Ontology-Driven Activity Recognition from Patterns of Object Use

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Abstract
The recognition of the activities of daily living of the elderly and the cognitively impaired has made it possible to provide assistance and support for them. We describe in this paper activity recognition from patterns of object use for activities and a combined activity ontology. Activity-object use patterns are discovered to provide the knowledge of object concepts for routine activity concepts for an enhanced ontology-driven activity recognition.

Author Keywords
Activity Recognition; Topic Model; Ontology Model; Latent Dirichlet Allocation

ACM Classification Keywords
I.5.2 [P]: attern Recognition: Design Methodology: Pattern Analysis; I.2.4 Knowledge Representation Formalisms and Methods: Representations (Procedural and RuleBased)

Introduction
Research into the recognition of the Activities of Daily Living (ADL) has been growing recently due to the need to provide support to the elderly and cognitively impaired [3]. In this process, the data captured from object use through videos, wearable sensors and object based sensor are classified using data-driven techniques [8] and in some cases modelled in knowledge-driven systems [2]. While these ar-

eas of activity recognition have made significant advances, they have some limitations. Data-driven techniques apply machine learning to recognise the most likely activity from a set of independently observed object data. Although this technique can handle uncertainties from noisy data, they lack semantic expressivity and do not incorporate context-rich features to enhance activity recognition. On the other hand, the knowledge-driven techniques build activity models that are semantically expressive, incorporating context-rich features following domain knowledge. But this knowledge most times are generic and is based on assumptions from everyday common knowledge of object usage for activities [2]. To overcome the limitations and harness the strengths of both techniques, data-driven technique can be used to provide the knowledge of the likely object usage for specific activities which would then be used as object and activity concepts for an ontology-driven activity recognition. We propose a framework which uses a topic model to discover the object use as the needed knowledge of ontology concepts for an enhanced ontology-driven activity recognition.

Related Work

Research efforts have made use of patterns for creating activity models and recommendations. Probabilistic topic models inspired by the text and natural language processing community have also been applied to discover and recognise human activity routines. A topic model approach was applied by Katayoun and Gatica-Perez [5] to discover routines from mobile phone data. Huynh et al. [3] also applied the Latent Dirichlet Allocation (LDA) to discovered activities like dinner, commuting, office work, etc. Although these efforts discovered activity categories and patterns, the activities recognised were largely latent and lacked semantic expressivity for the end user. Features used were only limited to the data captured. Ontology models follow Description Logic (DL) for the specification of conceptual structures and their relationships. Modelling in Ontology is dependent on the conceptual knowledge of activities and their properties. The author of [2] with regards to this, followed generic activity knowledge to develop ontology model for the smart home user which did not follow evidenced patterns of the activities and object usage. We aim to use discovered object usage for activities for an ontology activity model. The framework we propose in this paper extends our previous work using the probabilistic latent semantic analysis with the inclusion of the activity ontology [4].

Our Activity Recognition Approach

In the home environment, activities are carried out by the interactions of objects. In most cases, certain objects in specific locations have been known to be directly linked to particular activities forming activity-object use patterns. Activity-object use patterns can enhance activity recognition knowing that home setting differs and individual object usage for activities also differs. The framework we propose discovers activity-object use (object use distribution per activity topic) in a context description module which is then used as context descriptors in the ontology module for activity recognition. An overview of the framework is as illustrated in Figure 1.

Activity-Object Use Discovery

The aim of the activity pattern discovery is to determine the object usage for particular activities. We apply the LDA which assumes that there are hidden themes or latent topics which have associations with the words contained in a corpus of documents [1]. We conversely apply this assumption to our activity-object use context, that latent activity topics would have associations with the features of sensor data or objects. The LDA requires words in documents known as 'bag of words'. So, we intuitively represent the objects, 'bag of object observations' and activity topics to correspond to the words, documents and topics of the LDA respectively. We construct

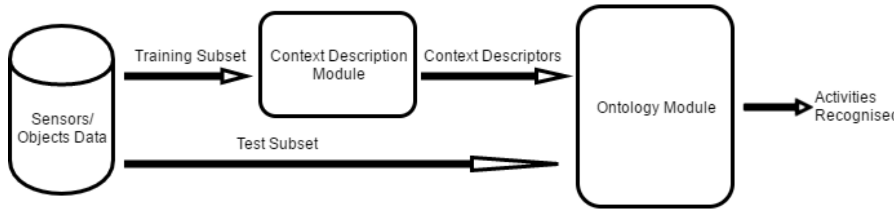

Figure 1: An Overview of the Activity Recognition Framework.

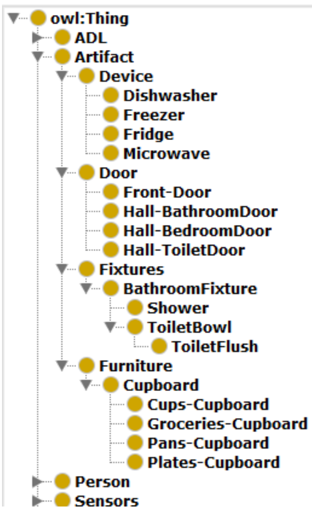

Figure 2: Object classes of the activity ontology

a 'bag of object observations' from the observed object data by partitioning based on a sliding window of fixed time intervals. In this paper, we have used the Kasteren dataset [8] from which the 'bag of object observations' were constructed to form an object-segment matrix. With D composed of object segments $d_1...d_D$, d_i would be made of objects represented as $x_{i1}...x_{in}$ from X objects of $x_1...x_n$. The probability of an 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 $\mathbb{L}$ of the data for documents d = $d_1...d_D$ as given in the equation 1 following Gibbs sampling for LDA parameter estimation [1].

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

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

The activity-object use are determined from the expression 2, where $n_z^{x_i}$ is the number of times an object x_i is assigned to a topic z.

Ontology Activity Model

The ontology activity model complements the activity pattern discovery for enhanced recognition. The discovered activity-object use as concepts are modelled in an ontology activity model using the ontology editor Protégé [1]. For each of the activity-object use as specified by P($x|z$), the object are modelled as context descriptors of the activity situation. An example of a formal model is as illustrated in Fig 2 depicting object classes of the activity ontology. Activities are described through class equivalence axiom which links them to object usage. The reasoner uses these modelled instances relative to object used to recognise ongoing activity. An instance of an activity involves linking it with the object property through class equivalence axioms. The specification of an activity in this process is built on the theories of description logic DL and reasoning which supports consistencies, subsumption, satisfiability, equivalence and disjointness [2]. The activation of these objects would suggest instances of the respective object usage specified by the object property hasUse.

Experiments and Results

To validate the framework, we used the Kasteren A [8] and Ordonez A [6] datasets captured in two different home set-

[1] http://protege.stanford.edu/

	Kas A	Ord A
Rooms	3	4
Days	22	14
Sensors	14	12

Table 1: Home Setting Descriptions for the Kasteren (Kas A) and Ordonez (Ord A) datasets

Activities	Kas A	Ord A
Sleeping	25	14
Toileting	114	44
Go Out	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 2: Activity Instances in the datasets

	Kasteren A		**Ordonez A**	
Activities	*Recall (%)*	*F-Score (%)*	*Recall (%)*	*F-Score (%)*
Sleeping	100	100	100	100
Toileting	100	100	100	100
Go Out	100	100	100	100
Showering	98.2	97.3	86	78.4
Grooming	Na	Na	93.5	81.4
Breakfast	87.7	84.1	98.7	89.7
Lunch	Na	Na	87	76
Dinner	90.5	81.8	Na	Na
Drink	92	78.5	Na	Na
Snack	Na	Na	85.8	73.9
Spare Time	Na	Na	100	100
Average	94.5	91.7	94.6	88.8

Table 3: Summary of the Activity Recognition Results.

tings with similar events and activities (See tables 1 and 2). Using the constructed bag of sensor observations as input generated from the datasets; Dirichlet hyperparameter $\alpha = 50/K$ in line with Steyvers and Griffths [7] where K is the activity topic number; the LDA generated activity-object use distributions. The activity-object use from the Kasteren A and Ordonez A were then used as ontology concepts to augment to activity ontology. Initial experimental results based on recall and F-Score are given in Table 3. *Toileting*, *Shower*, *Go Out* and *Sleeping* performed significantly well due minimal false positives for the datasets. Of particular interest are *Breakfast*, *Dinner*, *Drink* and *Snack*. These activities were recognised with significant false positives arising from same and similar object interactions for both datasets. *Breakfast*, *Lunch* and *Dinner* performed better than *Drink* because associating them to their temporal entities minimised false positives and improved recognition for them.

Conclusion and Future Work

In this paper, we presented activity recognition from knowledge of discovered activity pattern. We used the LDA topic model to discover activity-object use and activity topics which were assembled in an ontology activity model. Whilst we feel our framework is appealing, further validation test and experiments are ongoing on this framework.

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