z_i from $z_1 \ldots z_k$ would have a subset of likely objects defined as $x_{1z} \ldots x_{iz}$. The function f describes $x_{1z} \ldots x_{iz}$ objects for z_i as the likely objects for this activity such that:

$$f: \quad z_i \rightarrow x_{1z} \ldots x_{iz} \tag{5}$$

If this function f is replaced with the object property function in ontology object property `hasUse`, then (5) becomes:

$$z_i \quad \texttt{hasUse} \quad x_{1z}...x_{iz} \tag{6}$$

The expressions below encodes enhanced sensors outputs with temporal attributes.

$$z_i \quad \texttt{hasUse} \quad \{(x_{1z}\_On, \texttt{hasStartTime}t_{1z})...(x_{iz}\_On, \texttt{hasStartTime}t_{iz})\} \tag{7}$$

The objects are then modelled as ontology objects or objects class concepts accordingly and added to the ABox so that:

$$\begin{aligned} Z_i \quad \sqsubseteq ADL \sqcap \exists hasUse.\Big(((x_{1z}\_On \sqcap \exists hasStartTime.(=,t_{1z})) \\ ... \sqcap \exists(x_{iz}\_On \sqcap \exists hasStartTime.(=,t_{iz}))\Big) \end{aligned} \tag{8}$$

Activity recognition also follows the Temporal Ontology Querying Language (TOQL) [1] adapted based on object use to retrieve activity situations using sensor data concurrently available. The process uses object use query like constructs on the knowledge base to retrieve activity situation fitting the requirements of the query. As an advantage, sensor states and status of object use as implemented in the activity ontology can be used in queries to reflect real situations of object usage in the home environment. A typical query is comprised of SQL like construct (SELECT - FROM - WHERE) for OWL which treats the ontology classes and properties like database tables and columns. An additional AT construct in the query compares the time interval for which a property is true with a time interval or instant.

4 Experiments and Results

To validate the framework presented in this paper, we used the Kasteren A [16] and Ordonez A [11] datasets captured in two different home settings with similar events and activities (see tables 2 and 3 for an overview of the home setting descriptions and activity instances). Using the constructed bag of sensor observations as input generated from the datasets; Dirichlet hyperparameter $\alpha = 50/K$ in line with Steyvers and Griffths [14] where K is the activity topic number; the LDA generated activity-object use distributions. The activity-object patterns from the Kasteren A and Ordonez A were then used as ontology concepts to augment to activity ontology. Activity recognition experiments were carried out following a 4 fold cross validation.

	Kasteren A	Ordonez A
Setting	Apartment	Apartment
Rooms	3	4
Duration	22 Days	14 Days
Sensors	14	12

Table 2: Home Setting and Description

Activities	Kasteren A	Ordonez A
Sleeping	25	14
Toileting	114	44
Leaving	36	14
Showering	24	14
Grooming	Na	51
Breakfast	20	14
Lunch	Na	9
Dinner	10	Na
Drink	20	Na
Snack	Na	11
Spare Time	Na	11

Table 3: Activity Instances in the Kasteren and Ordonez Dataset

4.1 Performance and Evaluation

The recognition results and performance on accuracy and precision from the true positives TP, true negatives TN, false positives FP and false negatives FN are given in table 4. Toileting, Shower, Leaving Sleeping and Spare Time performed significantly well due minimal false positives for both datasets. Of particular interest are Breakfast, Lunch, Dinner, Drink and Snack. These activities were recognised with significantly high false positives arising from same and similar object interactions. These impacted on their performance causing confusions and ambiguities. Drink for the Kasteren House is associated to the interactions of Fridge and Cups Cupboard. These objects are also linked to Breakfast and Dinner which accounted for the confused recognition for Drink. Breakfast Lunch and Dinner performed better than Drink and Snack for both datasets because associating them to their temporal entities minimised false positives and improved recognition for them. The average precision, recall and F-Score for Kasteren A were 88.8%, 95.48% and 91.91% and Ordonez A 84.15%, 94.54% and 88.73% respectively. In comparison using the same dataset [16] for Kasteren A reported an F-Score of 63%, Riboni et al [12] for 80% Kasteren A and Ye [17] 90% for Kasteren A. On other hand, Ordonez et al [11] reported and F-Score of 69%. Comparing our results directly with these other methodologies, our work performed significantly better with 91.91% for the F-score. It is assumed the weaker performance reported by Kasteren et al [16], Ordonez et al [11] and Riboni [12] might be due to the evaluation methodology of "leave one day out" which meant fewer days representation for the objects data. Comparing our results with Ye [17], we achieved a slightly higher F-score which meant our proposed framework for recognition is robust and significantly good. Further, we also achieved better results in comparison to our previous works reported in [7] and [8] largely due to the activity ontology.

5 Conclusion and Future Work

In this paper, activity recognition from sensor data using the LDA topic model and ontology activity model was presented. It focused on the recognition of activities from patterns of objects usage in the home environment with regards to the home user. Realising that routine activity could have specific object(s) which are used to perform them and characterises the home user's habits, lifestyle and way of performing specific activities, the LDA topic mod-

Activities	True Positives (%)		False Positives (%)		False Negatives (%)	
	Kas A	Ord A	Kas A	Ord A	Kas A	Ord A
Leaving	100	100	0.00	0.00	0.00	0.00
Toileting	100	100	0.00	0.00	0.00	0.00
Showering	94.7	63.2	3.6	0.00	1.7	0.00
Grooming	Na	68.7	Na	26.6	Na	4.8
Sleeping	100	100	0.00	0.00	0.00	0.00
Spare Time	Na	100	Na	0.00	Na	0.00
Breakfast	72.5	81.4	17.3	17.5	10.2	1.1
Lunch	Na	61.3	Na	29.5	Na	9.2
Dinner	69.2	Na	23.5	Na	7.3	Na
Drink	64.5	Na	29.8	Na	5.6	Na
Snack	Na	58.7	Na	31.6	Na	9.7

Table 4: Activity recognition performance for Kasteren A and Ordonez A

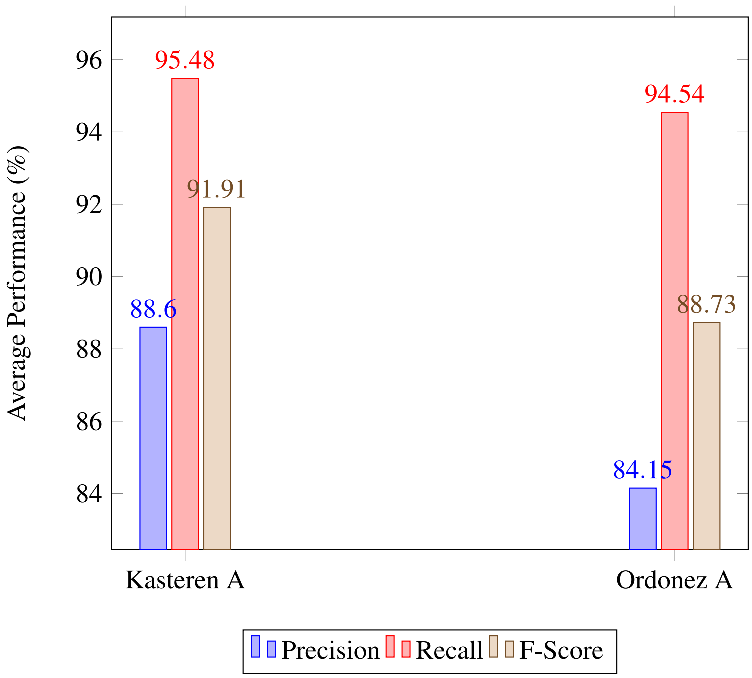

Figure 2: Average Precision, Recall and F-Score for Kasteren A and Ordonez A datasets

els was proposed to discover activity-object patterns. While the authors of [4] and [3] made suggestions on the strengths of the reusabilty of ontologies and building ontologies from generic assumptions and common sense *know how*, it is vital to build ontologies which suits the home user and home setting for the specific purpose. It should be noted that in some cases, certain activities may not be captured without the express consideration of patterns when building ontologies.The knowledge of the activity-object patterns can complement the domain knowledge to build activity ontologies capable of providing technology solutions to support independent and autonomous living for the elderly and cognitively impaired. The patterns augment the ontology based knowledge-driven phase to develop user specific activity ontology for activity recognition. In this process, activity-object pattern discovery which requires as input bag of sensor observations was constructed using the Kasteren dataset. The performance of the proposed framework suggests good and significant results which is comparable. It also recommends that activity ontologies should be built consistent and dependent on the patterns of object use of the home user and home setting. The future work should involve extending the ontology activity model by the consideration of more contextual features for the different types of sensing devices. It should also consider extending the temporal entities and features for progressive activities as they evolve.

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