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Intelligent Recognition of Activities of Daily Living from Patterns of Object Use

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***Abstract*—The accurate recognition of Activities of Daily Living (ADL) is fundamental in the support and provision of assistance for the elderly and cognitively and the cognitively impaired. Current ontology-based techniques and knowledge-driven model object concepts from assumptions and everyday knowledge of object used for activities. Activities modelled from assumptions and everyday knowledge can lead to incorrect recognition results of routine activities and possible failure to detect abnormal activity trends. A significant step to the accurate recognition of activities of daily living is the discovery of the object usage for specific routine activities. This paper presents an approach which discovers object usage for routine activities using Latent Dirichlet Allocation (LDA) topic modelling. The object usage discovery augments an activity ontology which enables recognition of simple activities of daily living in the home environment. The proposed approach is evaluated and validated using the Kasteren and Ordonez datasets.**

Keywords*—Activity Recognition; Topic Model; Ontology Model; Latent Dirichlet Allocation

I. Introduction

Activity recognition is an emerging area of research in ubiquitous and pervasive computing with significant importance to the provision of support and assistance to the elderly, disabled and cognitively impaired. It is involved in the detection, identifying and recognition of what an individual is doing, e.g. sleeping, showering, making food. Recent efforts so have focused on the use of video [1,2], wearable sensors [3,4] and wireless sensor networks [5,6] to monitor simple human activities. Video-based activity recognition captures and monitors images which are segmented and then classified using context-based analysis. Sensor-based activity recognition use sensors to monitor object usage from the interactions of users. Unlike sensor-based activity recognition, video-based approaches suffer from accurate segmentation of captured images which affects classification process and also raises privacy concerns. The process of recognising activities via sensor-based activity recognition can be data-driven, knowledge-driven or a combination of both techniques. Data-driven techniques employ machine learning and statistical methods to discover the data patterns for activities to be inferred. Although data-driven techniques have been used by the authors in [5-7] demonstrating its strengths in the recognition of activities, inferences in most cases for data-driven approaches are hidden and or latent. Recognised activities are however needed to be expressed in an understandable format for the end user. Data-driven techniques, in addition, are unable to integrate context-aware features to enhance activity recognition.

Conversely, ontology-based and knowledge-driven techniques model activities as concepts. These concepts are associated to the everyday knowledge of object usage in the home environment through a knowledge engineering process. The modelling process involves associating low-level sensor data to the relevant activity to build a knowledge base of activities in relation to sensors and object. The recognition of activities is achieved by logical inference and or inclusion of subsumption reasoning. Unlike data-driven techniques, knowledge-driven techniques are expressively clear and activity recognition results are in the format easily understood by the end user [8]. Modelling activity ontology concepts for Knowledge-driven techniques largely depend on everyday knowledge of activities and object use to build and construct activity ontologies. Knowledge of object use are generic and mostly by assumptions - regular everyday knowledge of the objects are used for routine activities or even wiki-know-how [1] [9].

This paper follows a sensor-based approach to capture object use as the result of the interactions of objects in the home environment. These sensor-based object use and interactions are regarded as atomic events leading to activities. Activity situations should be a result of a set of observed objects. There may be cases of same object sets resulting in different activities, making the process of identifying activity from object use complex. This paper proposes an approach which follows object use as events and entries to recognise activities. This is in line with what is obtainable in real-world situations and most home environments. Interactions of objects as object

[1] http://www.wikihow.com

use in the home environment result in activities. These object use and interactions as atomic events result in particular routine activities. This paper's motivatio stems from the premise that knowledge-driven activity recognition constructed from the everyday knowledge of object use may not fit into certain activity situations or capture routine activities in specific home environments. If an activity model has been developed based on the generic and or assumed knowledge of object use, the recognition model may fail due to activities and objects fittings which differ with individuals and home environments. Generic ontology models have been designed and developed as in Chen et al. [7] to emphasise re-usability and shareability, however, they share accuracy.

As a way forward, it is essential to accommodate object concepts that are specific to the routine activities with regards to the individual and the contextual environment. To provide assistance and support to the elderly and cognitively impaired, the recognition of their ADLs must be accurate and precise with regards to the object use events. In this context, the major aim of this paper is to present a framework for activity recognition by extending knowledge-driven activity recognition techniques to include a process of acquiring knowledge of object use to describe contexts of activity situations. This approach also addresses the problem of object use specification for routine activities, especially where the object use has not been predefined. So the challenge becomes discovering specific object use for particular routine activities as a way to emphasise the object set for the routine activities. This paper focuses on the process of the recognition of ADL as a step towards the provision support and assistance to the elderly disabled and cognitively impaired. It also emphasises on knowledge-driven techniques and shows that the activity discovery process augments the activity ontology, thus extending it beyond the use of generic and common knowledge of object use to build activity ontology. Given these, the work in this paper harnesses the complementary strengths of data and the knowledge-driven techniques to provide solutions to the limitations and challenges highlighted above.

In particular, this paper makes the following contributions:

- Ability to deal with streaming data and segmentation using a novel time-based windowing technique to augment and include temporal properties to sensor data.
- Automated activity-object use discovery in context for the likely objects use for specific routine activities. We use Latent Dirichlet Allocation (LDA) topic modelling through activity-object use discovery to acquire knowledge for concepts formation as part of an ontology knowledge acquisition and learning system.
- Extend the traditional activity ontology to include the knowledge concepts acquired from the activity-object use discovery and context description which is vital for recognition especially where object use for routine activities have not been predefined.
- The evaluation and validation of the proposed framework to show that it outperforms the current state-of-the-art knowledge based recognition techniques.

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 for Kasteren and Ordonez datasets to validate the proposed framework and finally, Section 5 concludes this paper.

II. Related Work

Activity recognition approaches can be classified in two broad categories data and knowledge driven approaches. This classification is based on the methodologies adopted, how activities are modelled and represented in the recognition process. Data driven approaches can be generative or discriminative. According to [8], the generative approach builds a complete description of the input (data) space.The resulting model induces a classification boundary which can be applied to classify observations during inference. The classification boundary is implicit and a lot of activity data is required to induce it. Generative classification models includes Dynamic Bayes Networks (DBN) [10,11], Hidden Markov Model (HMM) [12,13], Naive Bayes (NB) [14,15], Topic model Latent Dirichlet Allocation (LDA) [16,17]. Discriminative models, as opposed to generative models, do not allow generating samples from the joint distribution of the models [8]. Discriminative classification models includes nearest neighbour [18, 19], decision trees [20], support vector machines (SVMs) [21,22], conditional random fields (CRF) [23], multiple eigenspaces [24], and k-means [18]. Data driven approaches have the advantage of handling incomplete data and managing noisy data. A major drawback associated with data driven approaches is that they lack the expressiveness to represent activities.

Topic modelling inspired by the text and natural language processing community have been applied to discover and recognise human activity routines by Katayoun and Gatica-Perez [16] and Huynh et al [3]. Huynh et al [3] applied the bag of words model of the Latent Dirichlet Allocation (LDA) to discover activities like dinner, commuting, office work etc. Whilst Katayoun and Gatica-Perez [16] discovered activity routines from mobile phone data, Huynh et al [3] used wearable sensors attached to the body parts of the user. Activities discovered in both work were latent, lacked expressiveness and minimal opportunities to integrate context rich features. The approach presented in the paper also significantly differs from Katayoun and Gatica-Perez [16] and Huynh et al [3] with the modelling using an ontology activity model.

Knowledge driven ontology models follow web ontology language (OWL)– theories for the specification of conceptual structures and their relationships. Ontology based activity recognition is a key area within knowledge-driven approaches. It involves the use of ontological activity modelling and representation to support activity recognition and assistance. Ontology uses the formal and explicit specification of a shared conceptualization of a problem domain [25]. Vocabulary for modelling a domain is provided by specifying the objects and concepts, properties, and relationships. This then uses domain and prior knowledge to predefine activity models to define activity ontologies [8]. Chen et al. [8, 27] proposed an ontology-based approach to activity recognition in which they constructed context and activity ontologies for explicit domain modelling. Sensor activations over a period of time are mapped to individual contextual information and then fused to build a context at any specific time point. Subsumption reasoning were used to classify the activity ontologies, thus inferring the ongoing activity. Knowledge driven ontology models also follow web ontology language (OWL) theories for the specification of conceptual structures and their relationships [28]. OWL has been widely used for modelling human activities for recognition, which most of the time involves the description of activities by their specifications using their object and data properties [27]. 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 [29]. Recognising the activity then requires the modelled data to be fed to the ontology reasoner for classification. The authors of [8] and [29] followed generic activity knowledge to develop an ontology model for the smart home users. Whilst these approaches to model activities depending on common sense domain knowledge and its associated heuristics, which is commendable however they often lead to incorrect activity recognition due to lack of specificity of the object use and contexts describing the activity situations. The problem arises to the inability of the generic models to capture specific considerations to object use for routine activities, home settings and individual object usage between differing users. 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. In view of these limitations, an LDA enabled activity discovery technique as applied to discover likely object use for specific routine to augment the generic ontology modelling process. The approach presented in this paper, also extends the works in [30, 31] by the inclusion of the ontology activity model.

III. Overview of Our Activity Recognition Approach

The proposed approach (Figure 1) supports objects as contexts descriptors of activity situations by activity-object use discovery and information fusion of activity and object concepts through activity ontology design, development and modelling to achieve activity recognition.

This proposed approach is composed of two component modules - the context description module and the ontology module. The object use for the specific routine activities are discovered using the LDA topic model as activity-object use distributions in the context description module. In this paper, we refer the object use for the specific routine activities as the contexts describing the activity situation. These context descriptors discovered for the routine activities then form concepts to be modelled and encoded in an activity ontology which the ontology module is comprised of. Activities are recognised by mapping observed objects on the activity ontology using an object query to retrieve the relevant activity situation. The two component modules -context description and ontology function uniformly to provide a seamless activity recognition progressively with observed sensors/objects representing atomic events of activities as inputs. These component modules are further described in the subsections below.

A. Context Description Module

The context description module augments the activity ontology for the specification of the object set used for the routine activity very much unlike the traditional knowledge-driven activity recognition framework [7, 27, 32]. Its function is the discovery of the activity-object use distributions which forms the knowledge of object use for specific routine activities and context descriptors. To provide the basis for an activity recognition, the knowledge of object use for respective activity concepts are required. The necessity of these object use knowledge is such that activities as high-level events are a result of low-level tasks or atomic events of object interactions. Traditional ontology-driven and knowledge-driven activity recognition frameworks [7, 9] model activity ontologies from assumptions of object use and the knowledge of the everyday use of objects in the home environment. However, activity ontologies modelled traditionally from generic knowledge and assumptions may not fit into every home setting or environment and this may lead to erroneous object descriptions of low-level tasks and eventually incorrect activity recognition. An accurate process of determining the object set or context descriptors which describe activities specifically as a higher level of events must be employed to design and model activity situations ontologically. The context description module functions by discovering the activity-object use discovery and activity context description based on the activity-object use discovery enabled a topic model process. The modular process is described below:

1) Activity-Object use Discovery by Latent Dirichlet Allocation: The activity-object use discovery uses the LDA approach introduced by Blei et al [33]. The LDA generatively classifies a corpus of documents as a multinomial distribution of latent 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 then requires the bag of words (documents) from a corpus of documents as input and number of topics as a key parameter. In the context of the activity-object use discovery process, the activity topic number and bag of sensor observations corresponds to topic number and bag of words respectively of the LDA. The activity topic number and bag of sensor observations are explained below.

- **Activity Topic Number:** A key parameter needed by the LDA process is the topic number. In the context of the activity recognition proposed in this paper, the number of activities corresponds to the topic number. The activities to be recognised adds up to the activity topic number. For experimental purposes, this paper uses the number of activities specified in the dataset.
- **Bag of Sensor Observations:** The bag of objects observation is analogous to the"bag of words" used in the LDA text and document analysis. In text and document analysis, a document (bag) in a corpus of texts can be represented as a set of words with their associated frequencies independent of their order of occurrence [34].
This paper follows the LDA "bag of word" approach to representing discrete observations of objects or sensors of specific time windows generated as events in the use or interaction of home objects. Observed

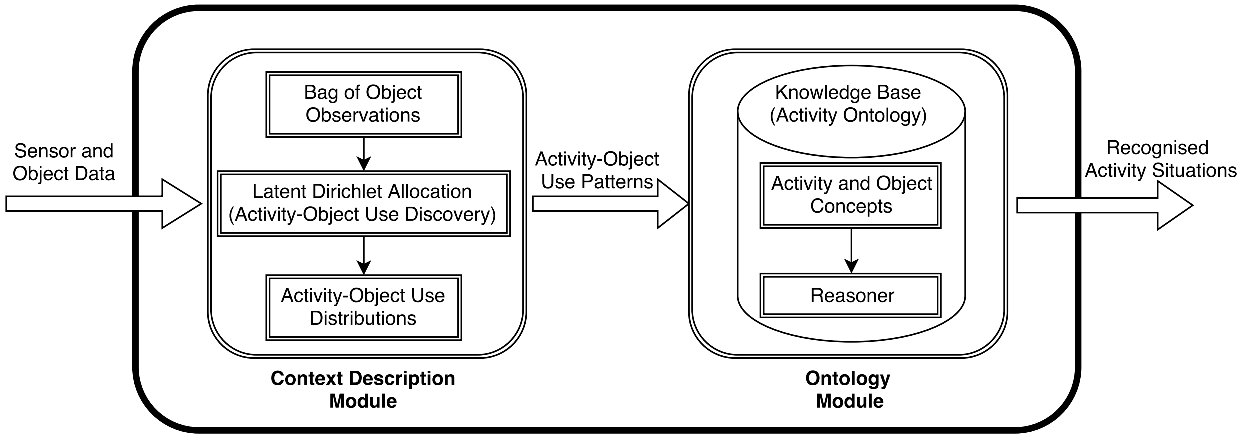

Fig. 1. An Overview of the Activity Recognition Approach.

objects in the time windows forms object segments which correspond to the LDA documents (bags). In this regard, it is referred to as the bag of object observations. To achieve bagging of the objects accordingly, the stream of observed sensors or objects data are partitioned into segments of suitable time intervals. The objects and the partitioned segments then respectively correspond to the words and documents of the "bag of words". If a dataset is given by D made of $x_1...x_n$ objects, D can be partitioned using suitable sliding time window intervals into $d_1...d_D$ segments similar to the schema 1.

$$D = \begin{bmatrix} \{x_1..., x_{n1}\} & objects & in & segment & d_1 \\ \{x_2..., x_{n2}\} & objects & in & segment & d_2 \\ ...... \\ \{x_{N1}..., x_N\} & objects & in & segment & d_1 \end{bmatrix} \quad (1)$$

The observed objects $x_1...x_n$ in each of the segments $d_1...d_D$ are then represented with their associated frequencies f to form a segment-object-frequency matrix similar to the schema given in 2.

$$BagofSensorObservation = \begin{bmatrix} d_1 & x_1 & f_1 \\ d_2 & x_2 & f_2 \\ & ...... & \\ d_D & x_N & F \end{bmatrix} \quad (2)$$

The LDA 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 and word distributions. We conversely apply this assumption to the activity-object pattern discovery context that latent activity topics would have associations with the features of object data in the partitioned segments of the bag of sensor observations discussed above. The documents are presented in the form of objects segments $d_1...d_D$ composed of co-occurring object data observations. With D composed of object segments $d_1...d_D$ similar to schema 1 above, d_i would be made of objects represented as $x_{i_1}...x_{i_n}$ from X objects of $x_1...x_n$. 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 $\mathbb{L}$ of the data for documents d = $d_1...d_D$ as given in the equation 3 following Gibbs sampling for LDA parameter estimation [33].

$$\mathbb{L}(\alpha, \beta) = \prod_{d=1}^{D} \int P(\theta_d|\alpha) \left(\prod_{x=1}^{X_D} \sum_{z=1}^{Z} P(x^d_{xi}|z, \beta) P(z|\theta_d) \right) d\theta_d \quad (3)$$

Given the assumptions above, the activity-object patterns can be calculated from the equation 4 below:

$$P(x|z, \phi) = \prod_{z=1}^{Z} \prod_{x_i=1}^{X} (\phi_z^{x_i})^{n_z^{x_i}} \quad (4)$$

where $n_z^{x_i}$ is the number of times an object x_i is assigned to a topic z.

In the context of the activity recognition, the context descriptors to be modelled as ontology concepts would rely on the activity-object use distributions. Eq 4 above computes the activity-object use distributions that are linked to specific activity topics. The activity-object use distributions given the specific activity topics form the object use and the respective activity context descriptions. These context descriptors are then modelled and encoded as object concepts and the respective activity concepts in the activity ontology model. Given the number of activities in a dataset D as activity topic number and the constructed bag of object observations as inputs, the activity-object use distributions determined could be expressed similarly to the schema 5. The process continues by annotating and linking of the objects to the specific activities using the activity-object use distribution as the contexts describing the activities.

$$P(x|z) = \begin{bmatrix} \{x_{k1a}, x_{k1b}, ..., x_{k1n}\}\, Assigned \quad to \quad k1 \\ \{x_{k2a}, x_{k2b}, ..., x_{k2n}\}\, Assigned \quad to \quad k2 \\ .... \\ \{x_{Ka}, x_{Kb}, ..., x_{KN}\}\, Assigned \quad to \quad K \end{bmatrix} \tag{5}$$

B. Ontology Module

The ontology module is comprised of the knowledge base which is made of activity ontology concepts, data and encoded rules to support activity recognition. The knowledge base also functions as an ontology repository of modelled concepts organized, shared and can be searched. The activities and the objects concepts from the context description module are modelled and encoded following Description Logic (DL), knowledge representation and formalism to populate the knowledge base. This process is such that the encoded concepts in the knowledge forms the TBox (Terminological Box), ABox (Assertional Box) and linked by properties. The terminological box is a collection of ontology concepts modelled as class concepts, and in this case, the different activities and objects. The class concepts could also be modelled hierarchically to reflect the relation between them given their properties and attributes. The class concepts and instances carry with evidence of semantics which does not only adds sense to the concepts and how they are related but also enhances their expressiveness and clarity. The activity ontology development process gradually populates the TBox by encoding the activities and context descriptors from the context description module as ontology concepts. The assertional box is the collection of the ontology concepts as instances and individuals. They are asserted through properties that may be object or data properties. For the class concepts in the TBox, instances and individuals of these are asserted through different properties to populate our ABox. In addition to the activities and context descriptors (objects) class concepts and instances, this paper introduces the use of temporal class concepts and instantiated them following the 4D fluent approach for a realistic reflection activity evolution and transition. The 4D fluent approach allows ontology concepts to be associated with time as an attribute. In addition, the activity ontology is further extended by modelling activities as either static or dynamic activities using their temporal properties as the basis. The resultant activity ontology is created with the fusion of likely object use and behavioural information from the activity context descriptions making it possible for activity inferencing. Also in the ontology module is the reasoner which checks the relationships between the concepts in the TBox and the consistencies in the ABox for the individuals and instances to perform activity recognition by information retrieval. The eventual results of the information retrieval are the activities or activities situations.

This paper models activity concepts from a set of objects and context descriptors by asserting all the objects concepts and with their times to be encoded to represent the activity situation (See Tables I and II for a list of concepts and notations used). 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 is therefore modelled as a list of the objects 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 6 below.

Ontology Concepts	**Descriptions**
ADL	Activity of Daily Living and super activity of all activity concepts
Activity or Activity situation	Concepts representing type of ADL examples include *Breakfast*, *Dinner*, *Drink*, *Toileting* etc.
Objects or Resources	Concepts representing concepts of object used in the home environment examples include *Microwave*, *Plates Cupboard*, *Fridge*, *Cup* etc.
TimeSlice	Time slice of an object
TimeInterval	Time interval of an activity
Ontology Properties	
hasUse	An object property used to associate usage of an object for an activity
hasStartTime	An data property used to associate time reference when an object was observed
tsTimeSliceOf	Fluent property for time slice of an object.
tsTimeIntervalOf	Fluent property for the interval describing range of time an activity.

TABLE I. ONTOLOGY CONCEPTS USED

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

TABLE II. ONTOLOGY NOTATIONS USED

$$\begin{aligned} Breakfast \quad & \sqsubseteq ADL \sqcap \exists hasUse.\Big((Microwave\_On \\ & \sqcap \exists hasStartTime.(=, t1)) \sqcap \exists (Fridge\_On \\ & \sqcap \exists hasStartTime.(=, t2))\Big) \end{aligned} \tag{6}$$

Typically, the activities performed in the home environment are a result of specific objects use. To model activities accurately, it is important to extend the traditional activity ontology modelling to include specific resources and the contexts describing the routine activity. The activity context descriptors resulting from the activity-object use discovery process forms the resources and the context concepts to be modelled in the activity ontology for the specific routine activities such that:

Activities: The activity topics are annotated as activity concepts analogous to the activity situations in the home environment. This represents a class collection of all types of activities set as $z_1...z_k$.

Objects: These represents class collection of all objects as activity context descriptors in the home environment set as $x_1...x_n$.

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

$$f: \quad z_i \rightarrow x_{1z}...x_{iz} \tag{7}$$

If the function f is replaced with the object property function in `hasUse`, then (7) becomes:

$$z_i \quad \texttt{hasUse} \quad x_{1z}...x_{iz} \tag{8}$$

The expressions below encodes enhanced sensors or object outputs with their temporal attributes.

$$\begin{aligned} z_i \quad & \texttt{hasUse} \;\; \{(x_{1z}\_On, \texttt{hasStartTime}t_{1z}) \\ & ...(x_{iz}\_On, \texttt{hasStartTime}t_{iz})\} \end{aligned} \tag{9}$$

The activity context descriptors are then modelled as resources and objects class concepts accordingly and then added to the ABox so that:

$$\begin{aligned} Z_i \quad & \sqsubseteq ADL \sqcap \exists hasUse.\Big(((x_{1z}\_On \sqcap \exists \\ & hasStartTime.(=, t_{1z}))... \sqcap \exists \\ & (x_{iz}\_On \sqcap \exists hasStartTime.(=, t_{iz}))\Big) \end{aligned} \tag{10}$$

1) Static and Dynamic Activities: Activities are performed differently, in different ways and times within the 24 hour day path in the home environment. Some of these activities can be performed at specific times or time intervals of the day making them have static times (Static activities). On the other hand, dynamic activities do not have specific times or time interval they are performed. Also, activities in some cases may have same or share similar object usage. This paper makes analogy using *Breakfast*, *Lunch*, *Dinner*, *Toileting* and *Showering* as examples of activities in the home environment. *Breakfast*, *Lunch* and *Dinner* are examples of different activity concepts which can be performed with same or share similar object usage given that they are food-related activities. In contrast, they are performed within a specific time interval of the day making them static activities.

Considering they share the same or have similar object usage, they can be modelled as subclasses of the activity *Make Food*, however, they differ with regards to their respective temporal properties. Whilst they inherit all the properties of *Make Food* by subsumption, they can be easily confused in the recognition process if modelled without the specification temporal properties. Dynamic activities like *Toileting* and *Showering* do not have specific times and intervals they are performed making them less dependent on their temporal properties. So, dynamic activities are not constrained within any time interval. Applying the 4D-fluent approach [35], this paper extends the traditional activity ontology to include static and dynamic activities as class concepts requiring the temporal class concepts *Timeslice* and *TimeInterval* to be specified using the relational properties `tsTimesliceOf` and `tsTimeIntervalOf` respectively. The time intervals *Interval1* and *Interval2* holds the temporal information of the time slices for the static and dynamic activities respectively. An instance of a *TimeSlice* of an activity whether static or dynamic is linked by the property `tsTimeSliceOf` and property `tsTimeInterval` which then links this instance of *TimeSlice* with an instance of the class *TimeInterval*.

Modelling Static Activities: Ontology modelling of static activities require that the activity concepts are encoded with the specification of their temporal attribute. In this case, the temporal attribute specification of the times and the time interval they are performed can be encoded by using the class concepts *TimeSlice*, *TimeInterval* and with the context descriptors for that activity. The `hasUse` object property is also used to encode the object usage for an activity and then specifying static activity as the domain class concept as well as ranging to all the object classes which describe the context descriptors. The `tsTimeInterval` property of a static activity is also encoded so that its domain are *TimeSlice* and *Resources* and it ranges to the class *TimeInterval* to capture specific time interval of the day through *Interval* (a sub class of *TimeInterval*). Further, the time instants of the static activity are captured through the `tsTimeSliceOf` with domain *TimeSlice* and *Resources* and it ranges to *TimeSlice*. The expression 11 encodes a static activity so that *Interval1* asserts the time interval of the day the static activity is performed using the object x_{1z}.

$$\begin{aligned} StaticActivity \quad & \sqsubseteq ADL \sqcap \exists hasUse.\Big(x_{1z}\_On \\ & \sqcap \exists tsTimeInterval.Interval1\Big) \end{aligned} \tag{11}$$

The expression 12 then asserts *Interval1* to cover the time instant t_{1z} through the property `tsTimeSliceOf`.

$$\begin{aligned} & Interval1 \sqsubseteq Interval \sqcap \exists tsTimeSliceOf. \\ & \Big(TimeSlice \sqcap \exists hasStartTime.(=, t_{1z}))\Big) \end{aligned} \tag{12}$$

Modelling a Dynamic Activity: Dynamic activities are also modelled in the similar manner as the static activities. An instance of a *TimeSlice* of a dynamic activity is linked by the property `tsTimeSliceOf` and property `tsTimeInterval` and then links this instance of the class *TimeSlice* with an instance of class *TimeInterval* which may be *Interval2*. Unlike the *Interval1* for the static activities, *Interval2* of the dynamic activities ranges to cover the full 24 hour cycle of the day as asserted by expression 13.

$$\begin{aligned} DynamicActivity \quad & \sqsubseteq ADL \sqcap \exists hasUse.\Big(x_{2z}\_On \\ & \sqcap \exists tsTimeInterval.Interval2\Big) \end{aligned} \tag{13}$$

The expression 14 then asserts *Interval2* to cover the time instant t_{2z} through the property `tsTimeSliceOf`.

$$\begin{aligned} & Interval2 \sqsubseteq Interval \sqcap \exists tsTimeSliceOf. \\ & \Big(TimeSlice \sqcap \exists hasStartTime.(=, t_{2z}))\Big) \end{aligned} \tag{14}$$

C. Activity Recognition by Object Use Query

Activity recognition is facilitated by the Algorithm 1 and achieved by an observed object use query by mapping this query on to the activity ontology to retrieve to closest activity situation from the activity ontology. A typical object use query uses constructs adapted from the Temporal Ontology Querying Language (TOQL) [35] on the knowledge base to retrieve activity situations 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. The inputs are observed sensors or objects along their timelines as x_1,...x_n from segments d_1...d_D. The process maps the sensors or objects x_i on to the ontology and by reasoning and inference rules to determine that x_i is a context descriptor for a static or dynamic activity. If an activity is returned, then it is reported as the activity recognised for the observed object x_i.

Algorithm 1: Activity recognition algorithm.

Input: Observed Sensors $X = \{x_1,...x_n\}$ in Partition of Sensor Segment $D = \{d_1...d_D\}$, ADL ontology (ADL)
Result: Static Activity (SA) or Dynamic Activity (DA).
Begin:;
while *data stream is active* **do**
  Extract observed object $x_i \in X = \{x_1... x_n\}$, from $d_i \in d_1...d_D$ **for each** $d_i \in D$.
  Create Activities $Z \equiv Z(x_1) \sqcup ... Z(x_n)$
  for each $x \in A$ do;
  Map x_i to a Static Activity (SA) or Dynamic Activity (DA)
  So that;
  $Z \equiv ADL \sqcap \exists$ hasUse.$\Big(x_i\_On \sqcap \exists$ hasStartTime.(=, t)$\Big)$
  Activity Inference
  if *an activity* Z_i *is returned* **then**
    Report (SA) or (DA) as recognised.;
    for all Repeat process for next x.
  end
end

IV. Experiments and Results

The approach presented in this paper is validated using the Kasteren A [6] and Ordonez A [5] datasets captured in two different home settings with similar events and activities (see tables III and III for an overview of the home setting descriptions and activity instances). The choice of these datasets was due to the fact that the Kasteren and Ordonez dataset contains a lot of sensor activations as object use with dense sensing applied. Multiple sensor types (e.g. pressure sensors, magnetic sensors tagged to home objects like microwave, dishes, cups) were used to capture object interactions for different activities. Also, the activities performed in varied ways and accurately annotated with the ground truth. Experiments were performed on the datasets following steps mentioned in the sections above and then validated using a 4-fold cross validation on the datasets. The criterion for evaluation is to compare recognised activities with the ground truth provided with the dataset based on the average true positives TP, false positives FP and false negatives FN per activity. The results are further evaluated based on the metrics precision, recall and F-score.

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

TABLE III. 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 IV. Activity Instances in the Kasteren and Ordonez Dataset

A. Activity-Object Use Discovery and Context Description Evaluation

The context descriptors for the routine activities were discovered following the process described in subsection III-A above. The number of activities as given in the dataset was used as the topic number which is an input requirement for the LDA activity discovery process. The datasets were partitioned using 60 seconds sliding windows to construct the bag of object observations also to be used as input requirement for the LDA activity discovery process. The activity-object use distributions are discovered using the input requirements (activity topic number and bag of object observations) and also by setting the Dirichlet hyperparameters α to $50/K$ and β to 0.01 as recommended by Steyvers and Griffiths [34]. The activity context descriptors for the specific routine activities were then annotated and linked from the distributions discovered as given in tables V and VI. The idea is that for an object to be a context describing an activity topic, it must have been assigned to an activity topic as in the activity-object use distribution discovered.

Activities	Context Descriptors
Leaving	Front Door.
Toileting	Hall Toilet Door, Toilet Flush.
Showering	Hall Bathroom Door.
Sleeping	Hall Bedroom Door.
Make Food	Fridge, Plates Cupboard, Cups Cupboard, Groceries Cupboard, Microwave, Freezer.
Make Drink	Fridge.

TABLE V. Activity Concepts and the discovered context descriptors for Kasterens House A

Activities	Context Descriptors
Leaving	Main Door.
Toileting	Toilet, Basin.
Showering	Shower.
Sleeping	Bed.
Make Food	Cupboard, Fridge, Microwave, Toaster.
Spare Time	Seat.
Grooming	Basin, Cabinet.

TABLE VI. Activity Concepts and the discovered context descriptors for Ordonez House A

Set 6 activity topics were discovered (from the 7 activity set in the Kasteren A ground truth) in this process and annotated as *Leaving*, *Toileting*, *Showering*, *Sleeping*, *Make Food* and

Drink. *Make Food* activity in this case represents *Breakfast* and *Dinner* due to same and similar context descriptors or object usage. However, these activities were distinguished modelled as static activities and encoding their temporal attributes. This is similar for Ordonez A with 7 activities annotated as *Leaving*, *Toileting*, *Showering*, *Sleeping*, *Make Food*, *Spare Time* and *Grooming*. Our *Make Food* topic maps to Ordonez House A's activity sets *Breakfast*, *Lunch* and *Snack.*

B. Activity Ontology and Recognition Performance

To this point, context descriptors for the activities for Kasteren A and Ordonez A houses have been discovered. The activities and context descriptors are modelled in an activity ontology to facilitate activity recognition. The activity and object concepts are further modelled to support a unified and reusable activity ontology model of commonly shared concepts for the Kasteren and Ordonez datasets as illustrated in Figure 2. The green coloured rounded rectangles represent common object concepts in both homes. The blue rounded rectangle has been used specifically Ordonez concepts which are not shared in Kasteren concepts. This unified ontology model can also be extended and adapted further for similar homes thus reducing the amount of time taken to construct and develop activity ontologies.

The activity concepts were also modelled accordingly, but due consideration was given to *Make Food* which represented a group of activities. *Make Food* correspond to a group of activities involving making of food and ranges from *Breakfast* and *Dinner*. For Kasteren dataset, *Breakfast* and *Dinner* are modelled as static activities with *Make Food* as superclass. The share same or similar context descriptors and are performed at specific times of the day. To enhance shared ontology concepts and reuse, the Kasteren and Ordonez activity concepts are harmonised to form a set of unified activity concepts as illustrated in Figure 2. The activity concepts have been colour coded so that the green rounded rectangle represents common activity concepts and blue rounded rectangle as activity concepts in the Ordonez house and not in the Kasteren House. In addition to this, instances and individuals have been added to the object concepts making the model more expressive (assertions used in populating the ABox) for example instantiating *Microwave* with *Microwave_On* to suggest the state of the object or sensor when in use. The ABox was further populated with assertions using object and data properties as explained in subsection III-B incorporating the context descriptors for the activity situations preparatory for activity recognition. The modelled activity situations or concepts are then linked to their respective context descriptors as object states through the properties as assertions added to the ABox. Activity recognition is achieved using observed sensors or objects use queries to retrieve activity situations as events representing the observed sensors or objects.

The experimental results were compared with the ground truth and evaluated for performance.*LeavingToileting*, *Sleeping* and *Showering* for both datasets were recognised with significantly high results as in Table VII. This performance can be attributed to the discovered object use and context descriptors for these activities. For these activities, the context descriptors were accurately specific with minimal false positives. The process of discovering likely object use for routine activities significantly ensured that these activities were associated with the objects used to perform them. *Breakfast* and *Dinner* for Kasteren House and *Breakfast* and *Lunch* for Ordonez House showed lower performance due to confusions from same and similar object use with *Drink* and *Snack* respectively. These activities have shared same and similar object interactions as observed with context description process hence been classed under the superactivity *Make Food*. Recall that to further distinguish *Breakfast* and *Dinner*, they were modelled as subclasses of *Make Food* and as static activities given the specific time of the day they are performed. To enhance their recognition, time interval properties and concepts enabled by 4D fluent approach were included. They were often recognised concurrently and led to high false positives in the process. Overall, the average precision, recall and F-Score with the datasets as illustrated in Table VIII show impressive performance.

C. Learning Performance of the framework

Activities can be performed in different ways or object use for activities may differ. An activity recognition approach should be able to recognise activities irrespective of the object use and interactions. This paper evaluates the learning capability at the activity level further using the ground truth as the basis for evaluation. It should be able to return almost the same number of activity traces as in the ground truth. The results as presented in Table IX shows good performance of the learning process. *Leaving*, *Toileting*, *Sleeping* and *Showering* were recognised with significantly high instances and very little difference with the ground truth for both datasets. *Breakfast*, *Lunch* and *Dinner* showed lower performance due to high false positives and confusions from same and similar object use with *Drink*. The number of correctly recognised instances in comparison to the ground truth is also high.

D. Comparison With Other Recognition Approaches

Comparisons were made with the results presented by Kasteren et al [6], Ordonez et al [5], Ye [36], Riboni et al [32] for the Kasteren and House A as illustrated in Figure 3. Kasteren et al [6], Ordonez et al [5] and Riboni et al [32] all performed the evaluations using a "leave one day out" cross-validation, while Ye [36] used a 10-fold validation. Although Ye [36] did not use timeslices, this paper used 60 seconds timeslices similar to Kasteren et al [6], Ordonez et al [5] and Riboni et al [32]. Comparing the results directly with these other approaches, the approach proposed in this paper performed significantly better with 91.9% for the F-Score. It is assumed the weaker performance reported by Kasteren et al [6], Ordonez et al [5] and Riboni et al [32] might be due to the effect of evaluation methodology a leave one day out which meant fewer day representation for the object data. Comparing our results with Ye [36], we achieved a slightly higher F-Score which means the proposed framework for recognition is robust and significantly good.

V. Summary and Conclusion

The proposed activity recognition approach provides the basis to learn and recognise activity situations. This paper evaluated the performance of the proposed approach using the results from experiments on two publicly available datasets. Given the performance and evaluations, it can be said that

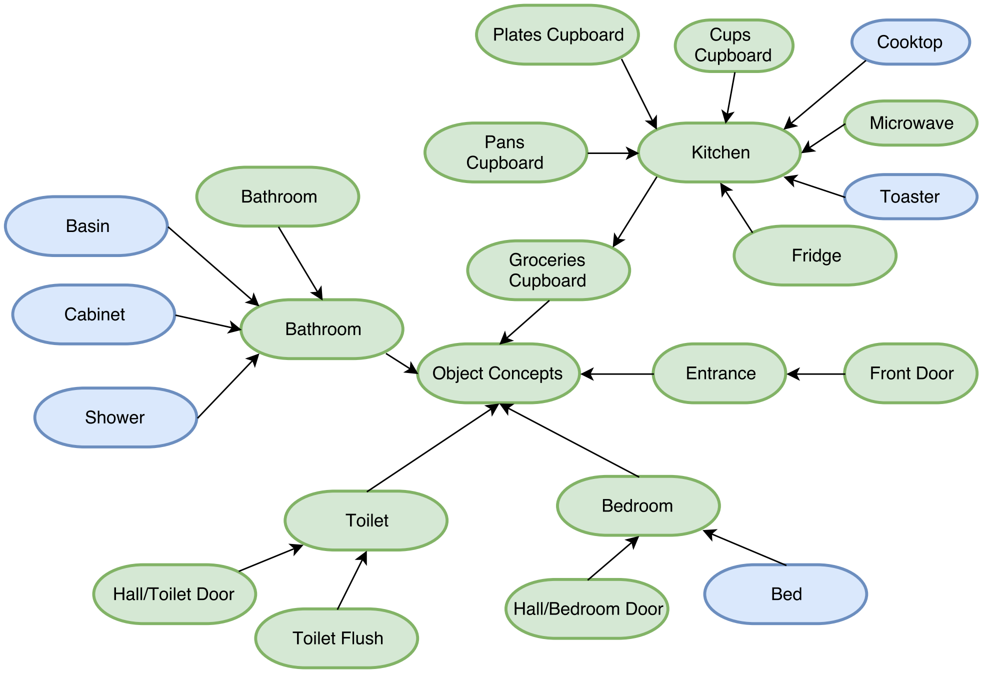

Fig. 2. Common object concepts for Kasteren and Ordonez Houses

Activities	True Positives (%)		False Positives (%)		False Negatives (%)	
	Kasteren A	Ordonez A	Kasteren A	Ordonez A	Kasteren A	Ordonez 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 VII. ACTIVITY RECOGNITION PERFORMANCE FOR KASTEREN A AND ORDONEZ A

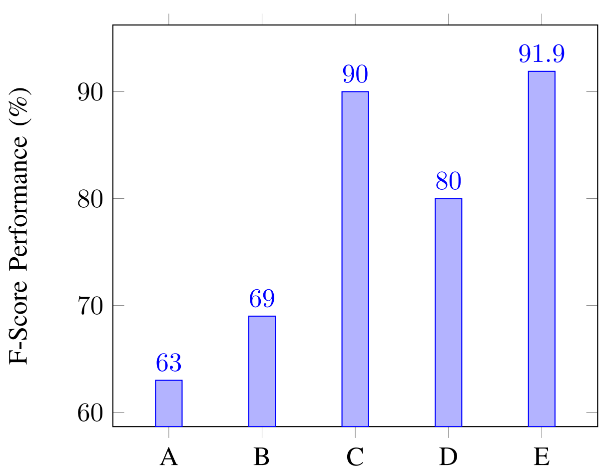

Fig. 3. A summary of evaluations using the Kasteren House A dataset for A= Kasteren et al [6]; B= Ordonez et al [5]; C= Ye [36]; D= Riboni et al [32]; E= This Paper

Data Set	Precision	Recall	F-Score
Kasteren A	88.60	95.48	91.91
Ordonez A	84.15	94.54	88.73

TABLE VIII. AVERAGE PRECISION, RECALL AND F-SCORE FOR KASTEREN A AND ORDONEZ A DATASETS

i) The discovered activity-object use distributions provide accurate context descriptors for routine activities which are then modelled as object concepts and the latter as activity concepts in an activity ontology. *ii)* Extending the activity ontology to include their temporal attributes of the objects and activity concepts as a reflection of activities evolving with time enhanced activity recognition. *iii)* Comparing the performance of the proposed approach with results published using the same datasets show it is significantly good and encouraging. The experimental and evaluation process using these datasets suggests that the features, components and the entire activity recognition process have been fully verified. The future work would involve extending the activity ontology to include more contextual features from multiple sensing devices. It should also consider extending the temporal entities and features for progressive activities as they evolve. In the future, we also intend to conduct a large-scale empirical study with other data

Activities	Ground Truth		Instances Recognised		Differences	
	Kasteren A	Ordonez A	Kasteren A	Ordonez A	Kasteren A	Ordonez A
Leaving	36	14	36	14	0	0
Toileting	114	44	114	44	0	0
Showering	24	14	22	9	2	5
Grooming	Na	51	Na	35	Na	16
Sleeping	25	14	25	14	0	0
Spare Time	Na	11	Na	11	Na	0
Breakfast	20	14	14	11	6	3
Lunch	Na	9	Na	6	Na	3
Dinner	10	Na	7	Na	3	Na
Drink	20	Na	13	Na	7	Na
Snack	Na	11	Na	6	Na	5

TABLE IX. SUMMARY OF CORRECTLY RECOGNISED ACTIVITY INSTANCES FOR KASTEREN AND ORDONEZ DATASETS

sets to establish the generality of the results reported in this paper.

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