The 2015 IEEE RIVF International Conference on Computing & Communication Technologies
Research, Innovation, and Vision for Future (RIVF)

Application of Description Logic Learning in Abnormal Behaviour Detection in Smart Homes

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***Abstract*—The population age requires assistant systems to assist the elderly to live in a familiar place as long as possible. In the wide range of the smart home applications, abnormal behaviour detection is attracting researchers due to its important benefits for the safety of the elderly people. In this research, a hybrid approach to description logic learning is proposed to learn normal behaviours of the elderly in smart homes. Negation As Failure (NAF) can be later used to detect abnormalities based on the learned rules. In addition, a methodology for generating context-awareness smart home datasets based on use cases is also proposed to evaluate the learning algorithm. The experimental results show that the proposed algorithm is suited to this problem. The learning speed and scalability of the proposed algorithm are significantly better than other description logic learning algorithms used in the comparison.**

I. Introduction

As the population ages, it is important to develop unobtrusive, affordable, computationally inexpensive, off-the-shelf smart home technologies for use in elder-care, particularly smart homes that cater for a single inhabitant. Such a system enables the elderly to live in a familiar place as long as possible. In particular elderly people who suffer from cognitive impairment are known to achieve a higher quality of life and remain independent longer when living in their own home. The reason is that many tasks fulfilled on a daily basis, often called ADLs (Activities of Daily Living), such as eating, dressing and grooming [1] are over-learned and automated processes that the elderly can still perform if they remain in a place where they are used to performing them, but are fragile when they have to be performed in unfamiliar places [2].

There are a number of related projects, such as Adaptive House [3], iDorm [4], MavHome [5], Georgia Tech Aware Home [6], and Gator Tech Smart House [6] dealing with various aspects of Smart Homes for the elderly.

During the last twenty years, the 'smart' in 'smart home' has become more important [7], [8], with a focus on behaviour recognition and subsequent abnormal behaviour detection. There have been many proposed frameworks and algorithms for behaviour recognition [9] and several discussions of what precisely a smart home that monitors behaviour should do [10]. However, there still has no system for identifying abnormal behaviours and suitable ways of dealing with them.

In this research, we are interested in the classification of normal and abnormal activities in smart homes environment, where elderly people are monitored by a system that can alert medical professionals if abnormal behaviour is detected [11]. The universal set of human behaviors is intractably large, as it is the subset of interest, the set of abnormal behaviors. If a complete set of normal behaviors were available to the smart home, it could identify abnormal behaviors by a trivial application of set theory; any behaviors that were not members of the set of normal behaviors would ipso facto be abnormal. Unfortunately, the complete set of normal behaviors, although smaller, is also so large as to be infeasible to collect.

However, it is conceivable that, with a considerable amount of effort, a significant number of the normal behaviors of a population of subjects could be documented. A smart home that was seeded with this subset of normal behaviors would be able to identify, and allow to continue without let or hindrance, a significant proportion of the inhabitant's normal behaviors. An abnormality detector that worked by complementing this subset of normal behaviors would inevitably produce annoying false positives, and a user-friendly smart home would need to be able to reduce their frequency by adding to its set of normal behaviors. Ideally, it would do this by learning about new normal behaviors for itself, but more likely by having its model corrected by a human when errors occurred.

It is important in this scenario that we do not miss any abnormal behaviours, in particular if these behaviours potentially pose a threat to the person living in the smart home. In technical terms, this means that we aim at avoiding false positives in the class of normal behaviours. In addition, using a symbolic (logic-based) approach in this context has the advantage that systems can be designed that are inherently more trustworthy than sub-symbolic machine learning approaches, as system decisions are traceable through the proofs associated with classifications.

A common problem in symbolic AI is to find the right set of rules. Here, by rules we mean the description that define concepts such as normal and abnormal behaviour. It takes a significant effort to create and maintain such a set of rules, and comprehensive validation against real world data is needed to assess its accuracy. An alternative approach is to learn the rules directly from sample datasets. This has several advantages: if it can be demonstrated by means of a formal proof that the learning algorithm produces expected rules and all available data have been fed into the learning algorithm, then validation is no longer necessary. Also, if new training

978–1–4799–8044–4/15/$31.00

data become available, the algorithm can be easily reapplied and the new definitions can be created. In other words, the system can easily be re-calibrated as needed. This implies the algorithm may be used often and the learned concept may be complex (long). Therefore, the learning speed of the algorithm and the scalability over the concept complexity becomes a major concern.

In this research, we propose a parallel and hybrid approach to description logic learning for learning normal behaviours in smart homes for abnormal behaviours detection. The algorithm employs parallelisation to speed-up the learning and the combination of the top-down and bottom-up approach to deal with the complexity of the learning. By the nature of the combination of the top-down and the bottom-up approach, our learning algorithm can be separated into two steps: first the generation of correct rules (i.e. they do not cover any negative examples) but not necessarily cover all positive examples, and then the aggregation of those rules into a (sufficiently) complete solution. In addition, there is no need to serialise these two steps: they can be performed concurrently. In particular, multiple branches within the tree of possible descriptions can be traversed concurrently by multiple workers to find partial results, while a central reducer aggregates partial results into the overall solution until all positive examples are covered. The reducer also has the responsibility of removing redundant definitions covering overlapping sets of positive examples. We discuss several strategies to do this in section 3. The experimental results will be compared with CELOE [12], one of the most up-to-date description logic learning algorithms in the DL-Learner framework [13].

In addition, we propose to use the context information in learning the normal behaviours as the ‘normality nature’ of elderly behaviours depends strongly on many environmental information [10] which we call context information. As the smart home datasets with rich context-awareness information have not been produced so far, the smart home use cases [10] have been used to generate the datasets for evaluation in this research. The methodology for generating datasets will be discussed in Section IV.

II. Related Work

Description logic learning has its roots in inductive logic programming (ILP) [14]. In ILP, sets of positive and negative examples (facts) and some background knowledge are given, and an ILP algorithm is used to compute a logic program that describes all the positive and none of the negative examples. There are two fundamentally different strategies to compute this program: top-down and bottom-up [14]. Combined strategies have also been investigated by different authors [15]. Amongst these approaches, the top-down approach is widely used as it can utilises the concept hierarchy of the description logic knowledge base effectively, such as the CELOE and OCEL algorithms in the DL-Learner framework.

Lisi [16] has proposed an alternative top-down approach based on the hybrid AL-log language which combines ALC description logic and Datalog for knowledge representation. This makes it possible to learn Datalog rules on top of ontologies.

Several other approaches to concept learning have been proposed. This includes LCSLearn [17], an early bottom-up approach that creates concepts by joining most specific concepts created for individuals (positive examples) using disjunction. This is a very simplistic approach that creates large concept definitions that are not truly intentional in a sense that those definitions are only enumerations of the sets of individuals they define. YinYang [18] is a hybrid learner that uses a combination of bottom-up (starting from most specific concepts) generalisation and top-down specialisation strategies.

In abnormal behaviour detection, there are two basic approaches: the probability-based and logic-based approaches. Most of the studies that use the probability approach have been extended from the behaviour recognition system. Most of them use the Hidden Markov Model (HMM) [19] and its variants such as Dynamic Hidden Markov Model, Hierarchical Context Hidden Markov Model (HC-HMM) [20], Switching Hidden Markov Model [21], etc.

On the other hand, the logic-based approach originally received less attention than the probabilistic-based approach. However, it is receiving more and more attention from researchers due to its expressive power and the capability for dealing with the context-awareness information. Augusto et al. [22] used event-condition-action (ECA) for representing abnormality detection rules. The system is implemented in an Active Database Management System for real-time detection. To describe complex events, the authors define an ECA-rule specification language based on Galton’s operators [23]. In Chen et al. [24], the authors use Event Calculus for cognitive modeling and abnormal behaviour reasoning within smart homes. A smart home is suggested to be formalised as a situation tree in which each node refers to a state and each edge refers to an event. Fuzzy logic is also employed to deal with this application domain in [25].

A hybrid approach is also used by Jakkula et al. [26]. The study combines both logic and probability approaches to detect abnormal behaviours. Allen temporal logic is used to describe activity patterns and the abnormalities are detected using a probabilistic model. In this method, the supporting evidence for the currently-occurring activity with respect to the previously-occurred activities is calculated to determine whether the current activity is abnormal or not.

The probabilistic approach has an advantage that it is used widely in many behaviour recognition systems. The negation as failure can be used to detect abnormal behaviour. However, this approach cannot benefit the context-awareness information as employing the context factors into Markov model may increase the model’s complexity extensively. In contrast, the logic-based approach has more expressive power and can handle the context-awareness easily. However, the detection rules currently must be defined manually. This requires a lot of efforts and it must be redefined when using the system for other smart homes.

III. A Hybrid Approach in Description Logic Learning for Abnormal Behaviour Detection

A description logic learning problem is to find a concept (description) that covers a set of examples. Given a knowledge base $\mathcal{K}$ and sets of positive $\mathcal{E}^+$ and negative $\mathcal{E}^-$ examples such that $\mathcal{E}^+ \cap \mathcal{E}^- = \emptyset$, description logic learning aims to find a description C such that $\mathcal{K} \models C(e)$ for all $e \in \mathcal{E}^+$ and $\mathcal{K} \not\models C(e)$ for all $e \in \mathcal{E}^-$. A description logic learning problem can be described as a tuple $\langle \mathcal{K}, (\mathcal{E}^+, \mathcal{E}^-)\rangle$.

In this research, a parallel description logic learning algorithm is proposed that combines both the top-down and bottom-up approaches to handle learning problems that require long definitions. In addition, a reduction operation between the top-down and bottom-up steps is also introduced to reduce the definition length. This operation can be customised to achieve other criteria instead of short definition length such as a smaller number of partial definitions (see Definition 2).

The learning process is separated into three steps: specialisation, reduction and generalisation (aggregation). First, the specialisation is used to generate correct, but not necessarily complete, description (i.e. each description must cover some positive examples and no negative ones). Then, the description produced in the first step are reduced to select the best candidates for building the final definition. Finally, the best candidates are aggregated to form the final definition. In this approach, the aggregation simply creates the disjunction of the best candidates.

Some concepts used in our approach are defined as follows:

Definition 1 (Irrelevant concept): Given a description logic learning problem $\langle \mathcal{K}, (\mathcal{E}^+, \mathcal{E}^-)\rangle$, a description C is called irrelevant if $\mathcal{K} \not\models C(e)$ for all $e \in \mathcal{E}^+$, i.e. it covers none of the positive examples.

Definition 2 (Partial definition): Given a learning problem $LP = \langle \mathcal{K}, (\mathcal{E}^+, \mathcal{E}^-)\rangle$, a concept is called a partial definition if it is correct (i.e. covers no negative example) and not irrelevant (covers some positive examples) with respect to LP. It is also called the definition of the covered positive examples.

Therefore, the first step of the approach aims to find partial definitions for the positive examples. Formally, given a learning problem $LP = \langle \mathcal{K}, (\mathcal{E}^+, \mathcal{E}^-)\rangle$, this step is to find a set of partial definitions $\mathcal{P}$ such that $\bigcup_{p_i \in \mathcal{P}} cover(\mathcal{K}, p_i, \mathcal{E}^+) = \mathcal{E}^+$. The finding of partial definitions uses the top-down approach, which starts from the most general concept `TOP`. Then, the downward refinement operator proposed by Lehmann et al. [27] is adopted to specialise the concepts until all positive examples are covered by the partial definitions. The descriptions are organised as a tree of descriptions called the *search tree*. The *children of a node* are the refinement result of their *parent node*. Therefore, the learning problem is a search for partial definitions in a search tree.

The downward refinement operator used in CELOE [27] is modified to make it suitable for our approach. The top-down step of our algorithm aims to find the partial definitions instead of a complete definition. In addition, since the disjunction is used in the generalisation step to combine the partial definitions, it is not necessary to use disjunction in the top-down step.

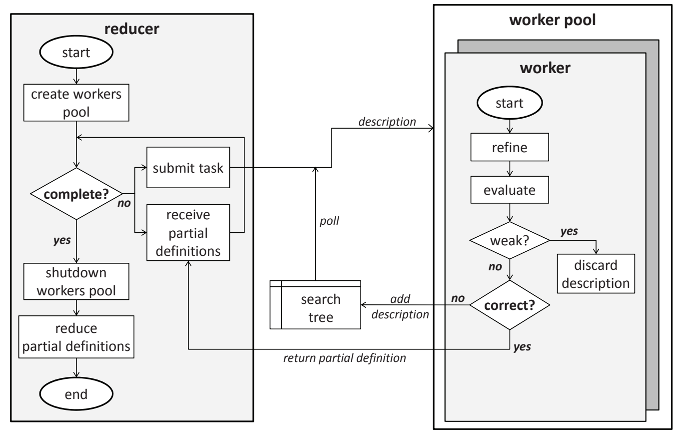

Fig. 1. Reducer-Worker interaction

The selection of nodes (descriptions) in the search tree is controlled by the score of the nodes that are calculated by a search heuristic. In addition, parallelisation is employed to find the partial definitions in parallel. In particular, multiple branches within the tree can be traversed by multiple *workers* to find the partial definitions. A central *reducer* monitors the finding of the partial definitions of the workers until the partial definitions cover all positive examples. Then, it aggregates the partial definitions to the overall definition. The reducer also has the responsibility of removing redundant partial definitions that cover overlapping sets of positive examples.

This approach follows the general idea of the map-reduce architecture [28] and therefore it lends itself to parallelisation using multiple threads to take advantage of multi-core processors. An informal illustration of the algorithm is given in Figure 1 that shows the interaction between the two parts of the algorithm: i) the workers that receive the assigned descriptions from the reducer and then produce the refinements of the descriptions and find the partial definitions within the refinement result, and ii) the reducer that monitors the workers and then compacts and aggregates the partial definitions when the learning is finished. The formal algorithms of the reducer and workers are given in Algorithm 1 and Algorithm 2 respectively.

The reducer creates a worker pool, which manages a number of workers, assigns new tasks (class expressions for refinement and evaluation) to the worker pool, and updates the agenda and the set of cumulative partial definitions based on the refinement result returned from workers until the completeness of the combined partial definitions is sufficient. Then the reducer tries to reduce the number of partial definitions in order to remove redundancies using a reduction function. The reduction algorithm is based on a set coverage algorithm [29] with different sorting strategies had been implemented.

The workers perform the heavy computations: they refine descriptions in the search tree and evaluate new descriptions. This is done using multiple workers. The evaluation of descrip-

Algorithm 1: Reducer Algorithm

Input: a description logic learning problem $\langle \mathcal{K}, (\mathcal{E}^+, \mathcal{E}^-) \rangle$ and a noise value $\varepsilon \in [0, 1]$ (0: no noise).

begin
- *search_space* = $\{\top\}$ /* $\top$: TOP */
- *cum_pdefs* = $\emptyset$ /* parital def. */
- *cum_upos* = $\mathcal{E}^+$ /* uncovered ex. */
- initialise the *worker_pool* /* worker pool */
- **while** $|cum\_upos| > (|\mathcal{E}^+| \times \varepsilon)$ **do**
  - execute the following tasks in parallel:
  - **begin** [**task**: submit tasks to *worker_pool*]
    - **if** *worker_pool* is not full **then**
      - select the highest score description *C* in *search_space*
      - submit new task $(C, \mathcal{E}^+, \mathcal{E}^-)$ to *worker_pool*
  - **begin** [**task**: receive result from workers]
    - wait for sets of (*descriptions*, *pdefs*) from workers
    - *search_space* = *search_space* $\cup$ *descriptions*
    - *cum_pdefs* = *cum_pdefs* $\cup$ *pdefs*
    - /* remove positive examples covered by *pdefs* */
    - *cum_upos* = *cum_upos* $\setminus cover(\mathcal{K}, pdefs, \mathcal{E}^+)$
- **return** REDUCE(*cum_pdefs*) /* Alg. ?? */

Algorithm 2: Worker Algorithm

Input: a description *C*, a set of positive $\mathcal{E}^+$ and negative $\mathcal{E}^-$ examples

begin
- *refinements* = $\rho(C)$ /* refine *C* */
- *descriptions* = $\emptyset$ /* new descriptions */
- *pdefs* = $\emptyset$ /* partial definitions */
- **foreach** *exp* $\in$ *refinements* **do**
  - evaluate(*exp*) /* calculate *exp* correctness and completeness */
  - **if** *exp* is not irrelevant **then**
    - **if** *exp* is correct **then**
      - *pdefs* = *pdefs* $\cup$ *exp*
    - **else**
      - *descriptions* = *descriptions* $\cup$ *exp*

return *(expressions, pdefs)*

tions (i.e. checking whether a given example is an instance of a concept) requires an ontology reasoner and Pellet [30] is used for this purpose.

The worker will first check whether descriptions are irrelevant. If it is the case, the descriptions can be safely removed from the computation as no partial definition can be computed through specialisation. If a description is a partial definition (i.e. correct and not irrelevant), it is added to the partial definitions set. If a description is not irrelevant, but also not correct, it is added to the set of new descriptions. Then the worker returns these sets back to the reducer.

The coordination of the reducer and workers is done using a search tree, which contains the descriptions to be refined, and ordering of the descriptions within the search tree is controlled by the expansion scores computed by an expansion heuristic. Given a learning problem $LP = \langle \mathcal{K}, (\mathcal{E}^+, \mathcal{E}^-) \rangle$, the expansion score of a description C is computed as follows:

$$
\begin{aligned}
score(C) = {} & correctness(C, LP) \\
& + \alpha \times gain(C, LP) \\
& + \beta \times completeness(C, LP) \\
& - \gamma \times length(C) \\
& (\alpha \geq 0, \beta \geq 0, \gamma \geq 0)
\end{aligned}
$$

where

$$
\begin{aligned}
gain(C, LP) &= \ accuracy(C, LP) - accuracy(C', LP) \\
correctness(C, LP) &= \frac{|un(C, LP)|}{|\mathcal{E}^-|} \\
completeness(C, LP) &= \frac{|cp(C, LP)|}{|\mathcal{E}^+|} \\
accuracy(C, LP) &= \frac{|un(C, LP) \cup cp(C, LP)|}{\mathcal{E}^+ \cup \mathcal{E}^-}
\end{aligned}
$$

in which $un(C, LP) = \mathcal{E}^- \setminus \{e \mid K \models C(e)\}$ is a set of negative examples not covered by C and $cp(c, LP) = \mathcal{E}^+ \cap \{e \mid K \models C(e)\}$ is a set of positive examples covered by C.

The reduction algorithm is actually the set covered algorithm [29]. We implemented three greedy set coverage algorithms that are based on the optimisation of the number of partial definitions, the partial definition length and the partial generation time. Due to the limitation of length of the paper, we do not present them here. More details can be found in [31].

IV. Evaluation

1) Evaluation datasets: Our research focuses on the context-awareness information of the smart homes as it effects strongly on the elderly people behaviours [11]. Adding more context-awareness information may help to identify the abnormal behaviours of the elderly more accurately. However, as there is currently no context-awareness smart homes dataset, we created the synthetic smart home datasets based on the use cases that particularly focus on describing normal and abnormal behaviours of an inhabitant in a smart home. A major

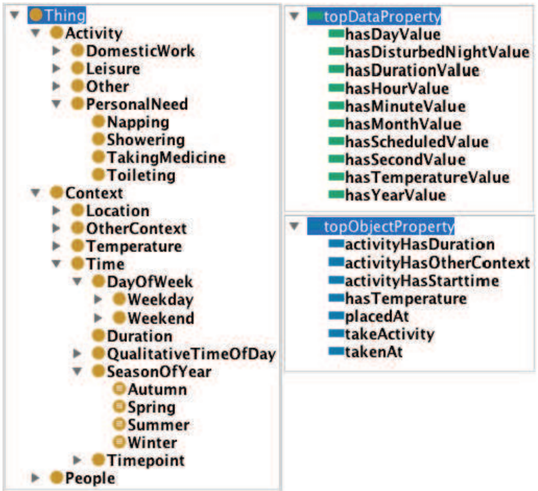

Fig. 2. Dataset knowledge base

difference between this dataset and other smart home datasets is that this dataset has richer context awareness information. In most of the existing smart home datasets such as MIT [32], the only context information involved is the time. However, the time data in that dataset is only used to represent the order of the activities in the dataset. Other information of the time data is not used such as the day of week and the season.

In our synthetic smart home dataset, more information is involved such as seasons, weekday/weekend, day of week, etc. A part of the dataset knowledge based is shown in Figure 2, visualized by Protege including the class hierarchy and properties. The knowledge base also contains some equivalent classes for reasoning about the seasons given the month of year.

In our experiments, two use cases UCA1 and UCA2 in [10] are simulated. The UCA1 describes an over-long shower while the later concerns a justifiably short shower. In both use cases, shower duration is supposed to depend upon the seasons. The scenarios were modeled using the Bayesian Network and then it was used to generate the synthetic datasets. The actual datasets contain a set of showering activities, their start times and durations. More details can be found in [31].

2) Experimental result: For the experiments, we used a Linux server with a 8 x Intel Xeon E5440 @2.83GHz processor, 32GB memory and the Redhat 4.1.2 (Linux version 2.6.18) operating system with a JRE 1.6.0 (64-bit) Java Virtual Machine (JVM). The heap size of the JMV in our experiments is 5GB.

The 10-fold cross validation method is used to measure the learning time and accuracy. The results are compared with CELOE. An investigation on description logic learning algorithms shows that this is one of the best description logic learning algorithms in the DL-Learner framework and outperforms most of the current description logic learning algorithms [33]. A t-test rejected the null hypothesis for all learning problems at the 95% confidence level is used to test the statistically significant difference between experimental

TABLE I
EXPERIMENTAL RESULTS (AVERAGE $\pm$ STANDARD DEVIATION OF 10 FOLDS). BOLD VALUES: STATISTICALLY SIGNIFICANTLY BETTER THAN THE UNFORMATTED VALUES AT 95% CONFIDENCE LEVEL.

Dataset	Learning time (s)		Accuracy (%)		Definition length	
	CELOE	Our alg.	CELOE	Our alg.	CELOE	Our alg.
UCA1	int.* @600s	**29.75 ±5.77**	91.42 ±7.01	**100.00 ±0.00**	9.00 ±0.00	51.00 ±0.00
UCA2	int.** @600s	**60.72 ±27.78**	94.61 ±2.45	**98.57 ±3.52**	12.00 ±0.00	52.80 ±4.47

*: *Interrupted by timeout*

results.

The experimental result is shown in Table I. On the UCA1 dataset, CELOE could not find an accurate definition for the training set after the learning timeout, which was set at 600s. The predictive accuracy of the learned definition on the test set is 91.42%. For our algorithm, it found a accurate definition for the test set after 29.75 $\pm$ 5.77s and the predictive accuracy of the learned definition on the test set is 100%. Both the learning time and the predictive accuracy of our algorithm are statistically significantly better than the CELOE algorithm at 95% confidence level. The definitions produced by the two algorithms are as follows:

- CELOE:
```
activityHasDuration SOME
(hasDurationValue >= 4.5 AND
hasDurationValue <= 19.5)
```
- Our algorithm (4 partial definitions):
  1)
  ```
  activityHasDuration SOME
  (hasDurationValue >= 4.5 AND
  hasDurationValue <= 15.5)
  ```
  2)
  ```
  activityHasDuration SOME
  (hasDurationValue >= 15.5 AND
  hasDurationValue <= 19.5) AND
  activityHasStarttime SOME Spring
  ```
  3)
  ```
  activityHasDuration SOME
  (hasDurationValue >= 15.5 AND <= 19.5)
  AND activityHasStarttime SOME Summer
  ```
  4)
  ```
  activityHasStarttime SOME Autumn AND
  activityHasDuration SOME
  (hasDurationValue >= 4.5 AND
  hasDurationValue <= 19.5)
  ```

On the UCA2 dataset, CELOE also could not find an accurate definition for the training set within the timeout and the predictive accuracy of CELOE on this dataset is 94.61 $\pm$ 2.45%. In contrast, our algorithm found an accurate definition for the training set within 60.72 $\pm$ 27.78s. The predictive accuracy of our algorithm on this dataset is 98.57 $\pm$ 3.52%, which is also statistically significantly better than CELOE at 95% confidence level.

V. CONCLUSION

Our description logic learning approach shows a promising result on the datasets used in the evaluation. By dividing the learning process into two stages, the task was able to be spread over several subprocesses that can run in parallel. As a result, multi-core machines were able to be utilised, which fastens the learning process.

In most datasets in the experiment, our learning algorithm produced promising results in terms of both accuracy and learning time. Decreasing of learning time was not only caused by the parallelisation, but also by the conquer and divide strategy, which is enabled by the combination of the top-down and the bottom-up learning approaches. Obviously, finding separate simple definitions is easier than finding one complete definition. Therefore, this approach is suitable for learning normal activities in smart home as the patterns of the normal behaviours are usually complex.

Moreover, due to the high expressiveness power of description logic, the produced definitions of the normal behaviours are human-friendly and readable. Therefore, the verification of the learned definitions can be taken easily. In addition, this feature can be combined with the justification capability of the description logic reasoners to issue the explanations for the conclusions produced by the detection system. This is an essential requirement for some types of application that require a high level of trust in the decisions of the system such as expert systems for human disease diagnosis, or decision support systems for elderly care.

A disadvantage of our learning approach is that it produced longer definitions than CELOE. In some circumstances, long definitions were needed to describe accurately the learning problems. However, there were also unnecessarily long definitions caused by overlap between partial definitions. Using normalisation and simplification can reduce the definition length [34]. This has not been implemented yet and it is left for future work. In addition, more experiments on more smart home datasets are also needed to have a more thoughtful investigation on this approach for smart home application.

References

[1] R. Newcomer, T. Kang, M. LaPlante, and S. Kaye, "Living quarters and unmet need for personal care assistance among adults with disabilities," *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, vol. 60, no. 4, pp. S205–S213, 2005.

[2] R. Bucks, D. Ashworth, G. Wilcock, and K. Siegfried, "Assessment of activities of daily living in dementia: development of the bristol activities of daily living scale," *Age and ageing*, vol. 25, no. 2, pp. 113–120, 1996.

[3] U. of Colorado, "The adaptive house," http://www.cs.colorado.edu/ mozer/house/, last visited: 1/09/2014.

[4] H. Hagras, V. Callaghan, M. Colley, G. Clarke, A. Pounds-Cornish, and H. Duman, "Creating an ambient-intelligence environment using embedded agents," *IEEE Intelligent Systems*, pp. 12–20, 2004.

[5] G. Youngblood, "MavHome research scope," http://serenity.uncc.edu/youngblood-old/papers/MVH-2003-2_MavHome_Scope_2003.pdf, last visited: 1/09/2014.

[6] U. of Florida, "Gator tech smart house," http://www.icta.ufl.edu/gt.htm, last visited: 1/09/2014.

[7] S. Giroux and H. Pigot, *From Smart Homes to Smart Care: ICOST 2005 (Assistive Technology & Research)*. IOS Press, USA, 2005.

[8] A. Carlos and M. Paul, "Ambient Intelligence: Concepts and applications," *Computer Science and Information Systems*, vol. 4, no. 1, pp. 1–27, 2007.

[9] S. Chua, S. Marsland, and H. Guesgen, "Spatio-temporal and context reasoning in smart homes," in *Proceeding of COSIT workshop on Spatial and Temporal Reasoning for AmI System*, 2009, pp. 9–20.

[10] P. Lyons, A. T. Cong, H. J. Steinhauer, S. Marsland, J. Dietrich, and H. W. Guesgen, "Exploring the responsibilities of single-inhabitant smart homes with use cases," *Journal of Ambient Intelligence and Smart Environments*, vol. 2, no. 3, pp. 211–232, 2010.

[11] A. C. Tran, S. Marsland, J. Dietrich, H. W. Guesgen, and P. Lyons, "Use cases for abnormal behaviour detection in smart homes," in *Aging Friendly Technology for Health and Independence*. Springer, 2010, pp. 144–151.

[12] J. Lehmann, *Learning OWL Class Expressions*. AKA Akademische Verlagesellschaft, 2010.

[13] ——, "DL-Learner: Learning concepts in Description logics," *The Journal of Machine Learning Research*, vol. 10, pp. 2639–2642, 2009.

[14] S. Muggleton, "Inductive logic programming," *New generation computing*, vol. 8, no. 4, pp. 295–318, 1991.

[15] J. Zelle, R. Mooney, and J. Konvisser, "Combining top-down and bottom-up techniques in inductive logic programming," in *Proceedings of the 11th International Conference on Machine Learning*, 1994, pp. 343–351.

[16] F. Lisi, "Building rules on top of ontologies for the semantic web with inductive logic programming," *Theory and Practice of Logic Programming*, vol. 8, no. 3, pp. 271–300, 2008.

[17] W. Cohen and H. Hirsh, "Learning the classic description logic: Theoretical and experimental results," in *Proceedings of the 4th international conference on principles of knowledge representation and reasoning*. Citeseer, 1994, pp. 121–133.

[18] L. Iannone and I. Palmisano, "An algorithm based on counterfactuals for concept learning in the semantic web," *Innovations in Applied Artificial Intelligence*, pp. 370–379, 2005.

[19] K. Hara, T. Omori, and R. Ueno, "Detection of unusual human behavior in intelligent house," in *Proc. Neural Networks for Signal Processing XII-proceedings of the 2002 IEEE Signal Processing Society Workshop*, 2002, pp. 697–706.

[20] P. Chung and C. Liu, "A daily behavior enabled hidden Markov model for human behavior understanding," *Pattern Recognition*, vol. 41, no. 5, pp. 1589–1597, 2008.

[21] T. Duong, H. Bui, D. Phung, and S. Venkatesh, "Activity recognition and abnormality detection with the switching hidden semi-Markov model," in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. IEEE Computer Society, 2005, pp. 20–25.

[22] J. Augusto and C. Nugent, "The use of temporal reasoning and management of complex events in smart homes," in *ECAI*, vol. 16, 2004, pp. 778–782.

[23] A. Galton, "Eventualities," *Handbook of temporal reasoning in Artificial Intelligence*, pp. 25–58, 2005.

[24] L. Chen, C. Nugent, M. Mulvenna, D. Finlay, X. Hong, and M. Poland, "Using Event Calculus for behaviour reasoning and assistance in a smart home," in *Proceedings of the 6th international conference on Smart Homes and Health Telematics*. Springer, 2008, pp. 81–89.

[25] G. Acampora and V. Loia, "Fuzzy control interoperability and scalability for adaptive domotic framework," *Industrial Informatics, IEEE Transactions on*, vol. 1, no. 2, pp. 97–111, 2005.

[26] V. Jakkula and D. Cook, "Anomaly detection using temporal data mining in a smart home environment," *Methods of Information in Medicine*, vol. 47, no. 1, pp. 70–75, 2008.

[27] J. Lehmann and P. Hitzler, "Concept learning in description logics using refinement operators," *Machine Learning*, vol. 78, no. 1, pp. 203–250, 2010.

[28] J. Dean and S. Ghemawat, "Mapreduce: Simplified data processing on large clusters," *Communications of the ACM*, vol. 51, no. 1, pp. 107–113, 2008.

[29] T. Cormen, *Introduction to algorithms*. The MIT press, 2001.

[30] B. Parsia and E. Sirin, "Pellet: An owl dl reasoner," in *Third International Semantic Web Conference-Poster*, 2004, p. 18.

[31] C. A. Tran, "Symmetric parallel class expression learning," Ph.D. dissertation, 2013.

[32] E. Tapia, S. Intille, and K. Larson, "Activity recognition in the home using simple and ubiquitous sensors," *Pervasive Computing*, pp. 158–175, 2004.

[33] S. Hellmann, "Comparison of concept learning algorithms," Master's thesis, The University of Leipzig, 2008.

[34] F. Baader, D. Calvanese, D. L. McGuinness, D. Nardi, and P. F. Patel-Schneider, *The description logic handbook: Theory, implementation and applications*. Cambridge University Press, 2010.